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D6.1

Analysis of task complexity factors

Safe tolerance zone calculation and interventions for driver-vehicle-environment interactions under challenging conditions

iDREAMS

Project identification

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Annex

Glossary and Abbreviations

Abbreviation	Description
ADAS	Advanced Driver Assistance Systems
AIC	Akaike Information Criteria
BIC	Bayesian Information Criterion
CC	Cubic Centimetres
CFI	Comparative Fit Index
DBN	Dynamic Bayesian Network
DCM	Discrete Choice Model
FCW	Forward Collision Warning
GFI	Goodness of Fit Index
GLM	Generalized Linear Model
HP	Horsepower
i-DREAMS	smart Driver and Road Environment Assessment and Monitoring System
IBI	Inter-Beat-Interval
LSTM	Long Short Term Memory network
PCW	Pedestrian Collision Warning
RMSEA	Root Mean Square Error Approximation
SEM	Structural Equation Model
STZ	Safety Tolerance Zone
TLI	Tucker Lewis Index
UK	United Kingdom

Executive Summary

The main goal of the *i*-DREAMS project was to establish a framework that enables the definition, development, testing and validation of a context-aware safety envelope for driving called the '**Safety Tolerance Zone**' (**STZ**). This could be accomplished through the implementation of a smart Driver, Vehicle & Environment Assessment and Monitoring System (*i*-DREAMS). With the i-DREAMS project, data was collected from car, truck and bus drivers during on-road trials conducted in Belgium, Germany, Greece, Portugal and the United Kingdom.

The aim of this deliverable is to analyse the impact of task complexity on risk within the context of a four-phase on-road trial. The study consisted of four consecutive phases; Phase 1 involved observing driving behaviour without intervention following the installation of the i-DREAMS system. In Phase 2, in-vehicle real-time warnings were given using adaptive Advanced Driver Assistance Systems (ADAS) while monitoring continued. Phase 3 combined in-vehicle warnings with feedback via an app, and in Phase 4, gamification features were added to the app with the added support of a web dashboard.

The aim of this report is to examine the impact of task complexity factors, such as road layout, traffic, time of day, weather, etc., on risk. The objectives are to determine which task complexity factors have the most significant impact on risk, create Structural Equation Models (SEM) to understand how task complexity affects the Safety Tolerance Zone (STZ) and compare the effects of task complexity on risk for different countries and transport modes during the four phases of the i-DREAMS road-trial.

Task complexity relates to the current status of the real-world context in which a vehicle is being operated. Since this context is consistent of various individual elements which, together, determine the complexity of the task imposed on the vehicle operator, a multi-dimensional approach in further operationalizing this concept is adopted. In particular, task complexity context is monitored via registration of road layout (i.e., highway, rural, urban), time and location, traffic volumes (i.e., high, medium, low) and weather.

In terms of the methodology, generalized linear and structural equation modelling techniques were utilized to investigate the factors that define task complexity and how it relates to risk. Both task complexity and risk were treated as latent variables, which are not directly observable. Despite a unified data collection design, technical issues such as sensor failures and driver availability arose during the data collection process in different countries. As a result, different datasets were obtained, and different variables were selected for the models to ensure their validity.

The SEM analysis involved the development of four models per risk factor (e.g., speeding and headway), one for each phase, to identify any differences in the way task complexity impacts risk. However, due to the issues mentioned earlier, it was not possible to make a direct comparison between countries or transport modes. In some cases, not only the variables that represent task complexity vary, but also the variables that represent risk differ. Thus, the results could only be interpreted on a country and transport mode basis. It is noteworthy that age and gender were not significant factors in any of the models across different countries and transport modes.

Measuring task complexity and relating this to risk was a challenging task as the number of variables that were collected and could be used was restricted and therefore, proxies were utilised. For instance, weather conditions were indicated by the use of the wipers and lighting conditions, or night-time driving was assessed by the use (or not) of the high beams.

In general, the collection of the initially planned variables was proven to be trickier than anticipated. Future research should consider these challenges and attempt to incorporate information on factors like road configuration, traffic density, and other relevant metrics that would be very useful for establishing the complexity of the driving task and its association with risk.

1 Introduction

The goal of this section is to provide a brief outline of the objectives of the specific deliverable, how those are aligned and relevant with the overall project, and which approach was followed in order to achieve them.

1.1 About the project

The overall objective of the *i*-DREAMS project is to setup a framework for the definition, development, 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).

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 'Safety Tolerance Zone' (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 comprises 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 behaviour to meet task demands.

Taking into account driver background factors and real-time risk indicators associated with the driving performance as well as the driver state and driving task complexity indicators, a continuous real-time assessment will be made to monitor and determine if a driver is within acceptable boundaries of safe operation (i.e., Safety Tolerance Zone). Moreover, the to-be-developed *i*-DREAMS platform will offer a series of in-vehicle interventions, meant to prevent drivers from getting too close to the boundaries of unsafe operation and to bring them back into the safety tolerance zone while driving. The safety-oriented interventions will be developed to inform or warn the driver real-time 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/behaviours. Consequently, the *i*-DREAMS platform will allow the implementation of the two aforementioned safety interventions, meant to motivate and enable human operators to develop the appropriate safety-oriented attitude.

Specifically, the in-vehicle interventions are meant to assist and support vehicle operators in real-time (i.e., while driving). Depending on how imminent crash risks are, a distinction can be made between a 'Normal driving' phase, a 'Danger' phase, and an 'Avoidable Accident' phase. In the normal driving phase, no abnormalities in a vehicle operator's driving style are detected by the monitoring pillar of the *i*-DREAMS platform, and no sign of a crash course initiating is present. Consequently, no real-time intervention is required. In the danger phase, abnormal deviations from the vehicle operator's driving style are detected by the *i*-DREAMS monitoring module, and the potential for a crash course to unfold is present. A warning signal is to be issued in that case. In the avoidable accident phase, deviations from normal driving have evolved even further, and the risk for a crash to occur will become imminent if the vehicle operator does not adapt appropriately to the present circumstances. A more intrusive warning signal is to support vehicle operators in avoiding a collision.

With regards to post-trip interventions, these are not operational while driving, but they are based on what happens during a trip. They hinge upon all the raw data that is captured by the *i*-DREAMS sensors, which is further processed and fused into information about a vehicle operator's driving style, how it evolved during a trip, how many (safety-critical) events occurred, and in which circumstances these events happened. This information can be further translated into feedback consultable for vehicle operators via an app in a pre- or post-trip setting. To establish a longer-term relationship with individual vehicle operators, app-supported feedback can be combined with the use of a web-based coaching platform, containing so-called gamification features meant to motivate drivers to work on a gradual and persistent improvement of their driving.

Figure 1 summarizes the conceptual framework, which has been tested in a simulator study and three stages of on-road trials in Belgium, Germany, Greece, Portugal and the United Kingdom with a total of 600 participants representing car, bus, truck and tram/train drivers.

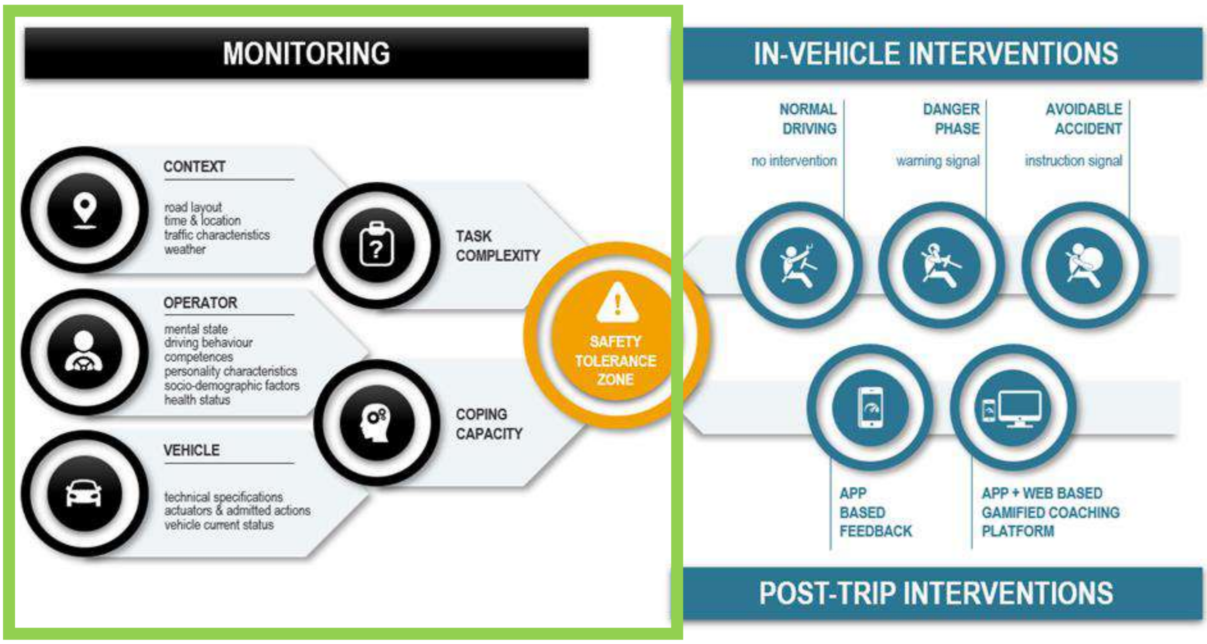

Figure 1: Conceptual framework of the i-DREAMS platform. The green frame indicates the thematic scope of D6.1 (see section 1.2)

Expected by the end of the project in 2023, the key output of the project will be an integrated set of monitoring and communication tools for intervention and support, including in-vehicle assistance and feedback and notification tools, as well as a gamified platform for self-determined goal setting, working with incentive schemes, training, and community building tools. Furthermore, a user-license Human Factors database with anonymised data from the simulator and field experiments will be developed.

1.2 About this report

The work presented in this deliverable relates to the left part of Figure 1 (see green box), i.e., the determination of safety tolerance zone via monitoring of task complexity and coping capacity. Staying within the Safety Tolerance Zone, vehicle operators avoid situations in which a collision becomes unavoidable. As can be seen in Figure 1, the Safety Tolerance Zone is subdivided in three segments, i.e., 'normal driving', the 'danger phase', and the 'avoidable accident phase'. For the real-time determination of this Safety Tolerance Zone, the monitoring module in the i-DREAMS platform continuously registers and processes data for all variables related to the context and to the vehicle. Regarding the operator however, continuous data registration and processing are limited to mental state and behaviour. Data related to operator competence, personality, socio-demographic background, and health status, are collected via survey questionnaires.

This report mainly focuses on the analysis of task complexity factors. Following exploratory analysis, the latent variable associated to task complexity will be estimated from the various relevant indicators, including weather, lighting conditions, vehicle specifications, actuators and admitted actions, etc. The effect of task demand on risk will be defined and further analysed for different countries, transport modes, age or gender groups, etc. The Task will develop and test pilot Structural Equation Models of the effect of the task complexity on the STZ levels regarding headway, speed measurements, and vehicle control events (harsh breaking, harsh acceleration, harsh cornering).

1.1.1 Aim and objectives

The aim of this deliverable is to investigate the effects of task complexity related factors (road layout, traffic, time of the day, weather, etc.) on risk. The objectives include the:

- **Identification of the impact of the most critical factors** of task complexity on risk.
- **Development of Structural Equation Models (SEMs)** of the effect of task complexity on the Safety Tolerance Zone (STZ).
- **Comparison of the effect of task complexity on risk** across the four phases of i-DREAMS road-trial on a country and transport mode basis.

1.1.2 Structure

The rest of the deliverable is divided into four chapters.

Chapter 2 provides a **detailed description of the field trial study design**. In particular, an overview of the obtained dataset, the questionnaire data collected as well as the procedure followed for data aggregation and cleaning is clearly explained. In addition, the definition of task complexity is provided, and the variables used to define task complexity and risk are presented.

This is followed by a **description of the methodological approach** (Chapter 3) in which the purpose of this analysis along with the concept of Multivariate Regression Analysis (e.g., Generalized Linear Modelling technique) and latent variables analysis (e.g., Structural Equation Models) are highlighted. The key performance indicators and appropriate metrics that are commonly used for model evaluation and selection are also descripted.

A major part of this deliverable is dedicated to the **mathematical modelling of the STZ** (Chapter 4), where Generalized Linear Models and Structural Equation Models are implemented in order to turn the available measurements into meaningful information on the Safety Tolerance Zone level. Comparisons among the examined countries (i.e., Belgium, UK, Germany, Greece) and different transport modes (i.e., cars and trucks) have also been attempted.

Lastly, Chapter 5 draws the **main findings along with practical conclusions** and gives recommendations for further research.

2 *i*-DREAMS Data Collection

2.1 Experiment description

Within the i-DREAMS project, a **naturalistic driving experiment** was carried out involving several drivers from Belgium, UK, Germany, Portugal and Greece and a large database of thousands trips was created. A detailed description of the on-road driving trials for identifying Safety Tolerance Zone and the performance of in-vehicle interventions can be found in previous Deliverable 5.3 (Hancox et al., 2021).

It should be highlighted that the i-DREAMS field trials are the first time that all components of the complete i-DREAMS system are combined in a real-world setting that can be used by individuals and organisations outside of the i-DREAMS project.

The objectives of the on-road trials in i-DREAMS are to:

- **test the driving behaviour** and validate the STZ mathematical model
- test if the i-DREAMS system **influences driver safety**
- **assess the effect of the interventions** (developed as part of the i-DREAMS system) for both real-time and post-trip warnings and
- obtain the user feedback about the **acceptance and acceptability** of the i-DREAMS system

The on-road trials in i-DREAMS were designed based on several proven principles derived from previous literature focusing on testing interventions in order to assist drivers in maintaining the Safety Tolerance Zone (STZ). As the first stage of the field trials, **pilot testing** was performed for a limited number of vehicles (i.e., five vehicles) for each test site. The purpose of the pilot tests was to fine-tune the i-DREAMS technology. This includes all the processes associated with production, installation, and interventions but also collection, processing and visualisation of data. In addition, it offered the chance to implement changes based on user feedback before transitioning to large-scale testing.

The on-road trials will focus on monitoring driving behaviour and the impact of real-time interventions (i.e., in-vehicle warnings) and post-trip interventions (i.e., post-trip-feedback & gamification) on driving behaviour.

The experimental design of the i-DREAMS on-road study is displayed in Table 1 and has been subdivided into **four consecutive phases**:

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

Table 1: Description and duration of each Phase

Phases	Description	Duration per participant
Phase 1	Baseline measurement (no interventions)	4 weeks
Phase 2	In-vehicle intervention	4 weeks
Phase 3	Post-trip feedback on the smartphone	4 weeks
Phase 4	Post-trip feedback on smartphone + gamified web platform	6 weeks

Firstly, **Phase 1** of the field trials refers to a reference period after the installation of the i-DREAMS system in order to monitor driving behaviour without interventions. Secondly, **Phase 2** of the field trials refers to a monitoring period during which only in-vehicle real-time warnings were provided using adaptive Advanced Driver Assistance Systems (ADAS). In **Phase 3** of the field trials, feedback via the i-DREAMS smartphone app is combined with in-vehicle warnings. Lastly, in **Phase 4** of the field trials, gamification features are added to the app, with additional support of a web-dashboard.

In its essence, the i-DREAMS project focuses on calibrating the subjective experience of coping capacity and task demand in driving. The interaction between these concepts is best investigated by applying a combined nudging-coaching approach (D3.3, Brijs, K., et al., 2020). This combined approach is used as the **blueprint of the on-road trials' experimental design**.

Figure 2 provides an overview of the different phases of the experimental design of the i-DREAMS on-road study.

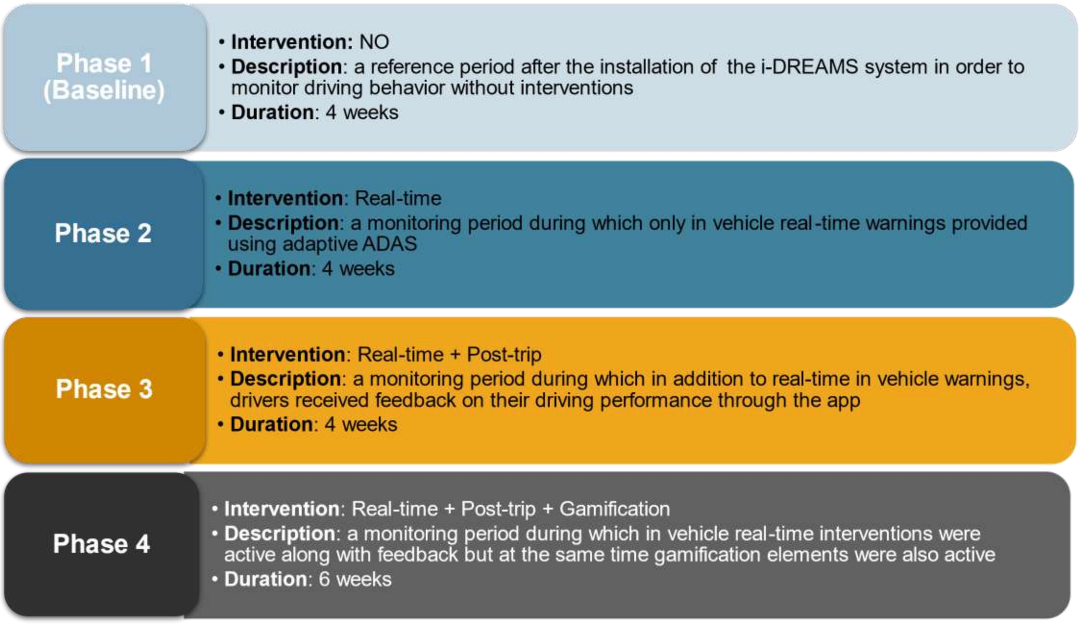

Figure 2: Overview of the different phases of the experimental design of the i-DREAMS on-road study

2.2 Overview of the backend platform

As the key output of the i-DREAMS project is an integrated set of monitoring and communication tools for intervention and support, state-of-the-art technologies and systems can be utilised in order to monitor driving performance indicators. More specifically, data from the **Mobileye system** (Mobileye, 2022), a dash camera and the **Cardio gateway** (CardioID Technologies, 2022) which records driving behaviour (e.g., speed, acceleration, deceleration, steering) along with GNSS signals were used. In particular, the Mobileye system is a network-based sensor that measures parameters, like time headway. Information about the current warning stage, as defined by Mobileye, were also collected for comparison with the i-DREAMS warning stage (i.e., normal driving, danger phase, avoidable accident phase). At the same time, information about the current state of the i-DREAMS platform were gathered.

The **fundamental challenge within the i-DREAMS project** is how explanatory variables (i.e., performance metrics and indicators of task complexity and coping capacity) are correlated with the dependent variable “risk” in order to predict STZ.

There are three main types of variables which are used in i-DREAMS:

- **Discrete variables**: variables that are categorical (ordinal or nominal) and can only take discrete values from the real numbers. A few examples of discrete variables in i-DREAMS could be fatigue (yes, no), time of the day (daytime, night-time driving) and STZ (normal phase, danger phase, avoidable accident phase).
- **Continuous variables**: variables that can take any values from the real numbers. A few examples of continuous variables in i-DREAMS could be speed, headway and composite variables, such as weighted sum or weighted average variables.
- **Latent variables**: variables that are not observed directly by the analyst and therefore, it is not known whether they are continuous or discrete. Examples of latent variables in i-DREAMS are task complexity and coping capacity which are latent explanatory variables and thus, observed indicators are needed to measure them. Risk is also conceived in i-DREAMS as a latent variable.

Explanatory variables of risk and the most **reliable indicators of task complexity**, such as weather and lighting conditions, average speed, headway, month, day of the week, harsh accelerations, harsh braking, distance travelled, duration, forward collision warnings, lane departure warnings or pedestrian collision warnings will be assessed.

Specifically, the **main risk factors** (variables to represent the latent construct of risk) that will be explored within the analyses of this deliverable are:

- Speeding
- Headway
- Overtaking
- Fatigue
- Harsh accelerations
- Harsh braking
- Vehicle control events (combination of harsh acceleration, braking and cornering events)

Table 2 provides an overview of the variables available along with their corresponding description.

Table 2: Driving performance indicators of the analyzed data along with their corresponding description (Source: Mobileye, CardioID)

Source	Variable	Description	Unit	Type	Range
	grpby_seconds	Total trip duration	seconds	Integer	
	trip_uuid	Unique ID of the trip		String	
	driver_uuid	Unique driver ID		String	
	vehicle_uuid	Unique ID of the vehicle		String	
	vehicle_class	Vehicle class identifier		String	Car, Bus, Truck, Train, Tram
	trip_start	The trip start date and time in ISO8601 format		String	
	trip_end	The trip stop date and time in ISO8601 format		String	
	Phase	phase of the experiment		Integer	1 - no interventions/monitoring , 2 - real-time warnings, 3 - real-time warnings and post-trip feedback, 4 - real-time warnings and post-trip feedback along with gamification
i-Dreams STZ	iDreams_Headway_Map_level__-1	Real-time headway intervention level -1 **level -1 => no vehicle detected (Normal Driving)**		Integer	0 - intervention level unequal to -1 1 - intervention level equal to -1
	iDreams_Headway_Map_level__0	Real-time headway intervention level 0 **level 0 => vehicle detected, but headway >= 2.5 (Normal Driving)**		Integer	0 - intervention level unequal to 0 1 - intervention level equal to 0
	iDreams_Headway_Map_level__1	Real-time headway intervention level 1 **level 1 => vehicle detected, headway < 2.5, but above warning threshold (Normal Driving)**		Integer	0 - intervention level unequal to 1 1 - intervention level equal to 1
	iDreams_Headway_Map_level__2	Real-time headway intervention level 2 **level 2 => first warning stage (Dangerous Driving)**		Integer	0 - intervention level unequal to 2 1 - intervention level equal to 2
	iDreams_Headway_Map_level__3	Real-time headway intervention level 3 **level 3 => second warning stage (Avoidable Accident)**		Integer	0 - intervention level unequal to 3 1 - intervention level equal to 3
	iDreams_Overtaking_Map_level__0	Real-time overtaking intervention level 0 **level 0 => no warning (Normal Driving)**		Integer	0 - intervention level unequal to 0 1 - intervention level equal to 0
	iDreams_Overtaking_Map_level__1	Real-time overtaking intervention level 1 **level 1 => visual warning (Normal Driving)**		Integer	0 - intervention level unequal to 1 1 - intervention level equal to 1

Source	Variable	Description	Unit	Type	Range
	iDreams_Overtaking_Map_level__2	Real-time overtaking intervention level 2 **level 2 => visual and auditory warning (Dangerous Driving)**		Integer	0 - intervention level unequal to 2 1 - intervention level equal to 2
	iDreams_Overtaking_Map_level__3	Real-time overtaking intervention level 3 **level 3 => frequent warning (Avoidable Accident)**		Integer	0 - intervention level unequal to 3 1 - intervention level equal to 3
	iDreams_Speeding_Map_level__0	Real-time speeding intervention level 0 **level 0 => no warning (Normal Driving)**		Integer	0 - intervention level unequal to 0 1 - intervention level equal to 0
	iDreams_Speeding_Map_level__1	Real-time speeding intervention level 1 **level 1 => visual indication (Normal Driving)**		Integer	0 - intervention level unequal to 1 1 - intervention level equal to 1
	iDreams_Speeding_Map_level__2	Real-time speeding intervention level 2 **level 2 => visual speeding warning (Dangerous Driving)**		Integer	0 - intervention level unequal to 2 1 - intervention level equal to 2
	iDreams_Speeding_Map_level__3	Real-time speeding intervention level 3 **level 3 => visual and auditory warning (Avoidable Accident)**		Integer	0 - intervention level unequal to 3 1 - intervention level equal to 3
	iDreams_Fatigue_Map_level__0	Real-time fatigue intervention level 0 **level 0 => no warning (Normal Driving)**		Integer	0 - intervention level unequal to 0 1 - intervention level equal to 0
	iDreams_Fatigue_Map_level__1	Real-time fatigue intervention level 1 **level 1 => visual warning (Dangerous Driving)**		Integer	0 - intervention level unequal to 1 1 - intervention level equal to 1
	iDreams_Fatigue_Map_level__2	Real-time fatigue intervention level 2 **level 2 => visual and auditory warning (Dangerous Driving)**		Integer	0 - intervention level unequal to 2 1 - intervention level equal to 2
	iDreams_Fatigue_Map_level__3	Real-time fatigue intervention level 3 **level 3 => frequent warnings (Dangerous Driving)**		Integer	0 - intervention level unequal to 3 1 - intervention level equal to 3
Gateway IMU	DrivingEvents_Map_lvl__H	H - High event (harsh acceleration, harsh braking, and harsh cornering) severity level		String	0 - high event severity level not detected 1 - high event severity level detected
	DrivingEvents_Map_lvl__L	L - Low event (harsh acceleration, harsh braking, and harsh cornering) severity level		String	0 - low event severity level not detected 1 - low event severity level detected
	DrivingEvents_Map_lvl__M	M - Medium event (harsh acceleration, harsh braking, and harsh cornering) severity level		String	0 - medium event severity level not detected 1 - medium event severity level detected

Source	Variable	Description	Unit	Type	Range
	DrivingEvents_Map_evt__ha	Type of event - harsh acceleration: 'ha'		String	0 - harsh acceleration not detected 1 - harsh acceleration detected
	DrivingEvents_Map_evt__hb	Type of event - harsh braking: 'hb'		String	0 - harsh braking not detected 1 - harsh braking detected
	DrivingEvents_Map_evt__hc	Type of event - harsh cornering: 'hc'		String	0 - harsh cornering not detected 1 - harsh cornering detected
	IBI_value	Time interval between successive heart beats	milliseconds	Integer	
Mobileye	ME_Car_speed	Vehicle speed	km/h	Integer	
	ME_Car_wipers	Wipers		Boolean	0 - missing values False - Wipers are off, True - Wipers are on
	ME_Car_high_beam	High-beam		Boolean	0 - missing values False - High-beam is off True - High-beam is on
	ME_AWS_hw_measurement	Headway measurement	seconds	Float	
	ME_AWS_tsr_level	Traffic sign recognition level	km/h or mp/h	Integer	0 - no warning, 1 - 0-5 units over speed limit, 2 - 5-10 units over speed limit, 3 - 10-15 units over speed limit, 4 - 15-20 units over speed limit, 5 - 20-25 units over speed limit, 6 - 25-30 units over speed limit, 7 - 30+ units over speed limit
	ME_AWS_fcw	Forward collision warning		Boolean	0 - missing values False - Forward collision warning is inactive True - Forward collision warning is active
	ME_AWS_ldw	Lane departure warning		Boolean	0 - missing values False - Lane departure warning is inactive True - Lane departure warning is active (left or right)
	ME_AWS_pcw	Pedestrian collision warning		Boolean	0 - missing values False - Pedestrian collision warning is inactive True - Pedestrian collision warning is active

Source	Variable	Description	Unit	Type	Range
	ME_AWS_pedestrian_dz	Pedestrian in danger zone		Boolean	0 - missing values False - Pedestrian not detected in danger zone True - Pedestrian detected in danger zone
	ME_AWS_time_indicator	Indicates lighting conditions		String	1 - day, 2 - dusk, 3 - night
	ME_TSR_tsr_1_speed	Display 1 speed traffic sign code		Integer	
	GPS_spd	Speed	km/h	Float	
	GPS_distances	Total trip distance	km	Float	
	ME_LDW_Map_type_L_mean	Left lane departure warning		Boolean	0 - missing values False - Left lane departure warning is inactive True - Left lane departure warning is active
	ME_LDW_Map_type_R_mean	Right lane departure warning		Boolean	0 - missing values False - Right lane departure warning is inactive True - Right lane departure warning is active

2.3 Questionnaires

In addition to the vehicle data, questionnaire data were also collected both before and after the trial. The number of participants who answered both for the entry and exit questionnaires and for which data was available at the time of writing this deliverable is:

- 54 car drivers in UK
- 45 car drivers and 40 truck drivers in Belgium
- 44 car drivers in Greece
- 29 car drivers in Germany.

The full questionnaires are given in i-DREAMS Deliverable 7.2 in Annex 2 (Brown et al., 2023). Information collected pre-trial included:

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

Information collected post-trial included:

- **User experience questionnaire**: opinions on the i-DREAMS system (ease of use, works as described), opinions on the i-DREAMS smartphone app (ease of use, usefulness).
- **Exit questionnaire**: opinions on the i-DREAMS system (improvement of driving, usefulness, trust, clarity of warnings, etc.,), experience of driving situations, driver behaviour (driving and non-driving related behaviours), overall experience rating.

In particular, a set of twelve questions were asked identically at both trial entry and trial exit (respectively EQ11 and EX3 in Annex 2 of i-DREAMS Deliverable 7.2), to allow analysis of before and after responses. These questions related to the areas of perceived knowledge, self-efficacy, attitude, personal norm, and subjective norm. The theory used in the development of these questions is described in more detail in i-DREAMS Deliverable 7.1 (Katrakazas et al., 2020).

2.4 Aggregation and cleaning

In the transportation research domain, traffic data used for behaviour prediction or safety assessment are usually aggregated (Abdel-Aty et al., 2005, Franke and Krems, 2013) in order for post-trip or post-event interventions to be applied. At the same time, real-time applications (Habtemichael et al., 2012, Vlahogianni and Barmpounakis, 2017) demand the use of highly disaggregated time-series data, in order to identify different behaviours or critical events in a very short time horizon.

Highly disaggregated data which describe all the available driving performance indicators, such as average speed, headway, harsh acceleration or harsh braking were collected. A methodological framework was employed in which data were aggregated in **30-second or 60-**

second intervals and the mean and standard deviations of the aforementioned kinematic characteristics were extracted. It should be noted that the aforementioned intervals have been also utilized in previous traffic safety studies (Katrakazas et al., 2019).

The most crucial step in the data aggregation and cleaning was to identify the **Not Available** (**NA) values and remove validly the missing data** from the dataset. Then, a basic procedure was followed per each type of variable. There are two different types of indicators that appear in the data: level-type variables and continuous variables. "Level-type" variables include the speeding, headway measurements, overtaking, fatigue and harsh events. Harsh events appear in a categorization of high, medium, and low events, but also as harsh braking, harsh acceleration, and harsh cornering events.

With regards to headway, overtaking, speeding and fatigue levels, for the trips that had at least one value per aggregation row, the remaining levels were imputed with 0. For instance, in case there were valid values for 2 (out of 4) levels and values for the 3rd and 4th level were NAs, an imputation with 0 in the remaining levels was made. In the case where there were NA values for all levels, a replacement of NA values with -9999 value was made. Afterwards, a check per each aggregation row was implemented to ensure the accuracy and the validity of the data aggregation approach. As the aggregated variables were added in the form of mean and sum, the summary of each aggregation row should be equal to 1 in the case of the mean and equal to 30 in the case of the sum (30s aggregation level). Similarly, a check per each aggregation row was implemented in order to ensure the accuracy and the validity of the data aggregation in the case of harsh events and the summary of each aggregation row for the aforementioned variables should be equal to the corresponding variable in total (low + medium + high).

Lastly, as per "**continuous"** variables, such as speed, distance, headway, forward collision warning, pedestrian collision warning, etc, the replacement of NA values was done by the imputation with the mean or median value of the corresponding variable per trip.

2.5 Variables used

After an extensive data cleaning and preparation, the next step of the analysis involved a collinearity testing so that any highly correlated variables were excluded from the models. When two variables have an absolute value of correlation coefficient at least 0.6, then these two variables are highly correlated. The **most appropriate variables were selected** to be included in the GLM and SEM analysis, using either correlation or feature selection algorithms.

➢ **<u>The context and definition of task complexity</u>**

The cornerstone of the i-DREAMS platform is the assessment of task complexity and coping capacity. According to the i-DREAMS concept of a context-aware Safety Tolerance Zone, 'risk' results from the interaction of 'task complexity' and 'coping capacity'. However, these three core aspects are **unobserved / latent variables**, which cannot be measured directly, but can be estimated by various metrics. Based on the aforementioned, task complexity as a latent variable can be measured by metrics and indicators related mostly to the road environment, traffic or weather. Coping capacity is also a latent variable, including two distinct aspects, each one being a latent variable itself. These are vehicle state and operator state. Risk as a latent variable can be measured by indicators such as danger phase events and avoidable accident events, as detected by the safety tolerance zone monitor. Latent variables analysis will be performed with dedicated techniques such as Structural Equation Modelling. Figure 3 illustrates the conceptual framework of the i-DREAMS platform for the prediction of risk in function of coping capacity and task complexity.

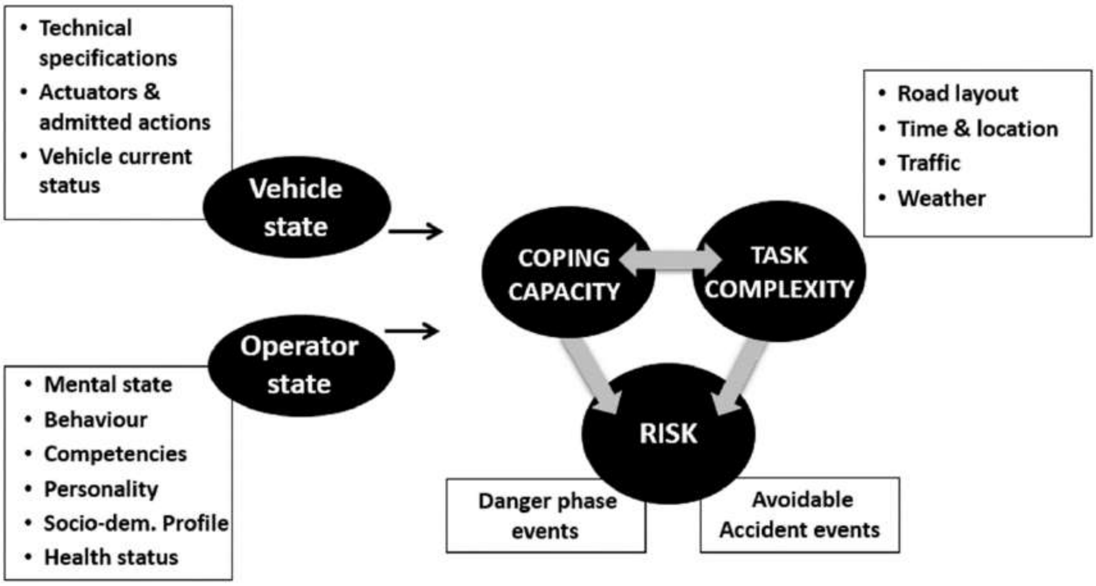

Figure 3: Post-hoc prediction of risk in function of coping capacity and task complexity

This deliverable is focused on the latent construct of task complexity, but i-DREAMS Deliverables 6.2 and 6.3 are relevant to coping capacity and the overall effect of task complexity and coping capacity to risk respectively.

Task complexity relates to the current status of the real-world context in which a vehicle is being operated. Since this context is consistent of various individual elements which, together, determine the complexity of the task imposed on the vehicle operator, a multi-dimensional approach in further operationalizing this concept is adopted. In particular, task complexity context is monitored via registration of road layout (i.e., highway, rural, urban), time and location, traffic volumes (i.e., high, medium, low) and weather.

The most appropriate variables which were eventually used in the frame of this study, in order to define task complexity, are shown in Table 3, along with the variables that were finally utilised to represent risk.

Table 3: Variables for task complexity and risk

Task complexity		Risk
Car wipers	Vehicle age	Headway map levels
Car high beam	Day of the week	Speeding map levels
Time indicator	Month	Overtaking map levels
Distance	Number of right lane departure warnings	Fatigue map levels
Duration	Number of pedestrian collision warnings	Harsh acceleration/braking
Average speed		Vehicle control events

Unfortunately, information about the road layout and traffic conditions that would be very relevant, they were not available in the data collected. Although a consistent data collection design was employed, technical difficulties such as sensor malfunctions and driver availability complications occurred during the data collection process in the different countries. As a consequence, diverse datasets were acquired, and distinct variables were chosen for the models to ensure their reliability. Descriptive statistics (i.e., average, standard deviation, max, min) for the available parameters in the database that were used for the different countries (i.e., Belgium, UK, Germany, Greece, Portugal) and transport modes (i.e., cars, trucks, buses) per each phase are presented in Annex 1.

3 Methodology

3.1 Purpose of the analysis

There are two main purposes for data analysis in i-DREAMS, prediction and explanatory analysis, and the type of analytical methods to be used depends on these purposes:

- **Prediction** is mostly done to identify (in real-time) the level of the STZ at which the driver is, and in order to trigger real-time in-vehicle interventions.
- **Explanatory analysis** is mostly done to identify the relationship between risk and factors contributing to risk. This relationship may help better understand the underlying reasons of driving behaviour and ultimately help improve interventions (both in-vehicle and post trip). In addition, understanding the effects of explanatory variables on risk may also help evaluating the effectiveness of interventions.

Another dimension of data analysis in i-DREAMS is the temporal element of data analysis:

- **Real-time**: The collected data may be analysed in real-time (e.g., large amount of data, time series nature of real-time data);
- **Post-trip**: The collected data may be aggregated and analysed after the trip has been completed.

Proper analytical methods have been used to capture the unique properties of data in both cases. However, it is noted that, while it seems intuitive that real-time data analysis corresponds to the **prediction purpose**, and post-trip data analysis corresponds to the explanatory analysis purpose, it may be worth investigating whether there are additional combinations applicable within the scope of i-DREAMS.

It should be mentioned that the analytical models for STZ identification have already been described in previous project deliverables, D3.2 (Katrakazas et al., 2020) and D4.2 (Yang et al., 2020). In summary, Dynamic Bayesian Networks (DBNs), Long-Short-Term-Memory networks (LSTMs), as well as Discrete Choice Models (DCM), Principal Component Analysis (PCA) and Structural Equation Models (SEM) can be used for STZ identification and explanation of measurement impacts. Furthermore, a plethora of analytical tools have been already documented in order to be able to predict or explain safety risk and the impact of interventions.

A schematic overview of the proposed mathematical models (DBN, LSTM, DCM and SEM) to be considered for the analysis is given in Figure 4.

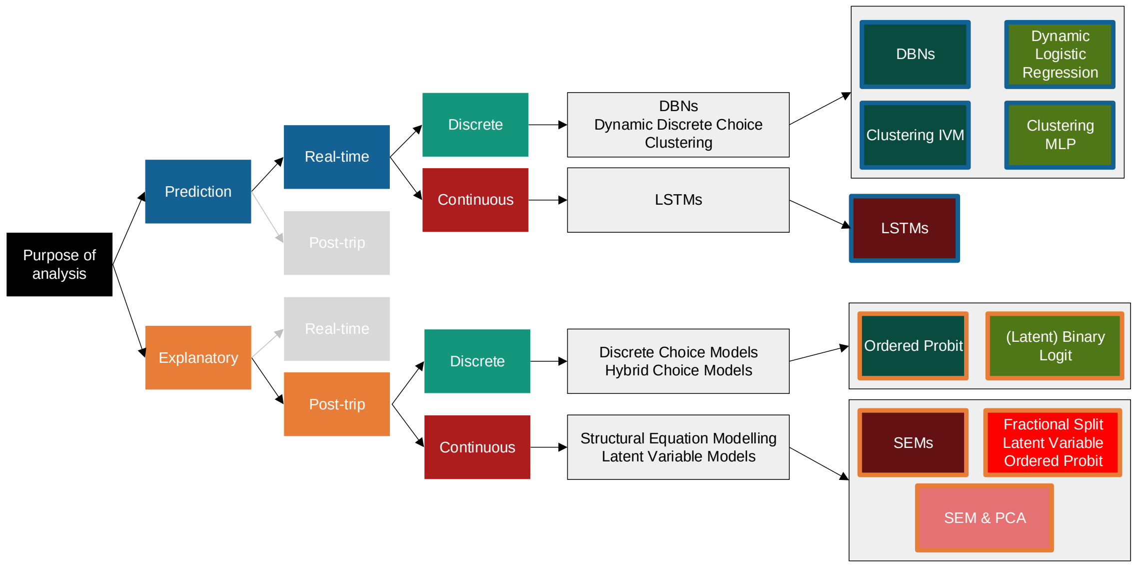

Figure 4: Schematic overview of modelling approaches considered for the analysis of risk factors

Following the **Big Data analysis** and processing carried out in previous Deliverables, the processed data analysis methods include two families of techniques:

- **Multivariate regression analysis** (e.g., Generalized Linear Models) for exploratory analysis in order to identify the key correlations between observed metrics while controlling for the differences between the sample groups.
- **Latent variables analysis** (e.g., Structural Equation Models) for latent analysis in order to quantify the effects between latent and observable variables of task complexity and coping capacity with complex relationships.

3.2 Generalized Linear Models (GLMs)

In statistics, the **Generalized Linear Model** (GLM) is a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution. The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value (Hastie & Pregibon, 2017).

Generalized linear models were formulated as a **way of unifying various other statistical models**, including linear regression, logistic regression and Poisson regression. In particular, Hastie & Tibshirani (1990) proposed an iteratively reweighted least squares method for maximum likelihood estimation of the model parameters. Maximum-likelihood estimation remains popular and is the default method on many statistical computing packages. Other approaches, including Bayesian approaches and least squares fits to variance stabilized responses, have been developed.

A key point in the development of GLM was the **generalization of the normal distribution** (on which the linear regression model relies) to the exponential family of distributions. This idea was developed by Collins et al. (2001). Consider a single random variable y whose probability (mass) function (if it is discrete) or probability density function (if it is continuous) depends on a single parameter θ. The distribution belongs to the exponential family if it can be written as follows (equation 1):

$$f(y;\theta) = s(y)t(\theta)e^{a(y)b(\theta)} \tag{1}$$

where: a, b, s, and t are known functions. The symmetry between y and θ becomes more evident if the equation above is rewritten as follows (equation 2):

$$f(y;\theta) = \exp[\alpha(y)b(\theta) + c(\theta) + d(y)] \tag{2}$$

where: $s(y)=exp[d(y)]$ and $t(\theta)=exp[c(\theta)]$

If a(y) =y then the distribution is said to be in the canonical form. Furthermore, any additional parameters (besides the parameter of interest θ) are regarded as nuisance parameters forming parts of the functions a, b, c, and d, and they are treated as though they were known. Many well-known distributions belong to the **exponential family**, including Poisson, normal or binomial distributions. On the other hand, examples of well-known and widely used distributions that cannot be expressed in this form are the student's t-distribution and the uniform distribution.

It should be mentioned that the **Variance Inflation Factor (VIF)** is a measure of the amount of multicollinearity in regression analysis. Multicollinearity exists when there is a correlation between multiple independent variables in a multiple regression model. VIF measures how much the variance of the estimated regression coefficient for a particular predictor variable is increased due to multicollinearity with the other predictor variables in the model. A VIF value of 1 indicates no multicollinearity, whereas higher VIF values indicate increasing severity of multicollinearity. The default VIF cut-off value is 5; only variables with a VIF less than 5 will be included in the model (VIF<5). However, in certain cases, even if VIF is less than 10, it can be accepted.

3.3 Structural Equation Models (SEMs)

Structural Equation Modelling (SEM) is widely used for **modelling complex and multi-layered relationships** between observed and unobserved variables, such as 'task complexity' etc. Observed variables are measurable, whereas unobserved variables are latent constructs – analogous to factors or components in a factor / principal component analysis.

Structural equation models 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 direct.

The **general formulation** of SEM is as follows (Washington et al., 2011; 2020):

$$\eta = \beta\eta + \gamma\xi + \varepsilon \quad (3)$$

where η is a vector of endogenous variables, ξ is a vector of exogenous variables, β and γ are vectors of coefficients to be estimated, and ε is a vector of regression errors.

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

$x = \Lambda_x\xi + \delta$, for the exogenous variables (4)

$y = \Lambda_y\eta + \zeta$, for the endogenous variables (5)

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, and 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 so as to reflect whether the explanatory variables are correlated causes, mediated causes, or independent causes to the dependent variable.

3.4 Model goodness-of-fit measures

In the context of model selection, **model Goodness-of-Fit measures** constitute an important part of any statistical model assessment. Several goodness-of-fit metrics are commonly used, including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the comparative fit index (CFI), the Tucker-Lewis Index (TLI), the (standardized) Root Mean Square Error Approximation (RMSEA), the goodness-of-fit index (GFI), and Hoelter's index. Such criteria are based on differences between the observed and modelled variance-covariance matrices. A detailed description of the aforementioned metrics is presented below:

The **Akaike Information Criterion (AIC),** which accounts for the number of included independent variables, is used for the process of model selection between models with different combination of explanatory variables (Vrieze, 2012).

$$AIC = -2L(\theta) + 2q \quad (6)$$

where: q is the number of parameters and $L(\theta)$ is the log-likelihood at convergence. Lower values of AIC are preferred to higher values because higher values of $-2L(\theta)$ correspond to greater lack of fit.

The **Bayesian Information Criterion (BIC)** is used for model selection among a finite set of models; models with lower BIC are generally preferred.

$$BIC = -2L(\theta) + q\ln(N) \quad (7)$$

The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) provide measures of model performance that account for model complexity. AIC and BIC combine a term reflecting how well the model fits the data with a term that penalizes the model in proportion to its number of parameters.

The **Comparative Fit Index (CFI)** is based on a noncentral x^2 distribution. It evaluates the model fit by comparing the fit of a hypothesized model with that of an independence model. The values of CFI range from 0 to 1, indicating a good fit for the model when the value exceeds 0.95 (Lee & Sohn, 2022). In general, values more than 0.90 for CFI are generally accepted as indications of very good overall model fit (CFI>0.90). The formula is represented as follows:

$$CFI = 1 - \frac{\max({x_H}^2 - df_H, 0)}{\max({x_H}^2 - df_H, {x_I}^2 - df_I)} \qquad (8)$$

where: x^2_H is the value of x^2 and df_H is degrees of freedom in the hypothesized model, and x^2_I is the value of x^2 and df_I is the degrees of freedom in the independence model.

The **Tucker Lewis Index (TLI)** considers the parsimony of the model. Therefore, if the fit indices of two models are similar, a simpler model (i.e. greater degrees of freedom) is chosen. TLISI is an unstandardized value, so it can have a value less than 0 or greater than 1. It indicates a good fit for the model when the value exceeds 0.95 (Lee & Sohn, 2022). In general, values more than 0.90 for TLI are generally accepted as indications of very good overall model fit (TLI>0.90). The formula is represented as follows:

$$TLI = \frac{\frac{{x_I}^2}{df_I} - \frac{{x_H}^2}{df_H}}{\frac{{x_I}^2}{df_I} - 1} \qquad (9)$$

where: x^2_H is the value of x^2 and df_H is the degrees of freedom in the hypothesized model, and x^2_I is the value of x^2 and df_I is the degrees of freedom in the independence model.

Currently, one of the most widely used goodness-of-fit indices is the **Root Mean Square Error Approximation (RMSEA)**. RMSEA measures the unstandardized discrepancy between the population and the fitted model, adjusted by its degrees of freedom (df). Different proposals have been made as to the correct use of RMSEA. The most common approach is to calculate and interpret the sample's RMSEA (McDonald & Ho, 2002). RMSEA is considered a "badness-of-fit measure," meaning that lower index values represent a better-fitting model. RMSEA index ranges between 0 and 1. Its value 0.05 or lower is indicative of model fit with observed data. P close value tests the null hypothesis that RMSEA is no greater than 0.05. If P close value is more than 0.05, the null hypothesis is accepted that RMSEA is no greater than 0.05 and it indicates the model is closely fitting the observed data (RMSEA<0.05). The formula is represented as follows:

$$RMSEA = \sqrt{\frac{{x_H}^2 - df_H}{df_H(n-1)}} \qquad (10)$$

where: x^2_H represents the discrepancy between the observed and predicted covariance matrices for each element H, df_H represents the degrees of freedom in the hypothesized model and n is the sample size.

The **Goodness of Fit Index (GFI)** is a measure of fit between the hypothesized model and the observed covariance matrix. The adjusted goodness of fit index (AGFI) corrects the GFI, which is affected by the number of indicators of each latent variable (Baumgartner & Hombur, 1996). The GFI and AGFI range between 0 and 1, with a value of over 0.9 generally indicating acceptable model fit. In general, values more than 0.90 for GFI are generally accepted as indications of very good overall model fit (GFI>0.90).

Lastly, the **Hoelter's** index is calculated to find if chi-square is insignificant or not. Hoelter's index involves calculating the critical value of the test statistic (e.g., t-value or F-value) at a predetermined significance level (alpha), and then identifying the sample size at which this critical value is equal to or greater than the maximum value of the test statistic that can be obtained for that sample size. This sample size is considered the minimum sample size required to achieve the desired level of statistical power. If Hoelter's index is more then 200, then the model is considered to be good fit with observed data (Hoelter>200). Values of less than 75 indicate very poor model fit. The Hoelter's index only makes sense to interpret if N > 200 and the chi square is statistically significant.

4 Task complexity analysis

4.1 Generalized Linear Models

A large number of distinct models were evaluated, with a wide range of variations in the explanatory variables and configurations, in order to comprehensively explore the potential relationships and determine the optimal model fit. For each configuration, different alternatives were tested through the respective log-likelihood test comparisons. Subsequently, the final models were selected as the ones with the independent variable configuration with the **lowest AIC and BIC values** for each developed model. Generalized Linear Models (**GLM**) were employed to investigate the relationship of key performance indicators (i.e., speeding, headway, overtaking and fatigue) for German, Belgian, Greek car drivers and Portuguese bus drivers.

4.1.1 Germany (Cars)

4.1.1.1 Speeding

The relationship between speeding and risk is widely recognized in the road safety community and as such, speeding is a commonly used dependent variable in transportation human factors research. The first Generalized Linear Regression model investigated the relationship between the **speeding and several explanatory variables of task complexity**, such as distance travelled, duration, harsh acceleration, time indicator as well as high beam. The model parameter estimates are summarized in Table 4.

Table 4: Parameter estimates and multicollinearity diagnostics of the GLM for speeding (German cars)

Variables	Estimate	Standard Error	z-value	Pr(|z|)	VIF
(Intercept)	1.396	0.025	55.011	< .001	-
grpby_seconds (trip duration)	0.002	3.317×10^{-5}	74.618	< .001	1.208
GPS_distances_sum	5.258×10^{-4}	3.626×10^{-5}	14.503	< .001	1.017
DrivingEvents_Map_evt_ha_mean	1.313×10^{-4}	1.954×10^{-6}	67.186	< .001	1.214
ME_Car_high_beam_median - Off	0.658	0.058	11.417	< .001	1.062
ME_AWS_time_indicator_median	8.107×10^{-5}	1.897×10^{-6}	42.736	< .001	1.064
Summary statistics					
AIC	127971.813				
BIC	127981.881				
Degrees of freedom	174299				

Based on Table 4, it can be observed that all the explanatory variables are statistically significant at a 95% confidence level; there is no issue of multicollinearity as the VIF values are much lower than 5. With regard to the coefficients, it was revealed that the indicators of task complexity such as time and high beam were positively correlated with speeding. Furthermore, it was demonstrated that harsh accelerations, distance and duration had a positive relationship with the dependent variable (i.e., speeding), indicating that as the values of the aforementioned independent variables increases, speeding also increases. This is a noteworthy finding of the current research as it confirms that harsh driving behaviour events present a statistically significant positive correlation with speeding.

4.1.1.2 Headway

One of the major contributors to road crashes is the headway between two vehicles; when it is too short to allow the following driver to react appropriately to sudden braking by the leading vehicle. The headway between two vehicles can be expressed in terms of time and space.

Within this framework, the second GLM investigated the relationship between the **headway and several explanatory variables of task complexity**, such as distance travelled, duration, harsh acceleration, time indicator as well as high beam. An attempt was made to use the same independent variables in the model applied. The model parameter estimates are summarized in Table 5.

Table 5: Parameter estimates and multicollinearity diagnostics of the GLM for headway (German cars)

Variables	Estimate	Standard Error	z-value	Pr(|z|)	VIF
(Intercept)	-5.744	0.077	-74.689	< .001	-
grpby_seconds	5.789×10^{-5}	1.236×10^{-5}	4.684	< .001	1.220
GPS_distances_sum	-6.874×10^{-4}	7.306×10^{-5}	-9.409	< .001	1.161
DrivingEvents_Map_evt_ha_mean	6.347×10^{-5}	6.411×10^{-6}	9.900	< .001	1.097
ME_Car_high_beam_median - Off	7.178	0.074	97.391	< .001	2.495
ME_AWS_time_indicator_median	-8.396×10^{-5}	8.515×10^{-6}	-9.861	< .001	2.519
Summary statistics					
AIC	62116.795				
BIC	62126.863				
Degrees of freedom	174299				

Findings derived from Table 5 demonstrated that all the explanatory variables were statistically significant at a 95% confidence level. In addition, there was no issue of multicollinearity as the VIF values are much lower than 5. With respect to the coefficients, it was found that time of the day (indicator of task complexity) was negatively correlated with headway, which means that drivers tend to keep safer distances from the vehicle in front of them during the night. This may probably be due to the fact that there is no heavy traffic during night hours; thus, headway events are avoided. Interestingly, high beam was positively correlated with headway. Moreover, harsh accelerations and duration appeared to have a positive relationship with the dependent variable (i.e., headway), while distance travelled was negatively correlated with headway.

4.1.1.3 Overtaking

The third GLM investigated the relationship between the **overtaking and several explanatory variables of task complexity**, such as distance travelled, duration, harsh acceleration, time indicator, as well as high beam. It should be noted here that overtaking variable has been coded as 0 for not risky overtaking and 1 for risky overtaking. The model parameter estimates are summarized in Table 6.

Table 6: Parameter estimates and multicollinearity diagnostics of the GLM for overtaking (German cars)

Variables	Estimate	Standard Error	z-value	Pr(|z|)	VIF
(Intercept)	-6.074	0.087	-69.466	< .001	-
grpby_seconds	8.142×10^{-5}	1.264×10^{-5}	6.439	< .001	1.221
GPS_distances_sum	-7.156×10^{-4}	7.363×10^{-5}	-9.718	< .001	1.163
DrivingEvents_Map_evt_ha_mean	6.628×10^{-5}	6.409×10^{-6}	10.341	< .001	1.098
ME_Car_high_beam_median - Off	7.433	0.084	88.281	< .001	3.041
ME_AWS_time_indicator_median	-1.144×10^{-4}	9.476×10^{-6}	-12.072	< .001	3.069
Summary statistics					
AIC	61147.387				
BIC	61157.455				
Degrees of freedom	174299				

Taking into account the aforementioned Table 6, a series of interesting findings can be provided. First of all, all the explanatory variables were statistically significant at a 95% confidence level and there was no issue of multicollinearity as the VIF values were much lower than 5. It is worth noting that a similar pattern as the previous GLM for headway was identified. The indicator of time of the day was negatively correlated with overtaking, which means that drivers were not willing to perform an illegal overtaking during night, probably due to low traffic volumes occurred. On the other hand, high beam was positively correlated with overtaking. Similarly, harsh accelerations and duration had a positive relationship with the dependent variable (i.e., overtaking), while distance travelled was negatively correlated with overtaking.

4.1.1.4 Fatigue

The fourth GLM investigated the relationship between the **fatigue and several explanatory variables of task complexity**, such as distance travelled, duration, harsh acceleration, time indicator as well as high beam. The model parameter estimates are summarized in Table 7.

Table 7: Parameter estimates and multicollinearity diagnostics of the GLM for fatigue (German cars)

Variables	Estimate	Standard Error	z-value	Pr(|z|)	VIF
(Intercept)	-4.376	0.027	-159.251	< .001	-
grpby_seconds	8.663×10^{-4}	6.611×10^{-6}	131.046	< .001	1.175
GPS_distances_sum	0.001	3.046×10^{-5}	39.920	< .001	1.108
DrivingEvents_Map_evt_ha_mean	-3.142×10^{-5}	3.687×10^{-6}	-8.522	< .001	1.044
ME_Car_high_beam_median - Off	4.410	0.033	132.190	< .001	1.258
ME_AWS_time_indicator_median	1.254×10^{-4}	2.998×10^{-6}	41.815	< .001	1.043
Summary statistics					
AIC	134848.401				
BIC	134858.470				
Degrees of freedom	174299				

All the explanatory variables were statistically significant at a 95% confidence level, as shown in Table 7. With regards to multicollinearity diagnostics, VIF values for all independent variables were much lower than 5. It was observed that the indicators of task complexity such as time and high beam were positively correlated with fatigue. Furthermore, distance travelled, and duration had a positive relationship with the dependent variable (i.e., fatigue), indicating that the longer the distance and duration is, the higher the probability of driver being fatigue becomes. This is a noteworthy finding of the current research as it confirms that exposure indicators present a statistically significant positive correlation with fatigue levels. Finally, harsh accelerations had a negative relationship with fatigue.

4.1.2 Belgium (Cars)

4.1.2.1 Speeding

The first Generalized Linear Regression model investigated the relationship between speeding **and several explanatory variables of task complexity**. In particular, the dependent variable of the developed model is the dummy variable "speeding", which is coded with 1 if there is a speeding event and with 0 if not. For task complexity, the variables used are time indicator, wipers, high beam, distance traveled and duration. The model parameter estimates are summarized in Table 8.

Table 8: Parameter estimates and multicollinearity diagnostics of the GLM for speeding (Belgium cars)

Coefficients	Estimate	Standard Error	z	p
(Intercept)	3.733	0.039	96.446	< .001
grpby_seconds	1.520×10^{-4}	1.935×10^{-5}	7.855	< .001
GPS_distances_sum	-7.223×10^{-5}	4.933×10^{-5}	-1.464	0.143
ME_AWS_time_indicator_median	0.086	0.038	2.283	0.022
ME_Car_wipers_median	0.009	4.062×10^{-4}	21.728	< .001
ME_Car_high_beam_median - Off	-0.019	6.310×10^{-4}	-29.606	< .001

Multicollinearity Diagnostics

	VIF
grpby_seconds	1.031
GPS_distances_sum	1.410
ME_AWS_time_indicator_median	1.612
ME_Car_wipers_median	1.271
ME_Car_high_beam_median	1.558

Based on Table 8, it can be observed that all explanatory variables are statistically significant at a 95% confidence level; there is no issue of multicollinearity as the VIF values are much lower than 5. With regard to the coefficients, it was revealed that the indicators of task complexity, such as time indicator and wipers were positively correlated with speeding. The former refers to the time of the day (day coded as 1, dusk coded as 2, night coded as 3) which means that higher speeding events occur at night compared to during the day. This may be due to fewer cars on the road, lower visibility, and a false sense of security that comes with driving in the dark. Interestingly, wipers (wipers off coded as 0, wipers on coded as 1) were also found to have a positive correlation with speeding which means that there are more speeding events during adverse (e.g., rainy) weather conditions. Taking into account the indicator of high beam (indicating lighting conditions; no high beam detected), a negative correlation was identified which means that when high beam was off - and, therefore, it was daytime - there were fewer speeding events. Total distance traveled was negatively correlated with speeding which may be due to the fact that the longer a person drives, the more fatigued they may become, causing them to drive slower and more cautiously.

4.1.2.2 Headway

The second GLM investigated the relationship between the headway and several explanatory variables of task complexity. More specifically, the dependent variable of the developed model is the dummy variable “headway”, which is coded with 1 if there is a headway event and with 0 if not. For task complexity, the variables used are time indicator, wipers, high beam, distance traveled and duration. The model parameter estimates are summarized in Table 9.

Table 9: Parameter estimates and multicollinearity diagnostics of the GLM for headway (Belgium cars)

Coefficients

	Estimate	Standard Error	z	p
(Intercept)	4.057	0.059	68.260	< .001
grpby_seconds	0.001	6.144×10^{-5}	17.806	< .001
GPS_distances_sum	0.001	8.553×10^{-5}	12.561	< .001
ME_AWS_time_indicator_median	-1.059	0.035	-30.005	< .001
ME_Car_wipers_median	-0.002	5.417×10^{-4}	-3.463	< .001
ME_Car_high_beam_median	0.014	0.002	6.710	< .001

Multicollinearity Diagnostics

	VIF
grpby_seconds	1.005
GPS_distances_sum	1.458
ME_AWS_time_indicator_median	1.574
ME_Car_wipers_median	1.650
ME_Car_high_beam_median	1.675

Findings derived from Table 9 demonstrated that all the explanatory variables were statistically significant at a 95% confidence level. In addition, there was no issue of multicollinearity as the VIF values are much lower than 5. With respect to the coefficients, it was found that time of the day (indicator of task complexity) was negatively correlated with headway, which means that drivers tend to keep safer distances from the vehicle in front of them during the night. This may probably be due to the fact that there is no heavy traffic during night hours; thus, headway events are avoided. Interestingly, high beam (indicating lighting conditions; no high beam detected) was positively correlated with headway which means that when high beam was off - and, therefore, it was daytime - there were more highway events. This finding comes in agreement with the previous argument with the indicator of time of the day that lower headway events occur at night compared to the rest of the day. In addition, wipers were also found to have a negative correlation with headway which means that there are less headway events during adverse (e.g. rainy) weather conditions. Furthermore, exposure indicators of distance and duration appeared to have a positive relationship with the dependent variable (i.e. headway).

4.1.2.3 Overtaking

The third GLM investigated the relationship between the overtaking and several explanatory variables of task complexity. For instance, the dependent variable of the developed model is the dummy variable “overtaking”, which is coded with 1 if there is a overtaking event and with 0 if not. With regards to task complexity, the variables used are time indicator, wipers, high beam, distance traveled and duration. The model parameter estimates are summarized in Table 10.

Table 10: Parameter estimates and multicollinearity diagnostics of the GLM for overtaking (Belgium cars)

Coefficients

	Estimate	Standard Error	z	p
(Intercept)	-1.289	0.014	-94.186	< .001
grpby_seconds	4.487×10^{-4}	6.675×10^{-6}	67.217	< .001
GPS_distances_sum	5.892×10^{-4}	1.809×10^{-5}	32.571	< .001
ME_AWS_time_indicator_median	-0.039	0.013	-2.962	0.003
ME_Car_wipers_median	0.001	9.280×10^{-5}	11.776	< .001
ME_Car_high_beam_median	0.008	2.573×10^{-4}	31.670	< .001

Multicollinearity Diagnostics

	VIF
grpby_seconds	1.009
GPS_distances_sum	1.508
ME_AWS_time_indicator_median	1.684
ME_Car_wipers_median	1.495
ME_Car_high_beam_median	1.600

Taking into account the aforementioned Table 10, a series of interesting findings can be provided. First of all, the majority of the explanatory variables (except for time indicator) were statistically significant at a 95% confidence level and there was no issue of multicollinearity as the VIF values were much lower than 5. It is worth noting that a similar pattern as the previous GLM for headway was identified. In particular, the indicator of time of the day was negatively correlated with overtaking, which means that drivers were not willing to perform an illegal overtaking during night, probably due to low traffic volumes occurred. On the other hand, wipers (indicating weather condition) were positively correlated with overtaking.

4.1.2.4 Fatigue

The fourth GLM investigated the relationship between fatigue and several explanatory variables of task complexity. In particular, the dependent variable of the developed model is the dummy variable “fatigue”, which is coded with 1 if there is a fatigue event and with 0 if not. For task complexity, the variables used are time indicator, wipers, high beam, distance traveled and duration. The model parameter estimates are summarized in Table 11.

Table 11:Parameter estimates and multicollinearity diagnostics of the GLM for fatigue (Belgium cars)

Coefficients

	Estimate	Standard Error	z	p
(Intercept)	-0.007	0.014	-0.478	0.632
grpby_seconds	-3.202×10^{-7}	5.999×10^{-6}	-0.053	0.957
GPS_distances_sum	-0.003	4.967×10^{-5}	-56.126	< .001
ME_AWS_time_indicator_median	0.586	0.018	32.598	< .001
ME_Car_wipers_median	0.003	1.068×10^{-4}	30.446	< .001
ME_Car_high_beam_median	-0.015	3.030×10^{-4}	-48.703	< .001

Multicollinearity Diagnostics

	VIF
grpby_seconds	1.013
GPS_distances_sum	1.163
ME_AWS_time_indicator_median	1.307
ME_Car_wipers_median	1.278
ME_Car_high_beam_median	1.360

All the explanatory variables were statistically significant at a 95% confidence level, as shown in

Table 11. With regards to multicollinearity diagnostics, VIF values for all independent variables were much lower than 5. It was observed that the indicators of task complexity such as wipers and time indicator were positively correlated with fatigue. For instance, it was revealed that during the night, drivers are more prone to becoming fatigued due to the body's natural circadian rhythm. It can be more challenging for drivers to stay alert and focused when driving at night, especially during the early morning hours when the body is naturally in a state of rest. At the same time, high beam (indicating lighting conditions; high beam no detected) was negatively correlated with fatigue, which implies that when high beam was off - and, therefore, it was daytime - there were less fatigue events. Exposure indicators of distance and duration were negatively correlated.

4.1.3 UK (Cars)

For the UK car trial, Generalized Linear Regression models were employed to explore the variables of **speeding and headway** and their relationship with driving **task complexity**. The variables that were used to represent task complexity are distance travelled, trip duration, the use of high beams, the use of wipers, the hour of the day and the day of the week.

4.1.3.1 Speeding

The model parameter estimates for speeding variable are summarized in Table 12.

Table 12: Parameter estimates and multicollinearity diagnostics of the GLM for speeding (UK cars)

Coefficients

					95 % Confidence Interval	
	Estimate	Standard Error	z	p	Lower Bound	Upper Bound
(Intercept)	-4.111	0.022	-185.196	< .001	-4.154	-4.067
grpby_seconds(duration)	3.994×10^{-5}	7.765×10^{-7}	51.437	< .001	3.841×10^{-5}	4.146×10^{-5}
GPS_distances_sum	0.002	1.827×10^{-5}	117.886	< .001	0.002	0.002
ME_Car_wipers_median	-0.222	0.023	-9.589	< .001	-0.268	-0.177
Hour	0.018	0.001	14.387	< .001	0.016	0.021
Day_of_week	0.067	0.003	22.895	< .001	0.061	0.072

Multicollinearity Diagnostics

	VIF
grpby_seconds	1.034
GPS_distances_sum	1.029
ME_Car_wipers_median	1.003
Hour	1.013
Day_of_week	1.005

As can be observed, all explanatory variables are statistically significant at a 95% confidence level and there is no issue of multicollinearity as the VIF values are much lower than 5. Regarding the coefficients, the use of wipers as an explanatory variable of task complexity is negatively correlated with speeding variable (coded as: 0-no speeding, 1-speeding). This possibly means that in rainy weather conditions, drivers maintain lower speeds. On the contrary, all the other selected indicators of task complexity appear to be positively correlated with speeding. More specifically, an increase in trip duration and distance travelled is associated with an increase in speeding. Moreover, speeding events increase in the last days of the week and during last hours of the day according to the model.

4.1.3.2 Headway

In terms of the model that was developed for the headway variable (0-no headway event, 1-headway event), all variables are statistically significant at a 95% confidence level and there is no issue of multicollinearity (VIF<5). The model summary is presented in Table 13.

Table 13: Parameter estimates and multicollinearity diagnostics of the GLM for headway (UK cars)

Coefficients

					95 % Confidence Interval	
	Estimate	Standard Error	z	p	Lower Bound	Upper Bound
(Intercept)	-2.205	0.013	-164.597	< .001	-2.231	-2.179
grpby_seconds(duration)	4.769×10^{-5}	6.034×10^{-7}	79.036	< .001	4.651×10^{-5}	4.887×10^{-5}
GPS_distances_sum	0.003	1.247×10^{-5}	222.130	< .001	0.003	0.003
ME_Car_wipers_median	-0.128	0.014	-9.122	< .001	-0.156	-0.101
ME_Car_high_beam_median	-1.533	0.085	-18.002	< .001	-1.704	-1.370
Hour	-0.022	8.154×10^{-4}	-26.884	< .001	-0.024	-0.020
Day_of_week	-0.036	0.002	-18.977	< .001	-0.039	-0.032

Multicollinearity Diagnostics

	VIF
grpby_seconds	1.024
GPS_distances_sum	1.021
ME_Car_wipers_median	1.003
ME_Car_high_beam_median	1.001
Hour	1.010
Day_of_week	1.010

All explanatory variables appear to be negatively correlated with headway events except for the trip duration and the distance travelled. An increase in trip duration and distance is associated with shorter headways while the use of high beams and wipers, the last hours of the day and the end of the week are associated with a decrease in headway events. Therefore, according to the model, drivers tend to keep safer distances in the night and during rainy weather conditions. The decrease in the headway events during the last hours of the day and the end of the week could be potentially explained by the lower traffic conditions that typically occur at those specific periods.

4.1.4 Greece (Cars)

4.1.4.1 Speeding

The GLM applied investigated the relationship between the speeding and several explanatory variables of task complexity. In particular, the dependent variable of the developed model is the dummy variable "speeding", which is coded with 1 if there is a speeding event and with 0 if not. For task complexity, the variables used are time indicator, distance traveled and duration. The model parameter estimates are summarized in Table 14.

Table 14: Parameter estimates and multicollinearity diagnostics of the GLM for speeding (Greece cars)

Coefficients

	Estimate	Standard Error	z	p
(Intercept)	-0.443	0.043	-10.232	< .001
grpby_seconds	5.730×10^{-4}	2.072×10^{-5}	27.646	< .001

Coefficients

	Estimate	Standard Error	z	p
GPS_distances_sum	0.002	7.083×10^{-5}	27.346	< .001
ME_AWS_time_indicator_median	0.237	0.018	13.206	< .001

Multicollinearity Diagnostics

	VIF
grpby_seconds	1.015
GPS_distances_sum	1.015
ME_AWS_time_indicator_median	1.001

Based on Table 14, it can be observed that all explanatory variables are statistically significant at a 95% confidence level; there is no issue of multicollinearity as the VIF values are much lower than 5. With regard to the coefficients, it was revealed that the indicators of task complexity, such as time indicator were positively correlated with speeding. Time indicator refers to the time of the day (day coded as 1, dusk coded as 2, night coded as 3) which means that higher speeding events occur at night compared to during the day. This may be due to fewer cars on the road, lower visibility, and a false sense of security that comes with driving in the dark. Furthermore, it was demonstrated that distance and duration had a positive relationship with the dependent variable (i.e., speeding), indicating that as the values of the aforementioned independent variables increase, speeding also increases.

4.1.5 Portugal (Buses)

GLMs were employed to investigate the relationship of key performance indicators (i.e., speeding, headway, overtaking and fatigue) for Portuguese bus drivers.

4.1.5.1 Speeding

The first GLM investigated the relationship between speeding **and several explanatory variables of task complexity.** In particular, the dependent variable of the developed model is the dummy variable “speeding”, which is coded with 1 if there is a speeding event and with 0 if not. For task complexity, the variable used is time indicator, distance traveled and duration. The model parameter estimates are summarized in Table 15.

Table 15: Parameter estimates and multicollinearity diagnostics of the GLM for speeding (Portugal buses)

Coefficients

	Estimate	Standard Error	z	p
(Intercept)	-3.228	0.020	-158.159	< .001
duration	-1.643×10^{-4}	4.870×10^{-6}	-33.735	< .001
distance	0.026	4.960×10^{-4}	52.766	< .001
ME_AWS_time_indicator	-0.154	0.008	-19.950	< .001

Multicollinearity Diagnostics

	VIF
duration	32.055
distance	32.043

Coefficients				
	Estimate	Standard Error	z	p
ME_AWS_time_indicator	1.002			

Based on Table 15, it can be observed that all explanatory variables are statistically significant at a 95% confidence level; there is no issue of multicollinearity as the VIF values are much lower than 5. With regard to the coefficients, it was revealed that the indicators of task complexity, such as time indicator were negatively correlated with speeding. Time indicator refers to the time of the day (day coded as 1, dusk coded as 2, night coded as 3) which means that higher speeding events occur during the day. Regarding the exposure indicators, distance had a positive relationship with the dependent variable (i.e., speeding), indicating that as the total distance traveled increases, speeding also increases, while duration found to be negatively correlated with speeding.

4.1.5.2 Headway

The second GLM investigated the relationship between the **headway and several explanatory variables of task complexity.** More specifically, the dependent variable of the developed model is the dummy variable "headway", which is coded with 1 if there is a headway event and with 0 if not. For task complexity, the variable used is time indicator, distance traveled and duration. The model parameter estimates are summarized in Table 16.

Table 16: Parameter estimates and multicollinearity diagnostics of the GLM for headway (Portugal buses)

Coefficients

	Estimate	Standard Error	z	p
(Intercept)	-5.192	0.056	-92.832	< .001
duration	-2.272×10^{-4}	1.240×10^{-5}	-18.322	< .001
distance	0.031	0.001	24.905	< .001
ME_AWS_time_indicator	-0.177	0.022	-8.043	< .001

Multicollinearity Diagnostics

	VIF
duration	26.486
distance	26.481
ME_AWS_time_indicator	1.005

Findings derived from Table 16 demonstrated that the majority of the explanatory variables were statistically significant at a 95% confidence level. In addition, there was no issue of multicollinearity as the VIF values are much lower than 5. With respect to the coefficients, it was found that time of the day (indicator of task complexity) was negatively correlated with headway, which means that drivers tend to keep safer distances from the vehicle in front of them during the night. This may probably be due to the fact that there is no heavy traffic during night hours; thus, headway events are avoided. Furthermore, exposure indicator of distance appeared to have a positive relationship with the dependent variable (i.e., headway).

4.1.5.3 Overtaking

The third GLM investigated the relationship between the **overtaking and several explanatory variables of task complexity.** For instance, the dependent variable of the developed model is the dummy variable “overtaking”, which is coded with 1 if there is a overtaking event and with 0 if not. For task complexity, the variable used is time indicator, distance traveled and duration. The model parameter estimates are summarized in Table 17.

Table 17: Parameter estimates and multicollinearity diagnostics of the GLM for overtaking (Portugal buses)

Coefficients

	Estimate	Standard Error	z	p
(Intercept)	-7.649	0.175	-43.653	< .001
duration	-2.621×10^{-5}	4.251×10^{-5}	-0.617	0.538
distance	0.010	0.004	2.303	0.021
ME_AWS_time_indicator	-0.150	0.065	-2.323	0.020

Multicollinearity Diagnostics

	VIF
duration	35.086
distance	35.084
ME_AWS_time_indicator	1.000

Taking into account the aforementioned Table 17, a series of interesting findings can be provided. First of all, the majority of the explanatory variables were statistically significant at a 95% confidence level and there was no issue of multicollinearity as the VIF values were much lower than 5. It is worth noting that a similar pattern as the previous GLM for headway was identified. In particular, the indicator of time of the day was negatively correlated with overtaking, which means that drivers were not willing to perform an illegal overtaking during night, probably due to low traffic volumes occurred. Moreover, distance appeared to have a positive relationship with the dependent variable (i.e., overtaking), indicating that as the values of the aforementioned independent variables increases, overtaking also increases. For instance, this means that the longer the distance of the trip is, the higher the number of overtaking events occur. On the other hand, duration had a negative correlation with overtaking which means that drivers tend to avoid overtaking when they perform shorter trips.

4.1.5.4 Fatigue

The fourth GLM investigated the relationship between the **fatigue and several explanatory variables of task complexity**. In particular, the dependent variable of the developed model is the dummy variable “fatigue”, which is coded with 1 if there is a fatigue event and with 0 if not. For task complexity, the variable used is time indicator, distance traveled and duration. The model parameter estimates are summarized in Table 18.

Table 18: Parameter estimates and multicollinearity diagnostics of the GLM for fatigue (Portugal buses)

Coefficients

	Estimate	Standard Error	z	p
(Intercept)	0.147	0.010	14.353	< .001
duration	2.554×10^{-4}	2.975×10^{-6}	85.845	< .001

Coefficients

	Estimate	Standard Error	z	p
distance	-0.017	3.116×10^{-4}	-55.823	< .001
ME_AWS_time_indicator	-0.104	0.004	-27.587	< .001

Multicollinearity Diagnostics

	VIF
duration	20.447
distance	20.446
ME_AWS_time_indicator	1.001

All the explanatory variables were statistically significant at a 95% confidence level, as shown in Table 18. With regards to multicollinearity diagnostics, VIF values for all independent variables were much lower than 5. It was observed that time indicator was negatively correlated with fatigue. This may be due to the fact that during the night, drivers are less prone to becoming fatigued due to the body's natural circadian rhythm. Moreover, the indicator of duration had a positive relationship with the dependent variable (i.e. fatigue), indicating that the longer the distance is, the higher the probability of driver being fatigue becomes. This is a noteworthy finding of the current research as it confirms that exposure indicators present a statistically significant positive correlation with fatigue levels.

4.2 Structural Equation Models

Following exploratory analysis, the **latent variable (or variables) associated to "Task Complexity"** were estimated from the various indicators. The effect of different contextual factors on 'task complexity' was defined, and further analysed for different countries (i.e., Belgium, UK, Germany, Greece) and different travel modes (i.e., cars, trucks). Twenty-eight Structural Equation Models were employed in order to identify the impact of Task Complexity on the Safety Tolerance Level, controlling for the above exogenous factors. It is important to acknowledge that the presentation of results per country may vary due to differences in software employment for data analysis across the four countries.

4.2.1 UK (Cars)

4.2.1.1 Headway

A SEM analysis was performed based on data from 53 drivers (3073 trips) collected in **Phase 1** of the i-Dreams project trials where no interventions were present. The model was developed in IBM SPSS Amos 27 Graphics software, and it is graphically described in Figure 5.

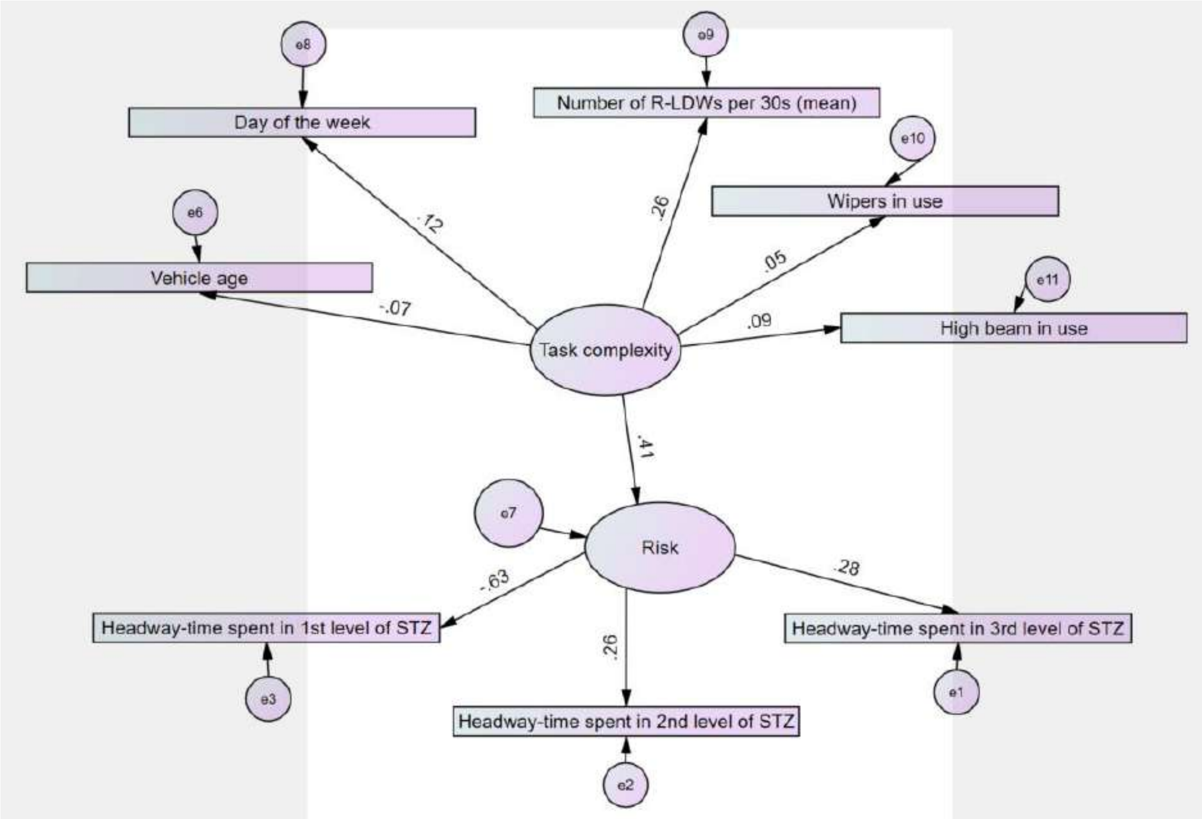

Figure 5: Results of SEM Task complexity & Risk (headway STZ)- UK car drivers-experiment Phase 1

Maximum likelihood estimation method was employed. Variables that were not statistically significant have been removed from the initial theoretical model and this final one presented, appears to be a good fit to the data. The Comparative Fit Index (CFI) is 0.906; TLI is 0.862 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.019. More details about the model fit can be found in Table 19.

Table 19: Model Fit Summary for headway – UK car drivers – experiment Phase 1

Model Fit Summary	
AIC	874
BIC	1038
CFI	0.906
TLI	0.862
RMSEA	0.019
GFI	0.998
HOELTER	0.5-4080 | 0.1- 4899

Unstandardised coefficients details are presented in *Table 20.*

Table 20: Regression weights for headway- UK car drivers - experiment Phase 1

			Estimate	S.E.	C.R.	P
Risk	<---	task_complexity	.128	.012	10.971	***
iDreams_Headway_Map_level_23_mean	<---	Risk	.780	.018	42.238	***
iDreams_Headway_Map_level_1_0_mean	<---	Risk	-3.048	.111	-27.471	***
SQ_Vehicle_age	<---	task_complexity	-1.042	.128	-8.113	***
Day_of_week	<---	task_complexity	1.000			
ME_LDW_Map_type_R_mean_A	<---	task_complexity	.428	.036	11.814	***
iDreams_Headway_Map_level_1_mean	<---	Risk	1.000			
ME_Car_wipers_median	<---	task_complexity	.059	.009	6.441	***
ME_Car_high_beam_median	<---	task_complexity	.026	.003	9.248	***

All the observed indicators of the two latent variables task complexity and risk are statistically significant at 99.9% confidence level. The latent variable of task complexity has a statistically significant positive effect on risk that is significantly interpreted by the time spent in each of the three levels of STZ regarding the headway measurement. The more the time a driver spends in the second and third level of STZ, the higher the risk. Overall, increased task complexity relates to increased risk according to the model (standardised coefficient=0.41).

The latent construct of task complexity is represented by the indicator variables of vehicle age, day of week, the number of lane departure warnings per 30s, high beam and wipers use. Wipers can be an indication of weather conditions, most specifically, they can be indicative of rain presence during the trip while high beams can indicate lighting conditions, for example, low visibility or dark. The age of the vehicle can affect its performance and render the driving task more difficult or easier. For example, an older car without a hydraulic wheel can relate with increased task complexity while simultaneously an older car being driven by the same driver may render the driving task easier due to the familiarity that have been gained by the driver. The number of Lane departure warnings can indicate the difficulty of the driving task, intuitively the higher the number, the greater the task complexity. Lastly, the day of the week can relate with traffic conditions on the road, thus it can be linked with task complexity.

In this model for Phase 1, task complexity seems to relate positively with the number of LDW, the day of the week, the wipers and high beam use, and negatively with the vehicle age. According to results, when wipers and high beam are in use, hence in rainy weather and in dark, the task complexity is increased. Similarly increased task complexity is related to increased number of LDW per 30s, as expected, and the last days of the week. Fridays and weekends tend to be the busiest days of the week regarding traffic and the roads could be more congested, raising the levels of driving task demand.

Following the same approach, a SEM analysis was employed for driving data on **Phase 2** of the on-road trials (54 drivers, 3317 trips) where interventions notifications have been introduced to the drivers. The model is graphically described in Figure 6.

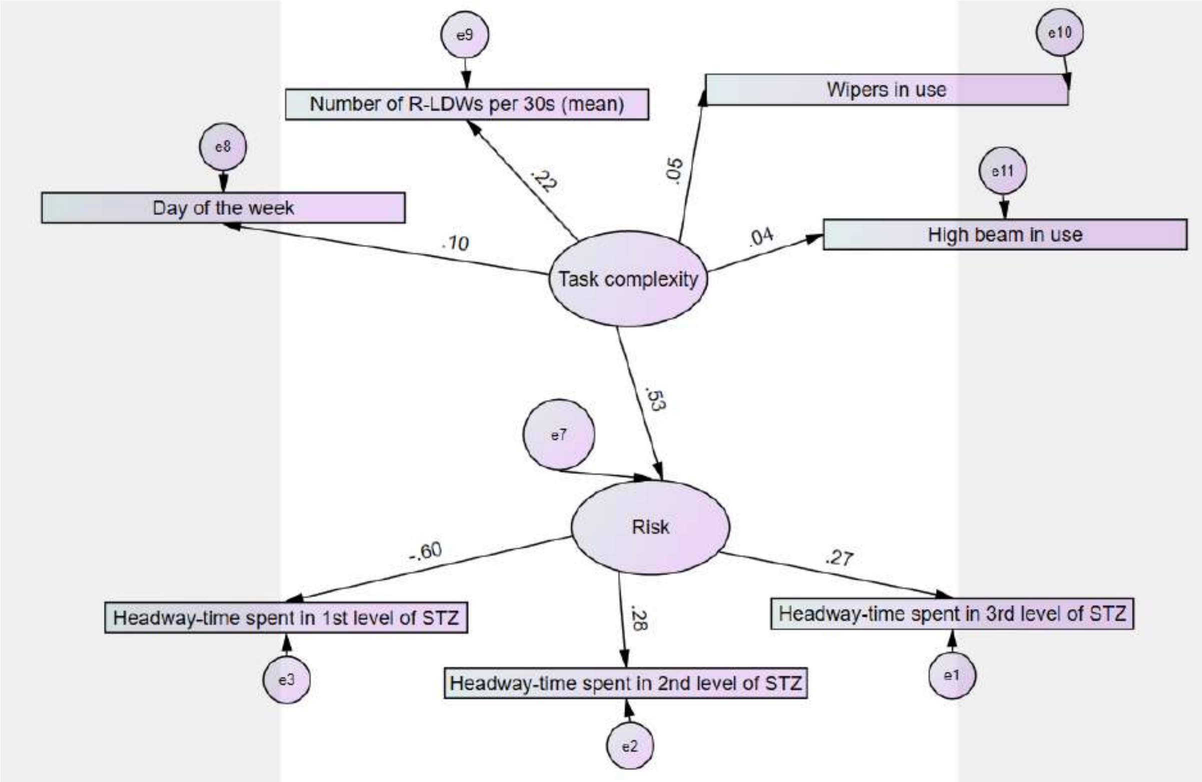

Figure 6: Results of SEM Task complexity & Risk (headway STZ)- UK car drivers-experiment Phase 2

The results indicate that the model is reasonably consistent with the data as CFI is 0.896, TLI is 0.831, and RMSEA is 0.024. More details about the model fit can be found in Table 21.

Table 21: Model Fit Summary for headway – UK car drivers – experiment Phase 2

Model Fit Summary	
AIC	56
BIC	326.73
CFI	0.896
TLI	0.831
RMSEA	0.024
GFI	0.998
HOELTER	0.5-2915 | 0.1-3610

Unstandardised coefficients details are presented in Table 22 that follows.

Table 22: Regression weights for headway- UK car drivers - experiment Phase 2

			Estimate	S.E.	C.R.	P
Risk	<---	task_complexity	.341	.045	7.644	***
iDreams_Headway_Map_level_23_mean	<---	Risk	1.000			

			Estimate	S.E.	C.R.	P
iDreams_Headway_Map_level_1_0_mean	<---	Risk	-4.300	.152	-28.22	***
Day_of_week	<---	task_complexity	2.529	.228	11.073	***
ME_LDW_Map_type_R_mean	<---	task_complexity	1.000			
iDreams_Headway_Map_level_1_mean	<---	Risk	1.509	.036	41.645	***
ME_Car_wipers_median	<---	task_complexity	.183	.028	6.616	***
ME_Car_high_beam_median	<---	task_complexity	.038	.007	5.754	***

The observed indicators of task complexity and risk that are statistically significant, are the same as in Phase 1 except for the vehicle age. Task complexity has again a positive significant impact on risk (standardised coefficient= 0.53) translating to higher risk levels when task complexity raises. Increased levels of risk are similarly linked to higher time spent in the last two more critical levels of headway measurements of STZ. The rest of the regression weights appear to be in correspondence with Phase I with number of right LDWs to be the predominant variable describing task complexity latent factor.

A SEM analysis was also performed for **Phase 3** of the on-road trials (53 drivers, 3417 trips) where the drivers could interact with the i-DREAMS smart phone application. The path diagram of the model is presented in Figure 7 that follows.

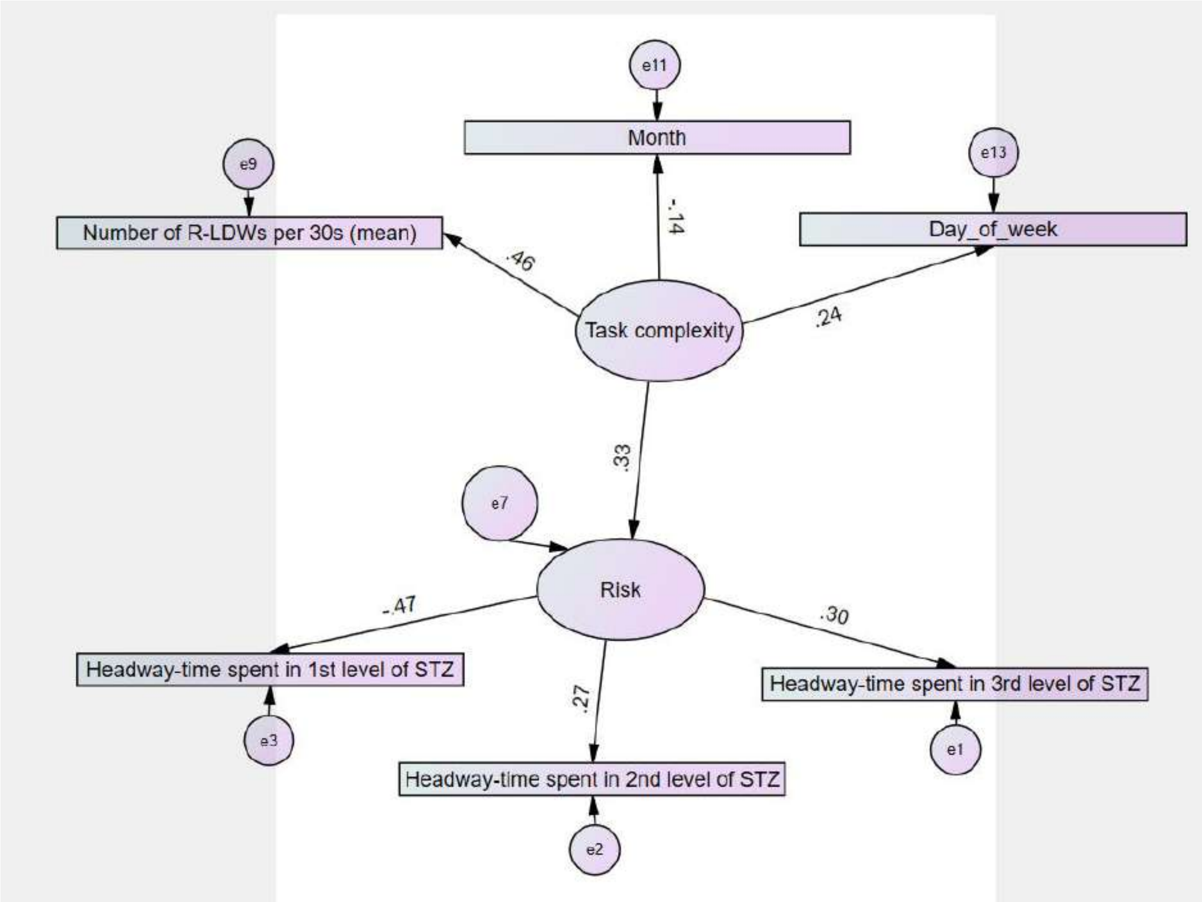

Figure 7: Results of SEM Task complexity & Risk (headway STZ)- UK car drivers-experiment Phase 3

The results indicate that the model is reasonably consistent with the data as CFI is 0.923, TLI is 0.856, and RMSEA is 0.027. More details about the model fit can be found in Table 23 below.

Table 23: Model Fit Summary for headway – UK car drivers – experiment Phase 3

Model Fit Summary	
AIC	707.64
BIC	833.58
CFI	0.923
TLI	0.856
RMSEA	0.027
GFI	0.998
HOELTER	0.5-2710 | 0.1-3511

Unstandardised coefficients details are presented in Table 24 that follows.

Table 24: Regression weights for headway- UK car drivers - experiment Phase 3

			Estimate	S.E.	C.R.	P
Risk	<---	task_complexity	.113	.007	17.127	***
iDreams_Headway_Map_level_23_mean	<---	Risk	1.000			

			Estimate	S.E.	C.R.	P
iDreams_Headway_Map_level_1_0_mean	<---	Risk	-2.795	.093	-30.06	***
ME_LDW_Map_type_R_mean	<---	task_complexity	1.000			
iDreams_Headway_Map_level_1_mean	<---	Risk	1.224	.035	35.447	***
Month	<---	task_complexity	-3.056	.180	-17.01	***
Day_of_week	<---	task_complexity	2.854	.153	18.711	***

For the data of this phase, the variables related to wipers and high beam use were not statistically significant as indicators of task complexity. However, the variable indicating the month became significant. This result can be related to the traffic conditions and the weather of the time period the trials of phase 3 took place. There are months that are statistically colder or rainier, therefore, the task complexity can be affected by several factors, such as frost, ice on the road or slippery pavements and disturbed visibility. Furthermore, pre-Christmas period or bank holidays can impose an effect on road traffic conditions that in turn affects driving task demand.

Task complexity has a significant positive effect on risk as in the previous phases with the number of right LDWs to appear as the most significant indicator (higher standardised coefficient=0.46) following by the day of the week and month.

A SEM analysis was finally performed for driving data from **Phase 4** (54 drivers, 4594 trips) where gamification was available to the drivers. A graphical presentation of the model is shown in Figure 8.

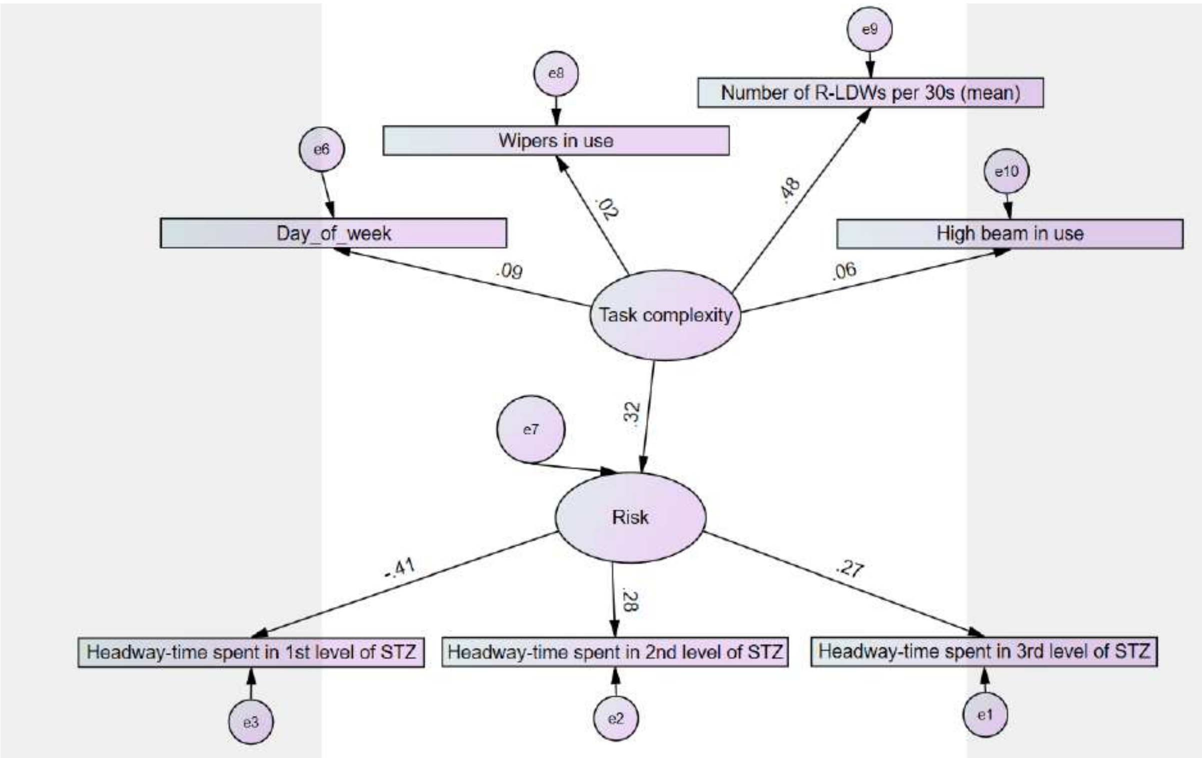

Figure 8: Results of SEM Task complexity & Risk (headway STZ)- UK car drivers-experiment Phase 4

The results indicate that the model is consistent with the data as CFI is 0.905, TLI is 0.846, and RMSEA is 0.018. More details about the model fit can be found in Table 25 below.

Table 25: Model Fit Summary for headway – UK car drivers – experiment Phase 4

Model Fit Summary	
AIC	842.93
BIC	995.09
CFI	0.905
TLI	0.846
RMSEA	0.018
GFI	0.999
HOELTER	0.5-5171 | 0.1-6402

Unstandardised coefficients details are presented in Table 26 that follows.

Table 26: Regression weights for headway- UK car drivers - experiment Phase 4

Variable			Estimate	S.E.	C.R.	P
Risk	<---	task_complexity	.090	.006	15.380	***
iDreams_Headway_Map_level_23_mean	<---	Risk	1.000			
iDreams_Headway_Map_level_1_0_mean	<---	Risk	-2.931	.086	-33.97	***
Day_of_week	<---	task_complexity	1.000			
ME_Car_wipers_median	<---	task_complexity	.033	.007	4.929	***
ME_LDW_Map_type_R_mean	<---	task_complexity	.937	.121	7.728	***
iDreams_Headway_Map_level_1_mean	<---	Risk	1.644	.043	38.531	***
ME_Car_high_beam_median	<---	task_complexity	.025	.002	10.617	***

The model for the driver data of this Phase is similar to this of Phase 2 as the same variables were identified as significant (wipers and high beam use, right LDWs and day of the week). All the observed indicators of the two latent variables task complexity and risk are statistically significant at 99.9% confidence level and task complexity has a statistically significant positive effect on risk (standardised coefficient=-0.17) that is significantly interpreted by the time spent in each of the three levels of STZ regarding the headway indicator. As in the other models, more time spent in the first level of STZ indicates lower levels of risk and the positive relationship of task complexity with risk shows that as the former increases, risk levels rise.

<u>An overview of the models for the four phases</u>

Overall, four SEM analyses were performed to assess the effect of task complexity on risk across the four phases of two waves on-road trials. The time that was spent in each level of safety tolerance zone regarding the headway measurements were significant indicators of the latent construct of risk in all the phases. However, the variables that construct the latent concept of task complexity (these that were proved to be statistically significant) slightly differ from phase to phase. More specifically, the variables that remain **significant across all phases** are the **number of right LDWs per 30s** and the **day of the week**. Wipers and high beam in use variables were also consistently significant in the three (1, 2, 4) out of the four phases - although the effect was smaller than this of the other variables - while vehicle age appears only in Phase 1 and month in Phase 3.

A rise in wipers and high beam use that could be translated to rain and low visibility conditions, the **last days of the week** probably denoting different traffic conditions, and an **increased number of right lane departure warnings** (could be indicative of demanding road layout, high cognitive workload) is linked to **raised levels of driving task demand** and this in turn results to **higher risk levels**. Last days of the week (weekends), except for different traffic density and composition, could be linked to higher consumption of alcohol or other substances that could affect task complexity and risk (European Monitoring Centre for Drugs and Drug Addiction, 2012).

The **results are aligned with previous literature** regarding the effect of weather and dark on driving task demand. More specifically, studies have proved that driving complexity increases by rain intensity or duration (Brijs et al., 2008), as well as by rainfall height (Fridstrøm and Ingebrigtsen, 1991, Elvik et al., 2013). Similarly, darkness was shown to increase the task demand and crash risk (Johansson et al., 2009).

The variable of month has a negative relationship with task complexity, thus the later in the year, the lower the task complexity in Phase 3 and this could be related to the **two data collection waves** and different traffic or weather conditions on different months of the year. The same occurs with the car age in Phase 1 where it seems that the older the car, the less complex the driving task. This result can be probably explained by the familiarity that the drivers have acquired with their vehicle as the recent years, with the advancements of technology, more and more systems have been added in the cars that can be distracting, especially in the beginning until the driver can adjust.

The **number of right LDWs** was the **most representative indicator of task complexity** (higher coefficient) in all four models. Changing lanes adds certainly to task demand and as a lane departure warning results from a change of lane without the indicator on, this can imply high cognitive load or abrupt move.

Task complexity appears in all the models to have **a significant positive effect on risk** translated to **higher levels of the latter when the first shows an increase**. Although the models appear similar, this effect changes across the phases (larger in the first two phases than the last two) with the larger to be observed in Phase 2 (standardised coefficient= -0.53). This could be possibly explained by the fact that in Phase 2 is the first time that the interventions are introduced to the drivers, and this can add to the complexity of the driving task, while in the last two phases they have already adapted to the system.

4.2.2 Belgium (Cars)

4.2.2.1 Speeding

Four separate SEM models were estimated in order to explore the relationship between the latent variables of Task Complexity and Risk (expressed as the three phases of the STZ) of speeding. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 39 drivers, 1173 trips (23,725 minutes)
- Phase 2: real-time interventions - 43 Belgian car drivers, 1549 trips
- Phase 3: real-time & post-trip interventions - 51 Belgian car drivers, 1973 trips (40,121 minutes)
- Phase 4: real-time, post-trip interventions & gamification - 49 Belgian car drivers, 2468 trips (52,077 minutes)

The results for Phase 1 are shown in Figure 9.

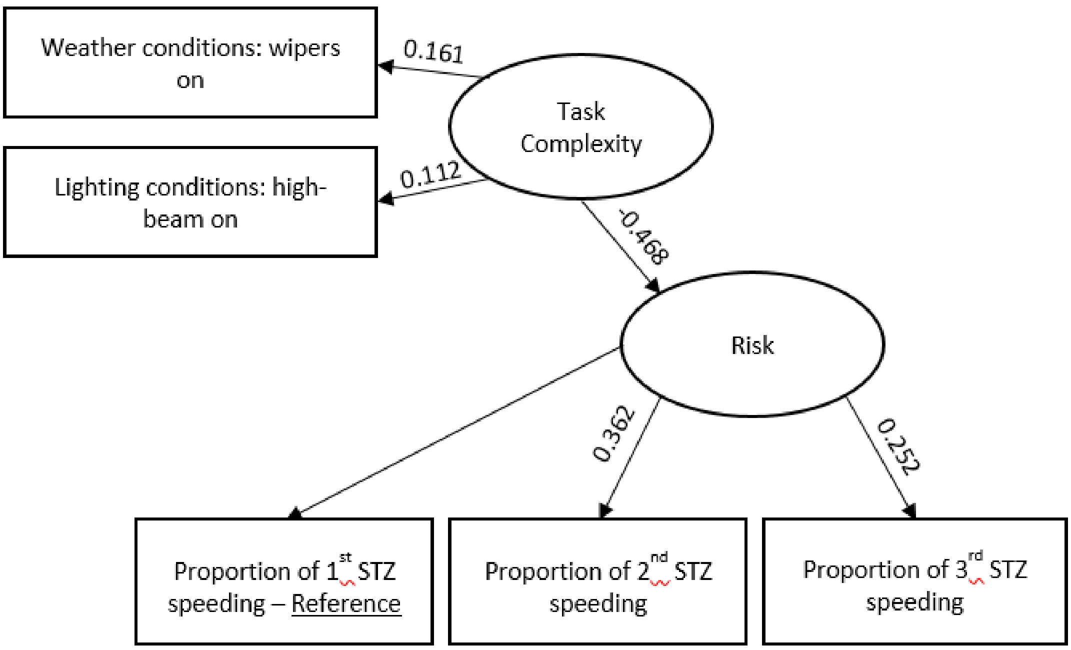

Figure 9: Results of SEM Task Complexity & Risk (speeding STZ) – Belgian car drivers – experiment Phase 1

Details about the model fit can be found in Table 27.

Table 27: Model Fit Summary for speeding – Belgian car drivers – experiment Phase 1

Model Fit Summary	
AIC	-77254.6
BIC	-77165.8
CFI	0.607
TLI	0.214
RMSEA	0.037

Standardised coefficients are presented in the path diagram while residual variances details can be found in Table 28 that follows.

Table 28: Residual variances for speeding – Belgian car drivers – experiment Phase 1

	Estimate	Std.Err	z-value	P(>|z|)
.Wiper	0.040	0.001	62.358	0.000
.HBeam	0.018	0.000	89.948	0.000
.iSP2	0.011	0.000	38.236	0.000
.iSP3	0.046	0.001	69.769	0.000
TC	0.001	0.001	1.999	0.046
.RISK	0.001	0.000	4.155	0.000

It is shown that the latent variable Task Complexity is measured by means of the environmental indicators 'wipers on' (indicating rainy weather conditions) and 'high-beam on' (indicating night-time or poor visibility conditions), both with a positive correlation with Task Complexity. Risk is measured by means of the STZ levels for speeding (level 1 'normal driving' used as the reference case), with positive correlations of Risk with the STZ indicators. The structural model between Task Complexity and Risk shows a negative coefficient, which is counter-intuitive. It is noted however that the lack of the Coping Capacity latent variable clearly affects this structural relationship, as the current model is only a partial depiction of the theoretical model of i-DREAMS, in which the inter-relation of Task Complexity and Coping Capacity affects Risk.

Figure 10, Figure 11 and Figure 12 show the results of the 2nd, 3rd and 4th phase of the experiment.

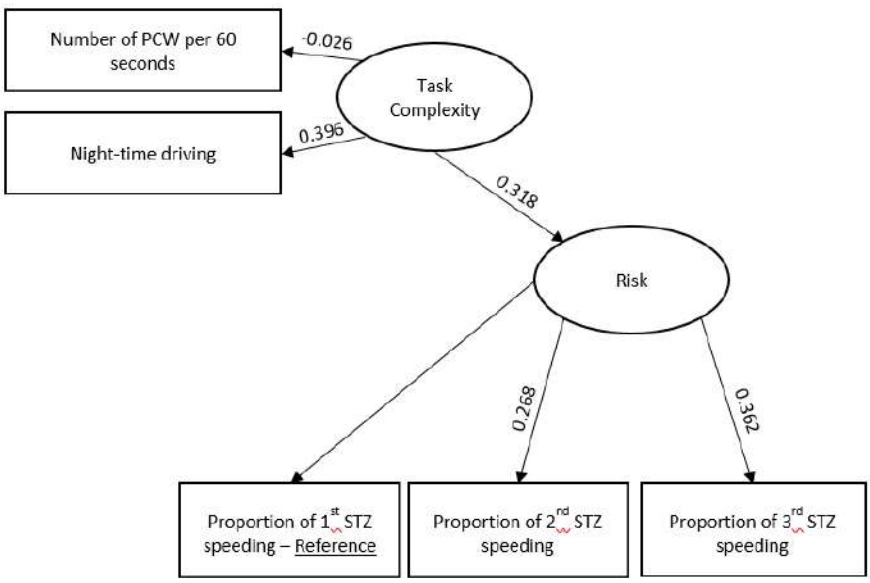

Figure 10: Results of SEM Task Complexity & Risk (speeding STZ) – Belgian car drivers – experiment Phase 2

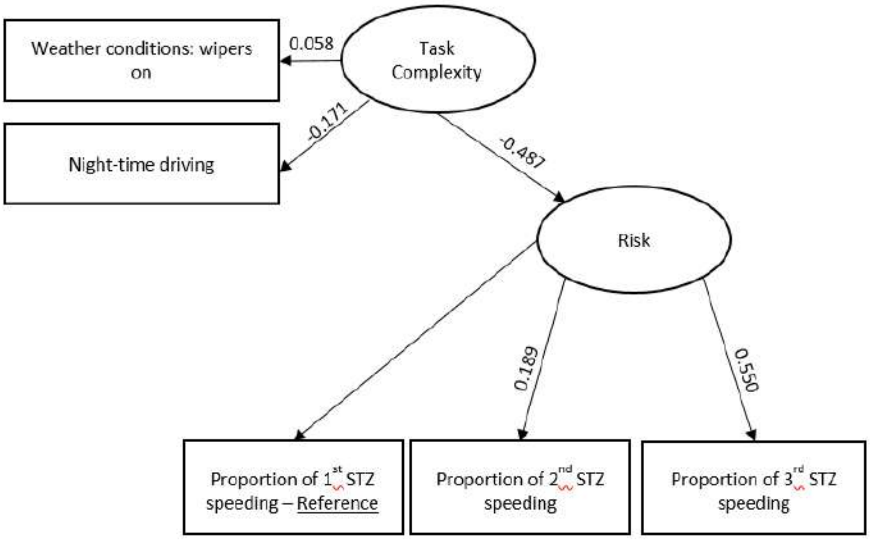

Figure 11: Results of SEM Task Complexity & Risk (speeding STZ) – Belgian car drivers – experiment Phase 3

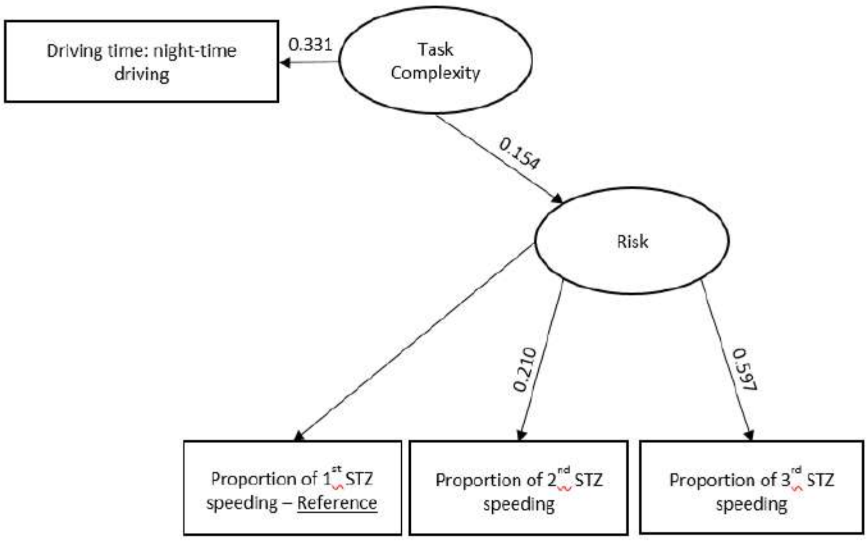

Figure 12: Results of SEM Task Complexity & Risk (speeding STZ) – Belgian car drivers – experiment Phase 4

Details about the model fit of the three models can be found in Table 29 below.

Table 29: Model Fit Summary for speeding – Belgian car drivers – experiment Phase 2, 3 & 4

Model fit summary	Phase 2	Phase 3	Phase 4
AIC	-138260	-75084.7	-95471.2
BIC	-138168	-74990.1	-95400.3
CFI	0.582	0.647	0.944
TLI	0.165	0.294	0.874
RMSEA	0.034	0.033	0.019

It is observed that the measurement equations of Task Complexity are fairly consistent between the different phases; slight differences (e.g., the appearance of the PCW variable in

Phase 2, the inconsistent appearance of weather conditions) can be attributed to the differences in the samples of drivers / trips, as well as actual differences between the time periods of the trips (e.g., rainy weather observations). However, their loadings are not consistent between the different phases. At the same time, the loadings of the observed proportions of the STZ of speeding are consistent between the different phases.

The structural model between Task Complexity and Risk is also inconsistent between the 4 phases, but due to its incompleteness in relation to the theoretical model, it is not possible to draw conclusions about the partial interaction between these two latent constructs.

4.2.2.2 Headway

Four separate SEM models were estimated in order to explore the relationship between the latent variables of Task Complexity and Risk (expressed as the three phases of the STZ) based on headway measurement. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 38 Belgian car drivers, 633 trips (16,393 minutes)
- Phase 2: real-time interventions - 42 Belgian car drivers, 813 trips (21,412 minutes)
- Phase 3: real-time & post-trip interventions - 50 Belgian car drivers, 990 trips (27,691 minutes)
- Phase 4: real-time, post-trip interventions & gamification - 49 Belgian car drivers, 1222 trips (35,284 minutes)

The results for Phase 1 are shown in Figure 13 below.

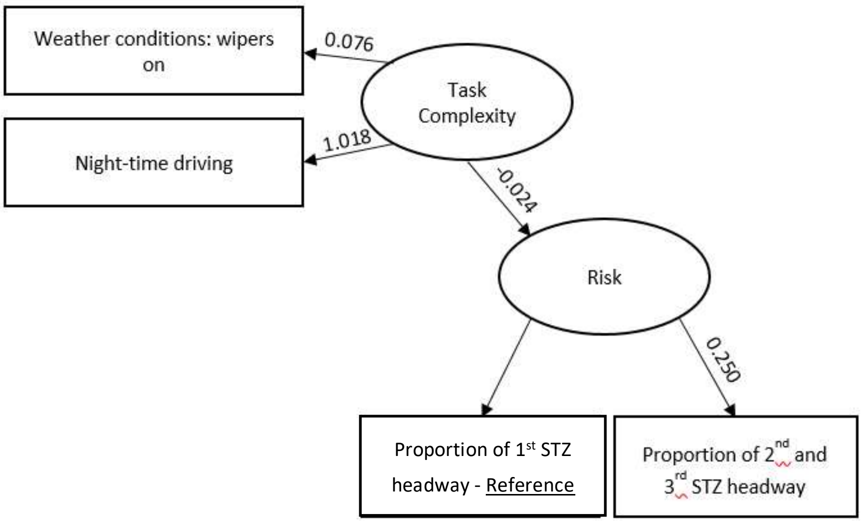

Figure 13: Results of SEM Task Complexity & Risk (headway STZ) – Belgian car drivers – experiment Phase 1

Details about the model fit can be found in Table 30 below.

Table 30: Model Fit Summary for headway – Belgian car drivers – experiment Phase 1

Model Fit Summary	
AIC	13556.7
BIC	13618.34
CFI	0.667
TLI	0.252
RMSEA	0.042

It is shown that the latent variable Task Complexity is measured by means of the environmental indicators ‘wipers on’ (indicating rainy weather conditions) and ‘high-beam on’ (indicating night-time or poor visibility conditions), both with a positive correlation with Task Complexity. Risk is measured by means of the STZ levels for headway (level 1 ‘normal driving’ used as the reference case), with positive correlation of Risk with the 2nd and 3rd level of the STZ headway indicators – which are here grouped together due to lack of sufficient data for the 3rd level. The structural model between Task Complexity and Risk shows a negative coefficient, which is counter-intuitive, as was in the previous case for the speeding-based STZ.

Figure 14, Figure 15, Figure 16 show the respective results of the 2nd, 3rd and 4th phase of the experiment.

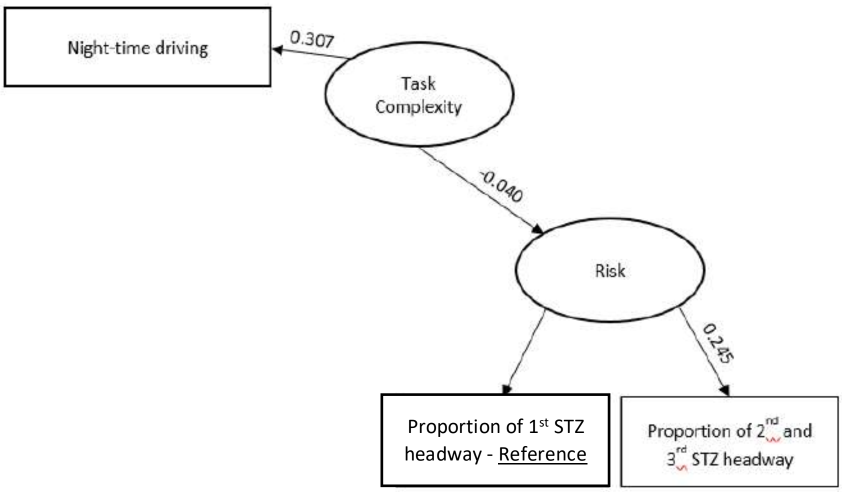

Figure 14: Results of SEM Task Complexity & Risk (headway STZ) – Belgian car drivers – experiment Phase 2

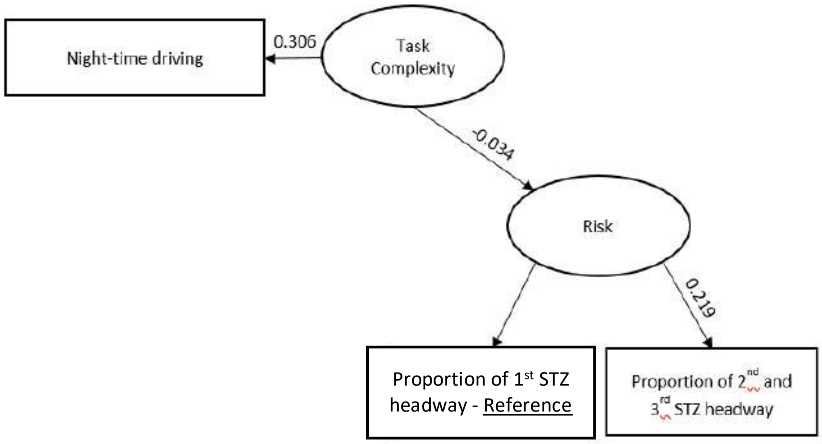

Figure 15: Results of SEM Task Complexity & Risk (headway STZ) – Belgian car drivers – experiment Phase 3

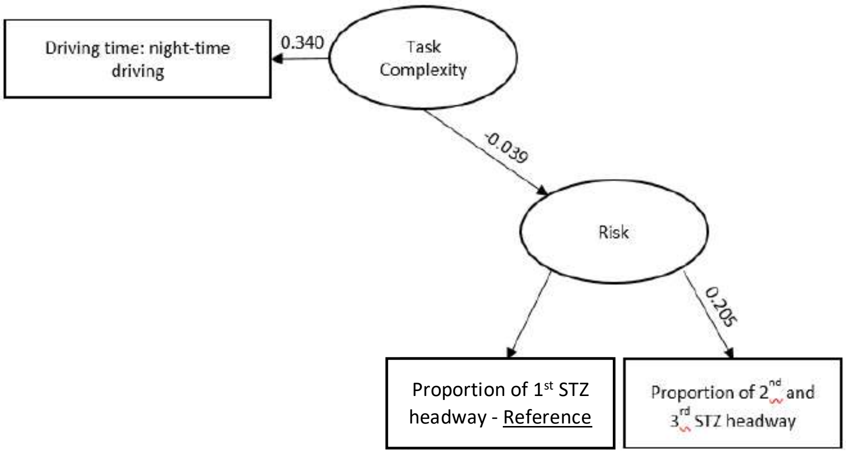

Figure 16: Results of SEM Task Complexity & Risk (headway STZ) – Belgian car drivers – experiment Phase 4

Details about the model fit of the three models can be found in Table 31 below.

Table 31: Model Fit Summary for headway – Belgian car drivers – experiment Phase 2, 3 & 4

Model fit summary	Phase 2	Phase 3	Phase 4
AIC	10585.9	7185.907	12058.62
BIC	10625.7	7227.052	12100.98
CFI	0.532	0.373	0.89
RMSEA	0.06	0.062	0.02

It is observed that the measurement equations of Task Complexity are consistent between the different phases, with night-time driving as the only variable loading on the latent variable. The loading of the observed proportions of the 2nd and 3rd STZ of headway are also consistent between the different phases. The structural model between Task Complexity and Risk indicates a negative correlation between the two constructs in all phases – a result that cannot be credibly interpreted in this partial model.

4.2.3 Belgium (Trucks)

4.2.3.1 Vehicle Control

Four separate SEM models were estimated in order to explore the relationship between the latent variables of Task Complexity and Risk where the latent variable risk, expressed as the three phases of the STZ, was formed as a composite of the vehicle control events, including acceleration, braking and cornering. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 23 Belgian truck drivers, 1418 trips (117,160 minutes)
- Phase 2: real-time interventions - 22 Belgian truck drivers, 1691 trips (146, 315 minutes)
- Phase 3: real-time & post-trip interventions - 22 Belgian truck drivers, 1440 trips (139,245 minutes)
- Phase 4: real-time, post-trip interventions & gamification - 23 Belgian truck drivers, 1767 trips (187,636 minutes)

The results for Phase 1 are shown in Figure 17 below.

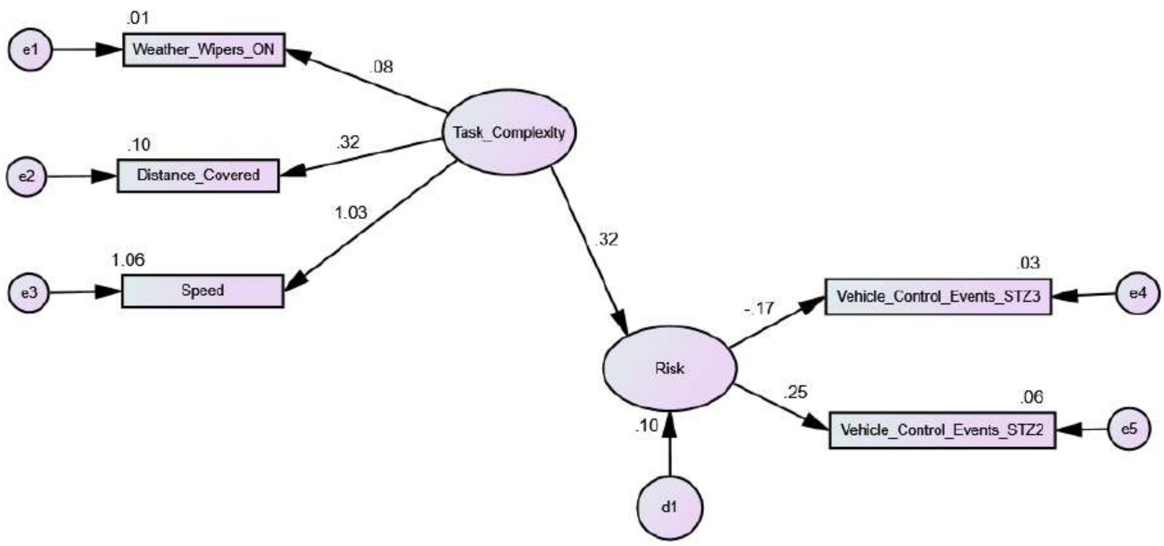

Figure 17: Results of SEM Task Complexity & Risk (Vehicle control STZ) – Belgian truck drivers – experiment Phase 1

The results indicate that the model is consistent with the data as CFI is 0.982, TLI is 0.956, and RMSEA is 0.024. More details about the model fit can be found in Table 32 below.

Table 32: Model Fit Summary for vehicle control – Belgian truck drivers – experiment Phase 1

Model Fit Summary	
AIC	286.543
BIC	392.136
CFI	0.982
TLI	0.956
RMSEA	0.024
GFI	0.999
HOELTER	0.5-3910 | 0.1-5472

Unstandardised coefficients details are presented in Table 33 that follows.

Table 33: Regression weights for vehicle control - Belgian truck drivers - experiment Phase 1

			Estimate	S.E.	C.R.	P
Risk	<---	Task_Complexity	3.622	0.193	18.749	***
ME_Car_wipers_median	<---	Task_Complexity	1			
DrivingEvents_Map_lvl_H_mean	<---	Risk	-0.177	0.011	-15.794	***
GPS_distances_sum	<---	Task_Complexity	65473.35	2599.272	25.189	***
Speed	<---	Task_Complexity	1419.671	116.058	12.232	***
DrivingEvents_Map_lvl_M_mean	<---	Risk	1			

It is shown that the latent variable Task Complexity is measured by means of the environmental indicator ‘wipers on’ (indicating rainy weather conditions), and situational indicators ‘speed’ and ‘distance covered’ (indicating context specific conditions) all with a positive correlation with Task Complexity. Risk is measured by means of the STZ levels for a composite vehicle control variable (level 1 ‘normal driving’ used as the reference case). The identified model indicated that level 1 of the composite vehicle control variable has no significant loading in the measurement model for latent variable risk and thus not included in the final model. Level 2 and level 3 of vehicle control variable (or STZ2 and STZ 3 indicators) have positive and negative correlations with the latent variable Risk, respectively. This is counter-intuitive. Since risk is a latent construct in the identified SEM, it is representing inverse of risk (i.e., normal driving). The structural model between Task Complexity and Risk (or normal driving) shows a positive coefficient, which is explained as increase in task complexity compels drivers to driver more carefully and depict normal driving behaviour. It is noted however that the lack of the Coping Capacity latent variable clearly affects this structural relationship, as the current model is only a partial depiction of the theoretical model of i-DREAMS, in which the inter-relation of Task Complexity and Coping Capacity affects Risk.

Figure 18 shows the results of the 2nd phase of the experiment.

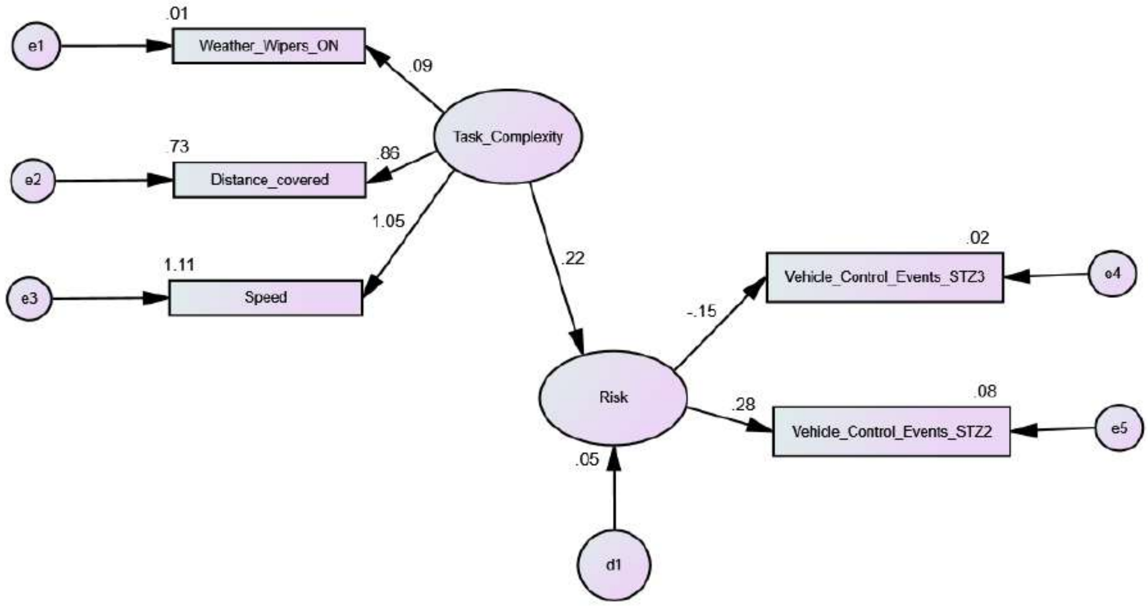

Figure 18: Results of SEM Task Complexity & Risk (Vehicle control STZ) – Belgian truck drivers – experiment Phase 2

The results indicate that the model is consistent with the data as CFI is 0.998, TLI is 0.996, and RMSEA is 0.026. More details about the model fit can be found in Table 34 below.

Table 34: Model Fit Summary for vehicle control – Belgian truck drivers – experiment Phase 2

Model Fit Summary	
AIC	402.381
BIC	511.011
CFI	0.998
TLI	0.996
RMSEA	0.026
GFI	0.999
HOELTER	0.5-3585 | 0.1-5016

Unstandardised coefficients details are presented in Table 35 that follows.

Table 35: Regression weights for vehicle control - Belgian truck drivers - experiment Phase 2

			Estimate	**S.E.**	**C.R.**	**P**
Risk	<---	Task_Complexity	2.625	0.127	20.614	***
ME_Car_wipers_median	<---	Task_Complexity	1			
DrivingEvents_Map_lvl_H_mean	<---	Risk	-0.13	0.011	-11.787	***
DrivingEvents_Map_lvl_M_mean	<---	Risk	1			
speed_mps	<---	Task_Complexity	1474.204	48.002	30.711	***
GPS_distances_sum	<---	Task_Complexity	61891.14	1752.966	35.307	***

Figure 19 shows the results of the 3rd phase of the experiment.

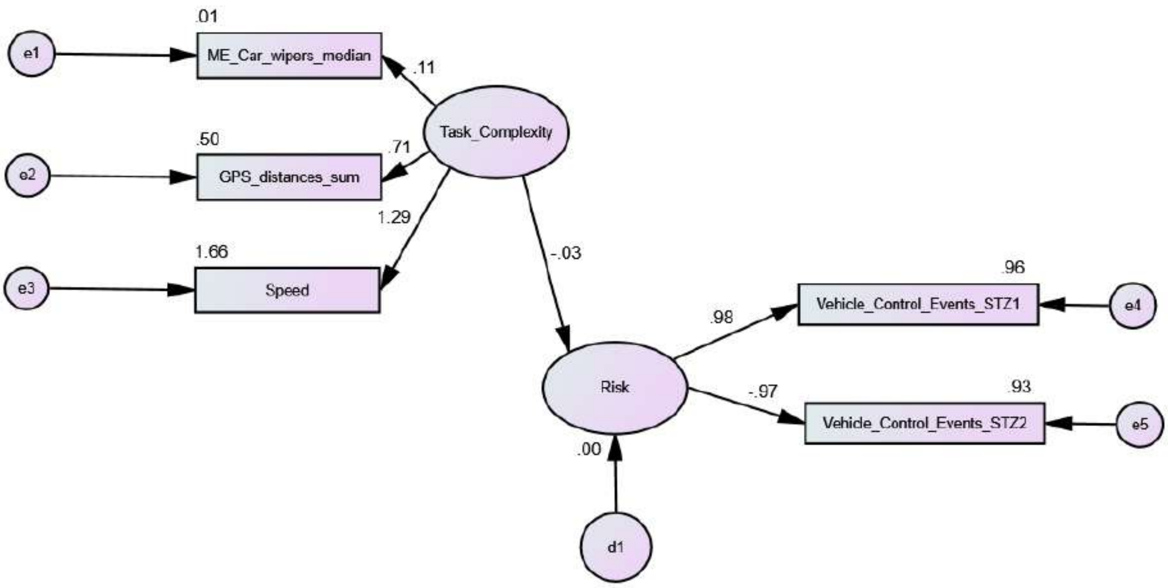

Figure 19: Results of SEM Task Complexity & Risk (Vehicle control STZ) – Belgian truck drivers – experiment Phase 3

The results indicate that the model is consistent with the data as CFI is 0.999, TLI is 0.998, and RMSEA is 0.03. More details about the model fit can be found in Table 36 below.

Table 36: Model Fit Summary for vehicle control – Belgian truck drivers – experiment Phase 3

Model Fit Summary	
AIC	211.81
BIC	309.412
CFI	0.999
TLI	0.998
RMSEA	0.03
GFI	0.999
HOELTER	0.5-2636 | 0.1-3689

Unstandardised coefficients details are presented in Table 37 that follows.

Table 37: Regression weights for vehicle control - Belgian truck drivers - experiment Phase 3

			Estimate	S.E.	C.R.	P
Risk	<---	Task_Complexity	-1.153	0.099	-11.63	***
ME_Car_wipers_median	<---	Task_Complexity	1			
DrivingEvents_Map_lvl_L_mean	<---	Risk	1			
DrivingEvents_Map_lvl_M_mean	<---	Risk	-0.959	0.026	-36.74	***
Speed	<---	Task_Complexity	1343.46	75.594	17.772	***
GPS_distances_sum	<---	Task_Complexity	39121.5	1237.14	31.623	***

Figure 20 shows the results of the 4th phase of the experiment.

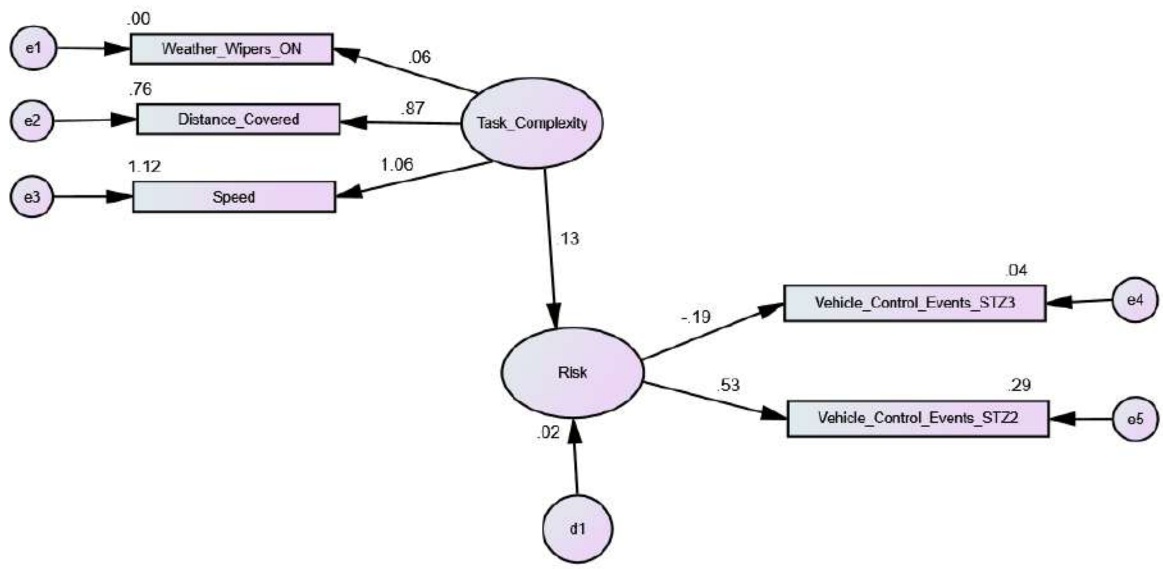

Figure 20: Results of SEM Task Complexity & Risk (Vehicle control STZ)– Belgian truck drivers – experiment Phase 4

The results indicate that the model is consistent with the data as CFI is 0.998, TLI is 0.996, and RMSEA is 0.027. More details about the model fit can be found in Table 38 below.

Table 38: Model Fit Summary for vehicle control – Belgian truck drivers – experiment Phase 4

Model Fit Summary	
AIC	244.068
BIC	345.623
CFI	0.998
TLI	0.996
RMSEA	0.027
GFI	0.999
HOELTER	0.5-3228 | 0.1-4516

Unstandardised coefficients details are presented in the Table 39 that follows.

Table 39: Regression weights for vehicle control - Belgian truck drivers - experiment Phase 4

			Estimate	S.E.	C.R.	P
Risk	<---	Task_Complexity	9.297	0.693	13.419	***
ME_Car_wipers_median	<---	Task_Complexity	1			
DrivingEvents_Map_lvl_H_mean	<---	Risk	-0.152	0.021	-7.101	***
Speed	<---	Task_Complexity	4257.897	263.77	16.142	***
GPS_distances_sum	<---	Task_Complexity	184468.7	10427.2	17.691	***
DrivingEvents_Map_lvl_M_mean	<---	Risk	1			

It is observed that the measurement equations of Task Complexity are fairly consistent between the different phases. However, their loadings are not consistent between the different phases (can be attributed to the differences in the samples of drivers / trips). At the same time, the loadings of the observed proportions of the STZ of the vehicle control are consistent between the different phases.

The structural model between Task Complexity and inverse Risk (normal driving) is fairly consistent between the 4 phases, but due to its incompleteness in relation to the theoretical model, it is not possible to draw conclusions about the partial interaction between these two latent constructs.

4.2.4 Germany (Cars)

4.2.4.1 Speeding

Four separate SEM models were estimated in order to explore the relationship between the latent variables of Coping Capacity and Risk (expressed as the three phases of the STZ) of harsh braking. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 28 German car drivers, 1397 trips
- Phase 2: real-time interventions - 28 German car drivers, 1322 trips
- Phase 3: real-time & post-trip interventions - 27 German car drivers, 1129 trips
- Phase 4: real-time, post-trip interventions & gamification - 28 German car drivers, 1496 trips

The results for Phase 1 are shown in Figure 21 below. It is shown that the latent variable Task Complexity is measured by means of the environmental indicator of “ME_AWS_time_indicator_median” (indicating time of the day). It should be noted that based on the definition of task complexity, road layout, time, location, traffic and weather variables should be included in the analysis. However, road type (i.e. urban, rural, highway), location, traffic volumes and weather were not available in German dataset. Thus, only the time indicator was able to be used in the models applied. To that aim, exposure indicators, such as trip duration and distance travelled were included in the task complexity analysis. In particular, time of the day, distance and duration found to have a positive correlation with Task Complexity. Risk is measured by means of the STZ levels for speeding (level 1 ‘normal driving’ used as the reference case), with positive correlations of Risk with the STZ indicators. Overall, the structural model between Task Complexity and Risk shows a positive coefficient, which means that increased task complexity relates to increased risk according to the model (regression coefficient=0.63).

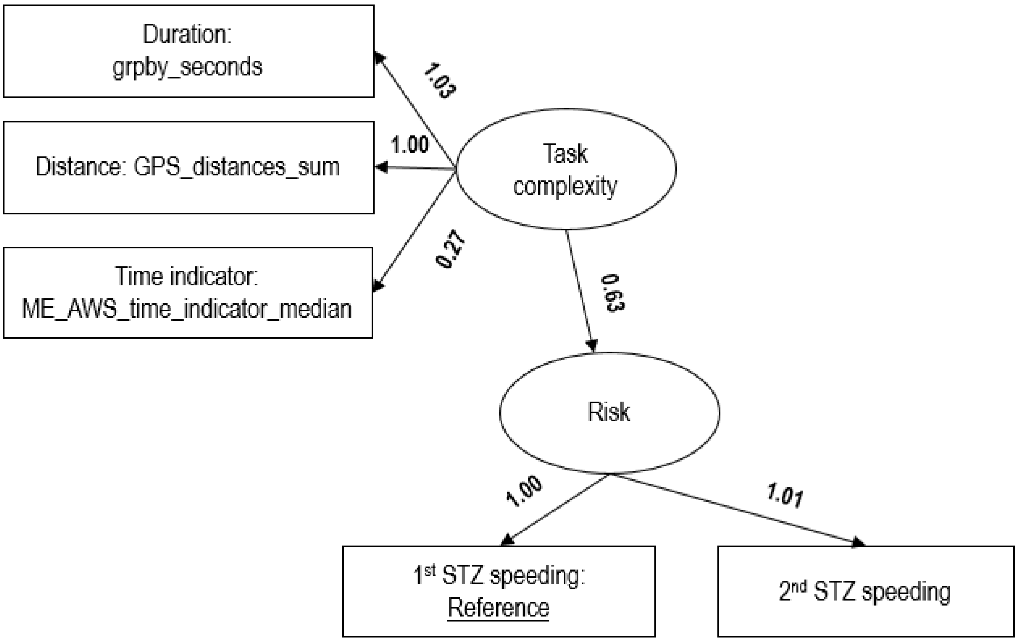

Figure 21: Results of SEM Task Complexity & Risk (speeding STZ) – German car drivers – experiment Phase 1

The Comparative Fit Index (CFI) of the model is equal 0.999; TLI is 0.997 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.059. More details about the model fit can be found in Table 40 below.

Table 40: Model Fit Summary for speeding – German car drivers – experiment Phase 1

Model Fit Summary	
AIC	131271.417
BIC	131412.355
CFI	0.999
TLI	0.997
RMSEA	0.059
GFI	0.989
HOELTER	0.05 - 688.952 0.01 - 963.690

Residual variances details are presented in Table 41 that follows.

Table 41: Residual variances for speeding – German car drivers – experiment Phase 1

Variable	Estimate	Std. Error	z-value	p
GPS_distances_sum	0.725	0.008	86.390	< .001
grpby_seconds	0.689	0.008	82.407	< .001
ME_AWS_time_indicator_median	0.978	0.008	117.831	< .001
iDreams_Speeding_Map_level_0_sum	0.007	2.008×10^{-4}	34.052	< .001
iDreams_Speeding_Map_level_1_sum	-0.007	2.034×10^{-4}	-33.553	< .001

The following path diagrams show the results of the 2nd, 3rd and 4th phase of the experiment. It is observed that the measurement equations of Task Complexity are fairly consistent between the different phases. At the same time, the loadings of the observed proportions of the STZ of speeding are consistent between the different phases. The structural model between Task Complexity and inverse Risk (normal driving) are positively correlated among the 4 phases. The results for Phase 2 are shown in Figure 22 below.

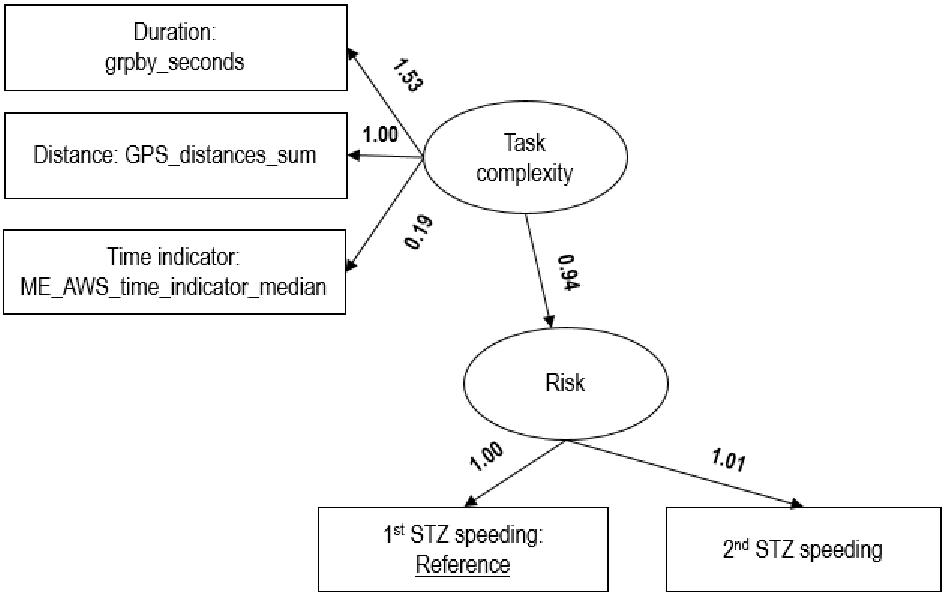

Figure 22: Results of SEM Task Complexity & Risk (speeding STZ) – German car drivers – experiment Phase 2

The Comparative Fit Index (CFI) of the model is equal 0.999; TLI is 0.999 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.031. Table 42 summarizes the model fit of SEM applied for speeding. More details about the model fit can be found in the Table 42 below.

Table 42: Model Fit Summary for speeding – German car drivers – experiment Phase 2

Model Fit Summary	
AIC	91721.549
BIC	91858.602
CFI	0.999
TLI	0.999
RMSEA	0.031
GFI	0.997
HOELTER	0.05 - 2354.290 0.01 - 3294.089

Residual variances details are presented in Table 43 that follows.

Table 43: Residual variances for speeding – German car drivers – experiment Phase 2

Variable	Estimate	Std. Error	z-value	p
GPS_distances_sum	0.854	0.008	111.421	< .001
grpby_seconds	0.654	0.010	63.763	< .001
ME_AWS_time_indicator_median	0.994	0.010	100.336	< .001
iDreams_Speeding_Map_level_0_sum	0.009	2.546×10^{-4}	37.094	< .001
iDreams_Speeding_Map_level_1_sum	-0.009	2.592×10^{-4}	-36.587	< .001

The results for Phase 3 are shown in Figure 23 below.

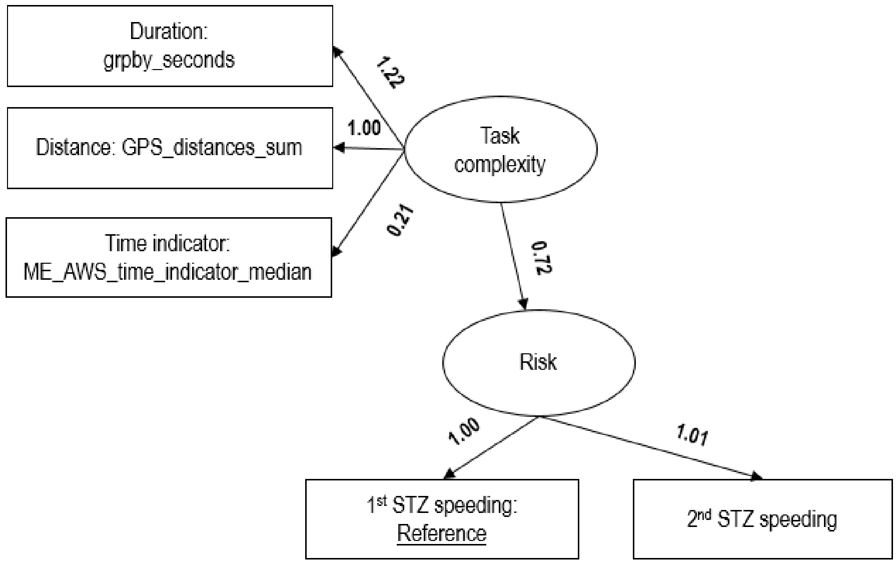

Figure 23: Results of SEM Task Complexity & Risk (speeding STZ) – German car drivers – experiment Phase 3

The Comparative Fit Index (CFI) of the model is equal to 0.999; TLI is 0.999 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.025. More details about the model fit can be found in Table 44 below.

Table 44: Model Fit Summary for speeding – German car drivers – experiment Phase 3

Model Fit Summary	
AIC	87861.859
BIC	87998.411
CFI	0.999
TLI	0.999
RMSEA	0.025
GFI	0.997
HOELTER	0.05 - 3554.235 0.01 - 4973.239

Residual variances details are presented in Table 45 that follows.

Table 45: Residual variances for speeding – German car drivers – experiment Phase 3

Variable	Estimate	Std. Error	z-value	p
GPS_distances_sum	0.751	0.007	100.621	< .001
grpby_seconds	0.626	0.008	74.568	< .001
ME_AWS_time_indicator_median	0.988	0.010	94.642	< .001
iDreams_Speeding_Map_level_0_sum	0.010	2.531×10^{-4}	40.113	< .001
iDreams_Speeding_Map_level_1_sum	-0.010	2.579×10^{-4}	-39.549	< .001

The results for Phase 4 are shown in Figure 24 below.

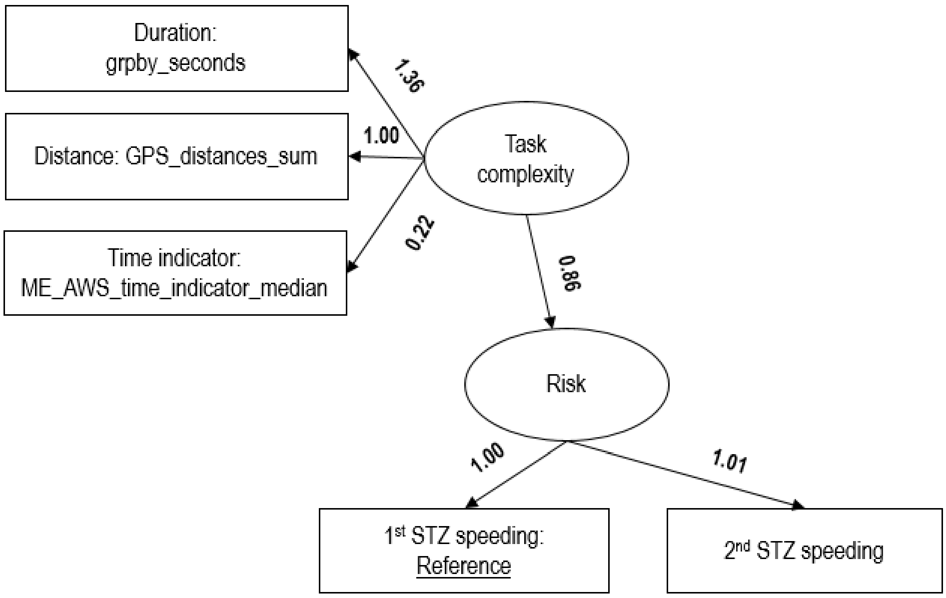

Figure 24: Results of SEM Task Complexity & Risk (speeding STZ) – German car drivers – experiment Phase 4

The Comparative Fit Index (CFI) of the model is equal to 0.999; TLI is 0.999 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.025. More details about the model fit can be found in the Table 46 below.

Table 46: Model Fit Summary for speeding – German car drivers – experiment Phase 4

Model Fit Summary	
AIC	113537.702
BIC	113676.427
CFI	0.999
TLI	0.999
RMSEA	0.025
GFI	0.997
HOELTER	0.05 - 3572.155 0.01 - 4998.315

Residual variances details are presented in Table 47 that follows.

Table 47: Residual variances for speeding – German car drivers – experiment Phase 4

Variable	Estimate	Std. Error	z-value	p
GPS_distances_sum	0.808	0.007	119.600	< .001
grpby_seconds	0.634	0.008	79.134	< .001
ME_AWS_time_indicator_median	0.991	0.009	108.144	< .001
iDreams_Speeding_Map_level_0_sum	0.011	2.398×10^{-4}	44.532	< .001
iDreams_Speeding_Map_level_1_sum	-0.011	2.446×10^{-4}	-43.897	< .001

4.2.5 Greece (Cars)

4.2.5.1 Speeding

Three separate SEM models were estimated in order to explore the relationship between the latent variables of task complexity, coping capacity and risk (expressed as the three phases of the STZ) of speeding. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 65 Greek car drivers, 2,937 trips (51,786 minutes)
- Phase 3: real-time & post-trip interventions - 65 Greek car drivers, 3,935 trips (69,962 minutes)
- Phase 4: real-time. post-trip interventions & gamification - 65 Greek car drivers, 2,194 trips (39,695 minutes)

It should be noted that due to technical difficulties, the app was used to collect data and therefore, real-time warnings were not available (Phase 2).

The results for phase 1 are shown in Figure 25 below. Risk is measured by means of the STZ levels for speeding (level 1 refers to 'normal driving' used as the reference case, level 2 refers to 'dangerous driving' while level 3 refers to 'avoidable accident driving'), with positive correlations of Risk with the STZ indicators.

To begin with, the latent variable task complexity is measured by means of the environmental indicators "ME_AWS_time_indicator_median" (indicating time of the day). The exposure indicator of trip duration was also included in the task complexity analysis.

Overall, the structural model between task complexity and risk shows a positive but negligible coefficient, which means that increased task complexity relates to increased risk according to the model (regression coefficient=0.05).

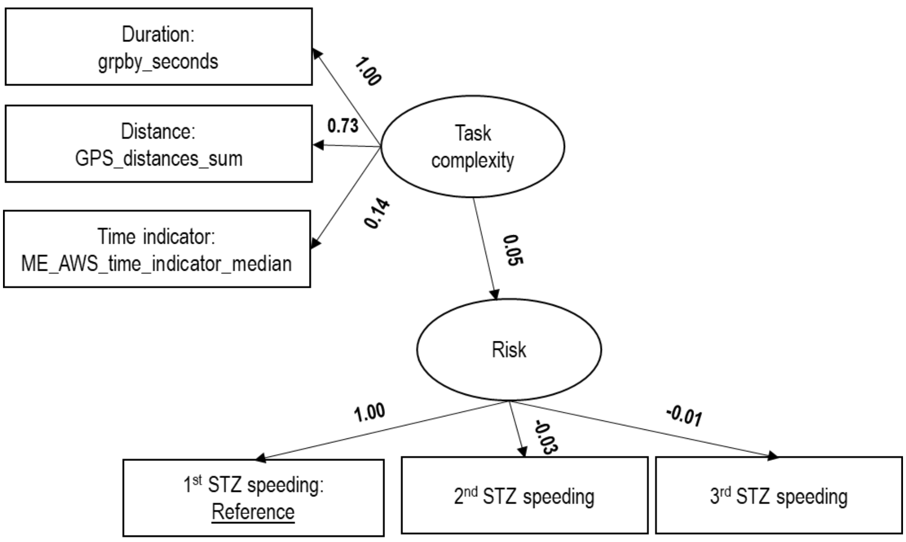

Figure 25: Results of SEM on Risk (Speeding STZ) – Greek car drivers – experiment Phase 1

The Comparative Fit Index (CFI) of the model is equal to 0.967; TLI is 0.939 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.091. Table 48 summarizes the model fit of SEM applied for speeding.

Table 48: Model Fit Summary for speeding – Greek car drivers – experiment Phase 1

Model Fit Summary	
AIC	314702.148
BIC	314854.909
CFI	0.967
TLI	0.939
RMSEA	0.091
GFI	0.975
HOELTER	0.05 - 232.504 0.01 – 300.920

Residual variances details are presented in Table 49 that follows.

Table 49:Residual variances for speeding – Greek car drivers – experiment Phase 1

Variable	Estimate	Std. Error	z-value	p
grpby_seconds	0.783	0.054	14.508	< .001
GPS_distances_sum	0.885	0.029	30.050	< .001
ME_AWS_time_indicator_median	0.996	0.009	105.704	< .001
iDreams_Speeding_Map_level_0_mean	-33.128	43.663	-0.759	0.448
iDreams_Speeding_Map_level_1_mean	0.975	0.033	29.423	< .001
iDreams_Speeding_Map_level_2_mean	0.967	0.010	94.075	< .001

The following Figures show the results of the 3rd and 4th phase of the experiment. It is observed that the measurement equations of task complexity and coping capacity are fairly consistent between the different phases. At the same time, the loadings of the observed proportions of the STZ of speeding are consistent between the different phases. The structural model between task complexity and inverse risk (normal driving) are positively correlated among the three phases. The results for phase 3 are shown in Figure 26 below.

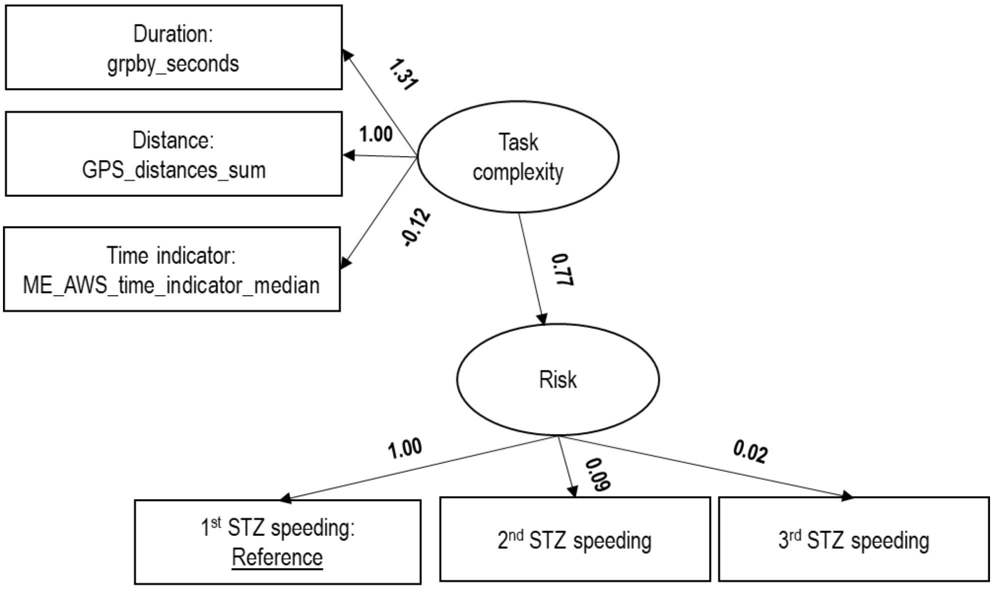

Figure 26: Results of SEM on Risk (Speeding STZ) – Greek car drivers – experiment Phase 3

The Comparative Fit Index (CFI) of the model is equal to 0.960; TLI is 0.925 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.088. Table 50 summarizes the model fit of SEM applied for speeding.

Table 50: Model Fit Summary for speeding – Greek car drivers – experiment Phase 3

Model Fit Summary	
AIC	$1.052\times10^{+6}$
BIC	$1.052\times10^{+6}$
CFI	0.960
TLI	0.925
RMSEA	0.088
GFI	0.975
HOELTER	0.05 - 248.125 0.01 – 321.159

Residual variances details are presented in Table 51 that follows.

Table 51:Residual variances for speeding – Greek car drivers – experiment Phase 3

Variable	Estimate	Std. Error	z-value	p
GPS_distances_sum	0.928	0.006	157.921	< .001
grpby_seconds	0.877	0.007	120.516	< .001
ME_AWS_time_indicator_median	0.999	0.005	193.616	< .001
iDreams_Speeding_Map_level_0_mean	10.802	2.145	5.035	< .001
iDreams_Speeding_Map_level_1_mean	1.078	0.018	59.878	< .001
iDreams_Speeding_Map_level_2_mean	0.960	0.006	161.128	< .001

The results for phase 4 are shown Figure 27 below.

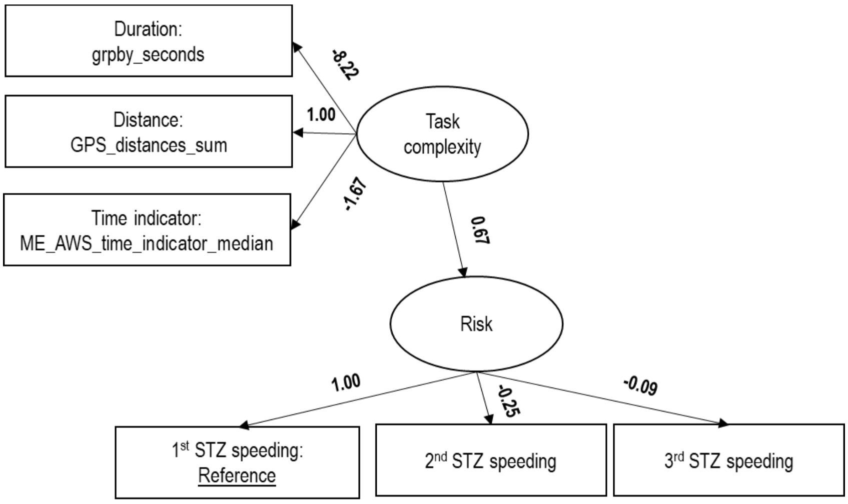

Figure 27: Results of SEM on Risk (Speeding STZ) – Greek car drivers – experiment Phase 4

The Comparative Fit Index (CFI) of the model is equal to 0.918, TLI is 0.847 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.134. Table 52 summarizes the model fit of SEM applied for speeding.

Table 52:Model Fit Summary for speeding – Greek car drivers – experiment Phase 4

Model Fit Summary	
AIC	$2.028{\times}10^{+6}$
BIC	$2.028{\times}10^{+6}$
CFI	0.918
TLI	0.847
RMSEA	0.134
GFI	0.943
HOELTER	0.05-108.695 0.01-140.523

Residual variances details are presented in Table 53 that follows.

Table 53: Residual variances for speeding – Greek car drivers – experiment Phase 4

Variable	Estimate	Std. Error	z-value	p
GPS_distances_sum	0.971	0.004	263.800	< .001
grpby_seconds	-0.759	0.059	-12.949	< .001
ME_AWS_time_indicator_median	0.927	0.004	227.104	< .001
iDreams_Speeding_Map_level_0_mean	-2.551	0.096	-26.536	< .001
iDreams_Speeding_Map_level_1_mean	0.783	0.007	117.887	< .001
iDreams_Speeding_Map_level_2_mean	0.927	0.004	219.034	< .001

4.2.6 Portugal (Buses)

4.2.6.1 Headway

Two separate SEM models were estimated in order to explore the relationship between the latent variables of task complexity and risk (expressed as the three phases of the STZ) of headway. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 29 Portuguese bus drivers, 2,459 trips (202,532 minutes)
- Phase 2: real-time interventions - 29 Portuguese bus drivers, 1,363 trips (123,132 minutes)

It is noteworthy that in Portugal technical challenges rendered impossible for the app to be installed, therefore data from phase 1 and Phase 2 were only collected.

To begin with, the results for phase 1 are shown in Figure 28 below. Risk is measured by means of the STZ levels for headway (level 1 'normal driving' used as the reference case; level 2 refers to 'dangerous driving', while level 3 refers to 'avoidable accident driving'. In particular, negative correlations of risk with the STZ indicators were found.

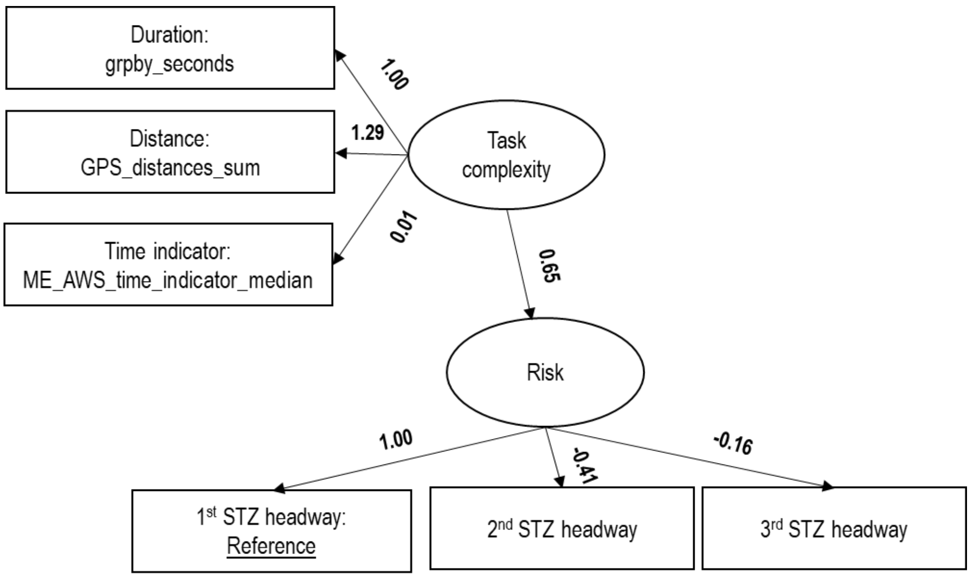

Figure 28: Results of SEM on Risk (Headway STZ) – Portuguese bus drivers – experiment Phase 1

The latent variable task complexity is measured by means of the environmental indicator of "ME_AWS_time_indicator_median" (indicating time of the day) and distance traveled and duration. It should be noted that based on the definition of task complexity, road layout, time, location, traffic volumes and weather variables should be included in the analysis. However, road type (i.e., urban, rural, highway), location, traffic volumes (i.e. high, medium, low) and weather were not available in Portuguese dataset. Thus, only the time indicator was able to be used in the models applied. To that aim, exposure indicators, such as trip duration and distance traveled were included in the task complexity analysis. In particular, time of the day and duration were found to have a positive correlation with task complexity. Overall, the structural model between task complexity and risk shows a positive coefficient, which means that increased task complexity relates to increased risk according to the model (regression coefficient=0.65).

The Comparative Fit Index (CFI) of the model is equal to 0.996; TLI is 0.992 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.045. Table 54 summarizes the model fit of SEM applied for headway.

Table 54: Model Fit Summary for headway – Portuguese bus drivers – experiment Phase 1

Model Fit Summary	
AIC	$2.017{\times}10^{+6}$
BIC	$2.017{\times}10^{+6}$
CFI	0.996
TLI	0.992
RMSEA	0.045
GFI	0.995
HOELTER	0.05-974.886 0.01-1262.702

Residual variances details are presented in Table 55 that follows.

Table 55:Residual variances for headway – Portuguese bus drivers – experiment Phase 1

Variable	Estimate	Std. Error	z-value	p
duration	0.253	0.001	196.001	< .001
ME_AWS_time_indicator	1.000	0.004	277.584	< .001
distance	-0.244	0.002	-138.554	< .001
iDreams_Headway_Map_level_-1_mean	-0.284	0.005	-52.418	< .001
iDreams_Headway_Map_level_0_mean	0.785	0.003	266.826	< .001
iDreams_Headway_Map_level_1_mean	0.967	0.003	279.716	< .001

Figure 29 shows the results of the 2nd phase of the experiment. Task complexity and inverse risk (normal driving) are negatively correlated in phase 2.

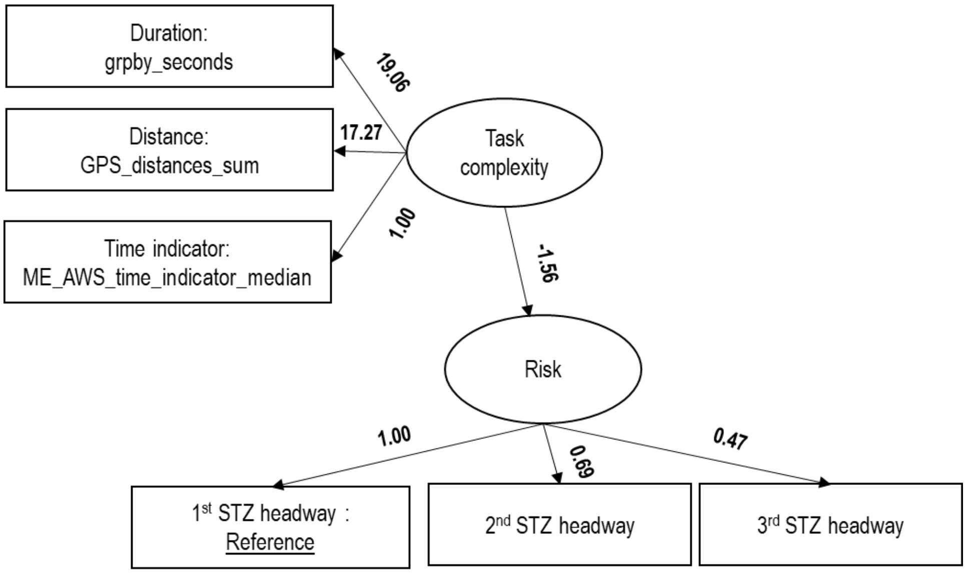

Figure 29: Results of SEM on Risk (Headway STZ) – Portuguese bus drivers – experiment Phase 2

The Comparative Fit Index (CFI) of the model is equal to 0.987; TLI is 0.991 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.018. Table 56 summarizes the model fit of SEM applied for headway.

Table 56:Model Fit Summary for headway – Portuguese bus drivers – experiment Phase 2

Model Fit Summary	
AIC	$1.019\times10^{+6}$
BIC	$1.019\times10^{+6}$
CFI	0.987
TLI	0.991
RMSEA	0.018
GFI	0.999
HOELTER	0.05-5680.018 0.01-7358.355

Residual variances details are presented in Table 57 that follows.

Table 57:Residual variances for headway – Portuguese bus drivers – experiment Phase 2

Variable	Estimate	Std. Error	z-value	p
ME_AWS_time_indicator	0.997	0.005	200.103	< .001
duration	0.100	0.004	25.298	< .001
distance	-0.096	0.005	-19.885	< .001
iDreams_Headway_Map_level_0_mean	1.004	0.006	156.623	< .001
iDreams_Headway_Map_level_1_mean	1.002	0.005	186.806	< .001
iDreams_Headway_Map_level_2_mean	1.001	0.005	196.723	< .001

4.2.7 Summary

The results of SEM analyses per every phase of the trials were presented for UK, Belgian, German, Greek cars, Belgian trucks and Portuguese buses driving data. Due to differentiations in the data collection process and technicalities that occurred with data collection equipment in every country, the datasets present various differences that are also depicted in the models developed.

Data from UK cars presents the greater number of trips and in most of the phases the variables loading to task complexity were more along with stronger correlation of the latter with Risk. For UK cars, the variables that represent the latent variable of task complexity change in some phases, but this is not the case with the Belgian trucks. For Belgian cars, in three out of four phases, there is only one variable loading in task complexity, this of the time of the day.

It should be noted though that for all the different datasets available, not only the variables that load to task complexity are varying but also the variables that represent risk are different. In some cases also (Belgian cars and trucks), the latent variable of risk is measured only by two levels of the STZ. In the case of Belgian cars, the risk is represented by the two levels of STZ for headway measurement while for Belgian trucks the risk is represented by the 2 levels of STZ regarding the vehicle control driving events. Furthermore, Portuguese data collected only for phase1 and 2 while Greek dataset lacks phase 3, rendering a direct comparison of results impossible.

5 Conclusions

Data from on road trials in Belgium, Germany, Greece, Portugal and United Kingdom was collected representing car, truck and bus drivers. The purpose of this deliverable was to investigate the effect of task complexity on risk in the framework of a four phase on-road trial. More specifically, the i-DREAMS on-road study included four consecutive phases:

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

Questionnaire data were also collected providing useful information about the participants.

Generalised linear and structural equation modelling were employed to explore the factors defining task complexity and the relationship of the latter with the risk. Both task complexity and risk were considered as latent (not observable) in the project study. Although data collection design was unified, during the data collection process in the different countries, various technicalities occur with regard to, e.g., systems (failure of sensors, app installation) or people (driver availability). This resulted in different datasets and in turn, to different variables being selected for the models to ensure validity.

In terms of the SEM analysis, four models were developed per risk factor (e.g., speeding and headway), one for every phase in order to detect any difference in the way task complexity affects risk. An explicit comparison between countries or transport modes was finally not feasible due to the aforementioned issues. In some cases, e.g., German data, not only the variables that represent task complexity vary, but also the variables that represent risk are different. Furthermore, in Greek and Portuguese dataset there were not data from all phases. Therefore, results can be interpreted only on a country and transport mode basis. Interestingly, in all models across the countries and transport modes, age and gender were not proven to be significant factors.

The effect of task complexity on risk per indicator/phase/country/transport mode according to the models developed can be found in Table 58.

Table 58: Effect of task complexity on risk per indicator/phase/country/transport mode

		Task Complexity			
Country (transport mode)	Risk (indicator)	Phase 1	Phase 2	Phase 3	Phase 4
Belgium (cars)	speeding	-	+	-	+
	headway	-	-	-	-
Belgium (trucks)	vehicle control events	+	+	-	+
UK (cars)	headway	+	+	+	+
Germany (cars)	speeding	+	+	+	+
Greece (cars)	speeding	+		+	+
Portugal (buses)	headway	+	-		

The positive sign is translated to a positive correlation of task complexity with risk while the negative sign indicates a negative relationship between the task complexity and the risk. In other words, in the case of the positive relationship, an increase in task complexity would be translated to an increase in risk while in the case of the negative correlation an increase in task complexity leads to a decrease in risk.

The measurement of task complexity and its correlation with risk posed a challenge due to the limited number of variables that could be collected and utilized, leading to the use of proxies. For instance, the weather conditions were approximated by the use (or not) of wipers and the lighting conditions or night-time driving was determined by the use of high beams.

Overall, collection of the intended variables proved more difficult than anticipated. Future research could take into consideration the aforementioned challenges, and through adequate planning, accommodate the extensive requirements of such an endeavour. Incorporating information on factors like road configuration, traffic density, and other relevant metrics would be very useful in order to establish the complexity of the driving task and its association with risk.

The results of D6.1 can contribute to informing road safety policies and interventions aimed at reducing the number of road crashes and saving lives. By identifying the factors that contribute to risk in real-world trials, policymakers and transportation authorities can develop targeted interventions and education campaigns to address hazardous behaviours. As task complexity was found to mostly increase risk, it is crucial for road safety to discover ways of efficiently reducing driving task demand. This could be accomplished by promoting the use of advanced driver assistance systems, improving road infrastructure and enhancing driver training.

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Annex 1:

Descriptive statistics for the available parameters

Table A 1: Descriptive statistics for the available parameters in database used for Belgium car drivers

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
Phase 1								
Gender - male	0	0	1	0,71	1	1		
Age	20	30	44	43,8	64	79		
Income	1	3	5	4,27	5	6		1: Less than €1.000, 2: €1.000 - €2.000, 3: €2000 - €3.000, 4: €3000 - €4.000, 5: €4000 - €5.000, 6: More than €5.000
% driving on urban roads	2	20	25	26,8	30	60		
% driving on rural roads	20	25	40	42,9	60	80		
Violation item 1	1	2	2	2,14	2,14	5		how often did you as a car driver, drive faster than the speed limit inside built-up areas? (1) Never, (2) Seldom, (3) About half the time, (4) Usually, (5) (almost) Always
Violation item 2	1	3	3	3,3	4	5		how often did you as a car driver, drive faster than the speed limit? (1) Never, (2) Seldom, (3) About half the time, (4) Usually, (5) (almost) Always
Driving style	0	0	0	0,45	1	1		0: Discrete average driver or Less experienced hesitant driver 1: Sportive ambitioned driver or risk-taking offensive driver
Confidence	0	0	1	0,65	1	1		How confident you are concerning your own driving skills? 1: Very confident or confident, 0: otherwise
Competence	3	3	3	3,503	4	5		How do you think you compare to the average driver, regarding general driving skills, I am: (1) Much worse, (2) Worse, (3) Not better nor worse, (4) Better, (5) Much better
Attitude item 1	1	2	3	3,27	5	5		Driving is … (5) Very dangerous, (4) Quite dangerous, (3) Neither dangerous nor safe, (2) Quite safe, (1) Very safe
Attitude item 2	3	4	4	4,14	4	5		a. I know the benefits of safe driving: (1) Strongly disagree, (2) Disagree, (3) Neutral, (4) Agree, (5) Strongly agree
Highest level of education	0	0	1	0,71	1	1		1: college or above, 0: otherwise
Employment status	0	0	1	0,59	1	1		1: full time or part time employed, 0: otherwise
Headway - STZ 1	0	0	0,07	0,17	0,27	1		Proportion of events in 60 seconds
Headway - STZ 2	0	0	0	0,13	0,17	1		Proportion of events in 60 seconds
Headway - STZ 3	0	0	0	0,03	0	1		Proportion of events in 60 seconds
Speeding - STZ 1	0	0	0,45	0,47	0,92	1	159	Proportion of events in 60 seconds
Speeding - STZ 2	0	0	0	0,05	0,02	1	824	Proportion of events in 60 seconds
Speeding - STZ 3	0	0	0	0,1	0,05	1	895	Proportion of events in 60 seconds

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
Harsh acceleration events	0	0	0,53	0,5	1	1	607	Proportion of events in 60 seconds
Harsh braking events	0	0	0	0,2	0,27	1	630	Proportion of events in 60 seconds
Harsh cornering events	0	0	0	0,31	0,7	1	895	Proportion of events in 60 seconds
KSS	35	35	35	35	35	39	5598	
IBI	376	755	807	811	871	1263	1230	
Wipers on	0	0	0	0,05	0	1		Proportion of events in 60 seconds
High beams on	0	0	0	0,018	0	1		Proportion of events in 60 seconds
FCW	0	0	0	0,02	0	3		Number of events in 60 seconds
PCW	0	0	0	0	0	2		Number of events in 60 seconds
Night-time driving	0	0	0	0,2	0	1		Proportion of events in 60 seconds
Day-time driving	0	1	1	0,78	1	1		Proportion of events in 60 seconds
Phase 2								
Gender - male	0	0	1	0,7	1	1		
Age	20	34	44	42,6	54	79		
Income	1	3	5	4,421	5	6		
% driving on urban roads	2	20	25	25,4	40	60		
% driving on rural roads	20	25	40	41,6	60	80		
Violation item 1	1	2	2,559	2,559	3	5		
Violation item 2	1	3	3	3,413	4	5		
Driving style	0	0	0	0,458	1	1		
Confidence	0	0	1	0,736	1	1		
Competence	3	3	3,561	3,561	4	5		
Attitude item 1	1	2	3	3,18	3,18	5		
Attitude item 2	3	4	4	4,203	4,203	5		
Highest level of education	0	0	1	0,684	1	1		
Employment status	0	0	1	0,615	1	1		
Headway - STZ 1	0	0	0,1	0,219	0,366	1		
Headway - STZ 2	0	0	0	0,117	0,15	1		
Headway - STZ 3	0	0	0	0,023	0	1		
Speeding - STZ 1	0	0	0,4	0,454	0,933	1	68	
Speeding - STZ 2	0	0	0	0,032	0,016	1	920	
Speeding - STZ 3	0	0	0	0,097	0,033	1	1015	
Harsh acceleration events	0	0	0,433	0,47	1	1	775	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
Harsh braking events	0	0	0	0,23	0,35	1	760	
Harsh cornering events	0	0	0	0,311	0,733	1	1379	
KSS	0	0	0	0,071	0	1		
IBI	0	0	0	0,012	0	3		
Wipers on	0	0	0	0,001	0	2		
High beams on	0	0	0	0,006	0	1		
FCW	35	35	35	35,01	35	39	1160	
PCW	371	751	791	798	858	1478	3497	
Night-time driving	0	0	0	0,105	0	1		
Day-time driving	0	1	1	0,877	1	1		
Phase 3								
Gender - male	0	0	1	0,728	1	1		
Age	20	30	43	43	60	79		
Income	1	3	5	4,391	5	6		
% driving on urban roads	2	20	25	26,6	40	60		
% driving on rural roads	20	30	40	40,2	55	80		
Violation item 1	1	2	3	2,795	3	5		
Violation item 2	1	3	3	3,514	5	5		
Driving style	0	0	0	0,47	1	1		
Confidence	0	1	1	0,754	1	1		
Competence	3	3	4	3,654	4	5		
Attitude item 1	1	3	3	3,384	5	5		
Attitude item 2	3	4	4	4,216	4,216	5		
Highest level of education	0	0	1	0,6	1	1		
Employment status	0	0	1	0,664	1	1		
Headway - STZ 1	0	0	0,1	0,217	0,366	1		
Headway - STZ 2	0	0	0	0,105	0,133	1		
Headway - STZ 3	0	0	0	0,018	0	1		
Speeding - STZ 1	0	0	0,45	0,478	1	1	1015	
Speeding - STZ 2	0	0	0	0,224	0,333	1	1123	
Speeding - STZ 3	0	0	0	0,311	0,766	1	2145	
Harsh acceleration events	0	0	0	0,071	0	1		
Harsh braking events	0	0	0	0,011	0	3		

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
Harsh cornering events	0	0	0	0	0	2		
KSS	0	0	0,316	0,425	0,9	1	176	
IBI	0	0	0	0,027	0	1	1018	
Wipers on	0	0	0	0,111	0,05	1	1345	
High beams on	0	0	0	0,011	0	1		
FCW	35	35	35	35,01	35	39	18150	
PCW	319	753	818	815	857	1651	8750	
Night-time driving	0	0	0	0,104	0	1		
Day-time driving	0	1	1	0,874	1	1		
Phase 4								
Gender - male	0	0	1	0,7	1	1		
Age	20	30	43	42,5	54	79		
Income	1	3	5	4,381	5	6		
% driving on urban roads	2	20	25	26	35	60		
% driving on rural roads	20	30	40	40	55	80		
Violation item 1	1	2	3	2,818	3	5		
Violation item 2	1	3	3	3,496	5	5		
Driving style	0	0	0	0,478	1	1		
Confidence	0	0	1	0,709	1	1		
Competence	3	3	4	3,571	4	5		
Attitude item 1	1	3	3	3,331	5	5		
Attitude item 2	3	4	4	4,195	4,195	5		
Highest level of education	0	0	1	0,65	1	1		
Employment status	0	0	1	0,648	1	1		
Headway - STZ 1	0	0	0,1	0,223	0,366	1		
Headway - STZ 2	0	0	0	0,095	0,1	1		
Headway - STZ 3	0	0	0	0,013	0	1		
Speeding - STZ 1	0	0	0,45	0,476	1	1	827	
Speeding - STZ 2	0	0	0	0,239	0,383	1	901	
Speeding - STZ 3	0	0	0	0,295	0,683	1	1934	
Harsh acceleration events	0	0	0	0,075	0	1		
Harsh braking events	0	0	0	0,011	0	4		
Harsh cornering events	0	0	0	0,001	0	2		

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
KSS	0	0	0,366	0,444	0,933	1		
IBI	0	0	0	0,027	0	1	1284	
Wipers on	0	0	0	0,096	0,016	1	2003	
High beams on	0	0	0	0,026	0	1		
FCW	35	35	35	35	35	35	25649	
PCW	471	762	829	822	867	1375	15919	
Night-time driving	0	0	0	0,133	0	1		
Day-time driving	0	1	1	0,84	1	1		

Table A 2: Descriptive statistics for the available parameters in database used for Belgium truck drivers

Variables	Min	Mean	Median	Std. Deviation	Max
Phase 1					
Vehicle_control_ STZ1	0,000	0,718	1,000	0,421	1,000
Vehicle_control_ STZ2	0,000	0,194	0,000	0,363	1,000
Vehicle_control_ STZ3	0,000	0,010	0,000	0,090	1,000
Trip duration	1,000	69,023	49,000	65,701	503,000
Age	25	45	50	11	56
Driving Style	2,000	2,220	2,000	0,414	3,000
Driver's Confidence	1,000	2,030	2,000	0,683	3,000
Driving Skills	1,000	2,470	3,000	0,602	3,000
Phase 2					
Vehicle_control_ STZ1	0,000	0,721	1,000	0,423	1,000
Vehicle_control_ STZ2	0,000	0,190	0,000	0,363	1,000
Vehicle_control_ STZ3	0,000	0,010	0,000	0,091	1,000
Trip duration	1,000	81,190	54,000	84,452	749,000
Age	25	46	50	10	66
Driving Style	2,000	2,250	2,000	0,430	3,000
Driver's Confidence	1,000	2,140	2,000	0,700	3,000
Driving Skills	1,000	2,530	3,000	0,634	3,000
Phase 3					
Vehicle_control_ STZ1	0,000	0,772	1,000	0,389	1,000
Vehicle_control_ STZ2	0,000	0,223	0,000	0,385	1,000

Variables	Min	Mean	Median	Std. Deviation	Max
Vehicle_control_ STZ3	0,000	0,022	0,000	0,134	1,000
Trip duration	1,000	92,083	59,000	102,783	791,000
Age	25	44	46	10	56
Driving Style	2,000	2,250	2,000	0,433	3,000
Driver's Confidence	1,000	2,040	2,000	0,707	3,000
Driving Skills	1,000	2,510	3,000	0,637	3,000
Phase 4					
Vehicle_control_ STZ1	0,000	0,766	1,000	0,393	1,000
Vehicle_control_ STZ2	0,000	0,221	0,000	0,384	1,000
Vehicle_control_ STZ3	0,000	0,033	0,000	0,168	1,000
Trip duration	1,000	99,532	68,000	100,835	779,000
Age	25	46	47	11	66
Driving Style	2,000	2,300	2,000	0,459	3,000
Driver's Confidence	1,000	2,190	2,000	0,743	3,000
Driving Skills	1,000	2,560	3,000	0,652	3,000

Table A 3: Descriptive statistics for the available parameters in database used for UK car drivers

Variables	Min	Mean	Std. Deviation	Max	1st quartile	2nd quartile	3rd quartile
Phase 1 (total observations 113705)							
iDreams_Headway_Map_level_1_mean	0	0,151	0,266	1	0	0	0,2
iDreams_Headway_Map_level_1_0_mean	0	0,764	0,351	1	0,6	1	1
iDreams_Headway_Map_level_23_mean	0	0,085	0,215	1	0	0	0
ME_Car_wipers_median	0	0,063	0,243	1	0	0	0
ME_Car_high_beam_median	0	0,004	0,063	1	0	0	0
DrivingEvents_Map_evt_ha_mean	0	0,444	0,454	1	0	0,267	1
ME_LDW_Map_type_R_mean	0	0,163	0,365	1	0	0	0
SQ_Vehicle_age	3	9,48	3,138	16	7	9	11
EQ17_General_sleep_rating	0	0,035	0,184	1	0	0	0
EQ1a_Adaptive_cruise_control	0	0,011	0,103	1	0	0	0
EQ1b_Forward_collision_warning	0	0,067	0,249	1	0	0	0
EQ4b_Speed_limit	1	1,747	0,937	4	1	1	2

Variables	Min	Mean	Std. Deviation	Max	1st quartile	2nd quartile	3rd quartile
EQ4e_Mobile_phone	0	0,702	0,664	3	0	1	1
EQ4g_Illegal_overtake	0	0,348	0,53	2	0	0	1
EQ5_Driving_style	1	2,39	0,712	4	2	2	3
EQ6_Driving_confidence	2	4,038	0,653	5	4	4	4
Hour	0	12,844	4,263	23	9	13	16
Day_of_week	0	2,947	1,859	6	1	3	4
Month	3	7,847	3,03	11	4	10	10
Phase 2 (total observations 116917)							
iDreams_Headway_Map_level_1_0_mean	0	0,78	0,339	1	0,633	1	1
iDreams_Headway_Map_level_1_mean	0	0,51	0,425	1	0	0,5	1
iDreams_Headway_Map_level_23_mean	0	0,072	0,193	1	0	0	0
ME_Car_wipers_median	0	0,08	0,27	1	0	0	0
ME_Car_high_beam_median	0	0,004	0,066	1	0	0	0
DrivingEvents_Map_evt_ha_mean	0	0,435	0,452	1	0	0,233	1
ME_LDW_Map_type_R_mean	0	0,142	0,343	1	0	0	0
SQ_Vehicle_age	3	9,227	2,952	16	7	9	11
EQ17_General_sleep_rating	0	0,056	0,229	1	0	0	0
EQ1a_Adaptive_cruise_control	0	0,015	0,123	1	0	0	0
EQ1b_Forward_collision_warning	0	0,085	0,28	1	0	0	0
EQ4b_Speed_limit	1	1,741	0,895	4	1	1	2
EQ4e_Mobile_phone	0	0,727	0,717	3	0	1	1
EQ4g_Illegal_overtake	0	0,365	0,543	2	0	0	1
EQ5_Driving_style	1	2,391	0,733	4	2	2	3
EQ6_Driving_confidence	2	4,063	0,638	5	4	4	4
Hour	0	13,144	4,401	23	9	14	16
Day_of_week	0	2,852	1,928	6	1	3	5
Month	4	8,751	3,038	12	5	11	11
Phase 3 (total observations 119112)							
iDreams_Headway_Map_level_1_mean	0	0,138	0,254	1	0	0	0,167
iDreams_Headway_Map_level_1_0_mean	0	0,788	0,333	1	0,667	1	1
iDreams_Headway_Map_level_23_mean	0	0,074	0,198	1	0	0	0
ME_Car_wipers_median	0	0,098	0,297	1	0	0	0

Variables	Min	Mean	Std. Deviation	Max	1st quartile	2nd quartile	3rd quartile
ME_Car_high_beam_median	0	0,005	0,067	1	0	0	0
DrivingEvents_Map_evt_ha_mean	0	0,432	0,452	1	0	0,233	1
ME_LDW_Map_type_R_mean	0	0,154	0,357	1	0	0	0
SQ_Vehicle_age	3	9,267	3,149	16	7	9	11
EQ17_General_sleep_rating	0	0,054	0,225	1	0	0	0
EQ1a_Adaptive_cruise_control	0	0,02	0,141	1	0	0	0
EQ1b_Forward_collision_warning	0	0,083	0,275	1	0	0	0
EQ4b_Speed_limit	1	1,831	0,909	4	1	2	2
EQ4e_Mobile_phone	0	0,715	0,663	3	0	1	1
EQ4g_Illegal_overtake	0	0,367	0,555	2	0	0	1
EQ5_Driving_style	1	2,431	0,749	4	2	2	3
EQ6_Driving_confidence	2	4,091	0,66	5	4	4	4
Hour	0	12,909	4,356	23	10	13	16
Day_of_week	0	2,963	1,935	6	1	3	5
Month	1	8,452	3,644	12	6	7	12
Phase 4 (total observations 187948)							
iDreams_Headway_Map_level_1_0_mean	0	0,795	0,325	1	0,667	1	1
iDreams_Headway_Map_level_1_mean	0	0,551	0,42	1	0,067	0,667	1
iDreams_Headway_Map_level_23_mean	0	0,062	0,176	1	0	0	0
ME_Car_wipers_median	0	0,056	0,23	1	0	0	0
ME_Car_high_beam_median	0	0,005	0,067	1	0	0	0
DrivingEvents_Map_evt_ha_mean	0	0,431	0,449	1	0	0,233	1
ME_LDW_Map_type_R_mean	0	0,116	0,315	1	0	0	0
SQ_Vehicle_age	3	10,089	3,552	16	7	9	13
EQ17_General_sleep_rating	0	0,033	0,178	1	0	0	0
EQ1a_Adaptive_cruise_control	0	0,022	0,147	1	0	0	0
EQ1b_Forward_collision_warning	0	0,063	0,243	1	0	0	0
EQ4b_Speed_limit	1	1,806	0,866	4	1	2	2
EQ4e_Mobile_phone	0	0,758	0,642	3	0	1	1
EQ4g_Illegal_overtake	0	0,331	0,541	2	0	0	1
EQ5_Driving_style	1	2,379	0,714	4	2	2	3
EQ6_Driving_confidence	2	4,171	0,705	5	4	4	5

Variables	Min	Mean	Std. Deviation	Max	1st quartile	2nd quartile	3rd quartile
Hour	0	13,076	4,322	23	10	14	16
Day_of_week	0	2,984	1,891	6	1	3	5
Month	1	3,629	2,892	9	1	2	7

Table A 4: Descriptive statistics for the available parameters in database used for Germany car drivers

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
Phase 1 (total observations 48629)						
grpby_seconds	0	270	720	1333	1560	14610
iDreams_Headway_Map_level_.1_mean	1	1	1	1	1	1
iDreams_Headway_Map_level_.1_sum	2	30	30	29,98	30	30
iDreams_Headway_Map_level_0_mean		0	0	0	0	0
iDreams_Headway_Map_level_0_sum	0	0	0	0	0	0
iDreams_Headway_Map_level_1_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_1_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_3_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_3_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_total_mean	0	0	0	0,0473	0	1
iDreams_Headway_Map_level_total_sum	0	0	0	1,419	0	30
iDreams_Overtaking_Map_level_0_mean	1	1	1	1	1	1
iDreams_Overtaking_Map_level_0_sum	2	30	30	29,98	30	30
iDreams_Overtaking_Map_level_1_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_1_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_total_mean	0	0	0	0,0461	0	1
iDreams_Overtaking_Map_level_total_sum	0	0	0	1.383	0	30
iDreams_Speeding_Map_level_0_mean	0	0	0	0,317	1.000	1

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
iDreams_Speeding_Map_level_0_sum	0	0	0	9.523	30.000	30
iDreams_Speeding_Map_level_1_mean	0	0	1.000	0,691	1.000	1
iDreams_Speeding_Map_level_1_sum	0	0	30	20,74	30	30
iDreams_Speeding_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_3_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_3_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_total_mean	0	10.000	10.000	0,8718	10.000	1
iDreams_Speeding_Map_level_total_sum	0	30	30	26,15	30	30
iDreams_Fatigue_Map_level_0_mean	0	1	1	0,79	1	1
iDreams_Fatigue_Map_level_0_sum	0	30	30	23,68	30	30
iDreams_Fatigue_Map_level_1_mean	0	0	0	0,25	0	1
iDreams_Fatigue_Map_level_1_sum	0	0	0	7,36	0	30
iDreams_Fatigue_Map_level_2_mean	0	0	0	0,14	0	1
iDreams_Fatigue_Map_level_2_sum	0	0	0	4,2	0	30
iDreams_Fatigue_Map_level_3_mean	0	0	0	0	0	0
iDreams_Fatigue_Map_level_3_sum	0	0	0	0	0	0
iDreams_Fatigue_Map_level_total_mean	0	0	0	0,1385	0	1
iDreams_Fatigue_Map_level_total_sum	0	0	0	4.155	0	30
DrivingEvents_Map_lvl_L_mean	0	0,433	1.000	0,736	1.000	1
DrivingEvents_Map_lvl_M_mean	0	0	0	0,242	0,4	1
DrivingEvents_Map_lvl_H_mean	0	0	0	0,062	0	1
ME_Car_speed_mean	0	0	0	0	0	0
ME_Car_wipers_median	0	0	0	0	0	0
ME_Car_high_beam_median	0	0	0	0	0	0
ME_AWS_hw_measurement_mean	0	0	0	0	0	0
ME_AWS_tsr_level_mean	0	0	0	0	0	0
ME_AWS_fcw_mean	0	0	0	0	0	0
ME_AWS_pcw_mean	0	0	0	0	0	0
ME_AWS_pedestrian_dz_mean	0	0	0	0	0	0

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
ME_AWS_time_indicator_median	1.000	1.000	1.000	1.709	3.000	3.000
ME_TSR_tsr_1_speed_median	0	5	9	64,33	39	254
GPS_spd_mean	0	26,05	52,68	53,2	71,74	198,58
GPS_distances_sum	0	221	450,6	455,7	611,5	14239,8
DrivingEvents_Map_evt_ha_mean	0	0	0,567	0,509	1.000	1
DEM_evt_ha_lvl_L_mean	0	0	0	0,403	1.000	1
DEM_evt_ha_lvl_L_sum	0	0	0	12,09	30	30
DEM_evt_ha_lvl_M_mean	0	0	0	0,088	0	1
DEM_evt_ha_lvl_M_sum	0	0	0	2.631	0	30
DEM_evt_ha_lvl_H_mean	0	0	0	0,018	0	1
DEM_evt_ha_lvl_H_sum	0	0	0	0,55	0	30
DrivingEvents_Map_evt_hc_mean	0	0	0	0,309	0,967	1
DEM_evt_hc_lvl_L_mean	0	0	0	0,154	0	1
DEM_evt_hc_lvl_L_sum	0	0	0	4.623	0	30
DEM_evt_hc_lvl_M_mean	0	0	0	0,143	0	1
DEM_evt_hc_lvl_M_sum	0	0	0	4.301	0	30
DEM_evt_hc_lvl_H_mean	0	0	0	0,012	0	1
DEM_evt_hc_lvl_H_sum	0	0	0	0,355	0	30
DrivingEvents_Map_evt_hb_mean	0	0	0	0,209	0,233	1
DEM_evt_hb_lvl_L_mean	0	0	0	0,197	0,167	1
DEM_evt_hb_lvl_L_sum	0	0	0	5.913	5.000	30
DEM_evt_hb_lvl_M_mean	0	0	0	0,009	0	1
DEM_evt_hb_lvl_M_sum	0	0	0	0,264	0	30
DEM_evt_hb_lvl_H_mean	0	0	0	0,003	0	1
DEM_evt_hb_lvl_H_sum	0	0	0	0,082	0	30
Drowsiness_level_median	35	35	35	35,1	35	39
IBI_value_mean	421,9	728,5	794,8	797,6	861,5	1788,1
ME_LDW_Map_type_L_mean	-9999	-9999	-9999	-9999	-9999	-9999
ME_LDW_Map_type_R_mean	-9999	-9999	-9999	-9999	-9999	-9999
Phase 2 (total observations 48629)						

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
grpby_seconds	0	240	570	1141	1230	13500
iDreams_Headway_Map_level_.1_mean	1	1	1	1	1	1
iDreams_Headway_Map_level_.1_sum	26	30	30	30	30	30
iDreams_Headway_Map_level_0_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_0_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_1_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_1_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_3_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_3_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_total_mean	0	0	0	0,0591	0	1
iDreams_Headway_Map_level_total_sum	0	0	0	1.773	0	30
iDreams_Overtaking_Map_level_0_mean	1	1	1	1	1	1
iDreams_Overtaking_Map_level_0_sum	26	30	30	30	30	30
iDreams_Overtaking_Map_level_1_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_1_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_total_mean	0	0	0	0,0588	0	1
iDreams_Overtaking_Map_level_total_sum	0	0	0	1.763	0	30
iDreams_Speeding_Map_level_0_mean	0	0	0	0,243	0,175	1
iDreams_Speeding_Map_level_0_sum	0	0	0	7,29	5,25	30
iDreams_Speeding_Map_level_1_mean	0	1.000	1.000	0,768	1.000	1
iDreams_Speeding_Map_level_1_sum	0	30	30	23,05	30	30
iDreams_Speeding_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_3_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_3_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_total_mean	0	10.000	10.000	0,8771	10.000	1

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
iDreams_Speeding_Map_level_total_sum	0	30	30	26,31	30	30
iDreams_Fatigue_Map_level_0_mean	0	1	1	0,78	1	1
iDreams_Fatigue_Map_level_0_sum	0	30	30	23,36	30	30
iDreams_Fatigue_Map_level_1_mean	0	0	0	0,32	1	1
iDreams_Fatigue_Map_level_1_sum	0	0	0	9,48	30	30
iDreams_Fatigue_Map_level_2_mean	0	0	0	0,07	0	1
iDreams_Fatigue_Map_level_2_sum	0	0	0	1,97	0	30
iDreams_Fatigue_Map_level_3_mean	0	0	0	0,02	0	1
iDreams_Fatigue_Map_level_3_sum	0	0	0	0,61	0	30
iDreams_Fatigue_Map_level_total_mean	0	0	0	0,1304	0	1
iDreams_Fatigue_Map_level_total_sum	0	0	0	3.912	0	30
DrivingEvents_Map_lvl_L_mean	0	0,367	1.000	0,725	1.000	1
DrivingEvents_Map_lvl_M_mean	0	0	0	0,254	0,5	1
DrivingEvents_Map_lvl_H_mean	0	0	0	0,058	0	1
ME_Car_speed_mean	0	0	0	0	0	0
ME_Car_wipers_median	0	0	0	0	0	0
ME_Car_high_beam_median	0	0	0	0	0	0
ME_AWS_hw_measurement_mean	0	0	0	0	0	0
ME_AWS_tsr_level_mean	0	0	0	0	0	0
ME_AWS_fcw_mean	0	0	0	0	0	0
ME_AWS_pcw_mean	0	0	0	0	0	0
ME_AWS_pedestrian_dz_mean	0	0	0	0	0	0
ME_AWS_time_indicator_median	1.000	1.000	1.000	1.497	2.000	3.000
ME_TSR_tsr_1_speed_median	0	5	7	64,27	39	254
GPS_spd_mean	0	23,35	52,07	50,43	68,85	224,05
GPS_distances_sum	0	199,2	439,2	432,2	585,2	30601,2
DrivingEvents_Map_evt_ha_mean	0	0	0,567	0,511	1.000	1
DEM_evt_ha_lvl_L_mean	0	0	0,033	0,404	1.000	1
DEM_evt_ha_lvl_L_sum	0	0	1	12,12	30	30
DEM_evt_ha_lvl_M_mean	0	0	0	0,089	0	1

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
DEM_evt_ha_lvl_M_sum	0	0	0	2.681	0	30
DEM_evt_ha_lvl_H_mean	0	0	0	0,017	0	1
DEM_evt_ha_lvl_H_sum	0	0	0	0,519	0	30
DrivingEvents_Map_evt_hc_mean	0	0	0	0,318	0,933	1
DEM_evt_hc_lvl_L_mean	0	0	0	0,15	0,033	1
DEM_evt_hc_lvl_L_sum	0	0	0	4.511	1.000	30
DEM_evt_hc_lvl_M_mean	0	0	0	0,155	0	1
DEM_evt_hc_lvl_M_sum	0	0	0	4,66	0	30
DEM_evt_hc_lvl_H_mean	0	0	0	0,012	0	1
DEM_evt_hc_lvl_H_sum	0	0	0	0,357	0	30
DrivingEvents_Map_evt_hb_mean	0	0	0	0,197	0,167	1
DEM_evt_hb_lvl_L_mean	0	0	0	0,188	0,133	1
DEM_evt_hb_lvl_L_sum	0	0	0	5.634	4.000	30
DEM_evt_hb_lvl_M_mean	0	0	0	0,008	0	1
DEM_evt_hb_lvl_M_sum	0	0	0	0,235	0	30
DEM_evt_hb_lvl_H_mean	0	0	0	0,001	0	1
DEM_evt_hb_lvl_H_sum	0	0	0	0,026	0	30
Drowsiness_level_median	35	35	35	35,17	35	39
IBI_value_mean	342,8	738,1	809,2	806,5	877,3	1636,7
ME_LDW_Map_type_L_mean	-9999	-9999	-9999	-9999	-9999	-9999
ME_LDW_Map_type_R_mean	-9999	-9999	-9999	-9999	-9999	-9999
Phase 3 (total observations 36606)						
grpby_seconds	0	240	630	1329	1500	12270
iDreams_Headway_Map_level_.1_mean	1	1	1	1	1	1
iDreams_Headway_Map_level_.1_sum	1	30	30	29,96	30	30
iDreams_Headway_Map_level_0_mean	0	0	0	0	0	0
iDreams_Headway_Map_level_0_sum	0	0	0	0	0	0
iDreams_Headway_Map_level_1_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_1_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
iDreams_Headway_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_3_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_3_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_total_mean	0	0	0	0,0211	0	1
iDreams_Headway_Map_level_total_sum	0	0	0	0,6327	0	30
iDreams_Overtaking_Map_level_0_mean	1	1	1	1	1	1
iDreams_Overtaking_Map_level_0_sum	1	30	30	29,96	30	30
iDreams_Overtaking_Map_level_1_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_1_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_total_mean	0	0	0	0,021	0	1
iDreams_Overtaking_Map_level_total_sum	0	0	0	0,6294	0	30
iDreams_Speeding_Map_level_0_mean	0	0	0	0,234	0	1
iDreams_Speeding_Map_level_0_sum	0	0	0	7.022	0	30
iDreams_Speeding_Map_level_1_mean	0	1.000	1.000	0,777	1.000	1
iDreams_Speeding_Map_level_1_sum	0	30	30	23,32	30	30
iDreams_Speeding_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_3_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_3_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_total_mean	0	1	1	0,8829	1	1
iDreams_Speeding_Map_level_total_sum	0	30	30	26,49	30	30
iDreams_Fatigue_Map_level_0_mean	0	0	1.000	0,687	1.000	1
iDreams_Fatigue_Map_level_0_sum	0	0	30	20,6	30	30
iDreams_Fatigue_Map_level_1_mean	0	0	0	0,31	1	1
iDreams_Fatigue_Map_level_1_sum	0	0	0	9,29	30	30
iDreams_Fatigue_Map_level_2_mean	0	0	0	0,33	1	1
iDreams_Fatigue_Map_level_2_sum	0	0	0	10,01	30	30
iDreams_Fatigue_Map_level_3_mean	0	0	0	0	0	0

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
iDreams_Fatigue_Map_level_3_sum	0	0	0	0	0	0
iDreams_Fatigue_Map_level_total_mean	0	0	0	0,141	0	1
iDreams_Fatigue_Map_level_total_sum	0	0	0	4.229	0	30
DrivingEvents_Map_lvl_L_mean	0	0,533	1.000	0,752	1.000	1
DrivingEvents_Map_lvl_M_mean	0	0	0	0,235	0,367	1
DrivingEvents_Map_lvl_H_mean	0	0	0	0,064	0	1
ME_Car_speed_mean	0	0	0	0	0	0
ME_Car_wipers_median	0	0	0	0	0	0
ME_Car_high_beam_median	0	0	0	0	0	0
ME_AWS_hw_measurement_mean	0	0	0	0	0	0
ME_AWS_tsr_level_mean	0	0	0	0	0	0
ME_AWS_fcw_mean	0	0	0	0	0	0
ME_AWS_pcw_mean	0	0	0	0	0	0
ME_AWS_pedestrian_dz_mean	0	0	0	0	0	0
ME_AWS_time_indicator_median	1.000	1.000	1.000	1.456	2.000	3.000
ME_TSR_tsr_1_speed_median	0	4	7	62,37	39	254
GPS_spd_mean	0	27,65	52,68	54,86	77,51	200,69
GPS_distances_sum	0	234,2	450,6	468,7	657,3	14773,7
DrivingEvents_Map_evt_ha_mean	0	0	0,533	0,501	1.000	1
DEM_evt_ha_lvl_L_mean	0	0	0	0,41	1	1
DEM_evt_ha_lvl_L_sum	0	0	0	12,3	30	30
DEM_evt_ha_lvl_M_mean	0	0	0	0,075	0	1
DEM_evt_ha_lvl_M_sum	0	0	0	2.256	0	30
DEM_evt_ha_lvl_H_mean	0	0	0	0,015	0	1
DEM_evt_ha_lvl_H_sum	0	0	0	0,459	0	30
DrivingEvents_Map_evt_hc_mean	0	0	0	0,311	0,933	1
DEM_evt_hc_lvl_L_mean	0	0	0	0,156	0,033	1
DEM_evt_hc_lvl_L_sum	0	0	0	4.685	1.000	30
DEM_evt_hc_lvl_M_mean	0	0	0	0,141	0	1
DEM_evt_hc_lvl_M_sum	0	0	0	4.226	0	30

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
DEM_evt_hc_lvl_H_mean	0	0	0	0,014	0	1
DEM_evt_hc_lvl_H_sum	0	0	0	0,426	0	30
DrivingEvents_Map_evt_hb_mean	0	0	0	0,221	0,267	1
DEM_evt_hb_lvl_L_mean	0	0	0	0,209	0,2	1
DEM_evt_hb_lvl_L_sum	0	0	0	6.256	6.000	30
DEM_evt_hb_lvl_M_mean	0	0	0	0,011	0	1
DEM_evt_hb_lvl_M_sum	0	0	0	0,326	0	30
DEM_evt_hb_lvl_H_mean	0	0	0	0,001	0	1
DEM_evt_hb_lvl_H_sum	0	0	0	0,038	0	30
Drowsiness_level_median	35	35	35	35,21	35	39
IBI_value_mean	338,9	722,3	783,8	787,9	848,3	1265,6
ME_LDW_Map_type_L_mean	-9999	-9999	-9999	-9999	-9999	-9999
ME_LDW_Map_type_R_mean	-9999	-9999	-9999	-9999	-9999	-9999
Phase 4 (total observations 48784)						
grpby_seconds	0	270	660	1162	1410	11220
iDreams_Headway_Map_level_.1_mean	0,97	1	1	1	1	1
iDreams_Headway_Map_level_.1_sum	29	30	30	29,99	30	30
iDreams_Headway_Map_level_0_mean	0	0	0	0	0	0,03
iDreams_Headway_Map_level_0_sum	0	0	0	0,14	0	1
iDreams_Headway_Map_level_1_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_1_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_3_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_3_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Headway_Map_level_total_mean	0	0	0	0,0428	0	1
iDreams_Headway_Map_level_total_sum	0	0	0	1.285	0	30
iDreams_Overtaking_Map_level_0_mean	1	1	1	1	1	1
iDreams_Overtaking_Map_level_0_sum	30	30	30	30	30	30
iDreams_Overtaking_Map_level_1_mean	-9999	-9999	-9999	-9999	-9999	-9999

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
iDreams_Overtaking_Map_level_1_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Overtaking_Map_level_total_mean	0	0	0	0,0412	0	1
iDreams_Overtaking_Map_level_total_sum	0	0	0	1.235	0	30
iDreams_Speeding_Map_level_0_mean	0	0	0	0,236	0	1
iDreams_Speeding_Map_level_0_sum	0	0	0	7.067	0	30
iDreams_Speeding_Map_level_1_mean	0	1.000	1.000	0,772	1.000	1
iDreams_Speeding_Map_level_1_sum	0	30	30	23,16	30	30
iDreams_Speeding_Map_level_2_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_2_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_3_mean	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_3_sum	-9999	-9999	-9999	-9999	-9999	-9999
iDreams_Speeding_Map_level_total_mean	0	1	1	0,8881	1	1
iDreams_Speeding_Map_level_total_sum	0	30	30	26,64	30	30
iDreams_Fatigue_Map_level_0_mean	0	1	1	0,8	1	1
iDreams_Fatigue_Map_level_0_sum	0	30	30	24,08	30	30
iDreams_Fatigue_Map_level_1_mean	0	0	0	0,17	0	1
iDreams_Fatigue_Map_level_1_sum	0	0	0	5,04	0	30
iDreams_Fatigue_Map_level_2_mean	0	0	1	0,57	1	1
iDreams_Fatigue_Map_level_2_sum	0	0	30	17,11	30	30
iDreams_Fatigue_Map_level_3_mean	0	0	0	0	0	0
iDreams_Fatigue_Map_level_3_sum	0	0	0	0	0	0
iDreams_Fatigue_Map_level_total_mean	0	0	0	0,1138	0	1
iDreams_Fatigue_Map_level_total_sum	0	0	0	3.414	0	30
DrivingEvents_Map_lvl_L_mean	0	0,5	1	0,744	1	1
DrivingEvents_Map_lvl_M_mean	0	0	0	0,25	0,467	1
DrivingEvents_Map_lvl_H_mean	0	0	0	0,055	0	1
ME_Car_speed_mean	0	0	0	0	0	0
ME_Car_wipers_median	0	0	0	0	0	0

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
ME_Car_high_beam_median	0	0	0	0	0	0
ME_AWS_hw_measurement_mean	0	0	0	0	0	0
ME_AWS_tsr_level_mean	0	0	0	0	0	0
ME_AWS_fcw_mean	0	0	0	0	0	0
ME_AWS_pcw_mean	0	0	0	0	0	0
ME_AWS_pedestrian_dz_mean	0	0	0	0	0	0
ME_AWS_time_indicator_median	1.000	1.000	1.000	1.529	2.000	3.000
ME_TSR_tsr_1_speed_median	0	4	7	60,54	39	254
GPS_spd_mean	0	25,45	51,16	52,39	73,94	172,63
GPS_distances_sum	0	215,2	430,3	447,1	627,8	8162,7
DrivingEvents_Map_evt_ha_mean	0	0	0,333	0,465	1.000	1
DEM_evt_ha_lvl_L_mean	0	0	0	0,378	1.000	1
DEM_evt_ha_lvl_L_sum	0	0	0	11,34	30	30
DEM_evt_ha_lvl_M_mean	0	0	0	0,077	0	1
DEM_evt_ha_lvl_M_sum	0	0	0	2.307	0	30
DEM_evt_ha_lvl_H_mean	0	0	0	0,01	0	1
DEM_evt_ha_lvl_H_sum	0	0	0	0,314	0	30
DrivingEvents_Map_evt_hc_mean	0	0	0	0,345	1.000	1
DEM_evt_hc_lvl_L_mean	0	0	0	0,178	0,033	30
DEM_evt_hc_lvl_L_sum	0	0	0	5.336	1.000	30
DEM_evt_hc_lvl_M_mean	0	0	0	0,155	0	1
DEM_evt_hc_lvl_M_sum	0	0	0	4.661	0	30
DEM_evt_hc_lvl_H_mean	0	0	0	0,012	0	1
DEM_evt_hc_lvl_H_sum	0	0	0	0,351	0	30
DrivingEvents_Map_evt_hb_mean	0	0	0	0,23	0,3	1
DEM_evt_hb_lvl_L_mean	0	0	0	0,218	0,233	1
DEM_evt_hb_lvl_L_sum	0	0	0	6.525	7.000	30
DEM_evt_hb_lvl_M_mean	0	0	0	0,01	0	1
DEM_evt_hb_lvl_M_sum	0	0	0	0,304	0	30
DEM_evt_hb_lvl_H_mean	0	0	0	0,002	0	1

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
DEM_evt_hb_lvl_H_sum	0	0	0	0,069	0	30
Drowsiness_level_median	35	35	35	35,07	35	39
IBI_value_mean	374,8	737,3	798,5	805,4	868,3	1776,4
ME_LDW_Map_type_L_mean	-9999	-9999	-9999	-9999	-9999	-9999
ME_LDW_Map_type_R_mean	-9999	-9999	-9999	-9999	-9999	-9999

Table A 5: Descriptive statistics for the available parameters in database used for Portuguese bus drivers

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
Phase 1						
duration	785.00	7217.00	7217.00	6359.00	7217.00	16598.00
iDreams_Headway_Map_level_.1_mean	-1.00	-1.00	-1.00	-0.98	-1.00	0.20
iDreams_Headway_Map_level_0_mean	-1.00	0.00	0.00	0.00	0.00	0.20
iDreams_Headway_Map_level_1_mean	-1.00	0.00	0.00	0.00	0.00	0.20
iDreams_Headway_Map_level_2_mean	-1.00	0.00	0.00	0.00	0.00	0.20
iDreams_Headway_Map_level_3_mean	-0.64	0.00	0.00	0.00	0.00	0.15
Headway_level_initial	-1.00	-1.00	-1.00	-0.98	-1.00	3.00
Headway_level	-1.00	-1.00	-1.00	-0.98	-1.00	0.20
Headway_avg_level	-1.00	-1.00	-1.00	-0.98	-1.00	3.00
iDreams_Speeding_Map_level_0_mean	0.00	0.00	0.00	0.01	0.00	0.94
iDreams_Speeding_Map_level_1_mean	0.00	0.00	0.00	0.00	0.00	0.94
iDreams_Speeding_Map_level_2_mean	0.00	0.00	0.00	0.00	0.00	0.94
iDreams_Speeding_Map_level_3_mean	0.00	0.00	0.00	0.00	0.00	0.94
Speeding_level_Initial	0.00	0.00	0.00	0.01	0.00	3.00
Speeding_level	0.00	0.00	0.00	0.01	0.00	0.94
Speeding_avg_level	0.00	0.00	0.00	0.01	0.00	3.00
iDreams_Overtaking_Map_level_0_mean	0.00	0.00	0.00	0.00	0.00	0.20
iDreams_Overtaking_Map_level_1_mean	0.00	0.00	0.00	0.00	0.00	0.16
iDreams_Overtaking_Map_level_2_mean	0.00	0.00	0.00	0.00	0.00	0.00

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
Ovetaking_level_initial	0.00	0.00	0.00	0.00	0.00	2.00
Overtaking_level	0.00	0.00	0.00	0.00	0.00	0.20
Overtaking_avg_level	0.00	0.00	0.00	0.00	0.00	1.00
iDreams_Fatigue_Map_level_0_mean	0.00	0.00	0.00	0.01	0.00	2.83
iDreams_Fatigue_Map_level_1_mean	0.00	0.00	1.00	0.71	1.00	2.83
iDreams_Fatigue_Map_level_2_mean	0.00	0.00	0.00	0.04	0.00	2.83
iDreams_Fatigue_Map_level_3_mean	0.00	0.00	0.00	0.07	0.00	2.84
Fatigue_level_initial	0.00	1.00	1.00	0.83	1.00	3.00
Fatique_level	0.00	1.00	1.00	0.83	1.00	2.84
Fatigue_avg_level	0.00	1.00	1.00	0.83	1.00	3.00
DrivingEvents_Map_evt_ha_mean	0.00	0.00	0.00	0.03	0.00	0.44
DrivingEvents_Map_evt_hb_mean	-0.89	0.00	0.00	-0.05	0.00	0.00
Driving_events_maxg	-0.89	-0.24	-0.13	-0.02	0.22	0.53
GPS_alt	-54.60	82.80	140.60	145.00	212.10	333.50
GPS_hdg	0.00	105.20	175.90	184.00	275.80	360.00
GPS_spd	0.00	0.00	28.34	31.87	50.19	107.42
ME_AWS_fcw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_hw_level	0.00	0.00	0.00	0.12	0.00	2.00
ME_AWS_hw_measurement	0.00	0.00	0.00	0.05	0.00	2.50
ME_AWS_hw_repeatable	0.00	0.00	0.00	0.00	0.00	0.00
ME_AWS_hw_valid	0.00	0.00	0.00	0.12	0.00	1.00
ME_AWS_hmw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw_left	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw_off	0.00	1.00	1.00	0.92	1.00	1.00
ME_AWS_ldw_right	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_pcw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_pedestrian_dz	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_tamper	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_time_indicator	1.00	1.00	2.00	1.99	3.00	3.00

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
ME_AWS_tsr_level	0.00	0.00	0.00	0.15	0.00	7.00
ME_AWS_tsr_on	0.00	0.00	0.00	0.05	0.00	1.00
ME_AWS_zero_speed	0.00	0.00	1.00	0.71	1.00	1.00
tsr_1_speed	1.00	4.00	11.00	92.11	254.00	254.00
tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
avg_tsr_1_speed	72.52	83.43	88.74	92.19	99.00	120.39
rolling_tsr_1_speed	2.00	7.00	64.00	92.11	129.50	254.00
avg_tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
rolling__tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
tsr_2_speed	3.00	201.00	254.00	229.90	254.00	254.00
tsr_2_sup	0.00	0.00	0.00	0.36	0.00	20.00
avg_tsr_2_speed	224.80	227.10	229.90	229.90	231.90	238.60
rolling_tsr_2_speed	5.00	227.00	254.00	229.90	254.00	254.00
avg_tsr_2_sup	0.00	0.28	0.41	0.36	0.47	0.63
rolling_tsr_2_sup	0.00	0.00	0.00	0.36	0.00	20.00
tsr_3_speed	3.00	254.00	254.00	250.90	254.00	254.00
tsr_3_sup	0.00	0.00	0.00	0.10	0.00	20.00
avg_tsr_3_speed	248.10	249.50	251.10	250.90	252.70	254.00
rolling_tsr_3_speed	5.00	254.00	254.00	250.90	254.00	254.00
avg_tsr_3_sup	0.00	0.03	0.09	0.10	0.19	0.23
rolling__tsr_3_sup	0.00	0.00	0.00	0.10	0.00	13.00
tsr_4_speed	7.00	254.00	254.00	253.90	254.00	254.00
tsr_4_sup	0.00	0.00	0.00	0.01	0.00	20.00
avg_tsr_4_speed	252.80	254.00	254.00	253.90	254.00	254.00
rolling_tsr_4_speed	130.50	254.00	254.00	253.90	254.00	254.00
avg_tsr_4_sup	0.00	0.00	0.00	0.01	0.00	0.10
rolling__tsr_4_sup	0.00	0.00	0.00	0.01	0.00	10.00
Phase 2						
duration	974.00	974.00	2007.00	4074.00	2007.00	17041.00
iDreams_Headway_Map_level_.1_mean	-1.00	-1.00	-1.00	-0.97	-1.00	0.20

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
iDreams_Headway_Map_level_0_mean	-1.00	0.00	0.00	-0.01	0.00	0.20
iDreams_Headway_Map_level_1_mean	-1.00	0.00	0.00	0.00	0.00	0.20
iDreams_Headway_Map_level_2_mean	-0.98	0.00	0.00	0.00	0.00	0.20
iDreams_Headway_Map_level_3_mean	-0.94	0.00	0.00	0.00	0.00	0.17
Headway_level_initial	-1.00	-1.00	-1.00	-0.98	-1.00	3.00
Headway_level	-1.00	-1.00	-1.00	-0.98	-1.00	0.20
Headway_avg_level	-1.00	-1.00	-1.00	-0.98	-1.00	3.00
iDreams_Speeding_Map_level_0_mean	0.00	0.00	0.00	0.02	0.00	1.44
iDreams_Speeding_Map_level_1_mean	0.00	0.00	0.00	0.01	0.00	1.44
iDreams_Speeding_Map_level_2_mean	0.00	0.00	0.00	0.00	0.00	1.27
iDreams_Speeding_Map_level_3_mean	0.00	0.00	0.00	0.00	0.00	1.44
Speeding_level_Initial	0.00	0.00	0.00	0.04	0.00	3.00
Speeding_level	0.00	0.00	0.00	0.04	0.01	1.44
Speeding_avg_level	0.00	0.00	0.00	0.04	0.00	3.00
iDreams_Overtaking_Map_level_0_mean	0.00	0.00	0.00	0.00	0.00	0.20
iDreams_Overtaking_Map_level_1_mean	0.00	0.00	0.00	0.00	0.00	0.20
iDreams_Overtaking_Map_level_2_mean	0.00	0.00	0.00	0.00	0.00	0.15
Ovetaking_level_initial	0.00	0.00	0.00	0.00	0.00	2.00
Overtaking_level	0.00	0.00	0.00	0.00	0.00	0.20
Overtaking_avg_level	0.00	0.00	0.00	0.00	0.00	1.00
iDreams_Fatigue_Map_level_0_mean	0.00	0.00	0.00	0.02	0.00	2.84
iDreams_Fatigue_Map_level_1_mean	0.00	0.00	0.00	0.01	0.00	2.84
iDreams_Fatigue_Map_level_2_mean	0.00	0.00	0.00	0.18	0.00	2.84
iDreams_Fatigue_Map_level_3_mean	0.00	0.00	0.00	0.94	3.00	3.00
Fatigue_level_initial	0.00	0.00	0.00	1.15	3.00	3.00
Fatique_level	0.00	0.00	0.06	1.15	3.00	3.00
Fatigue_avg_level	0.00	0.00	0.00	1.15	3.00	3.00
DrivingEvents_Map_evt_ha_mean	0.00	0.00	0.00	0.03	0.00	0.44
DrivingEvents_Map_evt_hb_mean	-0.89	0.00	0.00	-0.05	0.00	0.00
Driving_events_maxg	-0.89	-0.23	-0.12	-0.01	0.21	0.54

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
GPS_alt	-3.50	101.90	170.40	163.40	227.30	351.40
GPS_hdg	0.00	102.80	185.30	186.30	275.50	360.00
GPS_spd	0.00	0.00	24.08	31.71	49.82	145.48
ME_AWS_fcw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_hw_level	0.00	0.00	0.00	0.13	0.00	2.00
ME_AWS_hw_measurement	0.00	0.00	0.00	0.05	0.00	2.50
ME_AWS_hw_repeatable	0.00	0.00	0.00	0.00	0.00	0.00
ME_AWS_hw_valid	0.00	0.00	0.00	0.12	0.00	1.00
ME_AWS_hmw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw_left	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw_off	0.00	1.00	1.00	0.94	1.00	1.00
ME_AWS_ldw_right	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_pcw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_pedestrian_dz	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_tamper	0.00	0.00	0.00	0.00	0.00	0.00
ME_AWS_time_indicator	1.00	1.00	1.00	1.93	3.00	3.00
ME_AWS_tsr_level	0.00	0.00	0.00	0.13	0.00	7.00
ME_AWS_tsr_on	0.00	0.00	0.00	0.02	0.00	1.00
ME_AWS_zero_speed	0.00	0.00	1.00	0.75	1.00	1.00
tsr_1_speed	1.00	4.00	11.00	92.12	254.00	254.00
tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
avg_tsr_1_speed	72.52	83.43	88.74	92.32	99.00	120.39
rolling_tsr_1_speed	2.00	7.00	64.00	92.12	129.50	254.00
avg_tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
rolling__tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
tsr_2_speed	3.00	201.00	254.00	229.80	254.00	254.00
tsr_2_sup	0.00	0.00	0.00	0.36	0.00	20.00
avg_tsr_2_speed	224.80	227.10	229.00	229.80	231.90	238.60
rolling_tsr_2_speed	5.00	227.00	254.00	229.80	254.00	254.00

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
avg_tsr_2_sup	0.00	0.28	0.41	0.36	0.47	0.63
rolling_tsr_2_sup	0.00	0.00	0.00	0.36	0.00	20.00
tsr_3_speed	3.00	254.00	254.00	250.90	254.00	254.00
tsr_3_sup	0.00	0.00	0.00	0.10	0.00	20.00
avg_tsr_3_speed	248.10	249.50	251.10	250.90	252.70	254.00
rolling_tsr_3_speed	5.00	254.00	254.00	250.90	254.00	254.00
avg_tsr_3_sup	0.00	0.03	0.09	0.10	0.19	0.23
rolling__tsr_3_sup	0.00	0.00	0.00	0.10	0.00	13.00
tsr_4_speed	7.00	254.00	254.00	253.90	254.00	254.00
tsr_4_sup	0.00	0.00	0.00	0.01	0.00	20.00
avg_tsr_4_speed	252.80	254.00	254.00	253.90	254.00	254.00
rolling_tsr_4_speed	130.50	254.00	254.00	253.90	254.00	254.00
avg_tsr_4_sup	0.00	0.00	0.00	0.01	0.00	0.10
rolling__tsr_4_sup	0.00	0.00	0.00	0.01	0.00	10.00
Phase 3						
duration	115.00	11186.00	12617.00	15952.00	27908.00	27908.00
iDreams_Headway_Map_level_.1_mean	-1.00	-0.99	-0.99	-0.90	-0.95	0.08
iDreams_Headway_Map_level_0_mean	-0.99	0.00	0.00	-0.02	0.00	0.08
iDreams_Headway_Map_level_1_mean	-0.99	0.00	0.00	-0.01	0.00	0.08
iDreams_Headway_Map_level_2_mean	-0.99	0.00	0.00	0.00	0.00	0.08
iDreams_Headway_Map_level_3_mean	-0.99	0.00	0.00	0.00	0.00	0.08
Headway_level_initial	-1.00	-1.00	-1.00	-0.93	-1.00	3.00
Headway_level	-1.00	-0.99	-0.99	-0.93	-0.96	0.08
Headway_avg_level	-1.00	-1.00	-1.00	-0.93	-1.00	3.00
iDreams_Speeding_Map_level_0_mean	0.00	0.01	0.02	0.07	0.05	1.00
iDreams_Speeding_Map_level_1_mean	0.00	0.00	0.00	0.03	0.00	1.00
iDreams_Speeding_Map_level_2_mean	0.00	0.00	0.00	0.00	0.00	1.00
iDreams_Speeding_Map_level_3_mean	0.00	0.00	0.00	0.00	0.00	1.00
Speeding_level_Initial	0.00	0.00	0.00	0.10	0.00	3.00
Speeding_level	0.00	0.01	0.02	0.10	0.15	1.00

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
Speeding_avg_level	0.00	0.00	0.00	0.10	0.00	3.00
iDreams_Overtaking_Map_level_0_mean	0.00	0.00	0.00	0.01	0.01	0.26
iDreams_Overtaking_Map_level_1_mean	0.00	0.00	0.00	0.00	0.00	0.26
iDreams_Overtaking_Map_level_2_mean	0.00	0.00	0.00	0.00	0.00	0.00
Ovetaking_level_initial	0.00	0.00	0.00	0.01	0.00	3.00
Overtaking_level	0.00	0.00	0.00	0.01	0.01	0.26
Overtaking_avg_level	0.00	0.00	0.00	0.01	0.00	1.50
iDreams_Fatigue_Map_level_0_mean	0.00	0.00	0.00	0.11	0.00	2.96
iDreams_Fatigue_Map_level_1_mean	0.00	0.00	0.00	0.13	0.00	2.99
iDreams_Fatigue_Map_level_2_mean	0.00	0.00	0.00	0.64	1.84	2.99
iDreams_Fatigue_Map_level_3_mean	0.00	0.00	0.00	1.09	2.96	3.00
Fatigue_level_initial	0.00	1.00	2.00	1.99	3.00	3.00
Fatique_level	0.00	1.46	1.95	1.97	2.96	3.00
Fatigue_avg_level	0.00	1.00	2.00	1.99	3.00	3.00
DrivingEvents_Map_evt_ha_mean	0.00	0.00	0.00	0.03	0.00	0.44
DrivingEvents_Map_evt_hb_mean	-0.65	0.00	0.00	-0.05	0.00	0.00
Driving_events_maxg	-0.65	-0.24	-0.12	-0.01	0.22	0.53
GPS_alt	-39.60	94.60	155.00	154.30	215.70	350.60
GPS_hdg	0.00	110.00	182.30	188.30	280.90	360.00
GPS_spd	0.00	0.00	26.67	31.30	50.37	107.05
ME_AWS_fcw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_hw_level	0.00	0.00	0.00	0.14	0.00	2.00
ME_AWS_hw_measurement	0.00	0.00	0.00	0.06	0.00	2.50
ME_AWS_hw_repeatable	0.00	0.00	0.00	0.00	0.00	0.00
ME_AWS_hw_valid	0.00	0.00	0.00	0.14	0.00	1.00
ME_AWS_hmw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw_left	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw_off	0.00	1.00	1.00	0.92	1.00	1.00
ME_AWS_ldw_right	0.00	0.00	0.00	0.00	0.00	1.00

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
ME_AWS_pcw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_pedestrian_dz	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_tamper	0.00	0.00	0.00	0.00	0.00	0.00
ME_AWS_time_indicator	1.00	1.00	3.00	2.08	3.00	3.00
ME_AWS_tsr_level	0.00	0.00	0.00	0.16	0.00	7.00
ME_AWS_tsr_on	0.00	0.00	0.00	0.02	0.00	1.00
ME_AWS_zero_speed	0.00	0.00	1.00	0.71	1.00	1.00
tsr_1_speed	1.00	4.00	11.00	91.69	254.00	254.00
tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
avg_tsr_1_speed	72.52	83.43	88.03	91.95	99.00	120.39
rolling_tsr_1_speed	2.00	6.50	64.00	91.71	129.50	254.00
avg_tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
rolling__tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
tsr_2_speed	3.00	201.00	254.00	229.90	254.00	254.00
tsr_2_sup	0.00	0.00	0.00	0.36	0.00	20.00
avg_tsr_2_speed	224.80	227.10	229.00	229.80	231.90	238.60
rolling_tsr_2_speed	5.00	227.00	254.00	229.90	254.00	254.00
avg_tsr_2_sup	0.00	0.28	0.41	0.36	0.47	0.63
rolling_tsr_2_sup	0.00	0.00	0.00	0.36	0.00	20.00
tsr_3_speed	3.00	254.00	254.00	250.90	254.00	254.00
tsr_3_sup	0.00	0.00	0.00	0.10	0.00	20.00
avg_tsr_3_speed	248.10	249.50	251.10	250.90	252.70	254.00
rolling_tsr_3_speed	5.00	254.00	254.00	250.90	254.00	254.00
avg_tsr_3_sup	0.00	0.03	0.09	0.10	0.19	0.23
rolling__tsr_3_sup	0.00	0.00	0.00	0.10	0.00	13.00
tsr_4_speed	7.00	254.00	254.00	253.90	254.00	254.00
tsr_4_sup	0.00	0.00	0.00	0.01	0.00	20.00
avg_tsr_4_speed	252.80	254.00	254.00	253.90	254.00	254.00
rolling_tsr_4_speed	130.50	254.00	254.00	253.90	254.00	254.00
avg_tsr_4_sup	0.00	0.00	0.00	0.01	0.00	0.10

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
rolling__tsr_4_sup	0.00	0.00	0.00	0.01	0.00	10.00
Phase 4						
duration	638.00	12094.00	13905.00	12552.00	14853.00	22958.00
iDreams_Headway_Map_level_.1_mean	-1.00	-0.97	-0.93	-0.74	-0.72	0.17
iDreams_Headway_Map_level_0_mean	-0.97	0.00	0.00	-0.04	0.00	0.17
iDreams_Headway_Map_level_1_mean	-0.97	0.00	0.00	-0.01	0.00	0.17
iDreams_Headway_Map_level_2_mean	-0.97	0.00	0.00	0.00	0.00	0.17
iDreams_Headway_Map_level_3_mean	-0.97	0.00	0.00	0.00	0.00	0.17
Headway_level_initial	-1.00	-1.00	-1.00	-0.80	-1.00	3.00
Headway_level	-1.00	-0.97	-0.93	-0.80	-0.82	0.17
Headway_avg_level	-1.00	-1.00	-1.00	-0.80	-1.00	3.00
iDreams_Speeding_Map_level_0_mean	0.00	0.00	0.08	0.13	0.14	1.05
iDreams_Speeding_Map_level_1_mean	0.00	0.00	0.00	0.09	0.00	1.05
iDreams_Speeding_Map_level_2_mean	0.00	0.00	0.00	0.00	0.00	1.05
iDreams_Speeding_Map_level_3_mean	0.00	0.00	0.00	0.01	0.00	1.05
Speeding_level_Initial	0.00	0.00	0.00	0.23	0.00	3.00
Speeding_level	0.00	0.06	0.12	0.23	0.29	1.05
Speeding_avg_level	0.00	0.00	0.00	0.23	0.00	3.00
iDreams_Overtaking_Map_level_0_mean	0.00	0.00	0.01	0.02	0.01	0.26
iDreams_Overtaking_Map_level_1_mean	0.00	0.00	0.00	0.00	0.00	0.26
iDreams_Overtaking_Map_level_2_mean	0.00	0.00	0.00	0.00	0.00	0.13
Ovetaking_level_initial	0.00	0.00	0.00	0.02	0.00	3.00
Overtaking_level	0.00	0.00	0.01	0.02	0.02	0.26
Overtaking_avg_level	0.00	0.00	0.00	0.02	0.00	1.50
iDreams_Fatigue_Map_level_0_mean	0.00	0.00	0.00	0.16	0.00	3.00
iDreams_Fatigue_Map_level_1_mean	0.00	0.00	0.00	0.20	0.00	2.95
iDreams_Fatigue_Map_level_2_mean	0.00	0.00	0.00	0.55	1.60	3.00
iDreams_Fatigue_Map_level_3_mean	0.00	0.00	0.00	0.85	2.59	3.00
Fatigue_level_initial	0.00	1.00	2.00	1.74	3.00	3.00
Fatique_level	0.00	1.00	1.76	1.76	2.64	3.00

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
Fatigue_avg_level	0.00	1.00	2.00	1.74	3.00	3.00
DrivingEvents_Map_evt_ha_mean	0.00	0.00	0.00	0.03	0.00	0.42
DrivingEvents_Map_evt_hb_mean	-0.53	0.00	0.00	-0.05	0.00	0.00
Driving_events_maxg	-0.53	-0.23	0.12	0.00	0.22	0.54
GPS_alt	1.50	86.30	134.40	138.20	193.60	338.70
GPS_hdg	0.00	97.67	173.10	179.38	270.00	360.00
GPS_spd	0.00	2.96	30.56	32.09	48.89	107.79
ME_AWS_fcw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_hw_level	0.00	0.00	0.00	0.11	0.00	2.00
ME_AWS_hw_measurement	0.00	0.00	0.00	0.04	0.00	2.50
ME_AWS_hw_repeatable	0.00	0.00	0.00	0.00	0.00	0.00
ME_AWS_hw_valid	0.00	0.00	0.00	0.11	0.00	1.00
ME_AWS_hmw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw_left	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_ldw_off	0.00	1.00	1.00	0.94	1.00	1.00
ME_AWS_ldw_right	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_pcw	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_pedestrian_dz	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_tamper	0.00	0.00	0.00	0.00	0.00	1.00
ME_AWS_time_indicator	1.00	1.00	1.00	1.79	3.00	3.00
ME_AWS_tsr_level	0.00	0.00	0.00	0.12	0.00	7.00
ME_AWS_tsr_on	0.00	0.00	0.00	0.05	0.00	1.00
ME_AWS_zero_speed	0.00	1.00	1.00	0.77	1.00	1.00
tsr_1_speed	1.00	4.00	11.00	92.60	254.00	254.00
tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
avg_tsr_1_speed	72.52	83.43	88.74	92.24	99.00	120.39
rolling_tsr_1_speed	2.00	7.00	64.00	92.60	129.50	254.00
avg_tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00
rolling__tsr_1_sup	0.00	0.00	0.00	0.00	0.00	0.00

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
tsr_2_speed	3.00	201.00	254.00	229.90	254.00	254.00
tsr_2_sup	0.00	0.00	0.00	0.36	0.00	20.00
avg_tsr_2_speed	224.80	227.10	229.90	229.90	231.90	238.60
rolling_tsr_2_speed	5.00	227.00	254.00	229.90	254.00	254.00
avg_tsr_2_sup	0.00	0.28	0.41	0.36	0.47	0.63
rolling_tsr_2_sup	0.00	0.00	0.00	0.36	0.00	20.00
tsr_3_speed	3.00	254.00	254.00	250.80	254.00	254.00
tsr_3_sup	0.00	0.00	0.00	0.10	0.00	20.00
avg_tsr_3_speed	248.10	249.50	251.10	250.80	252.70	254.00
rolling_tsr_3_speed	5.00	254.00	254.00	250.80	254.00	254.00
avg_tsr_3_sup	0.00	0.03	0.09	0.10	0.19	0.23
rolling__tsr_3_sup	0.00	0.00	0.00	0.10	0.00	13.00
tsr_4_speed	7.00	254.00	254.00	253.90	254.00	254.00
tsr_4_sup	0.00	0.00	0.00	0.01	0.00	20.00
avg_tsr_4_speed	252.80	254.00	254.00	253.90	254.00	254.00
rolling_tsr_4_speed	130.50	254.00	254.00	253.90	254.00	254.00
avg_tsr_4_sup	0.00	0.00	0.00	0.01	0.00	0.10
rolling__tsr_4_sup	0.00	0.00	0.00	0.01	0.00	10.00

Table A 6: Descriptive statistics for the available parameters in database used for Greek car drivers

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
Phase 1								
trip_distance	0.5	6.4	10.9	32.8	22.2	334.7	NA	
time_indicator	1.0	1.0	2.0	1.8	3.0	3.0	NA	1: day , 2: dusk, 3: night
VC_acc_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	
VC_acc_high_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
VC_acc_no_low_sum	27.0	30.0	30.0	30.0	30.0	30.0	NA	
VC_dc_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	how often did you as a car driver, drive faster than the speed limit inside built-up areas? (1) Never, (2) Seldom, (3) About half the time, (4) Usually, (5) (almost) Always
VC_dc_high_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	
VC_dc_no_low_sum	27.0	30.0	30.0	30.0	30.0	30.0	NA	
Speed_high_sum	0.0	0.0	0.0	0.1	0.0	2.0	NA	
Speed_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	
Speed_no_low_sum	27.0	30.0	30.0	29.9	30.0	30.0	NA	
distraction_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	
VC_acc_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_acc_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_acc_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
VC_dc_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_dc_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_dc_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
Speed_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Speed_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Speed_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
distraction_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Gendre	0.0	0.0	0.0	0.4	1.0	1.0	NA	0: Male, 1: Female
SQ_Nationality	1.0	1.0	1.0	1.0	1.0	1.0	NA	1: Greek
SQ_Year_of_birth	1964.0	1993.0	1995.0	1993.0	1998.0	2000.0	NA	
SQ_Age	22.0	24.0	27.0	29.2	29.0	58.0	NA	
SQ_ Age_got_driving_license	18.0	18.0	18.0	18.9	19.0	27.0	NA	
SQ_Years_driving	2.0	5.0	8.0	10.3	11.0	40.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
SQ_Vehicle_brand	1.0	6.0	14.0	13.5	21.0	22.0	NA	
SQ_Vehicle_age	0.0	4.0	7.0	9.4	16.0	22.0	116.0	
STC_Second_Nat	0.0	0.0	0.0	0.0	0.0	0.0	NA	0: No, 1: Yes
STC_Highest_lev_education	1.0	2.0	2.0	2.5	3.0	5.0	NA	1:Higher education , 2:Highest education , 3: Master of Science, 4:PhD, 5:Secondary education
STC_Current_occupation	1.0	2.0	3.0	3.2	4.0	5.0	NA	1:Civil servant, 2:Freelancer / self-employed, 3: Military service, 4:Student, 5:Private employee
STC_Employment_stat	1.0	1.0	1.0	1.9	4.0	4.0	NA	1:Employed full time, 2:Employed part time, 3: Military service, 4: Student
STC_Net_income	1.0	1.0	3.0	3.4	5.0	7.0	NA	1: Less than €1.000, 2: €1.000 - €2.000, 3: €2000 - €3.000, 4: €3000 - €4.000, 5: €4000 - €5.000, 6: More than €5.000
STC_Med_condition_decleration	0.0	1.0	1.0	0.9	1.0	1.0	NA	Can you declare that you are not suffering from a medical condition that would be considered a legal exclusion to drive? 0: No, 1: Yes
STC_Fuel_type	1.0	2.0	3.0	2.5	3.0	3.0	NA	1:diesel, 2: hybrid, 3: petrol
STC_Gearbox	1.0	1.0	2.0	1.7	2.0	2.0	NA	1:Manual, 2: Automatic
STC_Disability_mod	0.0	0.0	0.0	0.0	0.0	1.0	NA	Has this vehicle been modified to cope with physical limitations of the driver? 0: No, 1: Yes
STC_Number_other_drivers	0.0	0.0	0.0	0.7	1.0	2.0	NA	-
STC_Drvr_1_split	10.0	80.0	100.0	86.5	100.0	100.0	NA	How is the use of this car split between all of the drivers who use it? (Note the total usage should add up to 100%).
STC_Drvr_2_split	0.0	0.0	0.0	11.2	20.0	70.0	NA	
STC_Drvr_3_split	0.0	0.0	0.0	2.4	0.0	65.0	NA	
STC_Drvr_4_split	0.0	0.0	0.0	0.0	0.0	0.0	NA	
STC_Weekly_km	1.0	1.0	2.0	2.3	4.0	4.0	NA	1: up to 50 km, 2:50 to 100 km, 3:100 to 500 km, 4:500 to 1000 km, 5:more than 1000 km
STC_Urban	10.0	40.0	60.0	56.0	80.0	100.0	7036.0	How much do you drive on urban, rural and motorways roads (%)?
STC_Rural	0.0	10.0	30.0	25.0	30.0	60.0	7036.0	
STC_Motorway	0.0	5.0	10.0	19.1	30.0	60.0	7036.0	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ1a_Adaptive_cruise_control	0.0	0.0	0.0	0.3	1.0	1.0	NA	Which Advanced Driving Assistance Systems are present in your car? 0:Not equipped 1:Equipped
EQ1b_Forward_collision_warning	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ1c_NV_PD	0.0	0.0	0.0	0.0	0.0	0.0	NA	
EQ1d_Traffic_sign_recognition	0.0	0.0	0.0	0.0	0.0	0.0	8506.0	
EQ1e_Lane_keeping_Assistance	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ1f_Blind_spot_warning	0.0	0.0	0.0	0.0	0.0	1.0	NA	
EQ1g_Drowsiness_alert	0.0	0.0	0.0	0.0	0.0	1.0	3228.0	
EQ1h_Parking_assist	0.0	0.0	0.0	0.4	1.0	1.0	NA	
EQ1i_High_speed_alert	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ1j_Automatic_emergency_braking	0.0	0.0	0.0	0.3	1.0	1.0	NA	
EQ2a_Adaptive_cruise_control	1.0	1.0	5.0	3.3	5.0	5.0	NA	How often do you use the following Advanced Driving Assistance Systems that are present in your car? 1: Almost never, 2:Sometimes, 3:Often, 4:Almost always, 5:Not applicable
EQ2b_Forward_collision_warning	1.0	4.0	5.0	3.9	5.0	5.0	NA	
EQ2c_NV_PD	1.0	5.0	5.0	4.2	5.0	5.0	NA	
EQ2d_Traffic_sign_recognition	1.0	4.0	5.0	4.1	5.0	5.0	NA	
EQ2e_Lane_keeping_Assistance	1.0	2.0	5.0	3.9	5.0	5.0	NA	
EQ2f_Blind_spot_warning	1.0	5.0	5.0	4.1	5.0	5.0	NA	
EQ2g_Drowsiness_alert	1.0	2.0	5.0	4.0	5.0	5.0	NA	
EQ2h_Parking_assist	1.0	2.0	5.0	3.7	5.0	5.0	1696.0	
EQ2i_High_speed_alert	1.0	2.0	5.0	3.8	5.0	5.0	NA	
EQ2j_Automatic_emergency_braking	1.0	4.0	5.0	4.0	5.0	5.0	NA	
EQ3a_Useful	3.0	4.0	4.0	4.3	5.0	5.0	NA	Indicate to what extent you agree with the following statements about ADAS in general. 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ3b_Increase_perform	3.0	3.0	4.0	3.9	5.0	5.0	NA	
EQ3c_Understandable	1.0	3.0	4.0	3.7	4.0	5.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ3d_Easy	2.0	3.0	4.0	3.8	5.0	5.0	NA	
EQ3e_Good_idea	2.0	4.0	4.0	4.1	5.0	5.0	NA	
EQ3f_Maintain_safe	2.0	3.0	4.0	4.0	5.0	5.0	NA	
EQ3g_Comfortable	1.0	3.0	3.0	3.5	4.0	5.0	NA	
EQ3h_Attention	1.0	3.0	3.0	3.4	4.0	5.0	NA	
EQ3i_Accident_risk	2.0	3.0	4.0	3.8	4.0	5.0	NA	
EQ3j_Trust	1.0	3.0	4.0	3.7	4.0	5.0	NA	
EQ3k_Distract	1.0	2.0	3.0	2.6	3.0	5.0	NA	
EQ4a_Speed_limit_built_up	1.0	2.0	3.0	2.8	3.0	4.0	11614.0	Please estimate: over the last year, how often did you as a car driver… a. drive faster than the speed limit inside built-up areas? b. drive faster than the speed limit? c. drive when you were so sleepy that you had trouble keeping your eyes open? d. realize that you were actually too tired to drive? e. used a hand-held mobile phone while driving? f. drive to close to a vulnerable road user (pedestrian, moped, cyclist, etc.)? g. illegally overtake another vehicle? h. drive without respecting a safe distance to the vehicle in front? i. cross the outer edges of the driving lane? 1:Never, 2:Seldom, 3:About half the time, 4:Usually
EQ4b_Speed_limit	2.0	3.0	3.0	3.2	4.0	4.0	11614.0	
EQ4c_Sleepy	1.0	1.0	2.0	1.9	2.0	4.0	NA	
EQ4d_Tired	1.0	1.0	2.0	1.8	2.0	3.0	2507.0	
EQ4e_Mobile_phone	1.0	2.0	3.0	2.6	3.0	4.0	20126.0	
EQ4f_VRU_close	1.0	2.0	2.0	2.3	3.0	4.0	1452.0	
EQ4g_Illegal_overtake	1.0	1.0	2.0	2.1	3.0	4.0	NA	
EQ4h_Safe_distance	1.0	2.0	2.0	2.4	3.0	4.0	53.0	
EQ4i_Driving_lane	1.0	2.0	2.0	2.2	3.0	4.0	NA	
EQ5_Driving_style	1.0	1.0	1.0	1.7	3.0	4.0	NA	Please select with which of the following driving styles you identify the most. 1:Discrete average driver, 2:Less experienced hesitant driver, 3:Sportive ambitioned driver, 4:Risk-taking offensive driver
EQ6_Driving_confidence	1.0	1.0	2.0	1.9	2.0	3.0	NA	1:Very confident, 2:Confident, 3:Neutral, 4:Insecure, 5:Very insecure

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ7_Driving_is	1.0	2.0	3.0	2.9	3.0	5.0	NA	1:Very dangerous, 2:Quite dangerous, 3:Neither dangerous nor safe, 4:Quite safe, 5:Very safe
EQ8a_Skill	2.0	3.0	4.0	3.9	4.0	5.0	NA	How do you think you compare to the average driver? a. Regarding general driving skills, I am: b. Regarding the ability to cope with hazards in traffic, I am: c. Regarding your risk of being involved in a crash, I am: 1:Much worse, 2:Worse, 3:Not better nor worse, 4:Better, 5:Much better
EQ8b_Hazards	2.0	3.0	3.0	3.7	4.0	5.0	NA	
EQ8c_Crash_risk	2.0	3.0	4.0	3.9	5.0	5.0	NA	
EQ9a_Police_close_following	1.0	1.0	2.0	2.3	3.0	4.0	NA	Please indicate to which extent you agree with the following statements. 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ9b_Overtake	1.0	1.0	1.0	1.8	3.0	4.0	NA	
EQ9c_Fast	1.0	1.0	3.0	2.7	4.0	4.0	NA	
EQ9d_Small_gap	1.0	1.0	2.0	2.3	3.0	4.0	NA	
EQ9e_Faster_speed_limit	1.0	1.0	2.0	2.2	3.0	4.0	NA	
EQ9f_Risky_overtake	1.0	1.0	1.0	1.4	2.0	4.0	NA	
EQ9g_Speed_drive_careful	1.0	1.0	2.0	1.9	2.0	4.0	NA	
EQ9h_Know_risks	1.0	1.0	3.0	2.4	3.0	5.0	NA	
EQ9i_Closer_recommended	1.0	1.0	1.0	1.8	3.0	4.0	NA	
EQ9j_Closer_flow	1.0	1.0	2.0	2.4	4.0	4.0	NA	
EQ10a_Attention	3.0	4.0	4.0	4.4	5.0	5.0	NA	Please rate your own driving skills. 1:Very weak, 2:Weak, 3:Not weak nor strong, 4:Strong, 5:Very strong
EQ10b_Keeping_distance	2.0	4.0	4.0	4.0	4.0	5.0	NA	
EQ10c_Adjusting_speed	3.0	4.0	4.0	4.5	5.0	5.0	NA	
EQ10d_Conforming_speed_limit	2.0	3.0	4.0	3.5	4.0	5.0	NA	
EQ11a_Benefits	1.0	1.0	1.0	2.0	4.0	5.0	NA	Please indicate to which extent you agree with the following statements. a. I know the benefits of safe driving
EQ11b_Needed_safe	1.0	1.0	1.0	2.5	4.0	5.0	NA	
EQ11c_Skills	1.0	1.0	1.0	2.4	4.0	5.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ11d_Competent	1.0	1.0	1.0	2.4	4.0	5.0	NA	b. I know what is needed to drive safely c. I have the skills to drive safely d. I feel competent enough to drive safely e. Safe driving is important to avoid crashes f. Safe driving makes me feel comfortable g. For me personally, safe driving is important h. Safe driving should be a personal obligation i. My friends think safe driving is important j. My colleagues find it important to drive safely k. I control whether I drive safely or not l. For me, safe driving is easy to do 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ11e_Important	1.0	1.0	1.0	2.1	4.0	5.0	NA	
EQ11f_Comfortable	1.0	1.0	1.0	2.1	4.0	5.0	NA	
EQ11g_Personally_important	1.0	1.0	1.0	1.9	3.0	5.0	NA	
EQ11h_Obligation	1.0	1.0	1.0	1.9	3.0	5.0	NA	
EQ11i_Friends_safe	1.0	1.0	3.0	2.8	4.0	5.0	NA	
EQ11j_Colleagues_safe	1.0	1.0	3.0	2.7	4.0	5.0	NA	
EQ11k_I_control	1.0	1.0	3.0	2.5	4.0	5.0	NA	
EQ11l_Safe_easy	1.0	1.0	3.0	2.7	4.0	5.0	NA	
EQ12_Accident_three_years	1.0	1.0	1.0	1.3	1.0	3.0	NA	Within the last three years, have you been involved in an accident with your car, which was self-inflicted? 1:Never, 2:Yes once, 3:Yes two times, 4:Yes three or more times
EQ14_Traffic_offence	0.0	0.0	0.0	0.2	0.0	1.0	NA	Within the last three years, have you been fined for a traffic offence while driving with your car? 0: No, 1: Yes
EQ16a_Sit_read	1.0	2.0	2.0	2.6	3.0	4.0	NA	How likely are you to doze off or fall asleep in the following situations, in contrast to feeling just tired? 1: Would never doze, 2:Slight chance of dozing, 3:Moderate chance of dozing, 4:High chance of dozing
EQ16b_Watching_TV	1.0	2.0	3.0	2.7	3.0	4.0	NA	
EQ16c_Sitting_inactive	1.0	1.0	2.0	1.7	2.0	3.0	NA	
EQ16d_Car_passenger	1.0	1.0	2.0	2.1	3.0	4.0	NA	
EQ16e_Lying_down	1.0	1.0	3.0	2.6	4.0	4.0	NA	
EQ16f_Sitting_talking	1.0	1.0	1.0	1.1	1.0	3.0	NA	
EQ16g_Sitting_lunch_alcohol	1.0	2.0	2.0	2.0	2.0	4.0	NA	
EQ16h_Car_stopped	1.0	1.0	1.0	1.1	1.0	2.0	NA	
EQ17_General_sleep_rating	1.0	2.0	2.0	2.6	3.0	4.0	NA	In general, how would you rate your sleep in the last 3 months? 1:very good, 2:Quite good, 3:Neither good nor bad, 4:Quite bad, 5:Very bad

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ18_Diagnosed_sleep_disorder	0.0	0.0	0.0	0.0	0.0	0.0	NA	0: No, 1: Yes
EQ19_Fight_sleep_in_car	1.0	1.0	2.0	1.5	2.0	2.0	NA	1:Never, 2:Occasionally, 3:2-4 times a month, 4:2-3 times a week, 5:4 or more times a week
EQ20_Stop_because_sleepiness	1.0	1.0	1.0	1.1	1.0	3.0	NA	1:Never, 2:Once, 3:Twice, 4:Three times, 5:More than three times
EQ21_Sleepiness_Wanted_to_stop	1.0	1.0	1.0	1.4	1.0	5.0	NA	
EQ22_Asleep_while_driving	1.0	1.0	1.0	1.0	1.0	1.0	NA	
EQ23_Crash_blame_sleep	0.0	0.0	0.0	0.0	0.0	0.0	NA	1:No, 2:Yes once, 3:Yes several times, 4:Do not remember
Phase 2								
trip_distance	0.5	6.8	11.8	38.4	26.8	319.7	NA	
time_indicator	1.0	1.0	2.0	1.7	2.0	3.0	NA	1: day , 2: dusk, 3: night
VC_acc_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	
VC_acc_high_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	
VC_acc_no_low_sum	27.0	30.0	30.0	30.0	30.0	30.0	NA	
VC_dc_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	how often did you as a car driver, drive faster than the speed limit inside built-up areas? (1) Never, (2) Seldom, (3) About half the time, (4) Usually, (5) (almost) Always
VC_dc_high_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	
VC_dc_no_low_sum	27.0	30.0	30.0	30.0	30.0	30.0	NA	
Speed_high_sum	0.0	0.0	0.0	0.1	0.0	2.0	NA	
Speed_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	
Speed_no_low_sum	27.0	30.0	30.0	29.9	30.0	30.0	NA	
distraction_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	
VC_acc_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_acc_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_acc_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
VC_dc_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
VC_dc_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_dc_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
Speed_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Speed_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Speed_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
distraction_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Gendre	0.0	0.0	0.0	0.4	1.0	1.0	NA	0: Male, 1: Female
SQ_Nationality	1.0	1.0	1.0	1.0	1.0	1.0	NA	1: Greek
SQ_Year_of_birth	1964.0	1990.0	1995.0	1992.0	1998.0	2000.0	NA	
SQ_Age	22.0	24.0	27.0	29.9	33.0	58.0	NA	
SQ_ Age_got_driving_license	18.0	18.0	18.0	18.9	19.0	27.0	NA	
SQ_Years_driving	3.0	5.0	9.0	11.0	14.0	40.0	NA	
SQ_Vehicle_brand	1.0	7.0	15.0	13.9	21.0	22.0	NA	
SQ_Vehicle_age	0.0	5.0	7.0	9.7	16.0	22.0	NA	
STC_Second_Nat	0.0	0.0	0.0	0.0	0.0	0.0	NA	0: No, 1: Yes
STC_Highest_lev_education	1.0	2.0	2.0	2.5	3.0	5.0	NA	1:Higher education , 2:Highest education , 3: Master of Science, 4:PhD, 5:Secondary education
STC_Current_occupation	1.0	2.0	2.0	3.1	4.0	5.0	NA	1:Civil servant, 2:Freelancer / self-employed, 3: Military service, 4:Student, 5:Private employee
STC_Employment_stat	1.0	1.0	1.0	1.8	3.0	4.0	NA	1:Employed full time, 2:Employed part time, 3: Military service, 4: Student
STC_Net_income	1.0	1.0	5.0	3.6	5.0	7.0	NA	1: Less than €1.000, 2: €1.000 - €2.000, 3: €2000 - €3.000, 4: €3000 - €4.000, 5: €4000 - €5.000, 6: More than €5.000
STC_Med_condition_decleration	0.0	1.0	1.0	0.9	1.0	1.0	NA	Can you declare that you are not suffering from a medical condition that would be considered a legal exclusion to drive? 0: No, 1: Yes
STC_Fuel_type	1.0	2.0	3.0	2.5	3.0	3.0	NA	1:diesel, 2: hybrid, 3: petrol

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
STC_Gearbox	1.0	1.0	1.0	1.3	2.0	2.0	NA	1:Manual, 2: Automatic
STC_Disability_mod	0.0	0.0	0.0	0.0	0.0	1.0	NA	Has this vehicle been modified to cope with physical limitations of the driver? 0: No, 1: Yes
STC_Number_other_drivers	0.0	0.0	0.0	0.7	1.0	2.0	NA	-
STC_Drvr_1_split	10.0	85.0	100.0	88.1	100.0	100.0	NA	How is the use of this car split between all of the drivers who use it? (Note the total usage should add up to 100%).
STC_Drvr_2_split	0.0	0.0	0.0	10.1	15.0	70.0	NA	
STC_Drvr_3_split	0.0	0.0	0.0	1.9	0.0	25.0	NA	
STC_Drvr_4_split	0.0	0.0	0.0	0.0	0.0	0.0	NA	
STC_Weekly_km	1.0	1.0	2.0	2.1	3.0	4.0	NA	1: up to 50 km, 2:50 to 100 km, 3:100 to 500 km, 4:500 to 1000 km, 5:more than 1000 km
STC_Urban	10.0	40.0	60.0	59.3	80.0	95.0	9399.0	How much do you drive on urban, rural and motorways roads (%)?
STC_Rural	0.0	10.0	20.0	22.9	30.0	60.0	9399.0	
STC_Motorway	0.0	5.0	10.0	17.9	30.0	60.0	9399.0	
EQ1a_Adaptive_cruise_control	0.0	0.0	0.0	0.3	1.0	1.0	NA	Which Advanced Driving Assistance Systems are present in your car? 0:Not equipped 1:Equipped
EQ1b_Forward_collision_warning	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ1c_NV_PD	0.0	0.0	0.0	0.0	0.0	1.0	NA	
EQ1d_Traffic_sign_recognition	0.0	0.0	0.0	0.0	0.0	0.0	8506.0	
EQ1e_Lane_keeping_Assistance	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ1f_Blind_spot_warning	0.0	0.0	0.0	0.0	0.0	1.0	NA	
EQ1g_Drowsiness_alert	0.0	0.0	0.0	0.0	0.0	1.0	4802.0	
EQ1h_Parking_assist	0.0	0.0	0.0	0.4	1.0	1.0	1574.0	
EQ1i_High_speed_alert	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ1j_Automatic_emergency_braking	0.0	0.0	0.0	0.3	1.0	1.0	NA	
EQ2a_Adaptive_cruise_control	1.0	1.0	5.0	3.4	5.0	5.0	NA	How often do you use the following Advanced Driving Assistance Systems that are present in your car? 1: Almost never, 2:Sometimes, 3:Often, 4:Almost always, 5:Not applicable
EQ2b_Forward_collision_warning	1.0	4.0	5.0	3.9	5.0	5.0	NA	
EQ2c_NV_PD	1.0	5.0	5.0	4.2	5.0	5.0	NA	
EQ2d_Traffic_sign_recognition	1.0	4.0	5.0	4.1	5.0	5.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ2e_Lane_keeping_Assistance	1.0	2.0	5.0	3.8	5.0	5.0	NA	
EQ2f_Blind_spot_warning	1.0	5.0	5.0	4.1	5.0	5.0	NA	
EQ2g_Drowsiness_alert	1.0	2.0	5.0	3.9	5.0	5.0	NA	
EQ2h_Parking_assist	1.0	2.0	4.0	3.6	5.0	5.0	6608.0	
EQ2i_High_speed_alert	1.0	2.0	5.0	3.9	5.0	5.0	NA	
EQ2j_Automatic_emergency_braking	1.0	4.0	5.0	4.0	5.0	5.0	NA	
EQ3a_Useful	3.0	4.0	4.0	4.2	5.0	5.0	NA	Indicate to what extent you agree with the following statements about ADAS in general. 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ3b_Increase_perform	3.0	3.0	4.0	3.9	4.0	5.0	NA	
EQ3c_Understandable	1.0	3.0	3.0	3.6	4.0	5.0	NA	
EQ3d_Easy	2.0	3.0	3.0	3.7	4.0	5.0	NA	
EQ3e_Good_idea	2.0	3.0	4.0	4.0	5.0	5.0	NA	
EQ3f_Maintain_safe	2.0	3.0	4.0	3.8	4.0	5.0	NA	
EQ3g_Comfortable	1.0	3.0	3.0	3.2	4.0	5.0	NA	
EQ3h_Attention	1.0	3.0	3.0	3.5	4.0	5.0	NA	
EQ3i_Accident_risk	2.0	3.0	4.0	3.7	4.0	5.0	NA	
EQ3j_Trust	1.0	3.0	4.0	3.5	4.0	5.0	NA	
EQ3k_Distract	1.0	2.0	3.0	2.7	3.0	5.0	NA	
EQ4a_Speed_limit_built_up	1.0	2.0	3.0	2.9	4.0	4.0	10210.0	Please estimate: over the last year, how often did you as a car driver… a. drive faster than the speed limit inside built-up areas? b. drive faster than the speed limit? c. drive when you were so sleepy that you had trouble keeping your eyes open? d. realize that you were actually too tired to drive? e. used a hand-held mobile phone while driving? f. drive to close to a vulnerable road user (pedestrian, moped, cyclist, etc.)?
EQ4b_Speed_limit	2.0	3.0	3.0	3.3	4.0	4.0	10210.0	
EQ4c_Sleepy	1.0	1.0	2.0	1.8	2.0	4.0	NA	
EQ4d_Tired	1.0	1.0	2.0	1.8	2.0	3.0	1704.0	
EQ4e_Mobile_phone	1.0	2.0	3.0	2.7	3.0	4.0	18099.0	
EQ4f_VRU_close	1.0	2.0	2.0	2.4	3.0	4.0	1574.0	
EQ4g_Illegal_overtake	1.0	1.0	2.0	2.0	3.0	4.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ4h_Safe_distance	1.0	2.0	2.0	2.3	3.0	4.0	252.0	g. illegally overtake another vehicle? h. drive without respecting a safe distance to the vehicle in front? i. cross the outer edges of the driving lane? 1:Never, 2:Seldom, 3:About half the time, 4:Usually
EQ4i_Driving_lane	1.0	1.0	2.0	2.1	3.0	4.0	NA	
EQ5_Driving_style	1.0	1.0	1.0	1.8	3.0	4.0	NA	Please select with which of the following driving styles you identify the most. 1:Discrete average driver, 2:Less experienced hesitant driver, 3:Sportive ambitioned driver, 4:Risk-taking offensive driver
EQ6_Driving_confidence	1.0	1.0	2.0	1.8	2.0	3.0	NA	1:Very confident, 2:Confident, 3:Neutral, 4:Insecure, 5:Very insecure
EQ7_Driving_is	1.0	3.0	3.0	3.0	3.0	5.0	NA	1:Very dangerous, 2:Quite dangerous, 3:Neither dangerous nor safe, 4:Quite safe, 5:Very safe
EQ8a_Skill	3.0	4.0	4.0	3.9	4.0	5.0	NA	How do you think you compare to the average driver? a. Regarding general driving skills, I am: b. Regarding the ability to cope with hazards in traffic, I am: c. Regarding your risk of being involved in a crash, I am: 1:Much worse, 2:Worse, 3:Not better nor worse, 4:Better, 5:Much better
EQ8b_Hazards	2.0	3.0	4.0	3.7	5.0	5.0	NA	
EQ8c_Crash_risk	3.0	3.0	4.0	4.0	5.0	5.0	NA	
EQ9a_Police_close_following	1.0	1.0	2.0	2.3	3.0	4.0	NA	Please indicate to which extent you agree with the following statements. 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ9b_Overtake	1.0	1.0	1.0	1.8	3.0	4.0	NA	
EQ9c_Fast	1.0	1.0	3.0	2.8	4.0	4.0	NA	
EQ9d_Small_gap	1.0	1.0	2.0	2.3	3.0	4.0	NA	
EQ9e_Faster_speed_limit	1.0	1.0	2.0	2.3	3.0	4.0	NA	
EQ9f_Risky_overtake	1.0	1.0	1.0	1.4	2.0	4.0	NA	
EQ9g_Speed_drive_careful	1.0	1.0	2.0	2.1	3.0	4.0	NA	
EQ9h_Know_risks	1.0	1.0	3.0	2.4	3.0	5.0	NA	
EQ9i_Closer_recommended	1.0	1.0	2.0	2.0	3.0	4.0	NA	
EQ9j_Closer_flow	1.0	2.0	3.0	2.6	4.0	4.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ10a_Attention	3.0	4.0	4.0	4.4	5.0	5.0	NA	Please rate your own driving skills. 1:Very weak, 2:Weak, 3:Not weak nor strong, 4:Strong, 5:Very strong
EQ10b_Keeping_distance	2.0	4.0	4.0	3.9	4.0	5.0	NA	
EQ10c_Adjusting_speed	4.0	4.0	4.0	4.4	5.0	5.0	NA	
EQ10d_Conforming_speed_limit	2.0	3.0	4.0	3.4	4.0	5.0	NA	
EQ11a_Benefits	1.0	1.0	1.0	2.0	4.0	5.0	NA	Please indicate to which extent you agree with the following statements. a. I know the benefits of safe driving b. I know what is needed to drive safely c. I have the skills to drive safely d. I feel competent enough to drive safely e. Safe driving is important to avoid crashes f. Safe driving makes me feel comfortable g. For me personally, safe driving is important h. Safe driving should be a personal obligation i. My friends think safe driving is important j. My colleagues find it important to drive safely k. I control whether I drive safely or not l. For me, safe driving is easy to do 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ11b_Needed_safe	1.0	1.0	3.0	2.6	4.0	5.0	NA	
EQ11c_Skills	1.0	1.0	3.0	2.6	4.0	5.0	NA	
EQ11d_Competent	1.0	1.0	4.0	2.6	4.0	5.0	NA	
EQ11e_Important	1.0	1.0	1.0	2.2	4.0	5.0	NA	
EQ11f_Comfortable	1.0	1.0	1.0	2.3	4.0	5.0	NA	
EQ11g_Personally_important	1.0	1.0	1.0	2.2	4.0	5.0	NA	
EQ11h_Obligation	1.0	1.0	1.0	2.2	4.0	5.0	NA	
EQ11i_Friends_safe	1.0	1.0	3.0	2.9	4.0	5.0	NA	
EQ11j_Colleagues_safe	1.0	1.0	3.0	2.9	4.0	5.0	NA	
EQ11k_I_control	1.0	1.0	3.0	2.6	4.0	5.0	NA	
EQ11l_Safe_easy	1.0	1.0	3.0	2.8	4.0	5.0	NA	
EQ12_Accident_three_years	1.0	1.0	1.0	1.2	1.0	2.0	NA	Within the last three years, have you been involved in an accident with your car, which was self-inflicted? 1:Never, 2:Yes once, 3:Yes two times, 4:Yes three or more times
EQ14_Traffic_offence	0.0	0.0	0.0	0.2	0.0	1.0	NA	Within the last three years, have you been fined for a traffic offence while driving with your car? 0: No, 1: Yes
EQ16a_Sit_read	1.0	2.0	2.0	2.5	3.0	4.0	NA	How likely are you to doze off or fall asleep in the following situations, in contrast to feeling just tired? 1: Would never doze, 2:Slight chance of dozing, 3:Moderate chance of dozing, 4:High chance of dozing
EQ16b_Watching_TV	1.0	2.0	3.0	2.8	3.0	4.0	NA	
EQ16c_Sitting_inactive	1.0	1.0	1.0	1.6	2.0	3.0	NA	
EQ16d_Car_passenger	1.0	1.0	2.0	2.1	3.0	4.0	NA	
EQ16e_Lying_down	1.0	1.0	3.0	2.5	3.0	4.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ16f_Sitting_talking	1.0	1.0	1.0	1.1	1.0	2.0	NA	
EQ16g_Sitting_lunch_alcohol	1.0	2.0	2.0	1.9	2.0	3.0	NA	
EQ16h_Car_stopped	1.0	1.0	1.0	1.1	1.0	2.0	NA	
EQ17_General_sleep_rating	1.0	2.0	2.0	2.4	3.0	4.0	NA	In general, how would you rate your sleep in the last 3 months? 1:very good, 2:Quite good, 3:Neither good nor bad, 4:Quite bad, 5:Very bad
EQ18_Diagnosed_sleep_disorder	0.0	0.0	0.0	0.0	0.0	0.0	NA	0: No, 1: Yes
EQ19_Fight_sleep_in_car	1.0	1.0	1.0	1.5	2.0	2.0	NA	1:Never, 2:Occasionally, 3:2-4 times a month, 4:2-3 times a week, 5:4 or more times a week
EQ20_Stop_because_sleepiness	1.0	1.0	1.0	1.1	1.0	3.0	NA	1:Never, 2:Once, 3:Twice, 4:Three times, 5:More than three times
EQ21_Sleepiness_Wanted_to_stop	1.0	1.0	1.0	1.5	2.0	5.0	NA	
EQ22_Asleep_while_driving	1.0	1.0	1.0	1.0	1.0	1.0	NA	
EQ23_Crash_blame_sleep	0.0	0.0	0.0	0.0	0.0	0.0	NA	1:No, 2:Yes once, 3:Yes several times, 4:Do not remember
Phase 3								
trip_distance	0.5	7.0	11.6	31.8	27.6	299.9	NA	
time_indicator	1.0	1.0	2.0	1.7	2.0	3.0	NA	1: day , 2: dusk, 3: night
VC_acc_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	
VC_acc_high_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	
VC_acc_no_low_sum	27.0	30.0	30.0	30.0	30.0	30.0	NA	
VC_dc_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	how often did you as a car driver, drive faster than the speed limit inside built-up areas? (1) Never, (2) Seldom, (3) About half the time, (4) Usually, (5) (almost) Always
VC_dc_high_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	
VC_dc_no_low_sum	27.0	30.0	30.0	30.0	30.0	30.0	NA	
Speed_high_sum	0.0	0.0	0.0	0.1	0.0	2.0	NA	
Speed_medium_sum	0.0	0.0	0.0	0.0	0.0	2.0	NA	
Speed_no_low_sum	27.0	30.0	30.0	29.9	30.0	30.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
distraction_sum	0.0	0.0	0.0	0.0	0.0	3.0	NA	
VC_acc_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_acc_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_acc_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
VC_dc_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_dc_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
VC_dc_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
Speed_high_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Speed_medium_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Speed_no_low_mean	0.9	1.0	1.0	1.0	1.0	1.0	NA	
distraction_mean	0.0	0.0	0.0	0.0	0.0	0.1	NA	
Gendre	0.0	0.0	0.0	0.4	1.0	1.0	NA	0: Male, 1: Female
SQ_Nationality	1.0	1.0	1.0	1.0	1.0	1.0	NA	1: Greek
SQ_Year_of_birth	1964.0	1990.0	1995.0	1992.0	1999.0	2000.0	NA	
SQ_Age	22.0	23.0	27.0	29.5	33.0	58.0	NA	
SQ_ Age_got_driving_license	18.0	18.0	18.0	18.8	19.0	27.0	NA	
SQ_Years_driving	3.0	5.0	8.0	10.7	11.0	40.0	NA	
SQ_Vehicle_brand	1.0	11.0	15.0	14.0	21.0	22.0	NA	
SQ_Vehicle_age	0.0	4.0	7.0	9.6	15.0	22.0	NA	
STC_Second_Nat	0.0	0.0	0.0	0.0	0.0	0.0	NA	0: No, 1: Yes
STC_Highest_lev_education	1.0	2.0	2.0	2.4	3.0	5.0	NA	1:Higher education , 2:Highest education , 3: Master of Science, 4:PhD, 5:Secondary education
STC_Current_occupation	1.0	2.0	4.0	3.2	4.0	5.0	NA	1:Civil servant, 2:Freelancer / self-employed, 3: Military service, 4:Student, 5:Private employee
STC_Employment_stat	1.0	1.0	1.0	2.1	4.0	4.0	NA	1:Employed full time, 2:Employed part time, 3: Military service, 4: Student

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
STC_Net_income	1.0	1.0	5.0	3.8	5.0	7.0	NA	1: Less than €1.000, 2: €1.000 - €2.000, 3: €2000 - €3.000, 4: €3000 - €4.000, 5: €4000 - €5.000, 6: More than €5.000
STC_Med_condition_decleration	0.0	1.0	1.0	0.9	1.0	1.0	NA	Can you declare that you are not suffering from a medical condition that would be considered a legal exclusion to drive? 0: No, 1: Yes
STC_Fuel_type	1.0	2.0	3.0	2.5	3.0	3.0	NA	1:diesel, 2: hybrid, 3: petrol
STC_Gearbox	1.0	1.0	1.0	1.3	2.0	2.0	NA	1:Manual, 2: Automatic
STC_Disability_mod	0.0	0.0	0.0	0.0	0.0	1.0	NA	Has this vehicle been modified to cope with physical limitations of the driver? 0: No, 1: Yes
STC_Number_other_drivers	0.0	0.0	0.0	0.6	1.0	2.0	NA	-
STC_Drvr_1_split	10.0	90.0	100.0	89.1	100.0	100.0	NA	How is the use of this car split between all of the drivers who use it? (Note the total usage should add up to 100%).
STC_Drvr_2_split	0.0	0.0	0.0	9.2	10.0	70.0	NA	
STC_Drvr_3_split	0.0	0.0	0.0	1.7	0.0	25.0	NA	
STC_Drvr_4_split	0.0	0.0	0.0	0.0	0.0	0.0	NA	
STC_Weekly_km	1.0	1.0	2.0	2.0	2.0	4.0	NA	1: up to 50 km, 2:50 to 100 km, 3:100 to 500 km, 4:500 to 1000 km, 5:more than 1000 km
STC_Urban	10.0	40.0	60.0	57.2	80.0	95.0	9222.0	How much do you drive on urban, rural and motorways roads (%)?
STC_Rural	0.0	10.0	30.0	24.9	35.0	60.0	9222.0	
STC_Motorway	0.0	5.0	10.0	17.9	30.0	60.0	9222.0	
EQ1a_Adaptive_cruise_control	0.0	0.0	0.0	0.3	1.0	1.0	NA	Which Advanced Driving Assistance Systems are present in your car? 0:Not equipped 1:Equipped
EQ1b_Forward_collision_warning	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ1c_NV_PD	0.0	0.0	0.0	0.0	0.0	1.0	NA	
EQ1d_Traffic_sign_recognition	0.0	0.0	0.0	0.0	0.0	0.0	6807.0	
EQ1e_Lane_keeping_Assistance	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ1f_Blind_spot_warning	0.0	0.0	0.0	0.0	0.0	1.0	NA	
EQ1g_Drowsiness_alert	0.0	0.0	0.0	0.1	0.0	1.0	4383.0	
EQ1h_Parking_assist	0.0	0.0	0.0	0.4	1.0	1.0	1139.0	
EQ1i_High_speed_alert	0.0	0.0	0.0	0.2	0.0	1.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ1j_Automatic_emergency_braking	0.0	0.0	0.0	0.2	0.0	1.0	NA	
EQ2a_Adaptive_cruise_control	1.0	1.0	5.0	3.3	5.0	5.0	NA	How often do you use the following Advanced Driving Assistance Systems that are present in your car? 1: Almost never, 2:Sometimes, 3:Often, 4:Almost always, 5:Not applicable
EQ2b_Forward_collision_warning	1.0	2.0	5.0	3.8	5.0	5.0	NA	
EQ2c_NV_PD	1.0	5.0	5.0	4.1	5.0	5.0	NA	
EQ2d_Traffic_sign_recognition	1.0	4.0	5.0	4.1	5.0	5.0	NA	
EQ2e_Lane_keeping_Assistance	1.0	1.0	5.0	3.7	5.0	5.0	NA	
EQ2f_Blind_spot_warning	1.0	5.0	5.0	4.1	5.0	5.0	NA	
EQ2g_Drowsiness_alert	1.0	1.0	5.0	3.8	5.0	5.0	NA	
EQ2h_Parking_assist	1.0	1.0	4.0	3.5	5.0	5.0	4770.0	
EQ2i_High_speed_alert	1.0	2.0	5.0	3.8	5.0	5.0	NA	
EQ2j_Automatic_emergency_braking	1.0	4.0	5.0	4.0	5.0	5.0	NA	
EQ3a_Useful	3.0	4.0	4.0	4.2	5.0	5.0	NA	Indicate to what extent you agree with the following statements about ADAS in general. 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ3b_Increase_perform	3.0	3.0	4.0	3.8	4.0	5.0	NA	
EQ3c_Understandable	1.0	3.0	3.0	3.7	4.0	5.0	NA	
EQ3d_Easy	2.0	3.0	4.0	3.8	5.0	5.0	NA	
EQ3e_Good_idea	2.0	4.0	4.0	4.0	5.0	5.0	NA	
EQ3f_Maintain_safe	2.0	3.0	4.0	3.8	4.0	5.0	NA	
EQ3g_Comfortable	1.0	3.0	3.0	3.3	4.0	5.0	NA	
EQ3h_Attention	1.0	3.0	3.0	3.5	4.0	5.0	NA	
EQ3i_Accident_risk	2.0	3.0	4.0	3.8	4.0	5.0	NA	
EQ3j_Trust	1.0	3.0	4.0	3.6	4.0	5.0	NA	
EQ3k_Distract	1.0	2.0	3.0	2.6	3.0	5.0	NA	
EQ4a_Speed_limit_built_up	1.0	2.0	3.0	3.0	4.0	4.0	12522.0	Please estimate: over the last year, how often did you as a car driver… a. drive faster than the speed limit inside built-up areas?
EQ4b_Speed_limit	2.0	3.0	3.0	3.3	4.0	4.0	12522.0	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ4c_Sleepy	1.0	1.0	2.0	1.9	2.0	4.0	NA	b. drive faster than the speed limit? c. drive when you were so sleepy that you had trouble keeping your eyes open? d. realize that you were actually too tired to drive? e. used a hand-held mobile phone while driving? f. drive to close to a vulnerable road user (pedestrian, moped, cyclist, etc.)? g. illegally overtake another vehicle? h. drive without respecting a safe distance to the vehicle in front? i. cross the outer edges of the driving lane? 1:Never, 2:Seldom, 3:About half the time, 4:Usually
EQ4d_Tired	1.0	1.0	2.0	1.8	2.0	3.0	5715.0	
EQ4e_Mobile_phone	1.0	2.0	3.0	2.7	3.0	4.0	21430.0	
EQ4f_VRU_close	1.0	2.0	2.0	2.4	3.0	4.0	1139.0	
EQ4g_Illegal_overtake	1.0	1.0	2.0	2.1	3.0	4.0	NA	
EQ4h_Safe_distance	1.0	2.0	2.0	2.5	3.0	4.0	144.0	
EQ4i_Driving_lane	1.0	1.0	2.0	2.1	3.0	4.0	NA	
EQ5_Driving_style	1.0	1.0	1.0	1.9	3.0	4.0	NA	Please select with which of the following driving styles you identify the most. 1:Discrete average driver, 2:Less experienced hesitant driver, 3:Sportive ambitioned driver, 4:Risk-taking offensive driver
EQ6_Driving_confidence	1.0	1.0	2.0	1.8	2.0	3.0	NA	1:Very confident, 2:Confident, 3:Neutral, 4:Insecure, 5:Very insecure
EQ7_Driving_is	1.0	2.0	3.0	3.0	3.0	5.0	NA	1:Very dangerous, 2:Quite dangerous, 3:Neither dangerous nor safe, 4:Quite safe, 5:Very safe
EQ8a_Skill	3.0	4.0	4.0	4.0	4.0	5.0	NA	How do you think you compare to the average driver? a. Regarding general driving skills, I am: b. Regarding the ability to cope with hazards in traffic, I am: c. Regarding your risk of being involved in a crash, I am: 1:Much worse, 2:Worse, 3:Not better nor worse, 4:Better, 5:Much better
EQ8b_Hazards	2.0	3.0	4.0	3.8	5.0	5.0	NA	
EQ8c_Crash_risk	3.0	3.0	4.0	3.9	5.0	5.0	NA	
EQ9a_Police_close_following	1.0	1.0	3.0	2.5	4.0	4.0	NA	Please indicate to which extent you agree with the following statements. 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ9b_Overtake	1.0	1.0	2.0	1.9	3.0	4.0	NA	
EQ9c_Fast	1.0	1.0	3.0	2.7	4.0	4.0	NA	
EQ9d_Small_gap	1.0	2.0	2.0	2.5	3.0	4.0	NA	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ9e_Faster_speed_limit	1.0	2.0	2.0	2.4	3.0	4.0	NA	
EQ9f_Risky_overtake	1.0	1.0	1.0	1.6	2.0	4.0	NA	
EQ9g_Speed_drive_careful	1.0	1.0	2.0	2.1	3.0	4.0	NA	
EQ9h_Know_risks	1.0	1.0	3.0	2.4	4.0	5.0	NA	
EQ9i_Closer_recommended	1.0	1.0	2.0	2.0	3.0	4.0	NA	
EQ9j_Closer_flow	1.0	1.0	3.0	2.5	4.0	4.0	NA	
EQ10a_Attention	3.0	4.0	4.0	4.4	5.0	5.0	NA	Please rate your own driving skills. 1:Very weak, 2:Weak, 3:Not weak nor strong, 4:Strong, 5:Very strong
EQ10b_Keeping_distance	2.0	3.0	4.0	3.8	4.0	5.0	NA	
EQ10c_Adjusting_speed	3.0	4.0	4.0	4.4	5.0	5.0	NA	
EQ10d_Conforming_speed_limit	2.0	3.0	4.0	3.4	4.0	5.0	NA	
EQ11a_Benefits	1.0	1.0	1.0	2.0	4.0	5.0	NA	Please indicate to which extent you agree with the following statements. a. I know the benefits of safe driving b. I know what is needed to drive safely c. I have the skills to drive safely d. I feel competent enough to drive safely e. Safe driving is important to avoid crashes f. Safe driving makes me feel comfortable g. For me personally, safe driving is important h. Safe driving should be a personal obligation i. My friends think safe driving is important j. My colleagues find it important to drive safely k. I control whether I drive safely or not l. For me, safe driving is easy to do 1:Strongly disagree, 2:Disagree, 3:Neutral, 4:Agree, 5:Strongly agree
EQ11b_Needed_safe	1.0	1.0	1.0	2.4	4.0	5.0	NA	
EQ11c_Skills	1.0	1.0	1.0	2.3	4.0	5.0	NA	
EQ11d_Competent	1.0	1.0	1.0	2.2	4.0	5.0	NA	
EQ11e_Important	1.0	1.0	1.0	2.2	4.0	5.0	NA	
EQ11f_Comfortable	1.0	1.0	1.0	2.3	4.0	5.0	NA	
EQ11g_Personally_important	1.0	1.0	1.0	2.3	4.0	5.0	NA	
EQ11h_Obligation	1.0	1.0	1.0	2.1	4.0	5.0	NA	
EQ11i_Friends_safe	1.0	3.0	3.0	3.0	4.0	5.0	NA	
EQ11j_Colleagues_safe	1.0	2.0	3.0	3.0	4.0	5.0	NA	
EQ11k_I_control	1.0	1.0	3.0	2.6	4.0	5.0	NA	
EQ11l_Safe_easy	1.0	1.0	3.0	2.6	4.0	5.0	NA	
EQ12_Accident_three_years	1.0	1.0	1.0	1.2	1.0	3.0	NA	Within the last three years, have you been involved in an accident with your car, which was self-inflicted? 1:Never, 2:Yes once, 3:Yes two times, 4:Yes three or more times

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
EQ14_Traffic_offence	0.0	0.0	0.0	0.3	1.0	1.0	NA	Within the last three years, have you been fined for a traffic offence while driving with your car? 0: No, 1: Yes
EQ16a_Sit_read	1.0	2.0	2.0	2.5	3.0	4.0	NA	How likely are you to doze off or fall asleep in the following situations, in contrast to feeling just tired? 1: Would never doze, 2:Slight chance of dozing, 3:Moderate chance of dozing, 4:High chance of dozing
EQ16b_Watching_TV	1.0	2.0	3.0	2.7	4.0	4.0	NA	
EQ16c_Sitting_inactive	1.0	1.0	1.0	1.7	2.0	3.0	NA	
EQ16d_Car_passenger	1.0	1.0	2.0	2.0	3.0	4.0	NA	
EQ16e_Lying_down	1.0	2.0	3.0	2.6	3.0	4.0	NA	
EQ16f_Sitting_talking	1.0	1.0	1.0	1.1	1.0	2.0	NA	
EQ16g_Sitting_lunch_alcohol	1.0	1.0	2.0	1.9	2.0	4.0	NA	
EQ16h_Car_stopped	1.0	1.0	1.0	1.1	1.0	2.0	NA	
EQ17_General_sleep_rating	1.0	2.0	3.0	2.6	3.0	4.0	NA	In general, how would you rate your sleep in the last 3 months? 1:very good, 2:Quite good, 3:Neither good nor bad, 4:Quite bad, 5:Very bad
EQ18_Diagnosed_sleep_disorder	0.0	0.0	0.0	0.0	0.0	0.0	NA	0: No, 1: Yes
EQ19_Fight_sleep_in_car	1.0	1.0	1.0	1.5	2.0	2.0	NA	1:Never, 2:Occasionally, 3:2-4 times a month, 4:2-3 times a week, 5:4 or more times a week
EQ20_Stop_because_sleepiness	1.0	1.0	1.0	1.1	1.0	3.0	NA	1:Never, 2:Once, 3:Twice, 4:Three times, 5:More than three times
EQ21_Sleepiness_Wanted_to_stop	1.0	1.0	1.0	1.3	1.0	5.0	NA	
EQ22_Asleep_while_driving	1.0	1.0	1.0	1.0	1.0	1.0	NA	
EQ23_Crash_blame_sleep	0.0	0.0	0.0	0.0	0.0	0.0	NA	1:No, 2:Yes once, 3:Yes several times, 4:Do not remember