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D6.2

Analysis of coping capacity factors: vehicle and operator state

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

iDREAMS

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Glossary and Abbreviations

Abbreviation	Description
ADAS	Advanced Driver Assistance Systems
AIC	Akaike Information Criteria
API	Application Programming Interfaces
BCC	Browne-Cudeck Criterion
BIC	Bayesian Information Criterion
CC	Cubic Centimetres
CFI	Comparative Fit Index
DBN	Dynamic Bayesian Network
DCM	Discrete Choice Model
FCW	Forward Collision Warning
FDR	False Discovery Rate
FMS	Fleet Management System
GFI	Goodness of Fit Index
GLM	Generalized Linear Model
HP	Horsepower
IBI	Inter-Beat-Interval
i-DREAMS	smart Driver and Road Environment Assessment and Monitoring System
LDW	Lane Departure Warning
LSTM	Long Short Term Memory Network
OBD-II	On-Board Diagnostic II
PCW	Pedestrian Collision Warning
RMSEA	Root Mean Square Error Approximation
SDK	Software Development Kit
SEM	Structural Equation Model
STZ	Safety Tolerance Zone
TLI	Tucker Lewis Index
UK	United Kingdom
VIF	Variance Inflation Factor

Executive Summary

The current Deliverable aimed to provide the analysis results for the coping capacity factors, both for the vehicle as well as the operator state and the effect these have on risk. This **aim was pursued by**:

(i) identifying the most critical factors of coping capacity,

(ii) developing SEM and GLM model in order to investigate the effect of 'vehicle state' and 'operator state' on the STZ level and

(iii) comparing the differences between different countries and transport modes.

After making a short summary of the project's aims and objective, the naturalistic driving experiment procedure in all of the countries involved was described along with the data acquisition, data cleaning and data aggregation procedures followed to extract the datasets that were used in the analyses. These strategies aimed to comprehend how the data were stored in the back-end database, how to deal with missing values, how to impute missing values taking into account the natural meaning of the recorded variables and how to best exploit the data for developing the **Structural Equation Model (SEM).** The volume, diversity and noise included in the dataset, due to the different experimental difficulties faced in each of the countries led to extensive efforts to acquire clean data.

The next section of the Deliverable describes in detail, the methodologies followed throughout the analyses. Apart from SEMs, **Generalized Linear Models (GLMs)** were also used and the goodness-of-fit-metrics for the models were explained.

The main results of those analyses are thoroughly described in Chapter 4 of the current Deliverable. The analysis found that age, confidence, and driving style were the strongest indicators for operator state, while vehicle age and gearbox were significant for vehicle state. Mixed results were found when looking at the correlation between coping capacity and risk in **different countries and transport modes**, however the majority of the modes point towards a negative correlation between coping capacity and risk (i.e. higher operator capacity leads to lower risk).

The lack of objective coping capacity indicators in the study may have contributed to the **lack of coherence** between all the developed models over all countries and modes. However, there was consistency in the increase of coping capacity's effect on risk throughout the phases of the experiment. Despite efforts to clean and homogenize the data, an overall "coping capacity against risk" model for a specific mode was not possible due to the volume and diversity of the data. Future trials may provide additional data to help address these limitations and produce more conclusive results.

Finally in the last chapter, **conclusions** are drawn for the relationship between coping capacity and risk, while explanations for the model drawbacks are given.

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). 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 is made to monitor and determine if a driver is within acceptable boundaries of safe operation (i.e. Safety Tolerance Zone). Moreover, the i-DREAMS platform 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 (STZ) while driving. The safety-oriented interventions are 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 or behaviors. Consequently, the i-DREAMS platform allows 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 will be tested in a simulator study and three stages of on-road trials in Belgium, Germany, Greece, Portugal and the United Kingdom (UK) with a total of 600 participants representing car, bus, truck and tram/train drivers.

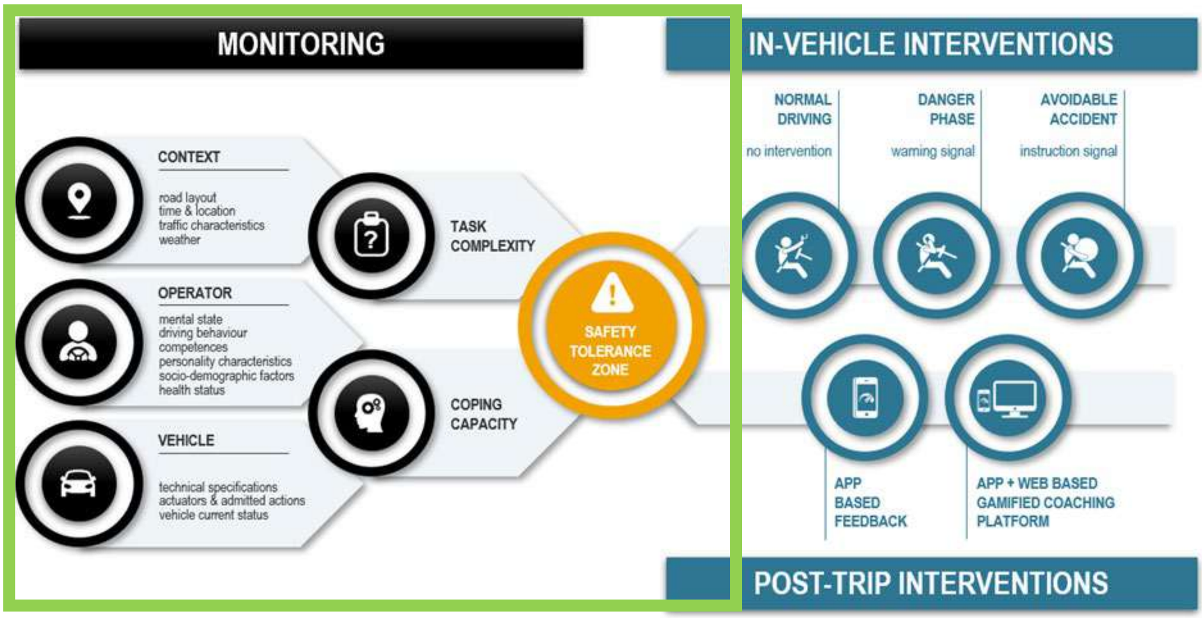

Figure 1: Conceptual framework of the i-DREAMS platform. The green frame indicates the thematic scope of this deliverable (see section 1.2)

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 anonymized 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 STZ via monitoring of task complexity and coping capacity. Staying within the STZ , vehicle operators avoid situations in which a collision becomes unavoidable. As can be seen in Figure 1, the STZ is subdivided in three segments, i.e. ‘normal driving’, the ‘danger phase’, and the ‘avoidable accident phase’. For the real-time determination of this STZ, the monitoring module in the i-DREAMS platform continuously registers and processes data for all the variables related to the context and to the vehicle. Regarding the operator however, continuous data registration and processing are limited to mental state and behavior. Data related to operator competence, personality, socio-demographic background, and health status, are collected via survey questionnaires.

It should be noted that the current Deliverable is directly related to the Deliverables 6.1 (Papazikou et al., 2023) and 6.3 (Michelaraki et al., 2023). In particular, this report mainly focuses on the analysis of coping capacity aspects related to vehicle state and operator state factors, while Deliverable 6.1 focuses on Task complexity and risk and Deliverable 6.3 deals with the integration of both task complexity and coping capacity as predictors of risk in an integrated way. Following exploratory analysis, the latent variables associated to “Vehicle State” will be estimated from the various relevant indicators, including technical specifications, actuators and admitted actions, vehicle current status etc. With regards to operator state, the latent variables associated to “Operator State” will be estimated on the basis of various metrics, such as mental state, behavior, competencies, personality, sociodemographic profile or health status. Thus, the effect of different vehicle and operator factors on risk will be defined and further analyzed for different countries, transport modes, age or gender groups etc. The Task will develop and test a pilot Structural Equation Model of the effect of the ‘Operator State’ aspect of coping capacity on the safety tolerance level.

1.2.1 Aims and objectives

This deliverable has following aims and objectives:

- **Identification of the impact of the most critical factors** of coping capacity (both for vehicle and operator state) on risk.
- **Development of a Structural Equation Model (SEM)** of the effect of the ‘vehicle state’ and ‘operator state’ aspect of coping capacity on the STZ.
- **Comparison of the effect of vehicle and operator state on risk** across the four phases of i-DREAMS road-trial on a country and transport mode basis.

1.2.2 Structure

The rest of 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 coping capacity (i.e. vehicle and operator state) is provided and the variables used to define coping capacity for both vehicle and operator state along with some descriptive statistics 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 Modeling 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.

The major part of this Deliverable is dedicated to the **mathematical modeling 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 STZ level. Comparisons among the examined countries (i.e. Belgium, UK, Germany, Greece, Portugal) and different transport modes (i.e. cars, trucks and buses) are also provided.

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 250 drivers from Belgium, UK, Germany, Greece and Portugal and a large database of 49,651 trips and 1,956,332 minutes was created. A detailed description of the on-road driving trials for identifying STZ 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, where it 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 behavior** 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 was 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. 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 visualization 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 focused on monitoring driving behavior and the impact of real-time interventions (i.e., in-vehicle warnings) and post-trip interventions (i.e., post-trip-feedback & gamification) on driving behavior.

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:** monitoring (i.e. 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

It should be noted that in Greece, data from an additional telematics experiment which took place for a 3-month timeframe were collected and analyzed in order to enhance the power of the analyses presented. The experimental design of the i-DREAMS on-road trials for Greece was subdivided into three phases (i.e. phase 1 – monitoring, phase 3 - real-time intervention and post-trip feedback and phase 4 - real-time intervention and post-trip feedback and gamification; while there was no real-time interventions provided by the app (phase 2 was not existed).

Table 1: Description and duration of each Phase

Phases	Description	Duration per participant
Phase 1	Monitoring (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 behavior without interventions.

Secondly, **Phase 2** of the field trials refers to a monitoring period during which only in-vehicle real-time warnings provided using adaptive Advanced Driver Assistance Systems (ADAS).

Thirdly, 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. 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.

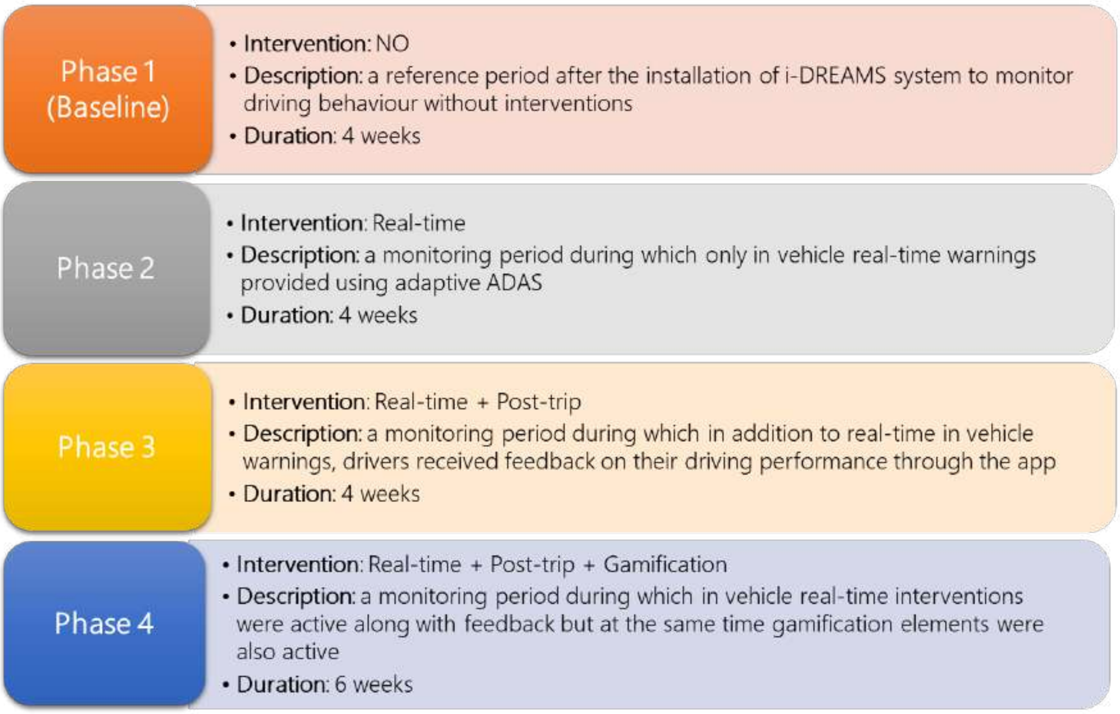

Figure 2: Overview of the different phases of the experimental design of the i-DREAMS on-road study

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 were utilized in order to monitor driving performance indicators. An OBD-II device supporting all OBD-II protocols is installed in each vehicle. A modern vehicle supports hundreds of parameters, which are recorded by the OBD-II device which accommodates the proper Software Development Kit (SDK) to extract the necessary data as well as a rich set of APIs (Application Programming Interfaces) to communicate with third party systems. This OBD-II integrates 2G or 3G GSM/GPRS technology through which all data recorded from the vehicle through its sensors is transmitted to remote servers (Cloud). The mobile network is used for data transmission without any user involvement.

More specifically, data from the **Mobileye system** (Mobileye, 2022), a dash camera and the **Cardio gateway** (CardioID Technologies, 2022) which records driving behavior (e.g., speed, acceleration, deceleration, steering) along with GNSS signals were used. In particular, the Mobileye system is as a sensor network 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 collected.

The **fundamental challenge within the i-DREAMS project** is how explanatory variables (i.e. various variables 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 speeding, headway and composite variables, such as weighted sum or weighted average variables.
- **Latent variables**: variables that are not observed by the analyst and so 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 so observable indicators are needed to measure these latent variables. Risk is also initially conceived in i-DREAMS as a latent variable.

Explanatory variables of risk and the most **reliable indicators of coping capacity**, such as average speed, headway, illegal overtaking, harsh accelerations, harsh brakings, distance traveled, duration, forward collision warnings or pedestrian collision warnings will be assessed.

Specifically, the **main risk factors** that will be explored within the i-DREAMS project are:

- Speeding
- Headway
- Overtaking
- Fatigue

- Harsh acceleration
- Harsh braking
- Vehicle control events (combination of harsh acceleration, braking and cornering events)

Table 2 provides an overview of the variables examined 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 shown below. It should be noted that at the time of writing this deliverable, the questionnaire data from Portugal were not completed yet; thus, questionnaire data for buses have not been included in the analysis.

- 45 car drivers in Belgium
- 23 truck drivers in Belgium
- 54 car drivers in UK
- 28 car drivers in Germany
- 65 car drivers in Greece

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

Information collected post-trial included:

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

In particular, a set of 12 questions were asked identically at both trial entry and trial exit (respectively EQ11 and EX3 in Annex 2 of 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 behavior 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 or time-series data, in order to identify different behaviors 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 **missing values (NA) 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. The latter 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.

2.5.1 Definition of coping capacity (vehicle and operator state)

The cornerstone of the i-DREAMS platform is the assessment of task complexity and coping capacity. To begin with, **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.

As for **coping capacity**, Figure 3 shows that this concept is dependent upon two underlying factors and it consists of several aspects of both vehicle and operator state. These are also multi-dimensional in nature.

More specifically, the latent variables associated to "**vehicle state**" are estimated on the basis of various metrics. The factor 'vehicle' entails three aspects, as shown below:

- **Technical specifications**, measured on the basis of average speed, braking power, acceleration performance, etc.
- **Actuators & admitted actions**, measured on the basis of accelerator, brakes, steering wheel, etc.
- **Current status**, measured on the basis of fuel efficiency, schedule maintenance, real-time information either from on board systems (OBD-II, FMS, Tachometer), Telematics/GPS, or smartphone, or additional information coming from ADAS systems (headway & collision monitoring, pedestrian warning, lane keeping monitoring), on board cameras, etc.

Additionally, the latent variables associated to "**operator state**" are estimated on the basis of various metrics. The factor 'operator' entails six aspects, as shown below:

- **Mental state**, measured on the basis of metrics on fatigue, drowsiness, alertness, attention, emotions experienced while driving, and impairment due to substance (ab)use, etc.
- **Behavior**, measured on the basis of metrics such as speeding, harsh acceleration / braking / cornering, seat belt use etc.
- **Competencies**, measured on the basis of metrics on risk assessment, attention regulation, self-appraisal, etc.
- **Personality**, measured on the basis of metrics on adventure seeking, disinhibition, experience seeking, boredom susceptibility, etc.
- **Sociodemographic profile**, measured on the basis of age, gender, experience, socio-economic status, nationality, ethnicity, cultural identity, etc.
- **Health status**, measured on the basis of metrics on current symptoms, neurologic and cardiovascular indicators, medication, etc.

As already outlined, coping capacity is not only dependent upon the status of the operator, but of the vehicle as well. Each of these operator- and vehicle-related aspects can be further operationalized by a combination of different variables, as shown in Figure 3.

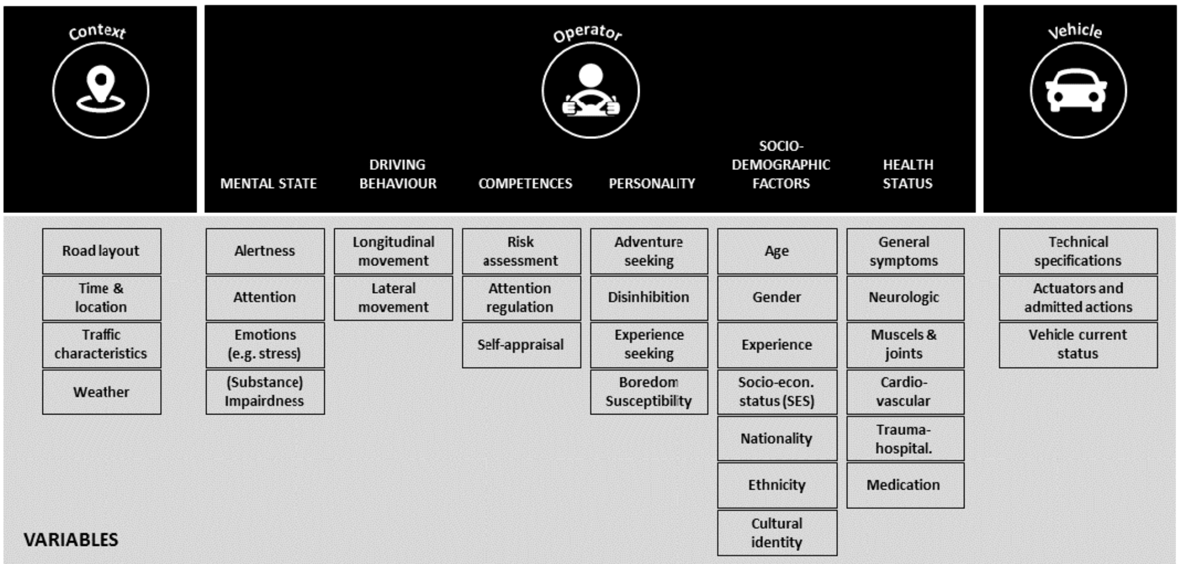

Figure 3: Monitoring context, operator & vehicle: an illustrative canvas

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 on the basis of various metrics. Based on the abovementioned, task complexity as a latent variable can be measured by metrics and indicators related to the road environment. 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 on the basis of dedicated techniques such as Structural Equation Modeling.

Figure 4 illustrates the conceptual framework of the i-DREAMS platform for the prediction of risk in function of coping capacity and task complexity.

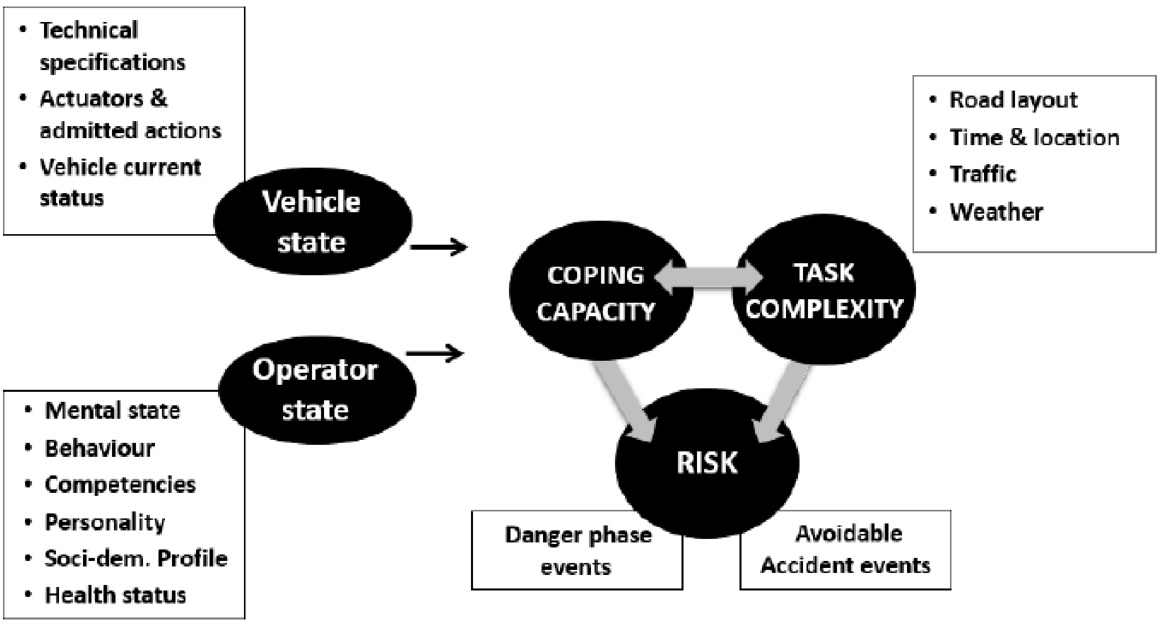

Figure 4: Post-hoc prediction of risk in function of coping capacity and task complexity

2.5.2 Variables used to define coping capacity

The most appropriate variables which were used in order to define coping capacity (vehicle and operator state) along with the variables that were finally utilized to represent risk are shown in Table 3.

Table 3: Variables for coping capacity (vehicle and operator state) and risk

Coping capacity - vehicle state	Coping capacity - operator state		Risk
Vehicle age	Distance	Inter Beat Interval (IBI)	Headway map levels
First vehicle registration	Duration	Headway	Speeding map levels
Fuel type	Average speed	Overtaking	Overtaking map levels
Engine Cubic Centimetres (CC)	Harsh acceleration/braking	Fatigue	Fatigue map levels
Engine Horsepower (HP)	Forward collision warning (FCW)	Gender	Harsh acceleration levels
Gearbox	Pedestrian collision warning (PCW)	Age	Harsh braking levels
Vehicle brand	Lane departure warning (LDW)	Educational level	Vehicle control events levels

2.5.3 Descriptive statistics

Before moving to more advanced statistical analyses, it would be useful to extract some basic information deriving from descriptive statistics (i.e. average, standard deviation, max, min, etc.). Descriptive statistics for the available parameters in the database used for the different countries (i.e. Belgium, UK, Germany, Greece and Portugal) and transport modes (i.e. cars, trucks and 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 behavior 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 analyzed 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 analyzed 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 3.2 (Katrakazas et al., 2020) and 4.2 (Yang et al., 2020). In summary, Dynamic Bayesian Networks (DBNs), Long-Short-Term-Memory networks (LSTMs), as well as Discrete Choice Models (DCM) 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 5.

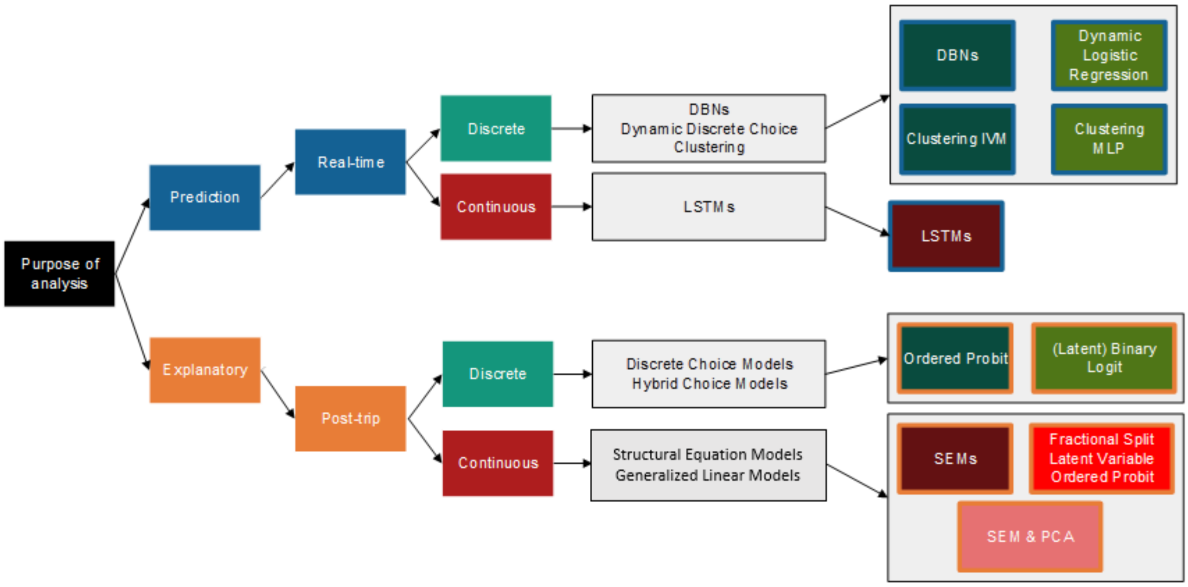

Figure 5: Schematic overview of modeling approaches considered for the analysis of risk factors

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 and 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 and 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:

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

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

where: s(y)=exp[d(y)] and t(θ)=exp[c(θ)]

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. The default VIF cutoff 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, then it can be accepted.

3.3 Structural Equation Models (SEMs)

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

$\eta = \beta\eta + \gamma\xi + \varepsilon$ (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 Equation 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** consist an important part of any statistical model assessment. Several goodness-of-fit metrics are commonly used, including the goodness-of-fit index (GFI), the (standardized) Root Mean Square Error Approximation (RMSEA), the comparative fit index (CFI) and the Tucker-Lewis Index (TLI). Such criteria are based on differences between the observed and modeled 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).

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

where: q is the number of parameters and L(θ) is the log-likelihood at convergence. Lower values of AIC are preferred to higher values because higher values of -2L(θ) 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.

$BIC = -2L(\theta) + q \ln(N)$ (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 **Browne-Cudeck Criterion (BCC)** is similar to the AIC. That is, the BCC and AIC both represent the extent to which the observed covariance matrix differs from the predicted covariance matrix--like the chi square statistic--but include a penalty if the model is complex, with many parameters. The BCC bestows an even harsher penalty than does the AIC.

The BCC equals the chi square divided by n plus 2k / (n- v - 2). In this formula:

$k = \frac{.5v}{v} + 1 - df$ (8)

where v is the number of variables and n = the sample size.

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 and 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:

$$CFI = 1 - \frac{\max(x_H{}^2 - df_H, 0)}{\max(x_H{}^2 - df_H, x_I{}^2 - df_I)} \quad (9)$$

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 and 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:

$$TLI = \frac{\frac{x_I{}^2}{df_I} - \frac{x_H{}^2}{df_H}}{\frac{x_I{}^2}{df_I} - 1} \quad (10)$$

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 and 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:

$$RMSEA = \sqrt{\frac{x_H{}^2 - df_H}{df_H(n-1)}} \quad (11)$$

where: x^2_H is the value of x^2 and df_H is the degrees of freedom in the hypothesized model; 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 and 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** index is calculated to find if chi-square is insignificant or not. If its value is more than 200 for the model 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 only makes sense to interpret if N > 200 and the chi square is statistically significant.

4 Coping capacity (vehicle and operator state) analysis

4.1 Generalized Linear Models

A high number of regression model tests were conducted for **different combinations of variables**. For each configuration, various alternatives were tested through the respective log-likelihood test comparisons. An attempt was made to use the same independent variables in the model applied. The optimal combination of variables was the one that had a sufficient number of statistically significant independent variables at a 95% confidence level (p-values ≤ 0.05).

In order to ensure that the results are reliable, accurate, and not biased by chance, it is important to account for **chance capitalization**, which refers to the possibility of obtaining significant results simply by chance, especially when testing a large number of variables. This can be done by adjusting the significance level or using methods such as Bonferroni or False Discovery Rate (FDR) correction to account for multiple comparisons. In this analysis, the Bonferroni correction was used that involves dividing the desired level of significance by the number of tests being conducted. This approach can be conservative, as it reduces the chance of false positives but also decreases the power of the test.

Moreover, the independent variables were also checked for multicollinearity through the Variance Inflation Factor (VIF). A standard guideline is that VIF values higher than 10 indicate high multicollinearity (Kutner et al., 2004). However, a threshold equal to 5 is also commonly used (Sheather, 2009). 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.

4.1.1 Belgium

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

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 coping capacity**. 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. It should be noted that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. With regards to the operator state, the variables used are duration, distance traveled, harsh acceleration and drowsiness. The results of the model are presented in Table 4.

Table 4: Parameter estimates and multicollinearity diagnostics of the GLM for speeding

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	3.634	0.033	109.938	< .001	-
Duration	2.613×10^{-5}	1.748×10^{-5}	1.495	0.135	1.010
Distance	2.178×10^{-4}	6.661×10^{-5}	3.269	0.001	1.033
Harsh acceleration	1.419	0.084	16.877	< .001	1.006
Drowsiness	-2.078×10^{-6}	5.239×10^{-7}	-3.967	< .001	1.038
Summary statistics					
AIC	24329.040				
BIC	24338.737				
Degrees of freedom	120191				

Based on Table 4, it can be observed that the majority of 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 coping capacity – operator state, such as 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 increase, speeding also increases. This is a noteworthy finding of the current research as it confirms that harsh driving behavior events present a statistically significant positive correlation with speeding. On the other hand, drowsiness was negatively correlated with speeding which means that the more the driver is being fatigued, the less the speeding events occur and the smoother their driving behavior becomes.

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 coping capacity. 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. It is worth mentioning that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. Regarding the operator state, the variables used are duration, distance traveled, harsh acceleration and drowsiness. The model parameter estimates are summarized in Table 5.

Table 5: Parameter estimates and multicollinearity diagnostics of the GLM for headway

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	3.496	0.045	76.942	< .001	-
Duration	0.001	5.266×10^{-5}	23.395	< .001	1.010
Distance	1.383×10^{-4}	9.683×10^{-5}	1.428	0.153	1.074
Harsh acceleration	0.003	8.804×10^{-4}	2.856	0.004	1.234
Drowsiness	-6.404×10^{-6}	5.851×10^{-7}	-10.945	< .001	1.252
Summary statistics					
AIC	21240.062				
BIC	21249.945				
Degrees of freedom	44818				

Findings derived from Table 5 demonstrated that the majority of 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 the indicators of coping capacity – operator state, such as duration, distance traveled and harsh accelerations had a positive relationship with the dependent variable (i.e. headway), indicating that as the values of the aforementioned independent variables increase, more headway events occur. Interestingly, drowsiness was negatively correlated with headway which means that when drivers are being fatigued while driving, they adjust their behavior and tend to keep safer distances.

4.1.1.3 Overtaking

The third GLM investigated the relationship between the **overtaking and several explanatory variables of coping capacity**. 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 operator state, the variables used are duration, distance traveled, harsh acceleration, Inter Beat Interval (IBI) and drowsiness. It should be noted that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. The model parameter estimates are summarized in Table 6.

Table 6: Parameter estimates and multicollinearity diagnostics of the GLM for overtaking

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-1.380	0.011	-123.659	< .001	1.007
Duration	4.673×10^{-4}	5.849×10^{-6}	79.903	< .001	3.365
Distance	4.192×10^{-4}	3.246×10^{-5}	12.913	< .001	1.237
Harsh acceleration	0.010	1.800×10^{-4}	56.145	< .001	3.528
IBI	5.479×10^{-4}	4.374×10^{-5}	12.525	< .001	1.214
Drowsiness	5.717×10^{-6}	1.744×10^{-7}	32.783	< .001	1.007
Summary statistics					
AIC	193247.445				
BIC	193257.328				
Degrees of freedom	144818				

Taking into account the aforementioned Table 6, a series of interesting findings can be provided. First of all, all 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, indicators of coping capacity – operator state, such as duration, distance, harsh accelerations, IBI and drowsiness appeared to have a positive relationship with the dependent variable (i.e. overtaking), indicating that as the values of the aforementioned independent variables increase, overtaking events also increase. For instance, this means that the longer the distance and duration of the trip is, the higher the number of the overtaking events occur.

4.1.1.4 Fatigue

The fourth GLM investigated the relationship between the **fatigue and several explanatory variables of coping capacity**. 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. It should be mentioned that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. With respect to operator state, the variables used are duration, average speed and harsh accelerations. The model parameter estimates are summarized in Table 7.

Table 7: Parameter estimates and multicollinearity diagnostics of the GLM for fatigue

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-0.637	0.009	-71.342	< .001	-
Duration	2.233×10^{-5}	5.414×10^{-6}	4.124	< .001	1.001
Harsh acceleration	0.032	2.355×10^{-4}	135.419	< .001	1.010
Average speed	-0.050	8.116×10^{-4}	-62.044	< .001	1.011
Summary statistics					
AIC	216526.282				
BIC	216536.249				
Degrees of freedom	157442				

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 indicator of coping capacity – operator state, such as harsh accelerations and duration had a positive relationship with the dependent variable (i.e. fatigue), indicating that the longer the duration is, the higher the probability of a driver being fatigue becomes. This is a noteworthy finding of the current research as it confirms that exposure indicators, such as duration present a statistically significant positive correlation with fatigue levels. Finally, average speed had a negative relationship with fatigue, which means that the more the driver exceeds the speed limits, the less is the probability of the driver being fatigued.

4.1.2 UK

GLMs were employed to investigate the relationship of key performance indicators (i.e. speeding and headway) for UK car drivers. It should be noted that results for overtaking and fatigue were not statistically significant; thus, they were not included.

4.1.2.1 Speeding

For the UK car trial, Generalized Linear Regression models were employed to explore the variables of speeding and headway and their relationship with coping capacity (vehicle and operator state). The variables used to represent coping capacity distance travelled, trip duration, harsh acceleration events, lane departure warnings, forward collision warnings and gender. The model parameter estimates for speeding variable are summarized in Table 8.

Table 8: Parameter estimates and multicollinearity diagnostics of the GLM for speeding

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-3.833	0.014	-276.412	< .001	-
Duration	4.698×10^{-5}	7.870×10^{-7}	59.688	< .001	1.056
Distance	0.002	1.875×10^{-5}	117.245	< .001	1.069
Right lane departure warning	0.359	0.014	25.484	< .001	1.025

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
Gender - Male	0.361	0.012	30.909	< .001	1.048
Harsh acceleration	-0.188	0.012	-15.424	< .001	1.014
Summary statistics					
AIC	263599.548				
BIC	263610.743				
Degrees of freedom	537681				

As it 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, explanatory variables of coping capacity are positively correlated with the speeding variable (0-speeding event, 1-not speeding event) except for the harsh acceleration events. More specifically, an increase in trip duration, the distance traveled, and a higher number of lane departure warnings are associated with a higher number of speeding events according to the model. Men are also associated with higher speeding events (gender variable was coded as 0-male, 1-female) while surprisingly an increase in harsh acceleration events is associated with a decrease in speeding.

4.1.2.2 Headway

The second GLM investigated the relationship between the **headway and several explanatory variables of coping capacity**. 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 operator state, the variables used are distance traveled, duration, gender, harsh acceleration and right lane departure warning. It should be noted that for vehicle state, variables such as fuel type, vehicle age and gearbox were not statistically significant; and thus, these independent variables were not included in the analysis. The model parameter estimates are summarized in Table 9.

Table 9: Parameter estimates and multicollinearity diagnostics of the GLM for headway

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-2.687	0.009	-311.231	< .001	-
Duration	4.637×10^{-5}	6.054×10^{-7}	76.595	< .001	1.036
Distance	0.003	1.262×10^{-5}	215.575	< .001	1.048
Right lane departure warning	0.102	0.010	10.314	< .001	1.019
Gender - Male	0.052	0.008	6.767	< .001	1.034
Harsh acceleration	0.157	0.008	20.163	< .001	1.009
Summary statistics					
AIC	549886.488				
BIC	549897.683				
Degrees of freedom	537681				

As it 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, explanatory variables of coping capacity are positively correlated with the headway variable (0-no headway event, 1-headway event). More specifically, an increase in trip duration and the distance travelled, a higher number of harsh acceleration events and lane departure warnings are associated with a higher number of headway events according to the model. Lastly, male drivers appear to keep shorter distances in relation to female ones (gender variable was coded as 0-male, 1-female).

4.1.3 Germany

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

4.1.3.1 Speeding

The first GLM investigated the relationship between the **speeding and several explanatory variables of coping capacity**. 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 vehicle state, the independent variables used are type of fuel and vehicle age, while for operator state, the variables used are distance traveled, duration, harsh acceleration, fatigue, gender and age. The results of the model are presented in Table 10.

Table 10: Parameter estimates and multicollinearity diagnostics of the GLM for speeding

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	0.729	0.054	13.417	< .001	-
Duration	0.003	3.384×10^{-5}	78.095	< .001	1.263
Distance	5.493×10^{-4}	3.621×10^{-5}	15.171	< .001	1.029
Harsh acceleration	1.232×10^{-4}	1.931×10^{-6}	63.779	< .001	1.216
Age	-0.004	0.001	-3.399	< .001	1.069
Gender - Female	-0.232	0.021	-11.159	< .001	1.261
Fuel type - Petrol	0.164	0.010	16.430	< .001	1.309
Vehicle Age	3.494×10^{-5}	3.304×10^{-6}	10.576	< .001	1.287
Drowsiness	1.524×10^{-5}	2.606×10^{-6}	5.848	< .001	1.107
Summary statistics					
AIC	127971.813				
BIC	127981.881				
Degrees of freedom	174299				

Based on Table 10, 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 coping capacity – vehicle state, such as fuel type and vehicle age were positively correlated with speeding. More specifically, the positive value of the variable "Fuel type" coefficient implied that when the fuel type was petrol (diesel coded as 1, hybrid electric coded as 2 and petrol coded as 3), the speeding percentage became higher. This indicated that vehicles with gasoline-powered engines provided higher speeding events compared to other types of vehicles, such as electric cars and hybrid cars. Additionally, the positive value of the "Vehicle Age" coefficient revealed that the higher the value of this variable, the higher the speeding percentage. This means that the increased proportion of older vehicles increases the risk to exceed the speed limits. This finding was also confirmed by Torok (2020) who found that by reducing the number of older vehicles on the roads, especially vehicles older than 15 years, road safety can be improved. This was probably due to the fact that in the current years, with the permanent development and safety improvements of the automotive sector, more and more vehicles are equipped with advanced driver assistance systems which include the ability of the vehicle to stop, the stability control of the vehicle, the passive safety systems (e.g. frontal and side airbags) or the ability of the vehicle to perceive its environment (e.g. frontal and backward sensors) in order to comply with the speed limits.

Furthermore, it was demonstrated that indicators of coping capacity – operator state, such as harsh accelerations, distance, duration and drowsiness 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. This is a noteworthy finding of the current research as it confirms that harsh driving behavior events present a statistically significant positive correlation with speeding. Taking into consideration socio-demographic characteristics, gender and age were negatively correlated with speeding. In particular, the negative value of the "Gender" coefficient implied that as the value of the variable was equal to 1 (males coded as 0, females as 1), the speeding percentage got lower. Results revealed that the vast majority of male drivers displayed less cautious behavior during their trips and exceeding more the speed limits than female drivers. It is also remarkable that the negative value of the "Age" coefficient implied that as the value of the variable increased (higher value indicates increased age and, therefore, increased years of participant's experience), the speeding percentage was lower. Young drivers appeared to have a riskier driving behavior than older drivers and were more prone to exceed the speed limits.

4.1.3.2 Overtaking

The second GLM investigated the relationship between the **overtaking and several explanatory variables of coping capacity**. 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 vehicle state, the variables utilized are type of fuel and vehicle age, while for operator state, the variables used are distance traveled, duration, harsh acceleration and drowsiness. The model parameter estimates are summarized in Table 11.

Table 11: Parameter estimates and multicollinearity diagnostics of the GLM for overtaking

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-1.968	0.038	-51.213	< .001	-
Duration	6.604×10^{-5}	5.958×10^{-6}	11.084	< .001	1.195
Distance	-8.157×10^{-4}	4.269×10^{-5}	-19.108	< .001	1.099
Harsh acceleration	2.158×10^{-5}	4.022×10^{-6}	5.364	< .001	1.052
Fuel type - Diesel	-0.198	0.013	-14.668	< .001	1.230
Vehicle Age	-2.310×10^{-5}	4.478×10^{-6}	-5.158	< .001	1.157
Drowsiness	6.416×10^{-5}	2.603×10^{-6}	24.649	< .001	1.146
Summary statistics					
AIC	61147.387				
BIC	61157.455				
Degrees of freedom	174299				

Taking into account the aforementioned Table 11, a series of interesting findings can be provided. First of all, all 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, indicators of coping capacity – vehicle state, such as fuel type and vehicle age were negatively correlated with overtaking. More specifically, the negative value of the variable "Fuel type" coefficient implied that when the fuel type was diesel, the overtaking percentage became lower. This indicated that vehicles with diesel engines provided lower overtaking events compared to other types of vehicles, such as electric, hybrid or gasoline-powered cars. Additionally, the negative value of the "Vehicle Age" coefficient revealed that drivers of older vehicle fleet were not willing to perform an illegal overtaking.

On the other hand, the indicators of coping capacity – operator state, such as harsh accelerations, duration and drowsiness appeared to have a positive relationship with the dependent variable (i.e. overtaking), indicating that as the values of the aforementioned independent variables increase, overtaking also increases. Interestingly, distance traveled was negatively correlated with overtaking.

4.1.3.3 Fatigue

The third GLM investigated the relationship between the **fatigue and several explanatory variables of coping capacity**. 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 vehicle state, the variables used are type of fuel and vehicle age, while for operator state, the variables used are distance traveled, duration, harsh acceleration and gender. The model parameter estimates are summarized in Table 12.

Table 12: Parameter estimates and multicollinearity diagnostics of the GLM for fatigue

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-2.497	0.028	-89.910	< .001	-
Duration	7.266×10^{-4}	5.498×10^{-6}	132.157	< .001	1.099
Distance	5.794×10^{-4}	2.620×10^{-5}	22.118	< .001	1.064
Harsh acceleration	-3.007×10^{-5}	2.922×10^{-6}	-10.291	< .001	1.049
Fuel type - Diesel	-0.500	0.010	-48.288	< .001	1.328
Vehicle Age	6.820×10^{-5}	3.174×10^{-6}	21.486	< .001	1.472
Gender - Female	-0.360	0.022	-16.206	< .001	1.174
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 12. With regards to multicollinearity diagnostics, VIF values for all independent variables were much lower than 5. It was observed that the indicator of coping capacity – vehicle state such as vehicle age was positively correlated with fatigue. On the other hand, fuel type had a negative impact on the dependent variable "fatigue". More specifically, the negative value of the variable "Fuel type" coefficient implied that when the fuel type was diesel, the fatigue percentage became lower. This indicated that vehicles with diesel engines provided lower fatigue events compared to other types of vehicles, such as electric, hybrid or gasoline-powered cars. Additionally, the positive value of the "Vehicle Age" coefficient revealed that drivers of older vehicle fleet were more prone to drive while being fatigued.

Furthermore, indicators of coping capacity – operator state, such as distance 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 a 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. Lastly, the negative value of the "gender" coefficient implied that female drivers were less fatigued as compared to male drivers.

4.1.4 Greece

GLMs were employed to investigate the relationship of key performance indicators (i.e. speeding and headway) for Greek car drivers. It should be noted that variables for headway, overtaking and fatigue were not available; thus, results for the aforementioned indicators were not included.

4.1.4.1 Speeding

The GLM applied investigated the relationship between the **speeding and several explanatory variables of coping capacity** (vehicle and operator state). 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 vehicle state, the independent variables used are type of fuel, gearbox and vehicle age, while for operator state, the variables used are distance traveled, duration, harsh acceleration, harsh braking, gender and age. The results of the model are presented in Table 13.

Table 13: Parameter estimates and multicollinearity diagnostics of the GLM for speeding

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	43.073	16.343	2.636	0.008	-
Duration	6.377×10^{-4}	2.556×10^{-5}	24.945	< .001	1.106
Distance	0.002	8.678×10^{-5}	21.851	< .001	1.141
Harsh acceleration	-0.403	0.051	-7.978	< .001	1.342
Harsh braking	0.117	0.066	1.754	0.079	1.448
Age	-0.045	0.002	-28.313	< .001	1.313
Vehicle Age	0.020	0.008	2.512	0.012	1.426
Gender - Male	0.315	0.059	5.354	< .001	1.708
Fuel type - Petrol	-0.300	0.046	-6.465	< .001	1.378
Gearbox - Manual	0.480	0.056	8.643	< .001	1.344
Summary statistics					
AIC	19378.588				
BIC	19386.426				
Degrees of freedom	18736				

Based on Table 13, 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 coping capacity – vehicle state, such as vehicle age were positively correlated with speeding. More specifically, the positive value of the variable "Fuel type" coefficient implied that when the fuel type was petrol (diesel coded as 1, hybrid electric coded as 2 and petrol coded as 3), the speeding percentage became higher. This indicated that vehicles with gasoline-powered engines provided higher speeding events compared to other types of vehicles, such as electric cars and hybrid cars. Additionally, the positive value of the "Vehicle Age" coefficient revealed that the higher the value of this variable, the higher the speeding percentage. This means that the increased proportion of older vehicles increases the risk to exceed the speed limits. This finding was also confirmed by Torok (2020) who found that by reducing the number of older vehicles on the roads, especially vehicles older than 15 years, road safety can be improved. This was probably due to the fact that in the current years, with the permanent development and safety improvements of the automotive sector, more and more vehicles are equipped with advanced driver assistance systems which include the ability of the vehicle to stop, the stability control of the vehicle, the passive safety systems (e.g. frontal and side airbags) or the ability of the vehicle to perceive its environment (e.g. frontal and backward sensors) in order to comply with the speed limits.

Furthermore, it was demonstrated that indicators of coping capacity – operator state, such as harsh braking, 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. This is a noteworthy finding of the current research as it confirms that harsh driving behavior events present a statistically significant positive correlation with speeding. Taking into consideration socio-demographic characteristics, age was negatively correlated with speeding, while gender was positively correlated with speeding. In particular, the positive value of the “Gender” coefficient implied that as the value of the variable was equal to 0 (males coded as 0, females as 1), the speeding percentage got higher. Results revealed that the vast majority of male drivers displayed less cautious behavior during their trips and exceeding more the speed limits than female drivers. It is also remarkable that the negative value of the “Age” coefficient implied that as the value of the variable increased (higher value indicates increased age and, therefore, increased years of participant’s experience), the speeding percentage was lower. Young drivers appeared to have a riskier driving behavior than older drivers and were more prone to exceed the speed limits.

4.1.5 Portugal

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 Generalized Linear Regression model investigated the relationship between the **speeding and several explanatory variables of coping capacity**. 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. It should be noted that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. With regards to the operator state, the variables used are duration, distance traveled, harsh acceleration and drowsiness. The results of the model are presented in Table 14.

Table 14: Parameter estimates and multicollinearity diagnostics of the GLM for speeding

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-3.749	0.015	-251.125	< .001	-
Harsh braking	0.303	0.082	3.712	< .001	1.051
Harsh acceleration	0.434	0.112	3.885	< .001	1.051
Fatigue	-0.091	0.008	-12.045	< .001	1.383
Distance	0.010	1.036×10-4	99.436	< .001	1.383
Summary statistics					
AIC	153657.374				
BIC	153668.223				
Degrees of freedom	380656				

Based on Table 14, 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 coping capacity – operator state, such as harsh accelerations, harsh brakings and distance 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. This is a noteworthy finding of the current research as it confirms that harsh driving behavior events present a statistically significant positive correlation with speeding. On the other hand, drowsiness was negatively correlated with speeding which means that the more the driver is being fatigued, the less the speeding events occur and the smoother their driving behavior becomes.

4.1.5.2 Headway

The second GLM investigated the relationship between the headway and several explanatory variables of coping capacity. 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. It is worth mentioning that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. Regarding the operator state, the variables used are duration, distance traveled, harsh acceleration and drowsiness. The model parameter estimates are summarized in Table 15.

Table 15: Parameter estimates and multicollinearity diagnostics of the GLM for headway

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-5.919	0.044	-134.086	< .001	-
Harsh braking	0.902	0.242	3.735	< .001	1.044
Harsh acceleration	0.053	0.317	0.169	0.866	1.044
Duration	7.458×10-5	2.844×10-6	26.223	< .001	1.383
Fatigue	0.003	0.022	0.128	0.898	1.383
Summary statistics					
AIC	27567.782				
BIC	27578.632				
Degrees of freedom	380656				

Findings derived from Table 15 demonstrated that the majority of 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 the indicators of coping capacity – operator state, such as duration, harsh events (i.e. harsh acceleration and harsh braking) and drowsiness had a positive relationship with the dependent variable (i.e. headway), indicating that as the values of the aforementioned independent variables increase, more headway events occur.

4.1.5.3 Overtaking

The third GLM investigated the relationship between the **overtaking and several explanatory variables of coping capacity**. 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 operator state, the variables used are average speed, distance traveled, harsh acceleration and harsh braking. It should be noted that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models. The model parameter estimates are summarized in Table 16.

Table 16: Parameter estimates and multicollinearity diagnostics of the GLM for overtaking

Variables	Estimate	Std.Err	z-value	Pr(|z|)	VIF
(Intercept)	-8.153	0.125	-65.363	< .001	-
Average speed	1.236	0.074	16.663	< .001	1.016
Distance	0.007	8.343×10^{-4}	7.827	< .001	1.016
Harsh braking	-0.314	0.689	-0.455	0.649	1.044
Harsh acceleration	0.631	0.993	0.635	0.525	1.044
Summary statistics					
AIC	4195.226				
BIC	4206.076				
Degrees of freedom	380656				

Taking into account the aforementioned Table 16, a series of interesting findings can be provided. First of all, the majority of 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, indicators of coping capacity – operator state, such as distance, average speed and harsh acceleration appeared to have a positive relationship with the dependent variable (i.e. overtaking), indicating that as the values of the aforementioned independent variables increase, overtaking events also increase. For instance, this means that the longer the distance of the trip is, the higher the number of the overtaking events occur. In addition, increased number of total harsh acceleration can be an indicator of overtaking which requires drivers to accelerate quickly to pass another vehicle. On the other hand, harsh braking had a negative correlation with overtaking which means that drivers tend to avoid overtaking when they perform harsh braking. Harsh braking can be a sign of aggressive driving, and drivers who exhibit this behavior may be less likely to take risks or make sudden maneuvers, such as overtaking.

4.1.5.4 Fatigue

The fourth GLM investigated the relationship between the **fatigue and several explanatory variables of task complexity and coping capacity** (operator state). 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. coping capacity - operator state, the variables used are distance traveled, harsh acceleration, harsh braking and average speed. It should be mentioned that the explanatory variables of vehicle state, such as fuel type, vehicle age or gearbox, or socio-demographic characteristics, such as gender, age or educational level are not statistically significant at a 95% confidence level; thus, these variables are not included in the models.The model parameter estimates are summarized in Table 17.

Table 17: Parameter estimates and multicollinearity diagnostics of the GLM for fatigue

Variables	Estimate	Standard Error	z-value	Pr(|z|)	VIF
(Intercept)	0.356	0.006	59.410	< .001	-
Average speed	-0.034	0.014	-2.370	0.018	1.074
Distance	0.009	7.424×10-5	123.946	< .001	1.074
Harsh braking	0.230	0.039	5.926	< .001	1.050
Harsh acceleration	0.310	0.057	5.445	< .001	1.050
Summary statistics					
AIC	455426.929				
BIC	455437.779				
Degrees of freedom	380656				

All the explanatory variables were statistically significant at a 95% confidence level, as shown in Table 17. With regards to multicollinearity diagnostics, VIF values for all independent variables were much lower than 5. It was observed that indicators of coping capacity – operator state, such as distance and harsh events 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. Lastly, average speed had a negative relationship with fatigue, which implies that the higher the average speed is, the lower the fatigue events are. This finding may be due to the fact that driving at a higher average speed makes drivers be alert and can help reduce fatigue.

4.2 Structural Equation Models

Following exploratory analysis, the latent variable (or variables) associated to the latent variable “**vehicle and operator state**” were estimated from the various indicators. This way, the effect of different personal factors on ‘operator state’ was defined, and further analyzed for different countries (i.e. Belgium, UK, Germany, Greece, Portugal) and different travel modes (i.e. cars, trucks, buses). Several SEMs were applied in order to identify the impact of ‘coping capacity’ on the STZ level, controlling for the above exogenous factors.

4.2.1 Belgium (Cars)

4.2.1.1 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 speeding. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 39 Belgian car drivers, 1,173 trips (23,725 minutes)
- Phase 2: real-time interventions - 43 Belgian car drivers, 1,549 trips (31,414 minutes)
- Phase 3: real-time & post-trip interventions - 51 Belgian car drivers, 1,973 trips (40,121 minutes)
- Phase 4: real-time, post-trip interventions & gamification - 49 Belgian car drivers, 2,468 trips (52,077 minutes)

The results for Phase 1 are shown in Figure 6 below. It is shown that the latent variable coping capacity is measured by means of operator state indicators, as follows:

- Driver’s age, with a negative correlation indicating that older drivers have lower coping capacity
- Better general driving skills are associated with higher coping capacity
- Higher exposure on rural roads per week is associated with lower coping capacity, possibly because those drivers have lower exposure in complex environments and cannot sustain sufficient skills to cope with them
- A sportive and ambitious driving style is associated with higher coping capacity, possibly indicating a younger age and a higher alertness of these drivers.
- Driver’s confidence to their own driving skills is associated with higher coping capacity.

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 coping capacity and risk shows a positive coefficient, which is counter-intuitive. It is noted however that the lack of the Task Complexity latent variable clearly affects this structural relationship, as the current model is only a partial depiction of the theoretical model of i-DREAMS and cannot be interpreted credibly.

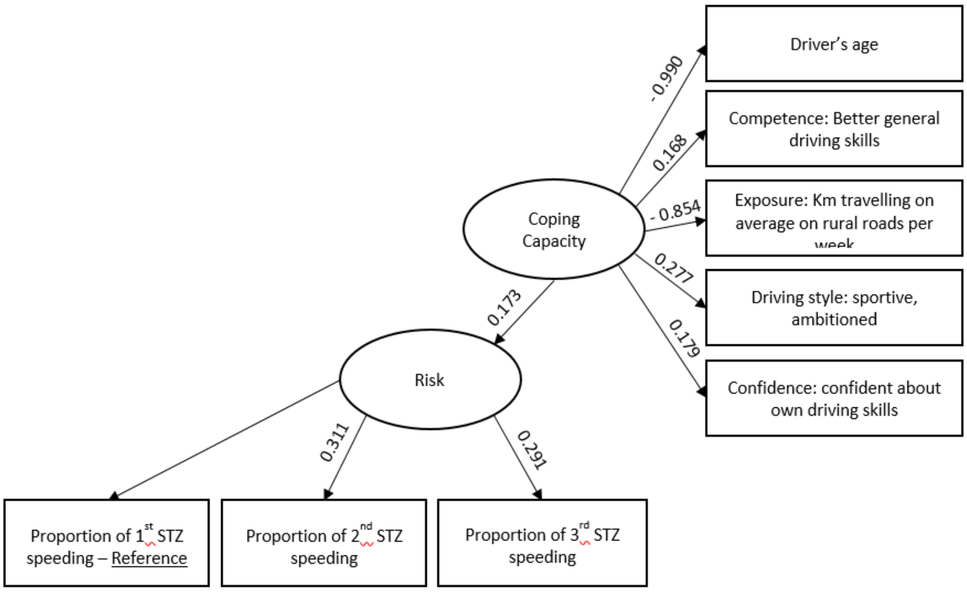

Figure 6: Results of SEM coping capacity & risk (speeding STZ) – Belgian car drivers – experiment Phase 1

The Comparative Fit Index (CFI) of the model is equal 0.780; TLI is 0.692 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.126. Table 18 summarizes the model fit of SEM applied for speeding.

Table 18: Model Fit Summary for speeding – Belgian car drivers – experiment Phase 1

Model Fit measures	Value
AIC	192625.4
BIC	192762.7
CFI	0.780
TLI	0.692
RMSEA	0.126

Residual variances details are presented in Table 19 that follows.

Table 19: Residual variances for speeding – Belgian car drivers – experiment Phase 1

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Age	0.019	0.010	1.864	0.062
.COMPT1	0.972	0.009	108.810	0.000
.Rural	0.271	0.008	33.997	0.000
.Style	0.218	0.002	108.358	0.000
.CONF	0.215	0.002	108.786	0.000

Variable	Estimate	Std.Err	z-value	P(>|z|)
.iSP2	0.011	0.000	57.310	0.000
.iSP3	0.045	0.001	63.417	0.000
CC	0.981	0.014	71.441	0.000
.RISK	0.001	0.000	6.797	0.000

Figures 7, 8 and 9 show the results of the 2nd, 3rd and 4th phase of the experiment. It is observed that the measurement equations of coping capacity are fairly consistent between the different phases, with only slight difference the appearance of the variable 'violations: always driving higher than the speed limit' in phases 2 and 3, which can be attributed to its high correlation with age, confidence and sportive driving style. Possibly the differences in the samples of drivers / trips as well as actual differences between the time periods of the trips may explain the slight variations between the loadings of the indicators on the latent variable. 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 coping capacity and risk is consistent between the four phases, but with a counter-intuitive sign. obviously due to its incompleteness in relation to the theoretical model.

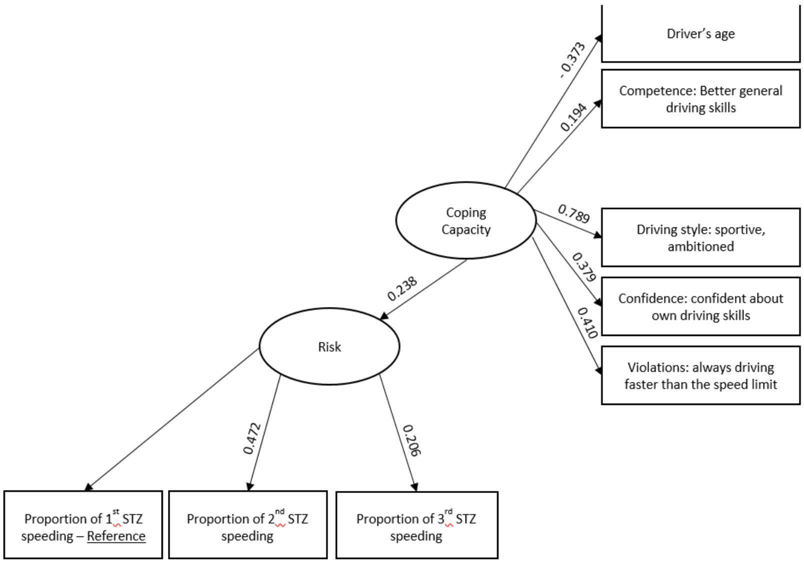

Figure 7: Results of SEM coping capacity & risk (speeding STZ) – Belgian car drivers – experiment Phase 2

The Comparative Fit Index (CFI) of the model is equal 0.479; TLI is 0.270 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.124. Table 20 summarizes the model fit of SEM applied for speeding.

Table 20: Model Fit Summary for speeding – Belgian car drivers – experiment Phase 2

Model Fit measures	Value
AIC	260582.7
BIC	260724
CFI	0.479
TLI	0.270
RMSEA	0.124

Residual variances details are presented in Table 21 that follows.

Table 21: Residual variances for speeding – Belgian car drivers – experiment Phase 2

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Age	0.861	0.008	110.815	0.000
.COMPT1	0.962	0.008	120.532	0.000
.Style	0.092	0.003	29.185	0.000
.CONF	0.161	0.001	110.260	0.000
.VIO2	0.832	0.008	106.845	0.000
.iSP2	0.006	0.000	22.232	0.000
.iSP3	0.048	0.001	94.037	0.000
CC	0.139	0.005	26.151	0.000
.RISK	0.002	0.000	6.114	0.000

The results for Phase 3 are shown in Figure 8 below.

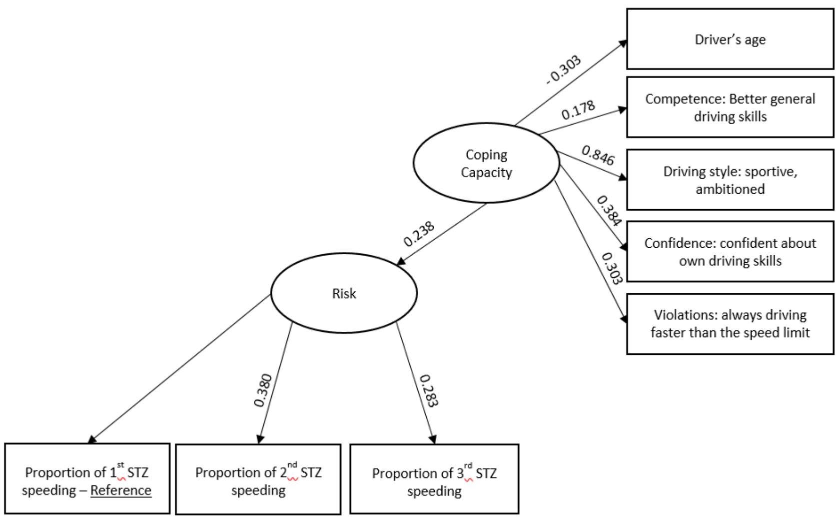

Figure 8: Results of SEM coping capacity & risk (speeding STZ) – Belgian car drivers – experiment Phase 3

The Comparative Fit Index (CFI) of the model is equal 0.481; TLI is 0.273 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.113. Table 22 summarizes the model fit of SEM applied for speeding.

Table 22: Model Fit Summary for speeding – Belgian car drivers – experiment Phase 3

Model Fit measures	Value
AIC	341267.4
BIC	341413.6
CFI	0.481
TLI	0.273
RMSEA	0.113

Residual variances details are presented in Table 23 that follows.

Table 23: Residual variances for speeding – Belgian car drivers – experiment Phase 3

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Age	0.908	0.007	132.903	0.000
.COMPT1	0.968	0.007	139.638	0.000
.Style	0.069	0.004	17.646	0.000
.CONF	0.157	0.001	122.428	0.000
.VIO2	0.908	0.007	132.896	0.000
.iSP2	0.005	0.000	50.351	0.000
.iSP3	0.053	0.001	87.938	0.000
CC	0.092	0.004	24.220	0.000
.RISK	0.001	0.000	8.606	0.000

The results for Phase 4 are shown in Figure 9 below.

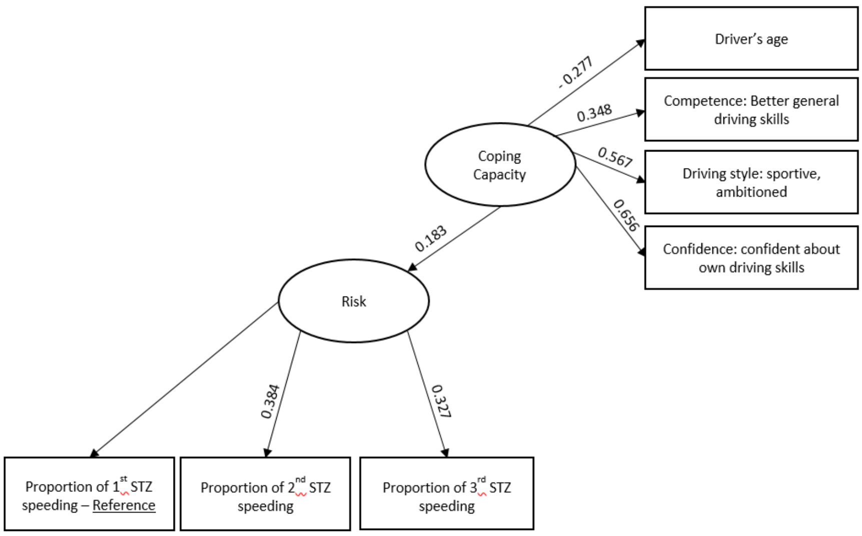

Figure 9: Results of SEM coping capacity & risk (speeding STZ) – Belgian car drivers – experiment Phase 4

The Comparative Fit Index (CFI) of the model is equal 0.767; TLI is 0.651 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.069. Table 24 summarizes the model fit of SEM applied for speeding.

Table 24: Model Fit Summary for speeding – Belgian car drivers – experiment Phase 4

Model Fit measures	Value
AIC	292352.6
BIC	292485.5
CFI	0.767
TLI	0.651
RMSEA	0.069

Residual variances details are presented in Table 25 that follows.

Table 25: Residual variances for speeding – Belgian car drivers – experiment Phase 4

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Age	0.923	0.006	151.858	0.000
.COMPT1	0.879	0.006	145.219	0.000
.Style	0.168	0.002	93.006	0.000
.CONF	0.112	0.002	65.859	0.000
.iSP2	0.005	0.000	46.082	0.000
.iSP3	0.044	0.001	63.691	0.000
CC	0.077	0.003	24.367	0.000
.RISK	0.001	0.000	8.127	0.000

4.2.1.2 Headway

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) 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, 1,222 trips (35,284 minutes)

The results for Phase 1 (monitoring driver behavior with no interventions) are shown in Figure 10 below. It is shown that the latent variable coping capacity is measured by means of the operator state indicators that were significant in the speeding-based SEM model (see previous section), with the addition of:

- Violations: always driving faster than the speed limit has a positive coefficient on coping capacity – as previously mentioned, this is highly correlated with the other indicators of driver competence, confidence etc.
- The IBI (Inter-Beat-Interval) is loading on the coping capacity, which is an interesting finding, as IBI is known to be associated with impairing factors such as fatigue and sleepiness, but also stress and other emotions.

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 coping capacity and risk shows a positive coefficient, which is intuitive.

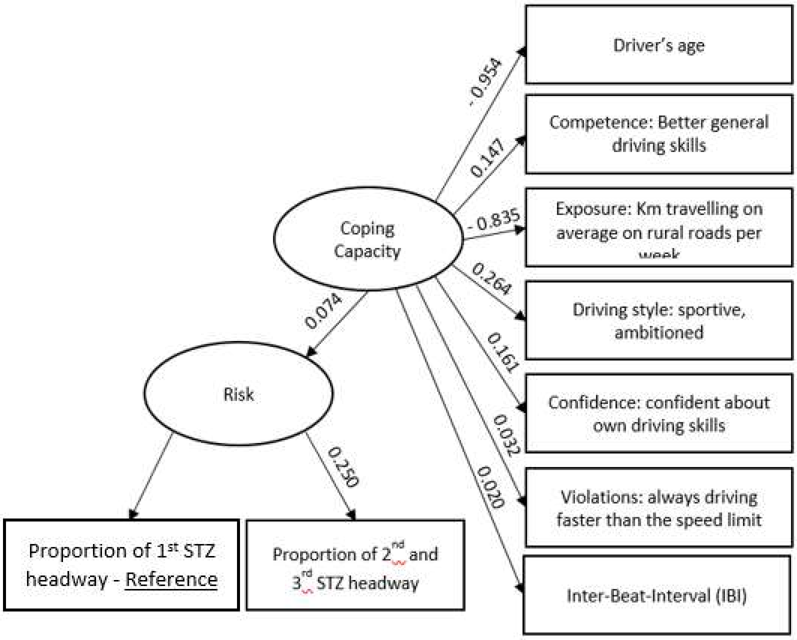

Figure 10: Results of SEM coping capacity & risk (headway STZ) – Belgian car drivers – experiment Phase 1

The Comparative Fit Index (CFI) of the model is equal 0.565; TLI is 0.437 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.160. Table 26 summarizes the model fit of SEM applied for headway.

Table 26: Model Fit Summary for headway – Belgian car drivers – experiment Phase 1

Model Fit measures	Value
AIC	235551.3
BIC	235688.6
CFI	0.565
TLI	0.437
RMSEA	0.160

Residual variances details are presented in Table 27 that follows.

Table 27: Residual variances for headway – Belgian car drivers – experiment Phase 1

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Age	0.080	0.013	6.045	0.000
.COMPT1	0.960	0.011	86.901	0.000
.Rural	0.243	0.010	25.232	0.000
.Style	0.232	0.003	86.361	0.000
.CONF	0.224	0.003	86.862	0.000
.VIO2	0.957	0.011	87.065	0.000
.IBI	1.000	0.011	87.069	0.000
CC	0.804	0.017	48.325	0.000
.RISK	0.062	0.001	87.032	0.000

Figures 11, 12 and 13 show the respective results of the 2nd, 3rd and 4th phase of the experiment. It is observed that the measurement equations of coping capacity are largely consistent between the different phases. 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 coping capacity and risk indicates a significant correlation between the two constructs in all phases, however their sign is inconsistent – these modeling results cannot be fully interpreted and the models are only shown for completeness.

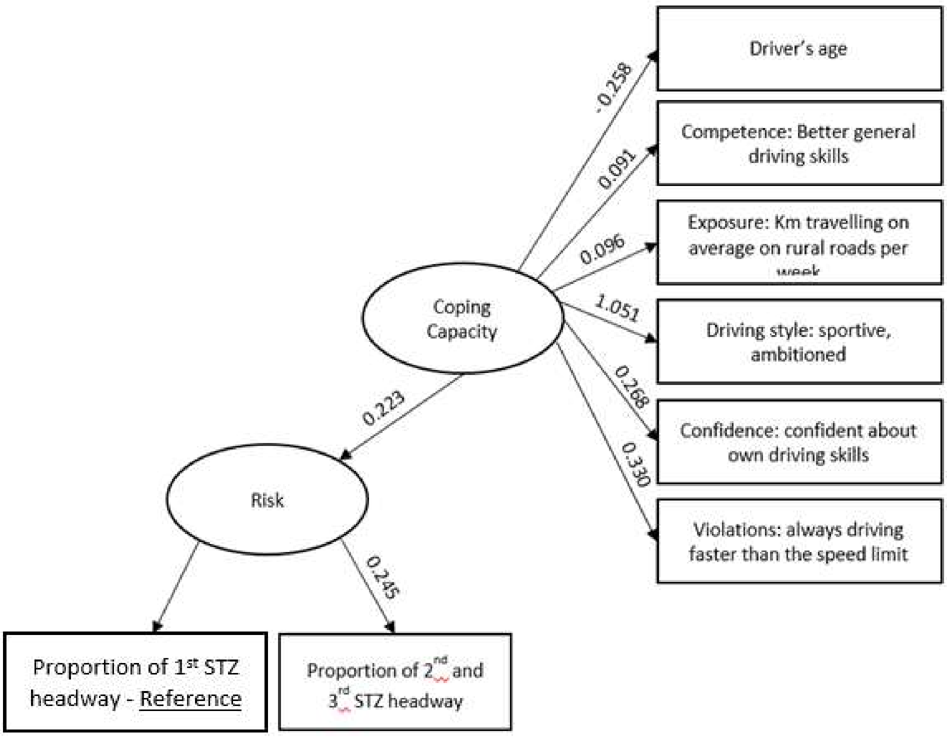

Figure 11: Results of SEM coping capacity & risk (headway STZ) – Belgian car drivers – experiment Phase 2

The Comparative Fit Index (CFI) of the model is equal 0.362; TLI is 0.141 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.158. Table 28 summarizes the model fit of SEM applied for headway.

Table 28: Model Fit Summary for headway – Belgian car drivers – experiment Phase 2

Model Fit measures	Value
AIC	292304.1
BIC	292431.6
CFI	0.362
TLI	0.141
RMSEA	0.158

Residual variances details are presented in Table 29 that follows.

Table 29: Residual variances for headway – Belgian car drivers – experiment Phase 2

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Age	0.934	0.009	101.097	0.000
.COMPT1	0.992	0.010	103.510	0.000

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Rural	0.991	0.010	103.508	0.000
.Style	-0.026	0.009	-2.967	0.003
.CONF	0.180	0.002	100.649	0.000
.VIO2	0.891	0.009	96.301	0.000
CC	0.066	0.004	16.677	0.000
.RISK	0.057	0.001	102.291	0.000

The results for Phase 3 are shown in Figure 12 below.

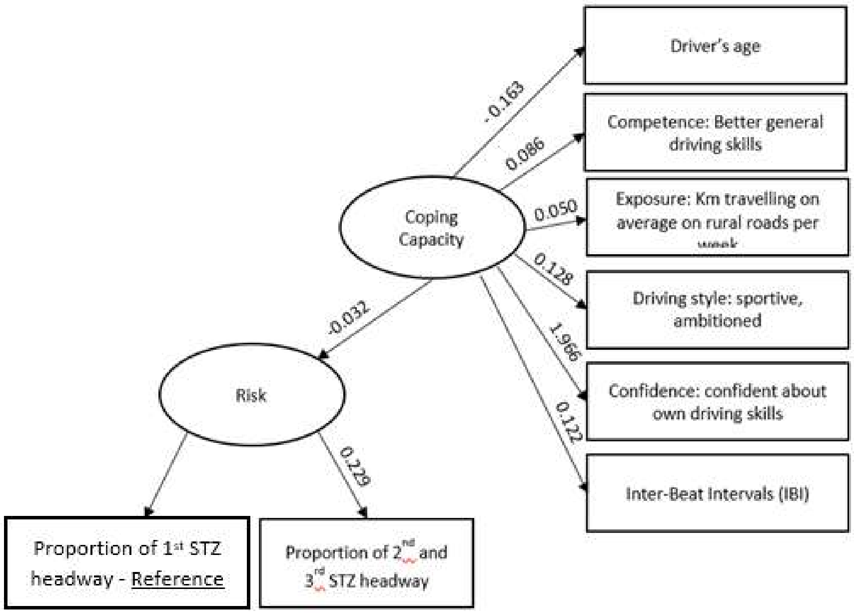

Figure 12: Results of SEM coping capacity & risk (headway STZ) – Belgian car drivers – experiment Phase 3

The Comparative Fit Index (CFI) of the model is equal 0.454; TLI is 0.266 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.120. Table 30 summarizes the model fit of SEM applied for headway.

Table 30: Model Fit Summary for headway – Belgian car drivers – experiment Phase 3

Model Fit measures	Value
AIC	237046.1
BIC	237171.7
CFI	0.454
TLI	0.266
RMSEA	0.120

Residual variances details are presented in Table 31 that follows.

Table 31: Residual variances for headway – Belgian car drivers – experiment Phase 3

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Age	0.800	0.009	89.697	0.000
.COMPT1	1.208	0.012	97.044	0.000
.Rural	0.333	0.003	97.411	0.000
.Style	0.246	0.003	94.589	0.000
.CONF	-0.580	0.129	-4.510	0.000
.IBI	0.985	0.010	95.180	0.000
CC	0.022	0.004	5.528	0.000
.RISK	0.051	0.001	97.380	0.000

The results for Phase 3 are shown in Figure 13 below.

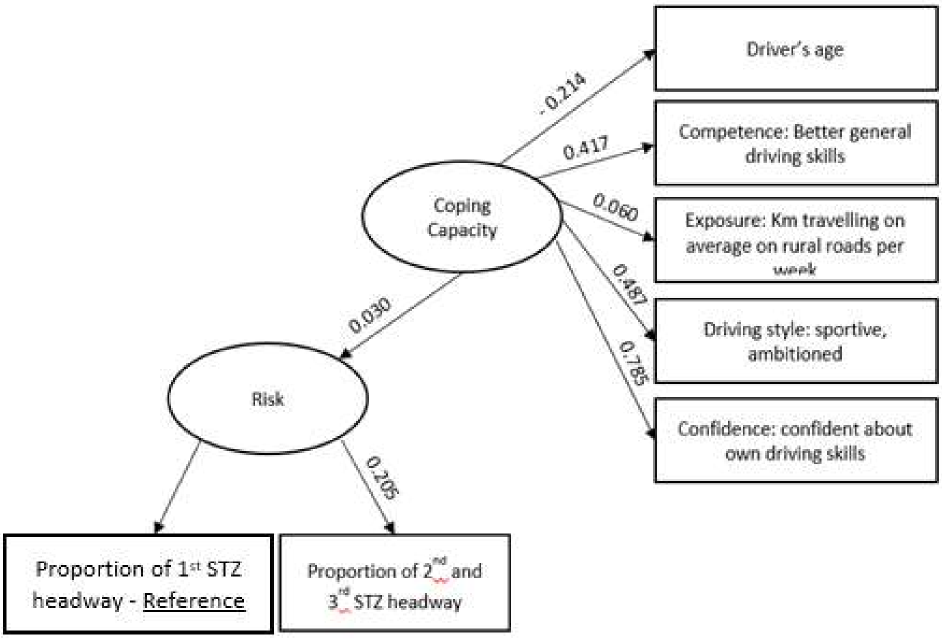

Figure 13: Results of SEM coping capacity & risk (headway STZ) – Belgian car drivers – experiment Phase 4

The Comparative Fit Index (CFI) of the model is equal 0.457; TLI is 0.229 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.141. Table 32 summarizes the model fit of SEM applied for headway.

Table 32: Model Fit Summary for headway – Belgian car drivers – experiment Phase 4

Model Fit measures	Value
AIC	372986.4
BIC	373104.9
CFI	0.457
TLI	0.229
RMSEA	0.141

Residual variances details are presented in Table 33 that follows.

Table 33: Residual variances for headway – Belgian car drivers – experiment Phase 4

Variable	Estimate	Std.Err	z-value	P(>|z|)
.Age	0.954	0.007	129.565	0.000
.COMPT1	0.826	0.007	113.245	0.000
.Rural	0.996	0.008	132.602	0.000
.Style	0.190	0.002	99.758	0.000
.CONF	0.079	0.003	29.113	0.000
CC	0.046	0.003	16.481	0.000
.RISK	0.042	0.000	132.768	0.000

4.2.2 Belgium (Trucks)

4.2.2.1 Vehicle Control Events

Four separate SEM models were estimated in order to explore the relationship between the latent variables of coping capacity and risk where risk, expressed as the three phases of the STZ, was formed as a composite of the vehicle control variables, 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, 1,448 trips (117,160 minutes)
- Phase 2: real-time interventions - 22 Belgian truck drivers, 1,691 trips (146,315 minutes)
- Phase 3: real-time & post-trip interventions - 22 Belgian truck drivers, 1,440 trips (139,245 minutes)
- Phase 4: real-time, post-trip interventions & gamification - 23 Belgian truck drivers, 1,767 trips (187,636 minutes)

The results for Phase 1 are shown in Figure 14 below. It is shown that the latent variable coping capacity is measured by means of operator state indicators, as follows:

- Driver's age, showing a negative correlation which indicates that older drivers have lower coping capacity
- The positive sign of driving skills indicate that better general driving skills are associated with higher coping capacity. Coping capacity can also be improved by practicing good driving techniques and being prepared for unexpected situations on the road.
- A sportive and ambitious driving style is associated with higher coping capacity, possibly indicating a younger age and a higher alertness of these drivers.
- Driver's confidence to their own driving skills is associated with higher coping capacity.

The latent variable 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 3 of the composite vehicle control variable does not have significant loading in the measurement model for the latent variable risk and thus not included in the final model. Level 1 and level 2 of vehicle control variable (or STZ 1 and STZ 2 indicators) have positive and negative loadings in relationship to the latent variable Risk. respectively. This is counter-intuitive. Since risk is a latent construct in the identified SEM, it is in fact the inverse of risk representing normal driving.

The structural model between coping capacity and (inverse) risk shows a negative coefficient, which indicates that increase in the coping capacity may incline drivers to move away from normal driving (i.e. making them more risk seekers). It is noted however that the lack of the Task Complexity latent variable clearly affects this structural relationship. as the current model is only a partial depiction of the theoretical model of i-DREAMS and cannot be interpreted credibly.

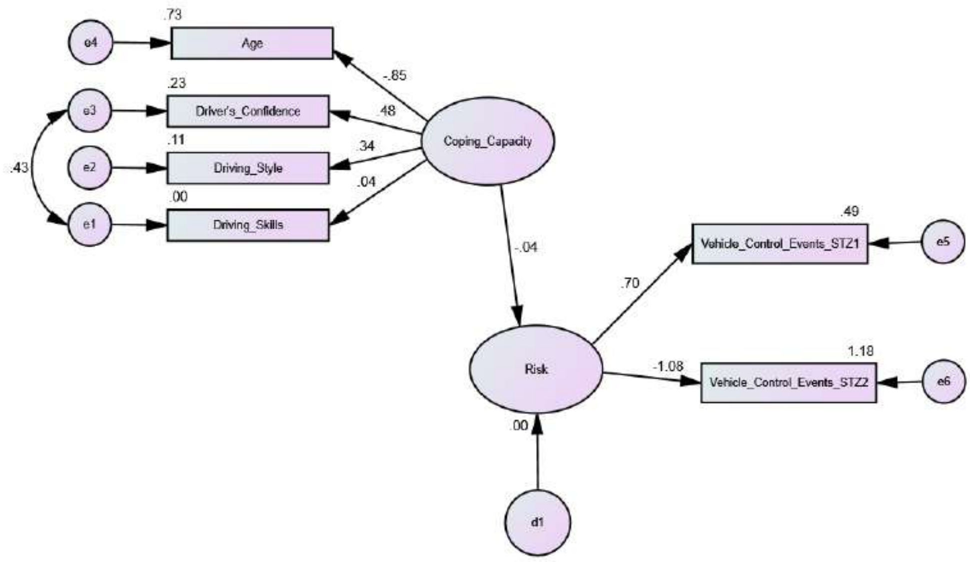

Figure 14: Results of SEM coping capacity & risk (Vehicle control STZ) – Belgian truck drivers – experiment Phase 1

The Comparative Fit Index (CFI) of the model is equal 0.994; TLI is 0.988 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.033. Table 34 summarizes the model fit of SEM applied for vehicle control.

Table 34: Model Fit Summary for vehicle control – Belgian truck drivers – experiment Phase 1

Model Fit measures	Value
AIC	940.49
BCC	940.492
CFI	0.994
TLI	0.988
RMSEA	0.033
Hoelter's critical N (α = .05)	1831
Hoelter's critical N (α = .01)	2404

Residual variances details are presented in Table 35 that follows.

Table 35: Residual variances for vehicle control – Belgian truck drivers – experiment Phase 1

Variable	Estimate	S.E.	C.R.	P
Coping_Capacity	0.109	0.002	53.411	***
Risk	0.086	0.006	13.319	***
Skills	0.362	0.001	241.923	***
Style	0.152	0.001	220.151	***
Confidence	0.357	0.002	162.836	***
DrivingEvents_Map_lvl_L_mean	0.091	0.006	14.143	***
DrivingEvents_Map_lvl_M_mean	-0.023	0.012	-1.997	0.046
Age	30.637	1.228	24.955	***

Figures 15, 16 and 17 show the results of the 2nd, 3rd and 4th phase of the experiment. It is observed that the measurement equations of coping capacity are fairly consistent between the different phases, with only slight difference the appearance of the variable 'trip duration' and no age variable in phase 4, the different signs of the variable 'driving skills' in phase 1 compared to other phase 2, 3 and 4. Possibly the differences in the samples of drivers / trips may explain the slight variations between the loadings of the indicators on the latent variable. At the same time, the loadings of the observed proportions of the STZ of vehicle control are consistent between the different phases.

The structural model between coping capacity and (inverse of) risk is inconsistent between the 4 phases (negative in phase 1 (a counter-intuitive sign) and positive in the following phases), obviously due to its incompleteness in relation to the theoretical model.

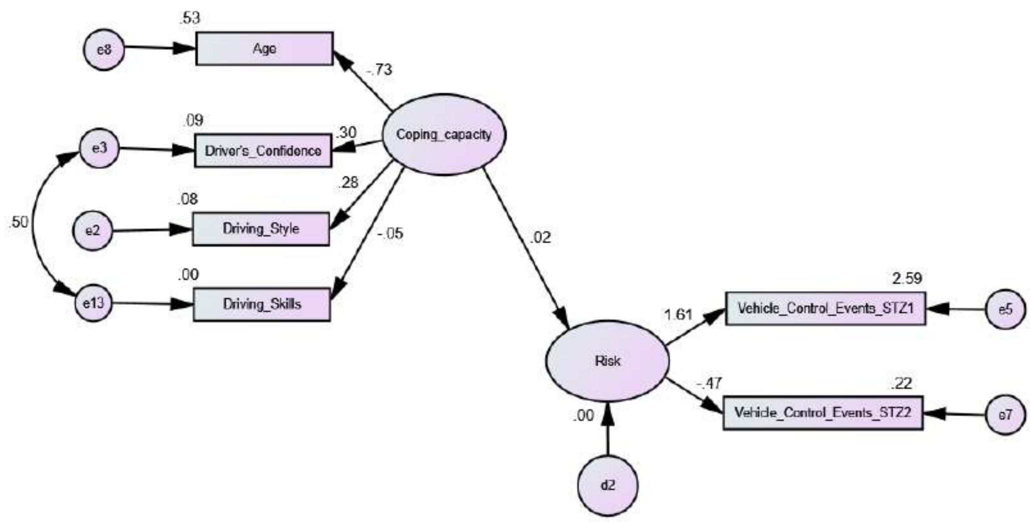

Figure 15: Results of SEM coping capacity & risk (Vehicle control STZ) – Belgian truck drivers – experiment Phase 2

The Comparative Fit Index (CFI) of the model is equal 0.994; TLI is 0.987 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.033. More details about the model fit can be found in the Table 36 below.

Table 36: Model Fit Summary for vehicle control – Belgian truck drivers – experiment Phase 2

Model Fit measures	Value
AIC	1133.147
BCC	1133.149
CFI	0.994
TLI	0.987
RMSEA	0.033
Hoelter's critical N (α = .05)	1883
Hoelter's critical N (α = .01)	2473

Residual variances details are presented in Table 37 that follows.

Table 37: Residual variances for vehicle control – Belgian truck drivers – experiment Phase 2

Variable	Estimate	S.E.	C.R.	P
Coping_capacity	0.044	0.001	32.038	***
Risk	0.463	0.122	3.81	***
Style	0.171	0.001	235.761	***
Confidence	0.445	0.002	220.685	***
DrivingEvents_Map_lvl_L_mean	-0.285	0.122	-2.341	0.019
DrivingEvents_Map_lvl_M_mean	0.103	0.008	13.659	***
Age	48.926	1.39	35.19	***
Driving Skills	0.401	0.001	269.843	***

The results for Phase 3 are shown in Figure 16 below.

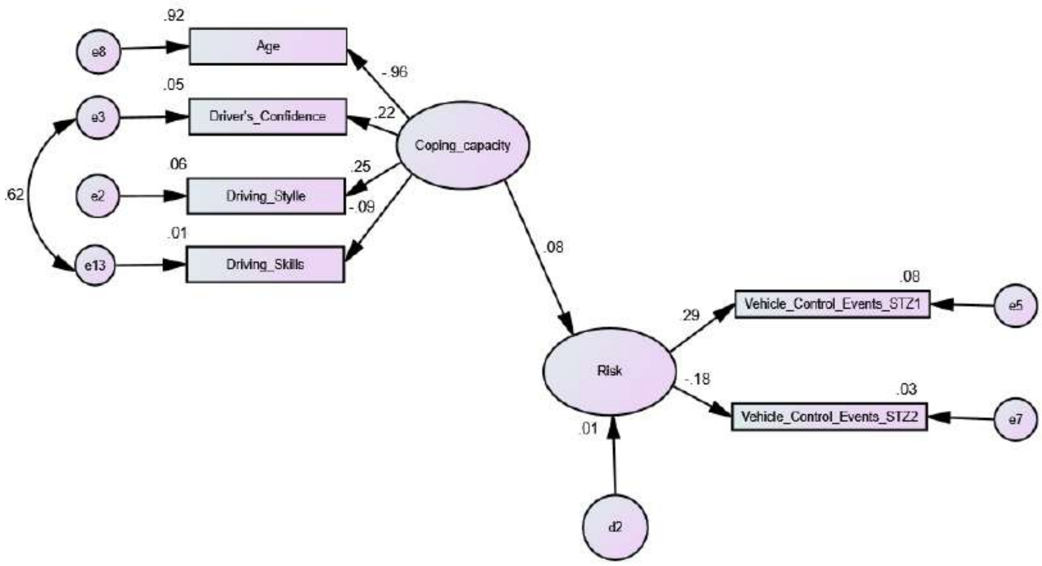

Figure 16: Results of SEM coping capacity & risk (Vehicle control STZ) – Belgian truck drivers – experiment Phase 3

The Comparative Fit Index (CFI) of the model is equal 0.981; TLI is 0.943 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.041. Table 38 summarizes the model fit of SEM applied for vehicle control.

Table 38: Model Fit Summary for vehicle control – Belgian truck drivers – experiment Phase 3

Model Fit measures	Value
AIC	1668.992
BCC	1668.994
CFI	0.981
TLI	0.943
RMSEA	0.041
Hoelter's critical N (α = .05)	1203
Hoelter's critical N (α = .01)	1580

Residual variances details are presented in Table 39 that follows.

Table 39: Residual variances for vehicle control – Belgian truck drivers – experiment Phase 3

Variable	Estimate	S.E.	C.R.	P
Coping_capacity	0.023	0.001	26.097	***
Risk	0.011	0.005	2.266	0.023
Style	0.176	0.001	235.987	***
Confidence	0.477	0.002	248.101	***
DrivingEvents_Map_lvl_L_mean	0.138	0.005	29.084	***
DrivingEvents_Map_lvl_M_mean	0.016	0.001	23.611	***
Age	3.403	2.62	1.298	0.194
Skills	0.403	0.002	263.215	***

The results for Phase 4 are shown in Figure 17 below.

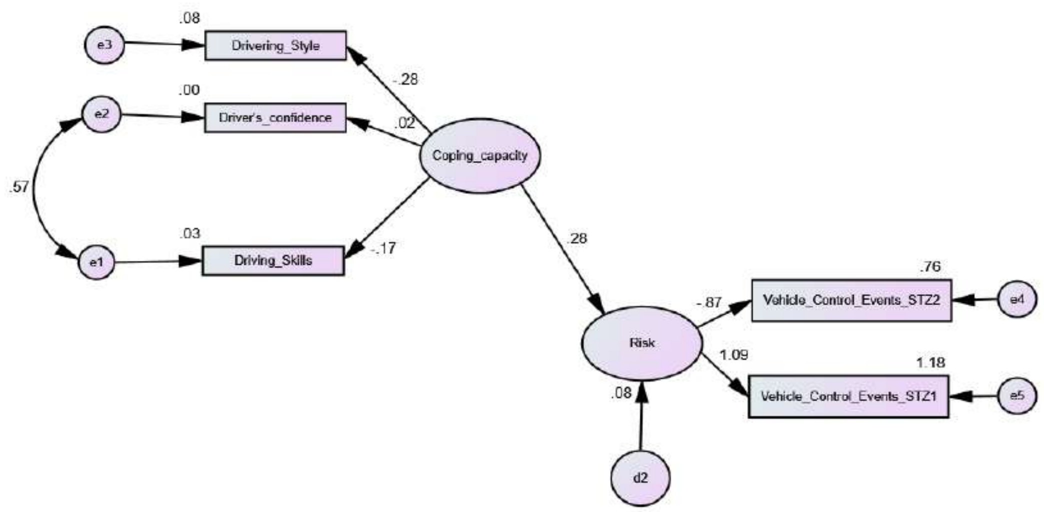

Figure 17: Results of SEM coping capacity & risk (Vehicle control STZ) – Belgian truck drivers – experiment Phase 4

The Comparative Fit Index (CFI) of the model is equal 0.994; TLI is 0.987 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.033. More details about the model fit can be found in the Table 40 below.

Table 40: Model Fit Summary for vehicle control – Belgian truck drivers – experiment Phase 4

Model Fit measures	Value
AIC	1133.147
BCC	1133.149
CFI	0.994
TLI	0.987
RMSEA	0.033
Hoelter's critical N (α = .05)	1883
Hoelter's critical N (α = .01)	2473

Residual variances details are presented in Table 41 that follows.

Table 41: Residual variances for vehicle control – Belgian truck drivers – experiment Phase 4

Variable	Estimate	S.E.	C.R.	P
Coping_capacity	0	0	1.9	0.057
Risk	0.168	0.002	75.717	***
Confidence	0.551	0.002	305.62	***
DrivingEvents_Map_lvl_M_mean	-0.028	0.002	-16.094	***
DrivingEvents_Map_lvl_L_mean	0.195	0.001	186.35	***
Skills	0.412	0.002	264.432	***
Style	0.034	0.001	31.915	***

4.2.3 UK (Cars)

4.2.3.1 Headway

Four separate SEM models were estimated in order to explore the relationship between the latent variables of coping capacity and risk where risk, expressed as the three phases of the STZ, was formed as a composite of headway. Each model corresponds with one of the phases of the i-DREAMS experiment namely:

- Phase 1: monitoring - 53 UK car drivers, 3,073 trips (56,853 minutes)
- Phase 2: real-time interventions - 54 UK car drivers, 3,317 trips (58,458 minutes)
- Phase 3: real-time & post-trip interventions - 53 UK car drivers, 3,417 trips (59,556 minutes)
- Phase 4: real-time, post-trip interventions & gamification - 54 UK car drivers, 4,594 trips (93,974 minutes)

To begin with, 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 18.

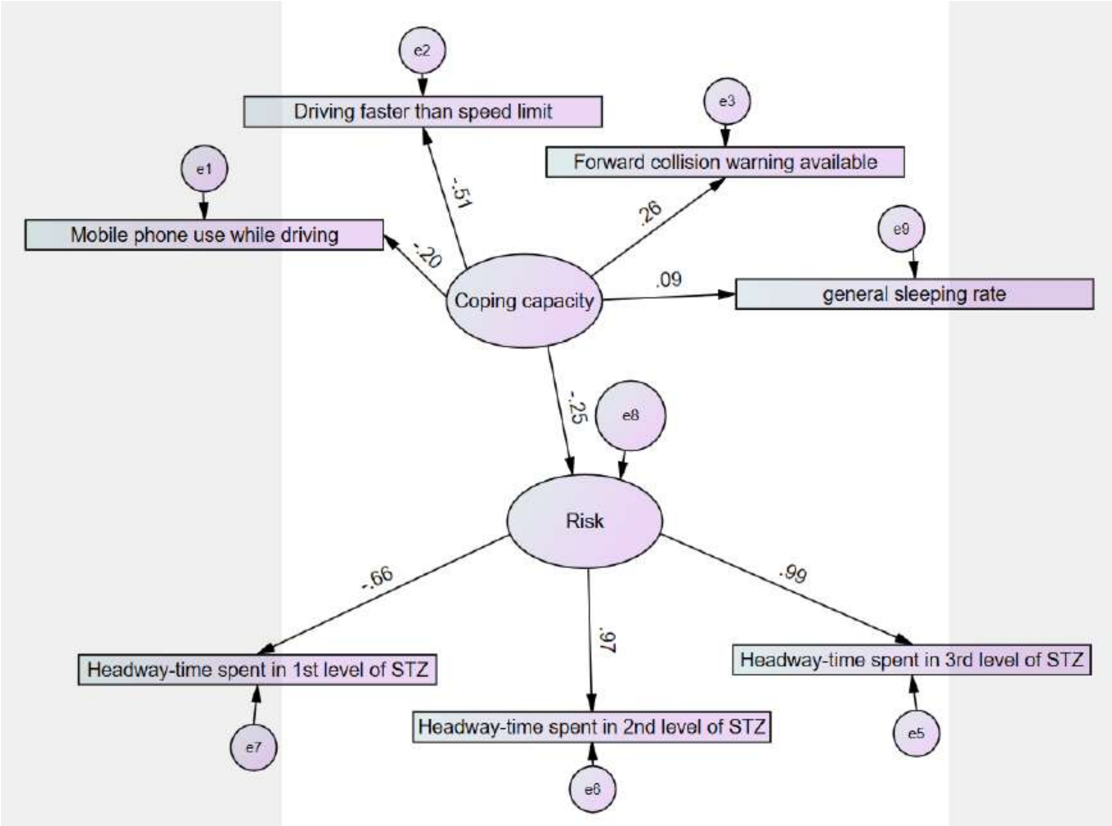

Figure 18: Results of SEM coping capacity & risk (headway STZ) – UK car drivers – experiment Phase 1

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 0.993; TLI is 0.989 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.040. More details about the model fit can be found in Table 42 below.

Table 42: Model Fit Summary for headway – UK car drivers – experiment Phase 1

Model Fit measures	Value
AIC	2397.192
BIC	2541.813
CFI	0.993
TLI	0.989
RMSEA	0.040
GFI	0.994
Hoelter's critical N (α = .05)	1075
Hoelter's critical N (α = .01)	1330

The results of SEM including residual variances details are presented in the Table 43 that follows.

Table 43: Residual variances for headway – UK car drivers – experiment Phase 1

Variable	Estimate	S.E.	C.R.	P
Coping_capacity	.002	.000	9.099	***
Risk	.042	.000	193.200	***
EQ4e_Mobile_phone	.422	.002	216.335	***
EQ4b_Speed_limit	.649	.008	76.709	***
EQ1b_Forward_collision_warning	.058	.000	197.931	***
iDreams_Headway_Map_level_23_mean	.001	.000	20.187	***
iDreams_Headway_Map_level_1_mean	.003	.000	67.119	***
iDreams_Headway_Map_level_1_0_mean	.070	.000	234.330	***
EQ17_General_sleep_rating	.204	.001	234.586	***

All the observed indicators of the two latent variables coping capacity and risk are statistically significant at 99.9% confidence level. The latent variable of coping capacity has a statistically significant negative effect on risk that is significantly interpreted by the time spent in each of the three levels of STZ regarding the headway indicator. The more the time a driver spends in the second and third level of STZ, the higher the risk. Overall, increased coping capacity relates to reduced risk according to the model (standardised coefficient=-0.25).

Coping capacity is represented by four variables in this phase: mobile phone use while driving, driving above speed limit, forward collision warning available and the general sleeping rate. More specifically, coping capacity seems to relate positively with the forward collision warning system and the general sleeping rate and negatively with the driving above the speed limit and the mobile phone use while driving. It is intuitive that drivers with better sleep rating and advanced driver systems available in their cars can exhibit higher coping capacity while drivers that usually or always use their mobile phone while driving and speed over the limit can be linked to lower coping capacity.

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 19.

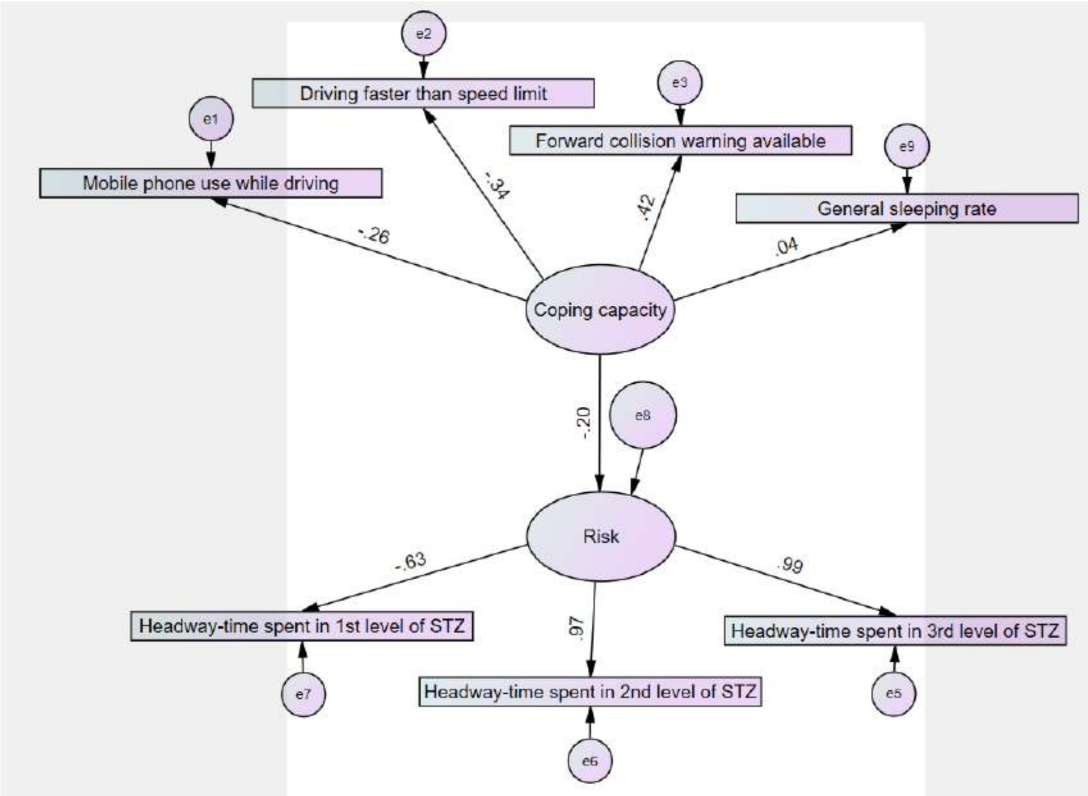

Figure 19: Results of SEM coping capacity & risk (headway STZ) – UK car drivers – experiment Phase 2

The results indicate that the model is reasonably consistent with the data as CFI is 0.994; TLI is 0.990; and RMSEA is 0.040. More details about the model fit can be found in Table 44 below.

Table 44: Model Fit Summary for headway – UK car drivers – experiment Phase 2

Model Fit measures	Value
AIC	2483.634
BIC	2628.672
CFI	0.994
TLI	0.990
RMSEA	0.040
GFI	0.994
Hoelter's critical N (α = .05)	1066
Hoelter's critical N (α = .01)	1320

The results of SEM including residual variances details are presented in the Table 45 that follows.

Table 45: Residual variances for headway – UK car drivers – experiment Phase 2

Variable	Estimate	S.E.	C.R.	P
Coping_capacity	.014	.001	27.386	***
Risk	.035	.000	211.354	***
EQ4e_Mobile_phone	.479	.002	201.349	***

Variable	Estimate	S.E.	C.R.	P
EQ4b_Speed_limit	.709	.004	161.833	***
EQ1b_Forward_collision_warning	.064	.001	119.692	***
iDreams_Headway_Map_level_23_mean	.001	.000	17.686	***
iDreams_Headway_Map_level_1_mean	.002	.000	55.543	***
iDreams_Headway_Map_level_1_0_mean	.069	.000	238.955	***
EQ17_General_sleep_rating	.204	.001	240.718	***

The observed indicators of coping capacity and risk that are statistically significant, are the same as in Phase 1. Coping capacity has again a negative significant impact on risk (standardised coefficient= -0.2). 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 1 with Forward collision warning to be the predominant variable describing coping capacity 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 smartphone application. The path diagram of the model is presented in Figure 20.

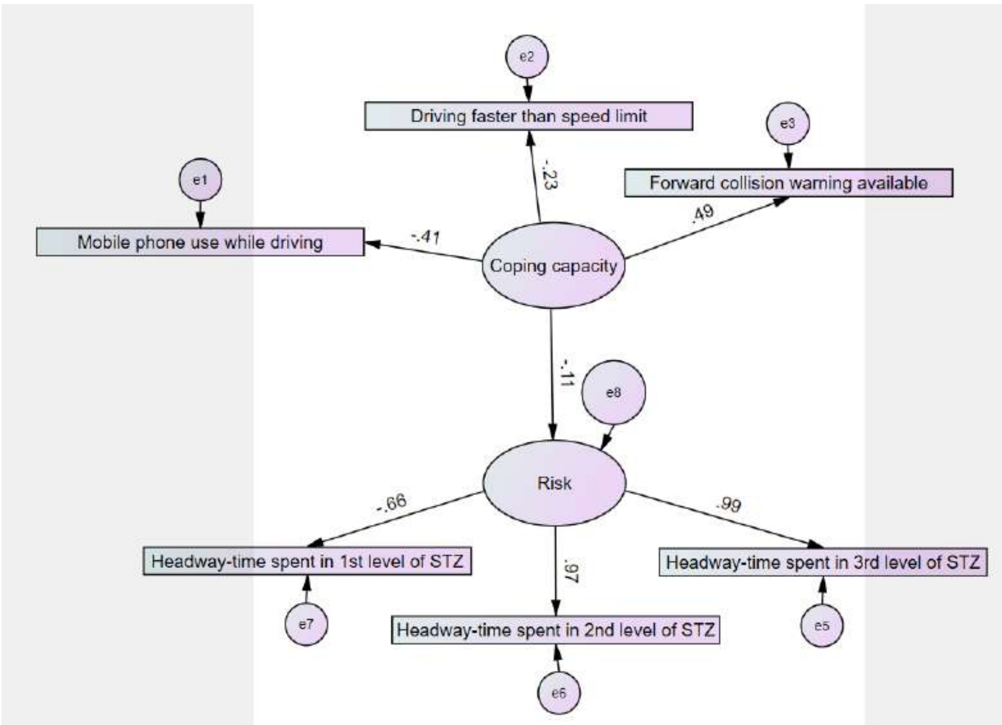

Figure 20: Results of SEM coping capacity & risk (headway STZ) – UK car drivers – experiment Phase 3

The model is a good fit to the data. The results indicate that the model is reasonably consistent with the data as CFI is 0.995, TLI is 0.991, and RMSEA is 0.044. More details about the model fit can be found in Table 46 below.

Table 46: Model Fit Summary for headway – UK car drivers – experiment Phase 3

Model Fit measures	Value
AIC	1892.078
BIC	2018.019
CFI	0.995
TLI	0.991
RMSEA	0.044
GFI	0.995
Hoelter's critical N (α = .05)	990
Hoelter's critical N (α = .01)	1283

Residual variances details are presented in Table 47 that follows.

Table 47: Residual variances for headway – UK car drivers – experiment Phase 3

Variable	Estimate	S.E.	C.R.	P
Coping_capacity	.018	.001	28.583	***
Risk	.031	.000	223.351	***
EQ4e_Mobile_phone	.365	.003	126.087	***
EQ4b_Speed_limit	.781	.004	218.192	***
EQ1b_Forward_collision_warning	.058	.001	89.319	***
iDreams_Headway_Map_level_23_mean	.001	.000	18.374	***
iDreams_Headway_Map_level_1_mean	.002	.000	58.538	***
iDreams_Headway_Map_level_1_0_mean	.063	.000	240.891	***

For the data of this phase, the general sleeping rate was not statistically significant as an indicator of coping capacity. Nevertheless, the rest of the variables (driving above speed limit, forward collision warning available and mobile phone use while driving) indicating the latent concept of coping capacity remained the same, with the latter to have a significant negative effect on risk (standardised coefficient=-0.11). As expected, higher levels of copying capacity can be linked to reduced risk.

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 21.

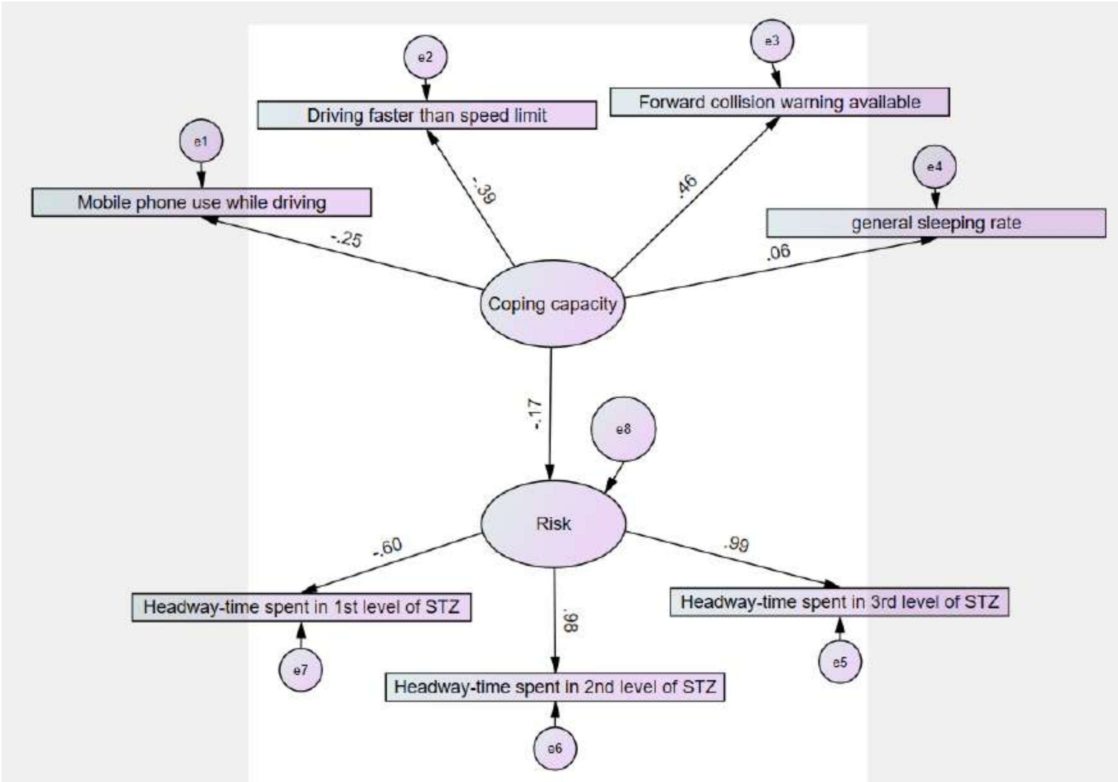

Figure 21: Results of SEM coping capacity & risk (headway STZ) – UK car drivers – experiment Phase 4

The results indicate that the model is consistent with the data as CFI is 0.995, TLI is 0.992, and RMSEA is 0.036. More details about the model fit can be found in Table 48 below.

Table 48: Model Fit Summary for headway – UK car drivers – experiment Phase 4

Model Fit measures	Value
AIC	3246.904
BIC	3399.063
CFI	0.995
TLI	0.992
RMSEA	0.036
GFI	0.995
Hoelter's critical N (α = .05)	1307
Hoelter's critical N (α = .01)	1618

Residual variances details are presented in Table 49 that follows.

Table 49: Residual variances for headway – UK car drivers – experiment Phase 4

Variable	Estimate	S.E.	C.R.	P
Coping_capacity	.013	.000	38.219	***
Risk	.030	.000	280.082	***
EQ4e_Mobile_phone	.386	.001	266.202	***
EQ4b_Speed_limit	.638	.003	183.910	***

Variable	Estimate	S.E.	C.R.	P
EQ1b_Forward_collision_warning	.047	.000	136.538	***
EQ17_General_sleep_rating	.201	.001	304.675	***
iDreams_Headway_Map_level_23_mean	.000	.000	16.129	***
iDreams_Headway_Map_level_1_mean	.001	.000	59.982	***
iDreams_Headway_Map_level_1_0_mean	.067	.000	304.174	***

The model is similar with the other phases as the same variables were identified as significant. All the observed indicators of the two latent variables coping capacity and risk are statistically significant at 99.9% confidence level and coping capacity has a statistically significant negative 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 negative relationship of coping capacity with risk shows that as the latter increases, risk levels reduce. Again, as expected, coping capacity seems to relate positively with the forward collision warning system and the general sleeping rate and negatively with the driving above the speed limit and the mobile phone use while driving.

<u>A general view of the models for the four phases</u>

Overall, four SEM analyses were performed in order to assess the effect of coping capacity to risk during the four phases of on-road trials. The variables that construct the latent concept of coping capacity and risk were the same (these that were proved to be statistically significant) for all phases except for the phase 3 where general sleeping rate was excluded. Forward collision warning system availability appears to be the more representative indicator of coping capacity (higher coefficient) in all four models. The availability of forward collision warning system in the car and a good sleep rating indicate increased coping capacity while the opposite is observed with habits as speeding and distracted driving due to mobile phone.

Coping capacity appears in all the models to have a significant negative effect on risk translated to lower levels of the latter when the first shows an increase. Although the models appear similar, this effect changes across the phases with the larger to be observed in Phase 1 (standardised coefficient= -0.25).

4.2.4 Germany (Cars)

4.2.4.1 Harsh braking

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, 1,397 trips (23,617 minutes)

- Phase 2: real-time interventions - 28 German car drivers, 1,322 trips (19,469 minutes)
- Phase 3: real-time & post-trip interventions - 27 German car drivers, 1,129 trips (17,704 minutes)
- Phase 4: real-time, post-trip interventions & gamification - 28 German car drivers, 1,496 trips (23,644 minutes)

The results for phase 1 are shown in Figure 22 below. It is shown that the latent coping capacity is measured by means of both vehicle state indicators, such as "VehicleAge" (indicating the age of the vehicle) and "Gearbox" (indicating the type of gearbox; automatic or manual) and operator state indicators, such as "GPS_distances_sum" (indicating the distance traveled), "GPS_spd_mean" (indicating the average speed), "grpby_seconds" (indicating the total duration), "Gender" (indicating the gender of the driver; male or female), "Age" (indicating the age of the driver), "iDreams_Fatigue_Map_level_total_mean" (indicating the fatigue level) and 'iDreams_Overtaking_Map_level_total_mean" (indicating the overtaking level). Risk is measured by means of the STZ levels for harsh braking (level 1 refers to 'normal driving' used as the reference case (i.e. DEM_evt_hb_lvl_L_mean), level 2 refers to 'dangerous driving', i.e. DEM_evt_hb_lvl_M_mean, while level 3 refers to 'avoidable accident driving' i.e. DEM_evt_hb_lvl_H_mean), with positive correlations of risk with the STZ indicators.

More specifically, distance, duration, average speed, fatigue, overtaking, and gender have a positive correlation with coping capacity. On the other hand, age and gearbox are associated with lower coping capacity. For instance, driver's age shows a negative correlation which indicates that older drivers have lower coping capacity. Overall, the structural model between coping capacity and risk shows a negative coefficient, which means that increased coping capacity relates to decreased risk according to the model (regression coefficient=-1.04).

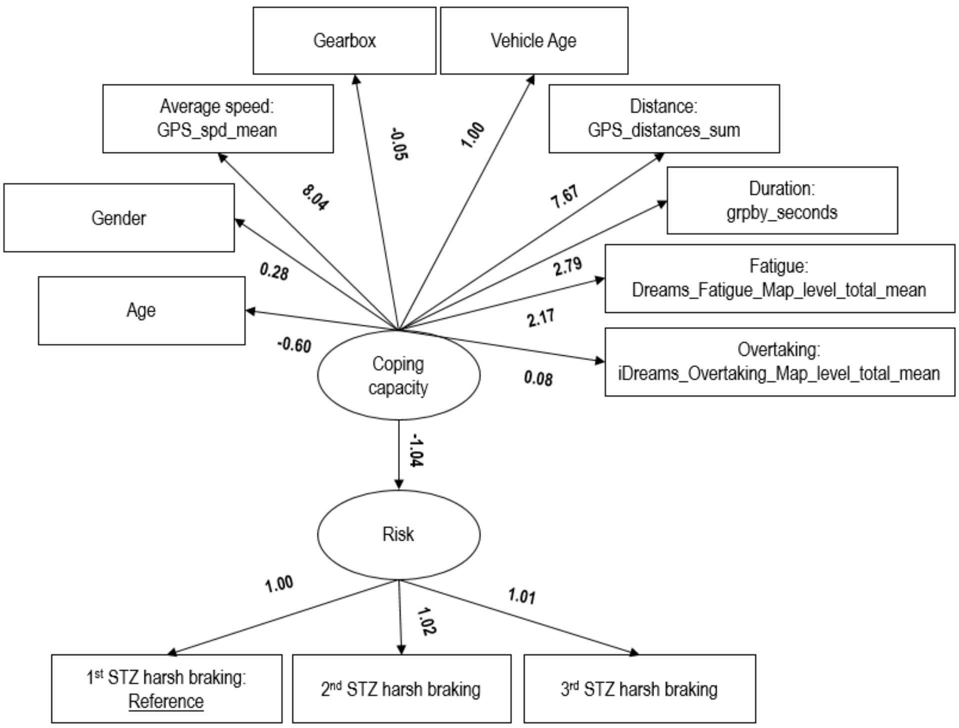

Figure 22: Results of SEM coping capacity & risk (harsh braking STZ) – German car drivers – experiment Phase 1

The Comparative Fit Index (CFI) of the model is equal 0.635; TLI is 0.545 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.140. Table 50 summarizes the model fit of SEM applied for harsh braking.

Table 50: Model Fit Summary for harsh braking – German car drivers – experiment Phase 1

Model Fit measures	Value
AIC	$1.427 \times 10^{+6}$
BIC	$1.427 \times 10^{+6}$
CFI	0.635
TLI	0.545
RMSEA	0.140
GFI	0.848
Hoelter's critical N (α = .05)	68.950
Hoelter's critical N (α = .01)	77.420

Residual variances details are presented in Table 51 that follows.

Table 51: Residual variances for harsh braking – German car drivers – experiment Phase 1

Variable	Estimate	Std. Error	z-value	P(>|z|)
VehicleAge	0.984	0.006	156800	< .001
Gearbox	1.000	0.006	157.231	< .001
GPS_distances_sum	0.115	0.004	32.404	< .001
GPS_spd_mean	0.029	0.004	7.699	< .001
Grpby_seconds	0.878	0.006	153.475	< .001
Gender	0.999	0.006	157.199	< .001
Age	0.994	0.006	157.079	< .001
iDreams_Fatigue_Map_level_total_mean	0.926	0.006	155.065	< .001
iDreams_Overtaking_Map_level_total_mean	1.000	0.006	157.229	< .001
DEM_evt_hb_lvl_L_mean	1.090	0.015	74.490	< .001
DEM_evt_hb_lvl_M_mean	1.024	0.008	127.937	< .001
DEM_evt_hb_lvl_H_mean	1.006	0.010	103.307	< .001

The following Figures show the results of the 2nd, 3rd and 4th phase of the experiment. It is observed that the measurement equations of coping capacity are fairly consistent between the different phases. At the same time, the loadings of the observed proportions of the STZ of harsh braking are consistent between the different phases. The structural model between coping capacity and inverse risk (normal driving) are negatively correlated among the 4 phases. The results for Phase 2 are shown in Figure 23 below.

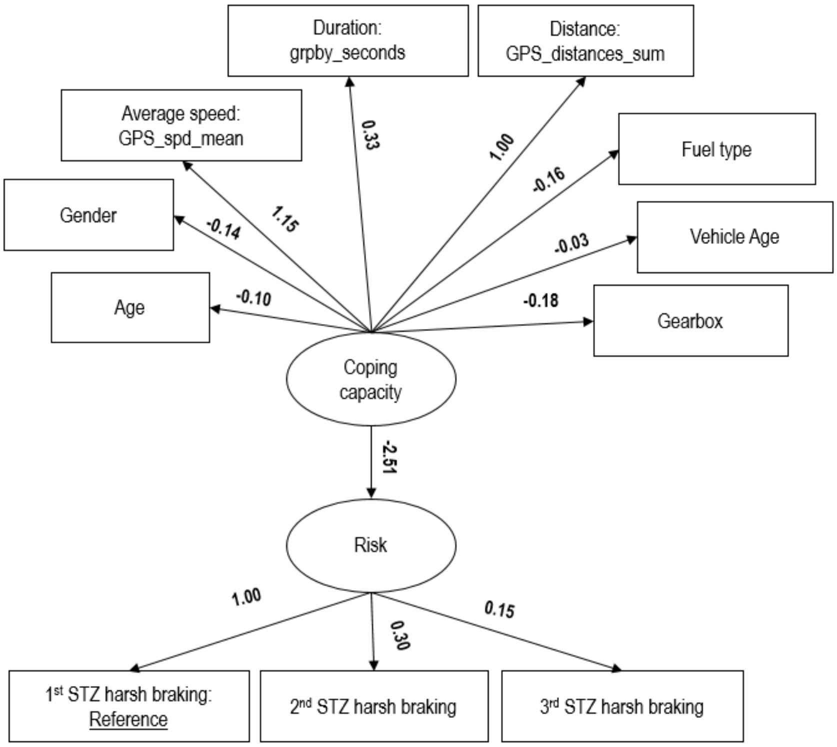

Figure 23: Results of SEM coping capacity & risk (harsh braking STZ) – German car drivers – experiment Phase 2

The Comparative Fit Index (CFI) of the model is equal 0. 598; TLI is 0. 485 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.130. More details about the model fit can be found in the Table 52 below.

Table 52: Model Fit Summary for harsh braking – German car drivers – experiment Phase 2

Model Fit measures	Value
AIC	$1.043 \times 10^{+6}$
BIC	$1.043 \times 10^{+6}$
CFI	0.598
TLI	0.485
RMSEA	0.130
GFI	0.882
Hoelter's critical N (α = .05)	81.893
Hoelter's critical N (α = .01)	93.018

Residual variances details are presented in Table 53 that follows.

Table 53: Residual variances for harsh braking – German car drivers – experiment Phase 2

Variable	Estimate	Std. Error	z-value	P(>|z|)
GPS_distances_sum	0.297	0.007	45.495	< .001
GPS_spd_mean	0.067	0.008	8.245	< .001
VehicleAge	0.999	0.007	139.236	< .001
Grpby_seconds	0.925	0.007	136.853	< .001
Gender	0.986	0.007	138.858	< .001
Age	0.992	0.007	139.050	< .001

Variable	Estimate	Std. Error	z-value	P(>|z|)
Fuel_type	0.981	0.007	138.727	< .001
Gearbox	0.978	0.007	138.639	< .001
DEM_evt_hb_lvl_L_mean	1.149	0.026	43.508	< .001
DEM_evt_hb_lvl_M_mean	1.013	0.008	121.406	< .001
DEM_evt_hb_lvl_H_mean	1.003	0.011	92.501	< .001

The results for Phase 3 are shown in Figure 24 below.

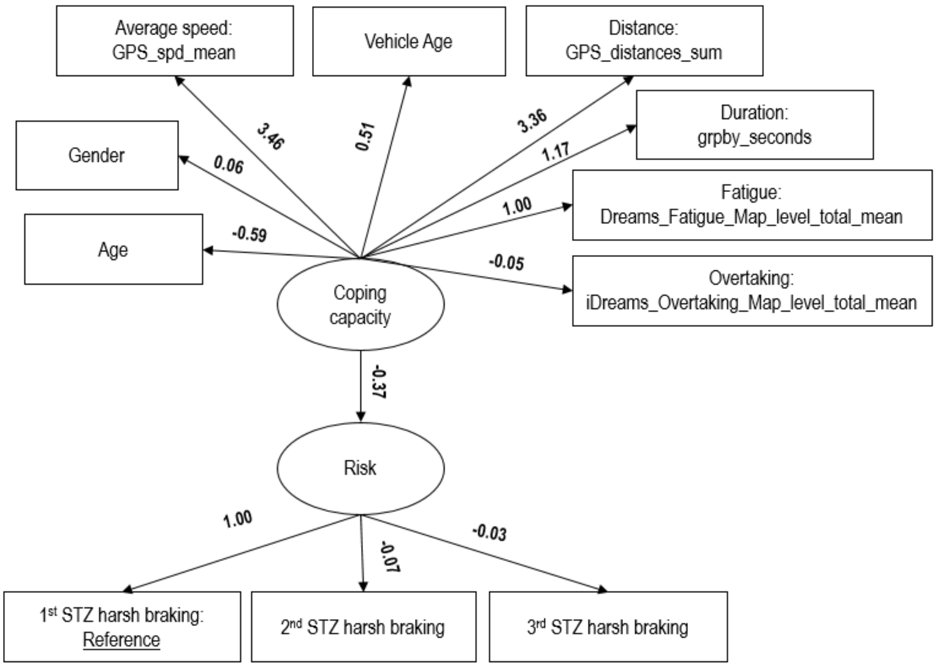

Figure 24: Results of SEM coping capacity & risk (harsh braking STZ) – German car drivers – experiment Phase 3

The Comparative Fit Index (CFI) of the model is equal 0.696; TLI is 0.611 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.140. Table 54 summarizes the model fit of SEM applied for harsh braking:

Table 54: Model Fit Summary for harsh braking – German car drivers – experiment Phase 3

Model Fit measures	Value
AIC	961245.259
BIC	961535.433
CFI	0.696
TLI	0.611
RMSEA	0.140
GFI	0.870
Hoelter's critical N (α = .05)	71.435
Hoelter's critical N (α = .01)	81.122

Residual variances details are presented in Table 55 that follows.

Table 55: Residual variances for harsh braking – German car drivers – experiment Phase 3

Variable	Estimate	Std. Error	z-value	P(>|z|)
iDreams_Fatigue_Map_level_total_mean	0.922	0.007	135.703	< .001
iDreams_Overtaking_Map_level_total_mean	1.000	0.007	137.093	< .001
GPS_spd_mean	0.054	0.004	12.646	< .001
GPS_distances_sum	0.107	0.004	26.278	< .001
Grpby_seconds	0.892	0.007	135.130	< .001
Gender	1.000	0.007	137.092	< .001
Age	0.973	0.007	130.250	< .001
VehicleAge	0.979	0.008	130.361	< .001
DEM_evt_hb_lvl_L_mean	0.184	0.662	0.278	0.781
DEM_evt_hb_lvl_M_mean	0.997	0.009	115.940	< .001
DEM_evt_hb_lvl_H_mean	0.999	0.012	85.942	< .001

The results for Phase 4 are shown in Figure 25 below.

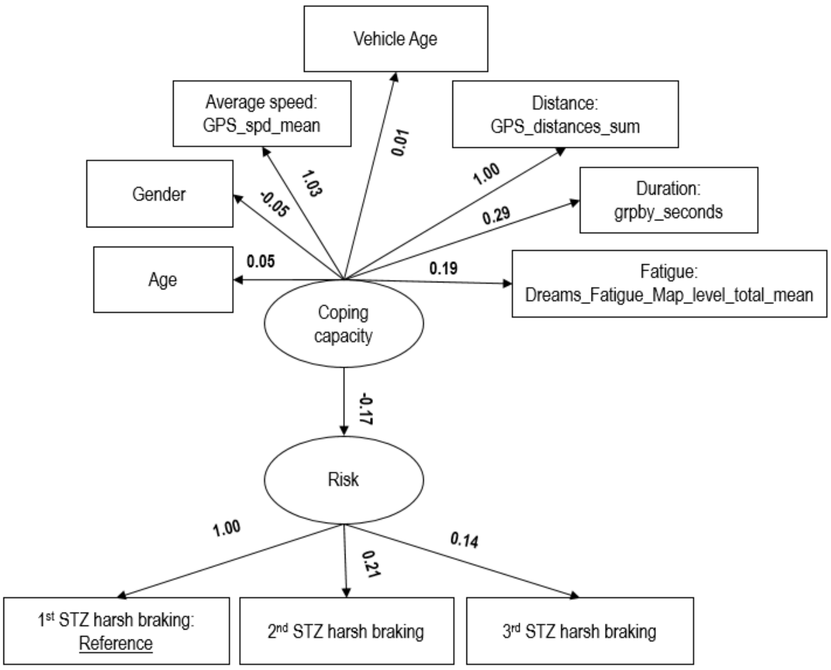

Figure 25: Results of SEM coping capacity & risk (harsh braking STZ) – German car drivers – experiment Phase 4

The Comparative Fit Index (CFI) of the model is equal 0.834; TLI is 0.780 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.113. More details about the model fit can be found in the Table 56 below.

Table 56: Model Fit Summary for harsh braking – German car drivers – experiment Phase 4

Model Fit measures	Value
AIC	925101.630
BIC	925370.409
CFI	0.834
TLI	0.780

Model Fit measures	Value
RMSEA	0.113
GFI	0.911
Hoelter's critical N (α = .05)	112.831
Hoelter's critical N (α = .01)	129.992

Residual variances details are presented in Table 57 that follows.

Table 57: Residual variances for harsh braking – German car drivers – experiment Phase 4

Variable	Estimate	Std. Error	z-value	P(>|z|)
GPS_distances_sum	0.087	0.004	20.419	< .001
iDreams_Fatigue_Map_level_total_mean	0.967	0.007	146.324	< .001
GPS_spd_mean	0.030	0.005	6.638	< .001
Grpby_seconds	0.925	0.006	145.753	< .001
Gender	0.998	0.007	146.701	< .001
Age	0.998	0.008	125.429	< .001
VehicleAge	1.000	0.008	125.450	< .001
DEM_evt_hb_lvl_L_mean	1.242	0.047	26.301	< .001
DEM_evt_hb_lvl_M_mean	1.011	0.008	124.622	< .001
DEM_evt_hb_lvl_H_mean	1.005	0.011	88.214	< .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 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)

The results for phase 1 are shown in Figure 26 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.

First of all, the latent coping capacity is measured by means of operator state indicators, such as duration, distance, harsh acceleration, harsh braking, age and gender. At the same time, the indicators of coping capacity - vehicle state, such as vehicle age, gearbox or fuel type are included in the SEM applied.

Overall, the structural model between coping capacity and risk shows a negative coefficient, which means that increased coping capacity relates to decreased risk according to the model (regression coefficient=-0.26).

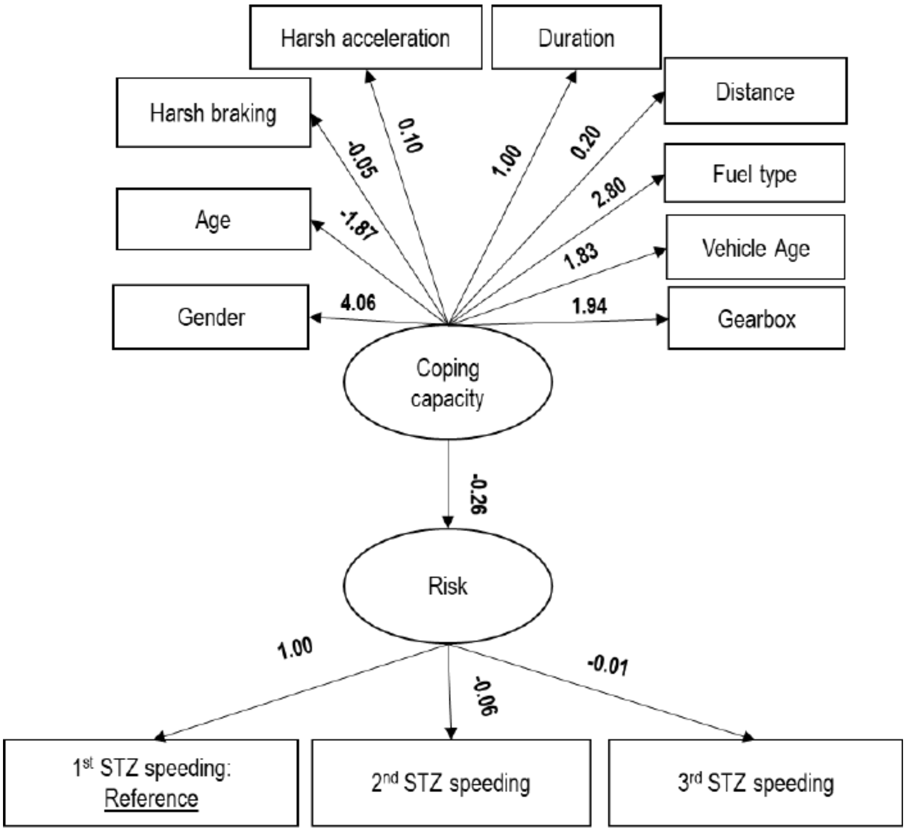

Figure 26: Results of SEM coping capacity & risk (Speeding STZ) – Greek car drivers – experiment Phase 1

The Comparative Fit Index (CFI) of the model is equal 0.850; TLI is 0.813 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.092. Table 58 summarizes the model fit of SEM applied for speeding.

Table 58: Model Fit Summary for speeding – Greek car drivers – experiment Phase 1

Model Fit measures	Value
AIC	627917.827
BIC	628215.310
CFI	0.850
TLI	0.813
RMSEA	0.092
GFI	0.925
Hoelter's critical N (α = .05)	156.811
Hoelter's critical N (α = .01)	176.234

Residual variances details are presented in Table 59 that follows.

Table 59: Residual variances for speeding – Greek car drivers – experiment Phase 1

Variable	Estimate	Std. Error	z-value	P(>|z|)
grpby_seconds	0.959	0.009	105.572	< .001
GPS_distances_sum	0.998	0.010	104.690	< .001
DEM_evt_ha_lvl_H_mean	1.000	0.013	76.548	< .001
Age	0.855	0.008	100.639	< .001
Gender	0.317	0.010	31.772	< .001
Fuel_type	0.674	0.008	84.382	< .001
VehicleAge	0.862	0.009	101.024	< .001
Gearbox	0.843	0.008	99.927	< .001
DEM_evt_hb_lvl_H_mean	1.000	0.013	76.555	< .001
iDreams_Speeding_Map_level_0_mean	-14.334	8.264	-1.735	0.083
iDreams_Speeding_Map_level_1_mean	0.945	0.031	30.328	< .001
iDreams_Speeding_Map_level_2_mean	0.966	0.010	94.063	< .001

The following Figures show the results of the 3rd and 4th phase of the experiment. It is observed that the measurement equations of 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 while coping capacity and inverse risk (normal driving) are negatively correlated among the three phases. The results for phase 3 are shown in Figure 27 below.

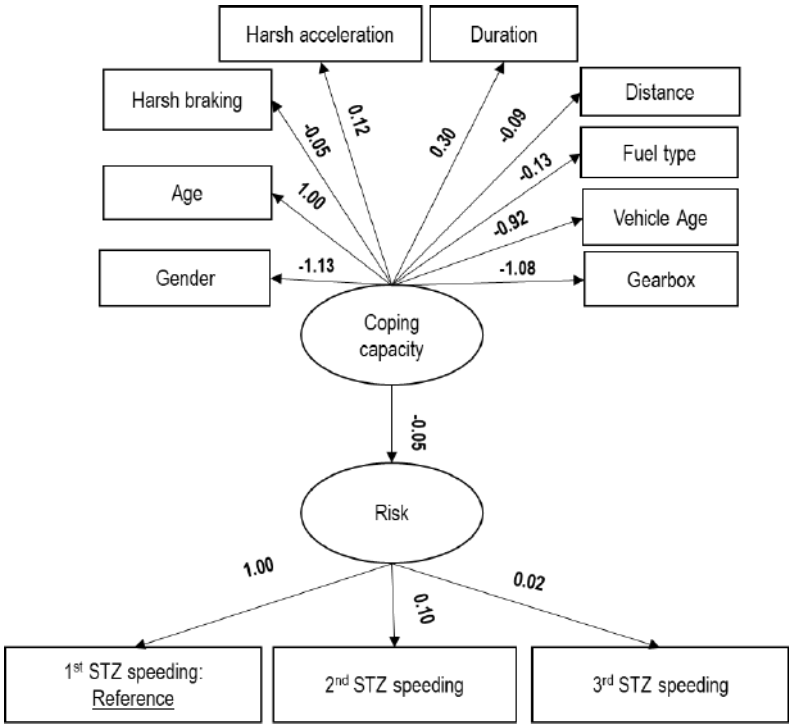

Figure 27: Results of SEM coping capacity & risk (Speeding STZ) – Greek car drivers – experiment Phase 3

The Comparative Fit Index (CFI) of the model is equal 0.815; TLI is 0.769 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.098. Table 60 summarizes the model fit of SEM applied for speeding.

Table 60: Model Fit Summary for speeding – Greek car drivers – experiment Phase 3

Model Fit measures	Value
AIC	$2.057 \times 10^{+6}$
BIC	$2.058 \times 10^{+6}$
CFI	0.815
TLI	0.769
RMSEA	0.098
GFI	0.903
Hoelter's critical N (α = .05)	141.664
Hoelter's critical N (α = .01)	159.199

Residual variances details are presented in Table 61 that follows.

Table 61: Residual variances for speeding – Greek car drivers – experiment Phase 3

Variable	Estimate	Std. Error	z-value	P(>|z|)
Age	0.632	0.004	151.404	< .001
GPS_distances_sum	0.997	0.005	191.286	< .001
grpby_seconds	0.966	0.005	192.843	< .001
Gender	0.532	0.004	128.544	< .001
Fuel_type	0.994	0.005	194.944	< .001
VehicleAge	0.687	0.004	161.350	< .001
Gearbox	0.572	0.004	138.444	< .001
DEM_evt_hb_lvl_H_mean	0.999	0.008	129.154	< .001
DEM_evt_ha_lvl_H_mean	0.995	0.008	129.345	< .001
iDreams_Speeding_Map_level_0_mean	9.928	1.890	5.253	< .001
iDreams_Speeding_Map_level_1_mean	1.085	0.019	57.401	< .001
iDreams_Speeding_Map_level_2_mean	0.960	0.006	160.597	< .001

The results for phase 4 are shown in Figure 28 below.

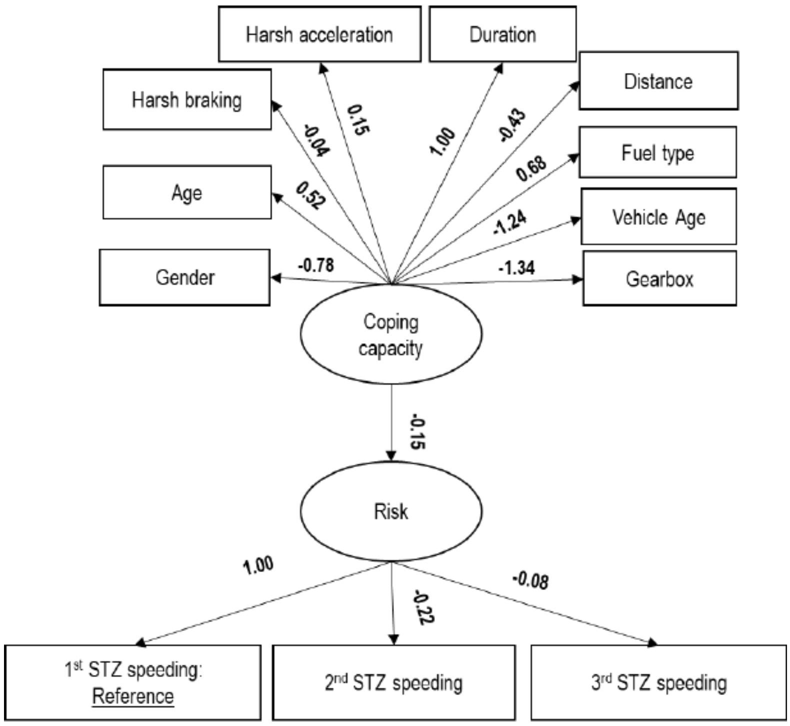

Figure 28: Results of SEM coping capacity & risk (Speeding STZ) – Greek car drivers – experiment Phase 4

The Comparative Fit Index (CFI) of the model is equal 0.816, TLI is 0.774 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.115. Table 62 summarizes the model fit of SEM applied for speeding.

Table 62: Model Fit Summary for speeding – Greek car drivers – experiment Phase 4

Model Fit measures	Value
AIC	$3.902\times10^{+6}$
BIC	$3.903\times10^{+6}$
CFI	0.816
TLI	0.771
RMSEA	0.115
GFI	0.869
Hoelter's critical N (α = .05)	102.409
Hoelter's critical N (α = .01)	115.051

Residual variances details are presented in Table 63 that follows.

Table 63: Residual variances for speeding – Greek car drivers – experiment Phase 4

Variable	Estimate	Std. Error	z-value	P(>|z|)
grpby_seconds	0.579	0.002	247.029	< .001
GPS_distances_sum	0.921	0.003	266.306	< .001
DEM_evt_ha_lvl_H_mean	0.995	0.006	168.010	< .001
Age	0.886	0.003	274.877	< .001
Gender	0.740	0.003	264.872	< .001
Fuel_type	0.806	0.003	269.842	< .001
VehicleAge	0.355	0.002	188.034	< .001
Gearbox	0.247	0.002	136.651	< .001
DEM_evt_hb_lvl_H_mean	1.000	0.006	167.717	< .001
iDreams_Speeding_Map_level_0_mean	-2.915	0.126	-23.181	< .001
iDreams_Speeding_Map_level_1_mean	0.805	0.007	114.329	< .001
iDreams_Speeding_Map_level_2_mean	0.925	0.004	217.575	< .001

4.2.6 Portugal (Buses)

4.2.6.1 Headway

Four 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 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)
- Phase 3: real-time & post-trip interventions - 26 Portuguese bus drivers, 1,411 trips (145,934 minutes)

- Phase 4: real-time. post-trip interventions & gamification - 22 Portuguese bus drivers, 2,098 trips (23,2323 minutes)

To begin with, the results for phase 1 are shown in Figure 29 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.

It is shown that the latent coping capacity is measured by means of operator state indicators, such as average speed, distance, harsh acceleration and harsh braking. It should be noted that vehicle state indicators, such as vehicle age, gearbox, type of fuel or socio-demographic characteristics were not provided.

More specifically, distance, harsh acceleration and harsh braking have a positive correlation with coping capacity. Risk is measured by means of the STZ levels for headway (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. On the other hand, average speed is associated with lower coping capacity. Overall, the structural model between coping capacity and risk shows a negative coefficient, which means that increased coping capacity relates to decreased risk according to the model (regression coefficient=-0.612).

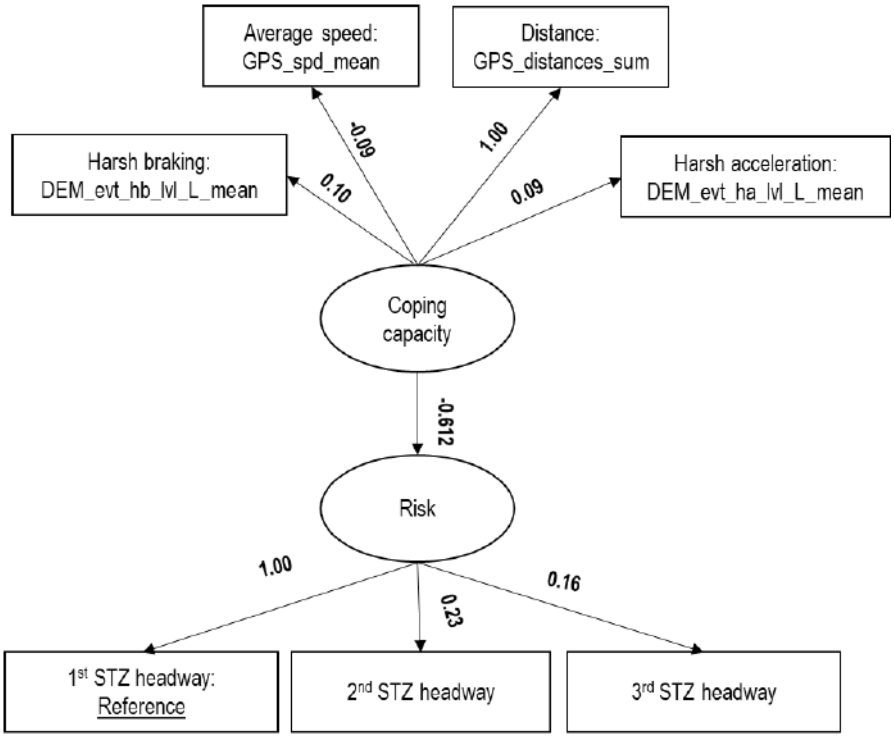

Figure 29: Results of SEM on Risk (Headway STZ) – Portuguese bus drivers – experiment Phase 1

The Comparative Fit Index (CFI) of the model is equal 0.685; TLI is 0.492 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.060. Table 64 summarizes the model fit of SEM applied for headway.

Table 64: Model Fit Summary for headway – Portuguese bus drivers – experiment Phase 1

Model Fit measures	Value
AIC	3.045×10+6
BIC	3.046×10+6
CFI	0.685
TLI	0.492
RMSEA	0.060
GFI	0.987
Hoelter's critical N (α = .05)	476.207
Hoelter's critical N (α = .01)	589.393

Residual variances details are presented in Table 65 that follows.

Table 65: Residual variances for headway – Portuguese bus drivers – experiment Phase 1

Variable	Estimate	Std. Error	z-value	P(>|z|)
distance	0.525	0.025	20.811	< .001
GPS_spd	0.996	0.004	276.456	< .001
DrivingEvents_Map_evt_ha_mean	0.996	0.004	276.416	< .001
DrivingEvents_Map_evt_hb_mean	0.996	0.004	276.384	< .001
iDreams_Headway_Map_level_0_mean	1.009	0.010	103.741	< .001
iDreams_Headway_Map_level_1_mean	1.000	0.004	275.085	< .001
iDreams_Headway_Map_level_2_mean	1.000	0.004	276.913	< .001

The following Figures show the results of the 2nd, 3rd and 4th phase of the experiment. It is observed that the measurement equations of coping capacity are fairly consistent between the different phases. At the same time, the loadings of the observed proportions of the STZ of harsh braking are consistent between the different phases. The structural model between coping capacity and inverse risk (normal driving) are negatively correlated among the 4 phases. The results for Phase 2 are shown in Figure 30 below.

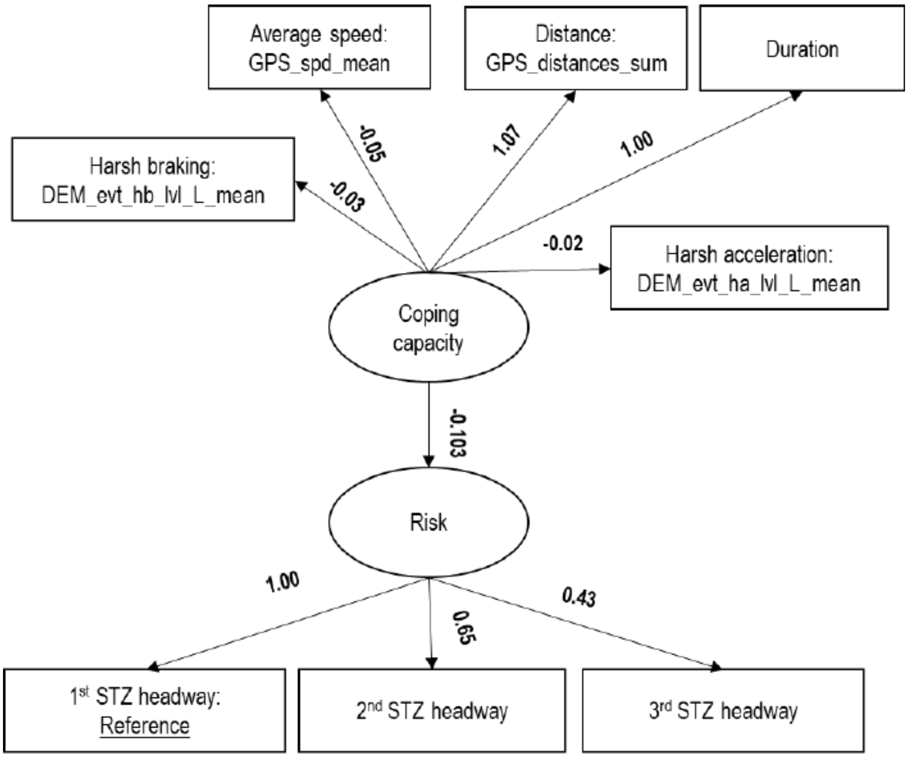

Figure 30: Results of SEM on Risk (Headway STZ) – Portuguese bus drivers – experiment Phase 2

The Comparative Fit Index (CFI) of the model is equal 0.987; TLI is 0.981 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.054. Table 66 summarizes the model fit of SEM applied for headway.

Table 66: Model Fit Summary for headway – Portuguese bus drivers – experiment Phase 2

Model Fit measures	Value
AIC	$1.473\times10^{+6}$
BIC	$1.473\times10^{+6}$
CFI	0.987
TLI	0.981
RMSEA	0.054
GFI	0.986
Hoelter's critical N (α = .05)	537.277
Hoelter's critical N (α = .01)	644.864

Residual variances details are presented in Table 67 that follows.

Table 67: Residual variances for headway – Portuguese bus drivers – experiment Phase 2

Variable	Estimate	Std. Error	z-value	P(>|z|)
duration	0.072	0.003	21.397	< .001
distance	-0.062	0.004	-16.198	< .001
GPS_spd	0.998	0.005	199.992	< .001
DrivingEvents_Map_evt_ha_mean	1.000	0.005	199.917	< .001
DrivingEvents_Map_evt_hb_mean	1.000	0.005	199.907	< .001
iDreams_Headway_Map_level_0_mean	1.005	0.007	151.512	< .001
iDreams_Headway_Map_level_1_mean	1.002	0.005	187.674	< .001

Variable	Estimate	Std. Error	z-value	P(>|z|)
iDreams_Headway_Map_level_2_mean	1.001	0.005	197.326	< .001

The results for phase 3 are shown in Figure 31 below.

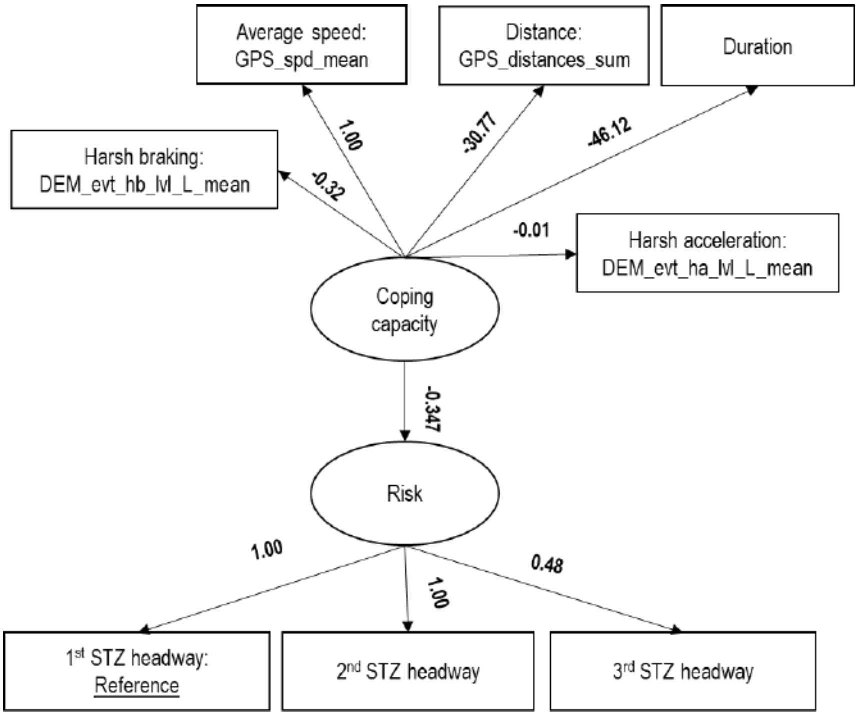

Figure 31: Results of SEM on Risk (Headway STZ) – Portuguese bus drivers – experiment Phase 3

The Comparative Fit Index (CFI) of the model is equal 0.987; TLI is 0.982 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.052. Table 68 summarizes the model fit of SEM applied for headway.

Table 68: Model Fit Summary for headway – Portuguese bus drivers – experiment Phase 3

Model Fit measures	Value
AIC	$1.511{\times}10^{+6}$
BIC	$1.511{\times}10^{+6}$
CFI	0.987
TLI	0.982
RMSEA	0.052
GFI	0.988
Hoelter's critical N (α = .05)	587.905
Hoelter's critical N (α = .01)	705.649

Residual variances details are presented in Table 69 that follows.

Table 69: Residual variances for headway – Portuguese bus drivers – experiment Phase 3

Variable	Estimate	Std. Error	z-value	P(>|z|)
GPS_spd	0.999	0.005	200.541	< .001
distance	0.340	0.033	10.414	< .001

Variable	Estimate	Std. Error	z-value	P(>|z|)
duration	-0.484	0.073	-6.608	< .001
DrivingEvents_Map_evt_hb_mean	1.000	0.005	200.512	< .001
DrivingEvents_Map_evt_ha_mean	1.000	0.005	200.524	< .001
iDreams_Headway_Map_level_0_mean	1.014	0.007	155.880	< .001
iDreams_Headway_Map_level_1_mean	1.014	0.006	156.199	< .001
iDreams_Headway_Map_level_2_mean	1.003	0.005	191.771	< .001

The results for phase 4 are shown in Figure 32 below.

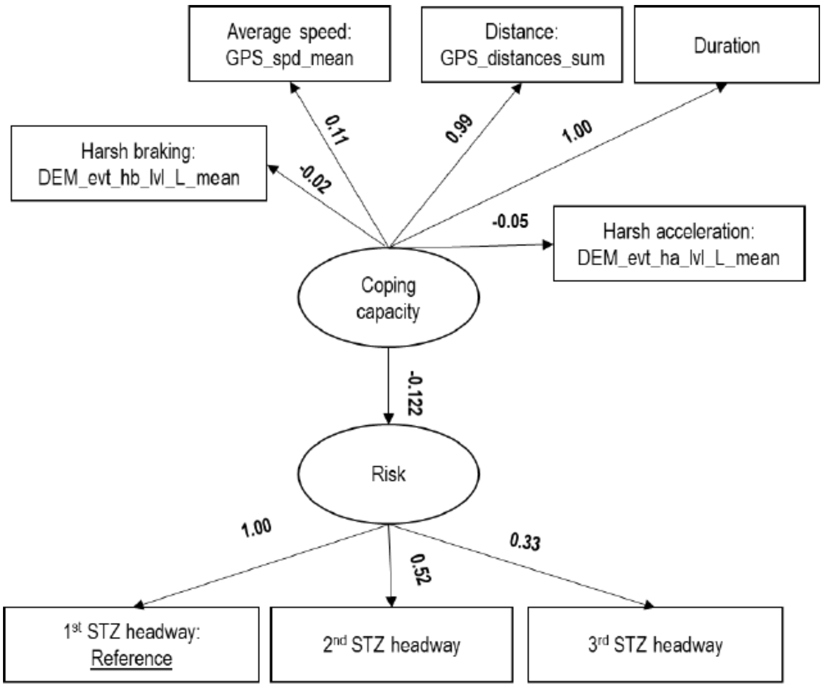

Figure 32: Results of SEM on Risk (Headway STZ) – Portuguese bus drivers – experiment Phase 4

The Comparative Fit Index (CFI) of the model is equal 0.969; TLI is 0.954 and the Root-Mean-Square-Error Approximation (RMSEA) is 0.053. Table 70 summarizes the model fit of SEM applied for headway.

Table 70: Model Fit Summary for headway – Portuguese bus drivers – experiment Phase 4

Model Fit measures	Value
AIC	$1.405\times10^{+6}$
BIC	$1.406\times10^{+6}$
CFI	0.969
TLI	0.954
RMSEA	0.053
GFI	0.987
Hoelter's critical N (α = .05)	564.877
Hoelter's critical N (α = .01)	678.001

Residual variances details are presented in Table 71 that follows.

Table 71: Residual variances for headway – Portuguese bus drivers – experiment Phase 4

Variable	Estimate	Std. Error	z-value	P(>|z|)
duration	0.096	0.009	10.372	< .001
distance	0.110	0.009	12.105	< .001
GPS_spd	0.989	0.005	182.651	< .001
DrivingEvents_Map_evt_ha_mean	0.998	0.005	182.741	< .001
DrivingEvents_Map_evt_hb_mean	1.000	0.005	182.761	< .001
iDreams_Headway_Map_level_0_mean	1.060	0.010	109.098	< .001
iDreams_Headway_Map_level_1_mean	1.016	0.006	168.538	< .001
iDreams_Headway_Map_level_2_mean	1.007	0.006	177.590	< .001

5 Conclusions

The current deliverable aimed to provide the analysis results for the coping capacity factors, both for the vehicle as well as the operator state and the effect these have on risk. This aim was pursued by:
(i) identifying the most critical factors of coping capacity,
(ii) developing GLM and SEM models on the effect of 'vehicle state' and 'operator state' on the STZ level as well as
(iii) comparing the differences between different countries and modes.

For that reason, the vast library of data from the naturalistic driving experiment was harvested in the four countries with the majority of data and GLM and SEM models were applied for the most prominent driving behavior indicators, such as speeding, headway and harsh events (i.e. harsh acceleration and harsh braking). For 'operator state' it was demonstrated that age, confidence of a driver in his/her skills, as well as a sport driving style were the strongest indicators influencing driving behavior, while vehicle age. fuel type and gearbox were the corresponding ones for 'vehicle state'.

When looking into the loadings of the SEM models, mixed results were reported. For instance, in Belgian cars a counter-intuitive positive correlation of coping capacity with risk was found, whereas in UK cars, German cars, Greek cars, Portuguese buses and Belgian trucks the expected result of a negative correlation of coping capacity with risk was validated. This inconclusiveness of results was probably due to the lack of objective coping capacity indicators utilized in the experimental study and their availability in the back-end database at the end of the experiments. Nevertheless, there was a consistency between the effect of coping capacity throughout the phases, with an increase of coping capacity's effect when looking the evolution from phase 1 to phase 4 of the experiment in most of the models.

However, due to the volume and diversity of the data included in each of the analyses, it was not possible to fit an overall 'coping capacity against risk' model for a specific mode, despite extensive efforts from partners to clean and homogenize the data. Nevertheless, ongoing trials may provide more data that could help address these limitations and produce more conclusive results.

The effect of coping capacity on risk per indicator/phase/country/transport mode according to the models developed can be found in the following Table 72. The positive sign is translated to a positive correlation of coping capacity with risk while the negative sign indicates a negative relationship between the coping capacity and the risk. In other words, in the case of the positive relationship, an increase in coping capacity would be translated to an increase in risk while in the case of the negative correlation an increase in coping capacity leads to a decrease in risk.

Table 72: Effect of coping capacity on risk per indicator/ phase/country/transport mode

		Coping capacity			
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)	harsh braking	-	-	-	-
Greece (cars)	speeding	-		-	-
Portugal (buses)	headway	-	-	-	-

The volume, noise and diversity of the data collected in the different countries led to different variables being investigated or being found statistically significant in different countries and the inability of fitting an overall model for a specific mode, despite extensive efforts for data cleaning and homogenization. Since at the time of writing of this deliverable some trials were still running, it is envisioned that the inclusion of more data into the models will shed more light and will produce even more explainable models in the future.

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Annex 1: Descriptive statistics for the available parameters

Belgium (Cars)

Table 73: 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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
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
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		

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
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	
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	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
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		
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	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	Description
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		
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		

Belgium (Trucks)

Table 74: 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

Variables	Min	Mean	Median	Std. Deviation	Max
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
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

UK (Cars)

Table 75: 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

Variables	Min	Mean	Std. Deviation	Max	1st quartile	2nd quartile	3rd quartile
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
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

Variables	Min	Mean	Std. Deviation	Max	1st quartile	2nd quartile	3rd quartile
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
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

Variables	Min	Mean	Std. Deviation	Max	1st quartile	2nd quartile	3rd quartile
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
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

Germany (Cars)

Table 76: 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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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	1.709	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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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)						
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Greece (Cars)

Table 77: 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	
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	
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	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
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	
Gender	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	
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
				Phase 5				
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	
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	
Gender	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	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
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
STC_Gearbox	1.0	1.0	1.0	1.3	2.0	2.0	NA	1:Manual, 2: Automatic
Phase 4								
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	
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	

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max	NAs	Description
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	
Gender	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
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

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

Portugal (Buses)

Table 78: 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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

Variables	Min	1st quartile	Median	Mean	3rd quartile	Max
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
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

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	250.80	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