DaCoTA

Road Safety Data, Collection, Transfer and Analysis

Deliverable 6.2 part A.

Study design of Naturalistic Driving observations within ERSO – Development of innovative indicators for exposure and safety performance measures

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EXECUTIVE SUMMARY

The objective of the Task 6.2 of DaCoTA is to specify the study design of naturalistic driving study in the perspective of the European Road Safety Observatory. More precisely, the task deals with three main issues: 1) the experimental design, 2) the procedures to Risk Exposure Data (RED) and Safety Performance Indicators (SPI) estimation, 3) legal, ethical and privacy requirements.

The Deliverable 6.2.A "Study design of Naturalistic Driving observations within ERSO – Development of innovative indicators for exposure and safety performance measures" aims to provide operational guidelines and recommendations that can be used to take maximum advantage of naturalistic driving data to observe road safety related phenomenon.

General design constraints are discussed. The design of new RED and SPI using Naturalistic Driving Data (NDD) has to be done by bringing added value to existing RED/SPI that can be obtained by classical investigation means (observation from the side of the road, surveys…). The design must also take into account the link between the data collection solution and the data available for the indicator computation as this has an important impact on the possible RED and SPI that can be measured.

Key principles about the possibilities of data aggregation (to present results at different levels), data filtering (to obtain homogenous driving conditions) and data clustering (to compare different conditions) are presented. The question of the accuracy of the results is also addressed. Some recommendations and best practices are given in order to establish some reference definitions of the key elements that may impact the RED/SPI results: obtaining homogeneous driving data in term of driving situation, aggregation using "trips", comparisons according to "night" and "day" conditions or "good" and "bad" weather conditions, systematic calculation of the "sub sample characteristics" to assess the amount of data used for the indicator computation…

Concerning the RED, authors propose a list of innovative RED and point out the limitations of the NDD that should be taken into account when interpreting the RED results. An accurate description of the process to compute the RED is proposed.

Concerning the SPI, authors propose a distinction of 3 kind of SPI: behavioural SPI, descriptive SPI and situational SPI. They also propose a list of innovative SPI and point out the limitations of the NDD that should be taken into account when interpreting the SPI results. An accurate description of the process to compute the SPI is proposed.

The aim of the RED/SPI description chapters is to gather all required information so that this part can be used as a practical handbook for SPI/RED development in the frame of ERSO. However, the aim of the RED/SPI description chapters was not to give the description of all possible calculations that could be made using NDD. Authors focused on a set of RED/SPI that they considered as the most relevant. Using the best practices and recommendation, it makes it possible to compute new SPI and RED that have not been described in detail.

The question of the driver sample of driver to monitor is also addressed. This aspect is discussed more in detail in deliverable 6.2.B which proposes an extensive discussion of the sampling methods and impact on the results. Some recommendations are given to help with the relevant criteria for the recruitment of the participants.

Finally, the key information concerning the legal and ethical issues is given, as it has to be taken into account, both at global and local level, when implementing the NDS.

1. CONTEXT AND OBJECTIVES

1.1. WP 6 Objectives

The aim of the WP6 of DaCoTA is to study the added value of Naturalistic Driving Studies (NDS) for collecting Road Safety data within the framework of the European Road Safety Observatory (ERSO).

Naturalistic driving studies involve the observation in naturalistic settings of a sample of drivers. The vehicle of each driver is instrumented in order to record during his/her everyday mobility, information on his/her behaviour, vehicle position and dynamics and driving context. So NDS design forces a focus on the individual mobility of a set of drivers at the wheel of specifically equipped vehicles. In balance, NDS provides the opportunity to have access to a continuous data stream describing the kilometre driven and the evolution of the driving context (which can be described in terms of road type, period of the day, period of the week, period of the year, weather conditions, presence or not of passengers…) and also describing the drivers behaviour (use of seat belt, use of light…) and vehicle dynamics (vehicle speed, acceleration …)

Compared to other Naturalistic Driving initiatives, the originality of Naturalistic Driving Observation within ERSO is the continuity of data gathering over the time, the scale by involving all European countries, both representativity and comparability of data across countries and the focus on risk exposure data (RED) and safety performance indicators (SPI). Indeed, the aim of DaCoTA WP6 is to give recommendation for a continuous monitoring exercise that involves a large number of vehicles to be instrumented in many European countries over a long period of time (i.e. continuous data collection during several years rather than just for a few months like in a traditional study). It is also important to notice that the scope of the work is limited drivers of passenger cars.

At a practical level, WP6 will develop an implementation plan including methodology, technology, feasibility aspects for continuous monitoring of relevant road safety data.

To reach this objective, WP6 involves 4 tasks, each building upon each other and culminating in an implementation plan for naturalistic driving research within ERSO (Figure 1).

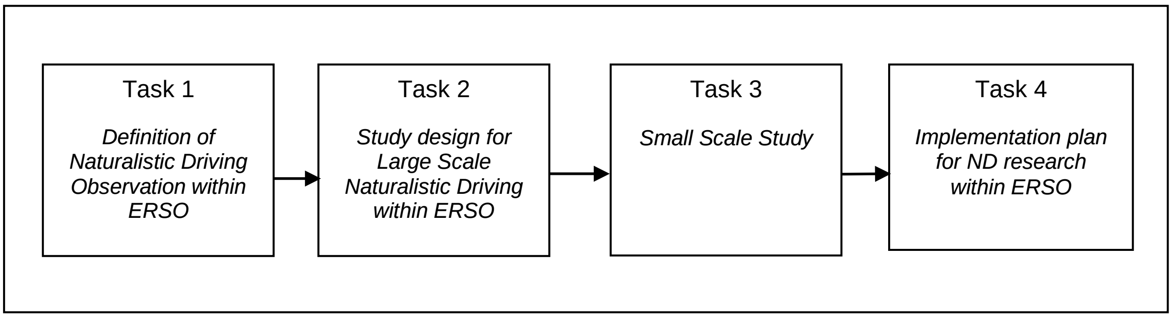


Figure 1 DaCoTA WP6 tasks

Task 6.1 of DaCoTA has identified two scenarios for the NDS according to the level of sophistication of the Data Acquisition system and for each of them has listed the target RED and SPI. Following this work, the objective of the task 6.2 is to specify the study design of naturalistic driving study in the perspective of the ERSO. More precisely, the task deals with three main issues: 1) the experimental design, 2) the procedures for RED and SPI estimation, 3) legal, ethical and privacy requirements.

Previous studies have been done to optimise the methodology to conduct Naturalistic Driving Studies. FESTA handbook describes the process to conduct a Field Operational Test (FOTs), a large-scale testing programme aiming at a comprehensive assessment of the efficiency, quality, robustness and acceptance of an in-vehicle technology. This approach is made of several steps: select research questions, define research hypothesis and specify a set of performance indicators that can be computed to validate the hypotheses, along with the data requirements, then make the computation and validate or invalidate the hypothesis (i.e. a sort of top-down approach). This approach has been used by most of the European projects performing FOT in the scope of the FP7. However, this approach cannot be used in the scope of DaCoTA. The objective of the work is rather to focus on the data that can be collected and to design what is relevant to be computed as safety indicators (i.e. a sort of bottom-up approach).

1.2. Objective of the document

This aim of the document is to propose accurate guidelines for the design of a “naturalistic driving study” to investigate road safety, in the perspective of the European Road Safety Observatory. It covers 3 dimensions:

- The experimental design. The definition of the sample size and characteristic will have a strong impact both on the operational recruitment of the drivers and on the possibilities to exploit the final SPI and RED results and their accuracies.
- The procedures to RED and SPI estimation. The definition of the calculation and requirements in terms of raw data / filtering / clustering will strongly constraint the data collection and the technical backend that will be necessary for the exploitation of the vehicle data.
- The legal, ethical and privacy requirements. It is important to make sure at all time during the preparation of the study that the designed solutions are compatible with the local regulations which can add additional constraints.

However, this guide does not aim to solve all the issues and give all the answers about what should be done in each country. The objective is rather to highlight all the aspects that should be taken into account and to give propositions about how to tackle the associated issues.

Regarding Risk Exposure Data, the objective is to propose a way to describe the mobility of drivers through a detailed analysis of driving data and trips. In addition to aggregated measures of driver and vehicle mobility, a detailed logbook presenting the full description of trip duration, trip length, trip timing, speed, presence of passengers and drivers' identification permit to explore several possibilities of data exploitation.

Regarding Safety Performance Indicators, the objective is to build on the work that was already done in SafetyNET and to propose new SPI specific to naturalistic driving data. Three 3 kinds of SPI will be distinguished: the behavioural SPI, the descriptive SPI and the situational SPI. Behavioural SPI refers to SPI that describe drivers’ behaviour toward a specific safety issue and permit the identification of some of its determinants. Descriptive SPI refers to SPI that quantify the occurrence of a phenomenon and can be useful to assess if a safety policy is followed or not. Situational SPI refers to SPI that describe driver behaviour in very specific situation which are relevant in term of road safety issues. They require a very accurate assessment of the driving situation and current manoeuvre in order to be relevant.

Data on crashes or near crashes is currently not collected directly. However, in this WP, data about the dynamics of the vehicle will be considered as a source of information for the future, when knowledge on this matter will permit to define accurately the link between extreme events (such as: very strong brakes, safety systems use (ABS, ESC)) and near crashes or accidents.

1.3. Contents of the document

This document is divided in 7 chapters. In order to give the reader a good overview of the document contents, these chapters are detailed below.

In the first chapter, "context and objectives", the organisation of the work in DaCoTA project is presented in order to provide the reader with enough information on the context in which the innovative RED and SPI were developed.

Chapter two, "Targeted RED and SPI to monitor by the ERSO through NDS", lists and explains the major design decisions that have been made by the consortium in term of data collection, data exploitation and scope. It also proposes a synthesis of the specific design decisions made for the development of the RED and SPI and the key rules that should be observed. At this level, we have defined 3 kinds of SPI: the behavioural, descriptive and situational ones.

Chapter three, "Experimental Design", discuss the sampling and estimation methods that can be used to obtain population values of RED and SPI items based on naturalistic driving study designs and give some recommendation for the selection of a sample.

Chapter four, "Indicators for risk exposure measures from naturalistic driving data", presents the general approach to obtain RED from naturalistic driving data. First, it gives a detailed overview of the measure requirements, data filtering needs, information clustering possibilities and aggregation at country level processes. Then, it instantiates these principles by giving a detailed description of five possible RED that can be computed using naturalistic driving data. We have defined 5 RED: vehicle kilometre, driver kilometre, driver time in traffic, trip number, trip characteristics.

Chapter five, "Indicators for safety performance measures from naturalistic driving data", presents the general approach to obtain SPI from naturalistic driving data. First, it gives a detailed overview of the measure requirements, data filtering needs, information clustering possibilities and aggregation at country level processes. Then, it instantiates these principles by giving a detailed description of six possible families of SPI which each contains from 2 to 6 SPI. In total, this chapter gives the full details of 22 SPI that can be computed using naturalistic driving data. The six families of SPI are the following ones: Excessive speed, Seat belt use, Daytime running light use, Short headway, Strong deceleration, Safety systems use.

Chapter six, "Legal and ethical issues", discuss the background work that have to be undertaken when implementing a naturalistic driving study, as several external juridical constraints have to be considered in order to make sure that the study complies with all local rules.

Chapter seven, "Conclusion", gives some final word with the authors' point of view about naturalistic driving studies RED & SPI.

The chapters four and five have been designed to be used a handbook for SPI and RED development. Therefore, they give a very accurate presentation of each RED/SPI. These chapters have been optimised to permit the reader to access directly and individually to each RED/SPI description. The sequential reading of all

RED/SPI might be repetitive as contents have been duplicated when necessary to make each RED/SPI paragraph as standalone as possible.

2. RED/SPI TO MONITOR BY ERSO THROUGH NDS: GENERAL DESIGN CONSTRAINTS AND RECOMMANDATIONS

2.1. General design approach

The objective of the general design of NDS within ERSO is to find the best complementarity between the classical methods of RED and SPI estimation (as defined in SafetyNet) and the potential new one.

When using naturalistic driving data, it is harder to control the data collection as driver can drive on any kind of road, in any kind of traffic, whatever the weather. This makes it crucial to be able to identify all the variables that might have an impact on the SPI & RED, in order to compute meaningful SPI & RED with a proper filtering and aggregation of meaningful indicators.

Another difficulty comes from the fact that the indicators have to be relevant for both national and ERSO levels. It is crucial to guarantee the validity of the collected data and determine, for each country, how representative of the country they are and how they can be compared with the other countries. It is also important to define the accuracy of the RED and SPI and to provide a confidence interval for each of them.

2.2. Data collection design

Two solutions have been identified for the data collection

1. Scenario 1 = a low cost data acquisition system including a GPS logger, a geographic information system for map matching and obtain road types and legal speed limits, accelerometers, robust identification of the driver

2. Scenario 2 = improvement of Scenario 1, with additional sensors or capability (CAN data), but video is not considered as part of scenario 2

If scenario 1 is more likely to be implemented in a large scale naturalistic driving study, as it presents less technical complexity and seems more cost effective, the associated limitation of the collected data has a strong impact on the possible SPI and RED that can be computed: only a small number of SPI can be computed without access to additional sensors or CAN data. Chapter 2.4 and 2.5 gives the details about the exact possibilities.

Authors are fully aware that, at the time being, the availability of CAN data puts severe constraints on cars that can be included in the study and it requires to obtain the description of CAN data for a large number of vehicles brands and models for the study to be performed all over Europe. Furthermore, by focusing the study on a small set of brands and models of vehicles, the representativeness of the sample would be influenced (e.g. if only CAN data from high-end vehicles are available, only high-end vehicles would be included in the study, which would bias the results).

In order not to restrict the possibilities offered by naturalistic driving data to design RED and SPI, we favored the most favorable hypothesis: scenario 2. We assumed that in the context of a large scale naturalistic driving study piloted by ERSO to measure road safety indicators, car manufacturers would agree more easily to give information about the CAN data required for the RED/SPI we proposed. As scenario 2 is favored, it is possible that, for some specific SPI, the raw data or data required for data filtering and clustering might not be available when considering scenario 1. If one aims to develop the RED and SPI presented in this document, it will be necessary to evaluate in detail the adequacy between the data collection solution (which will determine the data that are available) and the calculation requirements. These technical issues will have to be solved on a case by case basis as there is no reference standard for CAN data or for data acquisition systems.

Video has not been retained as part of the scenarios as it seems unlikely, on a practical point of view, that it can be used in a large scale naturalistic driving study. It requires far more additional hard disk space to store, huge volume to transfer and great computing power to process or man-months to watch. Thus, as video is not part of any of the scenario, it is not possible to use video to verify specific events that could be detected automatically in the data. It is know from the literature that using triggers to detect near misses and near crashes automatically requires video verification as there might be more than 80% of false positive [Dingus et al., 2006].

However, in the scope of ERSO, it appears interesting to provide data that can be used for automatic trigger detection (acceleration, speed...). Once research on this topic is advanced enough to assess correctly near misses and near crashes, it will be directly possible to use these data.

Concerning the robust identification of the driver, the definition of a technical solution for this purpose is not in the scope of this report. Specific investigations in the field of biometrics (e.g. identification of the face of the driver by a camera, identification of the finger print via a specific device…) or in the field of RFID systems (special tag on the driver key ring to identify the person that ignites the car…) could be undertaken.

The following chapters of the document will take these design choices into consideration when detailing the process to obtain the SPI.

2.3. Data exploitation design

Two solutions have been identified for the RED and SPI processing within the frame of ERSO. The steering committee of DaCoTA project has been asked to choose between the 2 solutions identified:

1. Solution 1: Each country is in charge of the calculation of their respective RED and SPI indicators, only the indicators necessary for the ERSO are shared.

2. Solution 2: Setting-up of a joint database shared by all members of the ERSO, the calculation of RED and SPI indicators is made at the central level.

For practical reasons, the first option was favoured. Indeed, it seems to be easier to protect the privacy of participants and to take into account local specificities (sample characteristics, other county level characteristics...) if the data are processed at the country level.

The following of the document will take this design choice into consideration when detailing the process to obtain the SPI.

2.4. Scenario 1: Targeted RED and SPI to monitor

Target RED, at country level and European level:

- Vehicle Kilometre

- Driver Kilometre
- Driver Time in traffic
- Trip Number
- Trips Characteristics

Target SPI, at country level and European level:

- Excessive Speed
- Strong deceleration

2.5. Scenario 2: Targeted RED and SPI to monitor

Target RED, at country level and European level:

- Vehicle Kilometre (same as scenario 1)
- Driver Kilometre (same as scenario 1)
- Driver Time in traffic (same as scenario 1)
- Trip Number (same as scenario 1)
- Trips Characteristics (same as scenario 1)

Target SPI, at country level and European level:

- Excessive Speed (same as scenario 1)
- Strong deceleration (same as scenario 1)
- Seat belt use
- Daytime running light use
- Short headway
- Safety Systems use
- Inappropriate speed
- Lane behaviour
- Turning indicators use

2.6. About near misses

As it has already been explained earlier in the document, near-misses will not be studied as such in the scope of DaCoTA. Data on crashes or near crashes is currently not collected directly. However, in this WP, data about the dynamics of the vehicle will be considered as a source of information for the future, when knowledge on this matter will permit the accurate definition of the link between as extreme events (such as: very strong brakes, safety systems use (ABS, ESC)) and near crashes or accidents.

2.7. Key concepts

While studying the specificities of naturalistic driving data (NDD) in order to develop new indicators for exposure and safety performance measures, authors discovered interesting and promising possibilities but also a few limits linked to the nature of naturalistic driving data. These findings have been synthesised in this chapter and are presented in 2 different categories: a set of new concepts proposed by the authors, a set of “best practices” that should be observed in order to cope with the limits of naturalistic driving data and associated recommendations.

In the following of the document, these principles will be discussed more in detail in the scope of each proposed RED/SPI. For each studied unsafe behaviour, we propose SPI that we assume bringing the highest added value to existing classical SPI, both at country level and at ERSO level. While authors are fully aware that it is possible to create other SPI than the ones proposed in this deliverable, authors strongly recommend to follow these principles as they should guarantee the relevance of the newly designed SPI.

2.7.1. New concepts when developing RED/SPI from NDD

While designing Safety Performance Indicators that could be obtained using naturalistic driving data, authors highlighted different observations that should be kept in mind while reading the following chapters of the document.

- It is possible to build “**Behavioural SPI**”, “**descriptive SPI**” and “**situational SPI**”.
    - Behavioural SPI refers to SPI that describe drivers’ behaviour toward a specific safety issue and permit the identification of some of its determinants (for example, behaviour in terms of speeding when traffic is light according to the road types or behaviour in terms of seat belt use according to the length of the trip)
    - Descriptive SPI refers to SPI that quantify the occurrence of a phenomenon and can be useful to assess if a safety policy is followed or not, but lack the possibility to understand the causes (for example, time spent driving over the speed limit or time spent without seat belt)
    - Situational SPI refers to SPI that describe driver behaviour in very specific situation which are relevant in term of road safety issues. They require a very accurate assessment of the driving situation and current manoeuvre in order to be relevant (for example, adequate use of turning indicator when overtaking other vehicles).
    - The three families are complementary. The SPI of these categories sometimes differ only from a filtering or a clustering perspective.
- The final accuracy of a RED/SPI is strongly linked to the time window chosen for the computation but also to the filtering and the clustering methods applied. As such, it is important to be able to give the information on the final data set used for the RED/SPI calculation: authors recommend that alongside each RED/SPI value, a second value should be given to indicate the amount of data included in the calculation. Authors propose to name this second value the **“Sub sample characteristics**”, or RED/SPI SSC, as it characterises the volume of information of the subset of naturalistic data. The sub sample characteristics may be different depending on the level of the calculation :
    - At the participant level, each RED/SPI should be given with its SPI Sub Sample Characteristics that gives the volume of data included in the calculation, expressed in minutes. For example, when selecting

the time window (for example, during the month of March or during year 2011…), when adding a filter (for example, only during peak hours…) and a specific clustering (for example, to compare motorway situation from urban situations…), with the objective to compute the following SPI : "percentage of time spent above the speed limit during the month of March, in peak hours, on motorway", the SPI results could be 15% of time and the SPI SCC could be 5 minutes, which permit to highlight how much data are included for the calculation with the criteria "month of March", "during peak hours" and "on motorway".

  - At the country level, when aggregating data from all the participants, the individual participant SSC should be carefully studied to determine if it is relevant or not to use the data of a participant for the country aggregation (for example, is it relevant to include a driver that only spent 1 minute in peak hours, on highway, during the month of March, to produce speed related SPI?). Once aggregated at country level, the country SPI should also be associated with a sub sample characteristic that describes the number of participant finally used for the calculation, and the sum of their total driving time.

2.7.2. Best practices when developing RED/SPI from NDD

2.7.2.1. General rules to observe

While designing Safety Performance Indicators that could be obtained using naturalistic driving data, authors highlighted different limitations that should be kept in mind while reading the following chapters of the document.

- The data sources relevance, accuracy and availability have to be investigated in detail and taken into consideration for the SPI interpretation
  - Data might be different according to the country, especially when using data coming from a Geographic Information System (GIS) (for example, the meaning of "urban" or "motorway" or the availability of legal speed limit…) or any third party database.
  - The measurement might be different if collected through a sensor or through the CAN bus (for example, vehicle speed…)
  - When comparing countries, it is critical to make sure that comparisons are done with similar base data.
- For the sake of homogeneity, it might be necessary to apply very selective filters that guarantee that the data that remains is homogeneous enough to observe the expected phenomenon. Thanks to the nature of naturalistic driving data and the volume of data that can be expected, even if the filters are selective, there should be enough raw materials to perform meaningful computations, which should still be verified. This has been used in two contexts in the document
  - When trying to obtain homogenous situations in term of traffic density. The filters consist in removing all the data collected during daily peak hours, which are more prone to traffic jams. The filter windows can be defined as 7h30-9h30 and 16h00-19h00.
  - When trying to obtain homogeneous "actually driving" driving situations. The filters consist in removing all the data collected with a vehicle speed below 5 km/h to exclude when the driver is stopped.

2.7.2.2. Trip definition

Some calculations of RED or SPI will need to consider the concept of trips. In the case of naturalistic driving observations with a continuous recording of driving, a trip consists usually in a data collection period, which starts when the data acquisition system (DAS) starts the data collection and finish when the DAS concludes the collection. According to the DAS technology, the events that turn on and turn of the DAS, and the delay taken by the DAS to start the collection can be very different. We propose to disregard the DAS technology and to consider that a trip starts once the ignition is engaged and finishes when the ignition is disengaged.

This can seem an obvious solution but it is not. Every definition has its shortcomings. Sometimes, for various reasons, drivers stop but let the engine run. The question is whether each stop defines another trip or not. If it does, the situation of traffic jam will be very tricky to be coded with a lot of very short trips! If it doesn't, (our choice), on one hand, one trip can aggregate several trips with different aims (drop or get someone before beginning another trip). On the other hand, if a driver decides to make a break during his trip, for example to take a coffee or put gas in his car, the trip will be segmented in two different trips. This trip definition could also lead to erroneous trip ends in case of engines switched off while waiting for a queue to dissolve or for a light to turn green, or the engine stalls. These issues can be addressed by joining two successive trips if the delay between the end of the former and the beginning of the latter is short [Wolf et al., 2004].

2.7.2.3. Definition of day time and night time

Some calculations of RED or SPI propose to compare day time and night time results. This concept is linked to the lighting conditions and aims to differentiate situations in daylight and night. As day light periods varies during the year and also according to the latitude, a specific approach has to be considered to obtain comparable and relevant "day" and "night" conditions for all the countries.

Two solutions are possible: the first consists in using a predetermined hour range; the second consists in using a floating hour range computed according to the time and position of the observation.

In the first solution, if one wants to define a day light period valid whatever the month and the place in the European countries, he has to define a very short period, for example from 9:30 to 16:30 in order to make sure that lighting conditions are homogeneous and stable. Following the same reasoning, night period can be defined from 23:30 to 06:00. However, this approach requires filtering out a very big amount of data, including data that would have been relevant (and in the commuting hours), but can also include, in some cases, irrelevant information.

The second solution would be to use an algorithm giving for each latitude, longitude and day of the year, the time of sunrise and the time of sunset, and to compute the day light period [United States Naval Observatory, 1990]. Following this reasoning, "day" can be defined from sunrise plus 1 hour to sunset minus 1 hour and "night" can be defined from sunset plus 1 hour to sunrise minus 1 hour. The periods close to sunset and sunrise are "twilight" periods and can be considered as unsteady in regards of lightning conditions as the luminosity changes very quickly: they should not be used for the analysis.

The authors propose to use the second solution, which is more accurate and permit to know, for each measure, if it occurs during the day or the night. This approach has been used successfully during EuroFOT project to study driver behaviour during daylight periods [Sanchez, 2012].

If the "daylight" processing is done at the country level, it will be important to make sure that each country shares the same table and algorithms so that results can be efficiently compared.

2.7.2.4. Definition of weather conditions

Some calculations of RED or SPI propose to filter out data collected during bad weather condition, for the sake of homogeneity.

Two solutions are possible: the first consists in using the sensors available in the vehicle (like the screen wipers activation, or the luminosity sensor used for automatic light activation…); the second consists in accessing a third party database, giving weather information each various location.

In the first solution, this information can be directly collected by the data acquisition system using the vehicle computer. However, numerous false positive or wrong detections could be measured. Indeed, it is possible that drivers could choose to use the wipers even though the weather conditions are very good (for example in order to clean the wind shield, or turn on the fog lights even if there is no need…) or it is possible that the weather conditions are bad, but the sensors are not relevant to detect it (for example, when there is a lot of snow on the road…).

In the second solution, the infrastructure to get the information is more complex as it will have to provide, during a post processing stage, for a given timestamp and a given position, a weather report of the surrounding area. This infrastructure can be provided by a commercial or free to use weather data provider available via the Internet. However, the updating frequency and the density of the weather forecast will have a direct impact on the accuracy of the available information, as sometimes, weather phenomenon, like rain, can be localised in a very narrow window both in terms of time and space. Using this source of information will only be satisfying to obtain a general weather profile in the geographical area of the vehicle and add a post processing step to the RED/SPI computation.

If the first solution is more realistic and easy to implement, and therefore more suitable for a cost constrained naturalistic driving observation, the authors propose to investigate the combination of the two approaches in order to take advantage of the benefits of each one and to increase the accuracy of the weather information. The general principle would be to use the GPS data collected on the vehicle to access, during a post processing stage, a weather forecast database in order to obtain the general weather in the vehicle vicinity. Then, during this post processing step, the data collected on the vehicle will have to be analysed and the sensors giving information about the weather conditions will be used to confirm the weather report from the database (for example, assuming that the vehicle drives in Paris, the weather database can indicate that there is a 90% probability of raining in the vicinity of Paris, but if the screen wipers are not active, then the weather algorithm will give a “about to rain/cloudy” condition). Combining the 2 sources makes it possible to build a very detailed topology of weather conditions, more interesting that the solution 1 which is too binary: raining vs. not raining.

The correct implementation of the weather algorithm should be done carefully in each country, taking into account the fact that it is important to make sure that each country can access to the same description and accuracy of weather conditions so that results can be efficiently compared. Then, the availability of the sensors on the vehicles should be investigated. The final weather classification will be strongly dependant of these technical possibilities.

For this deliverable, we propose to focus on only 2 classes: “good” weather, which is when the weather report is set to “sunny” or “cloudy” and the sensors show no use of “weather related” equipments and “bad” weather, which include all other possible weather reports (for example, like rain, snow, fog…) or when sensors show use of “weather related” equipments.

3. EXPERIMENTAL DESIGN

In this section we discuss what sampling and estimation methods can be used to obtain population values of RED and SPI items based on naturalistic driving study designs. Since it is impossible to study all car drivers of a country, a sample must be drawn.

In order to decide what sampling and estimation method is most appropriate, we first of all have to consider the type of sampling frame(s), i.e., the source(s) from which a sample is drawn, that are available in a country.

When this sampling frame contains information on all passenger car drivers in a country, then a simple random sample or a systematic sample may be considered, see Commandeur (2012). A random sample means that all car drivers in a country have an equal chance to find themselves in the sample.

When it is possible to define subgroups of car drivers that can be expected to be more homogeneous with respect to the RED and SPI variables, then stratified random sampling is recommended. A stratified sample means that the car driver population is first divided into mutually exclusive and homogeneous subgroups or strata; subsequently within each subgroup or stratum a random sample is drawn. This may help to increase the precision of the estimates of a variable for the total car driver population. This is important because more precise population estimates generally require smaller sample sizes.

For example, for RED and SPI items it is known that there are structural differences between men and women, between different age groups, and between drivers of a diesel or a petrol car, and it therefore makes sense to use stratified random sampling based on these subgroups of the total car driver population.

If the individual values of an additional variable that is highly correlated with the RED/SPI variable of interest are known for all car drivers in the sample, then precision can be further increased by replacing the direct estimator with a ratio or regression estimator, see Commandeur (2012). However, this usually requires knowledge of the sum total of the additional variable in the population. Should the individual values of such an additional variable also be known for all car drivers in the population, then the selection procedure with unequal probabilities discussed in Commandeur (2012) can be considered as a useful improvement.

When the sampling frame happens to be decentralised (e.g., municipal), on the other hand, then the two-stage sampling methods presented in Commandeur (2012) can be used, see also the two-stage method of Rofique, Humphrey, Pickering, and Tipping (2010) discussed below.

Even when the sampling frame contains information on all car drivers in a country, however, both stratified and multi-stage sampling methods can still be used.

For all these sampling strategies, it is possible to determine the optimal sample size, i.e., to answer the question how many car drivers need to be in the sample to get a reliable estimate of the actual situation of the RED or SPI at hand. The optimal sample size always depends on three factors:

- The amount of homogeneity/dispersion of the RED/SPI in the population;
- The required precision level of the estimate;
- The required probability of obtaining this required precision level.

The practical implication of the chosen precision level is that only changes between two consecutive time points or periods larger than twice this precision level will be detected with the corresponding sample size. If a precision level of ±5% is chosen for the estimation of the total number of kilometres driven by cars in a country, for example, then changes equal to or smaller than 10% in the total number of kilometres driven will go undetected. When a precision level of ±1% is chosen, on the other hand, then only changes equal to or smaller than 2% in the total number of kilometres driven will go undetected.

As an illustration consider a population of car drivers who on average drive 15,000 kilometres a year. Using a probablility of 95%, the minimal sample sizes required in a simple random sampling scheme in order to estimate the total annual mileage of cars with precision levels of ±10%, ±5%, and ±1%, and population standard deviations of SD = 5,000 kms, SD = 10,000 kms, and SD = 15,000 kms are given in the last row of Table 1. As the table indicates, sample size increases both when the required precision of the estimate increases, and when the standard deviation of the variable of interest in the population is larger. From Table 1 it can be concluded, for example, that:

- With a population standard deviation (SD) of 10,000 kms and a sample of around 700 car drivers, differences in the actual annual mileage up to 10% (plus or minus 5%) will remain undetected.
- With a population standard deviation (SD) of 10,000 kms, and a sample of around 17,000 car drivers only differences up to 2% will remain undetected.
- If, however, the population standard deviation (SD) is 15,000, a sample of over 38,000 car drivers would be needed to reach this level of precision of ±1%.

	SD = 5,000			SD = 10,000			SD = 15,000	
±10%	±5%	±1%	±10%	±5%	±1%	±10%	±5%	±1%
43	171	4,269	171	683	17,074	385	1,537	38,416

Table 1. Sample sizes required for the estimation of total number of vehicle kilometres driven by cars in a country with precision levels of ±10%, ±5%, and ±1%, population standard deviations of *SD* = 5,000 kms, *SD* = 10,000 kms, and *SD* = 15,000 kms, and a probablility of 95%.

The sample sizes in Table 1 are conservative in the sense that they are based on the direct estimator in simple random sampling, which have the largest standard errors and are thus the least precise. Other estimators like the ratio and regression estimators and other sampling techniques like stratified random sampling will usually require smaller sample sizes in order to obtain the same amount of precision. However, the latter approaches also all require more information about the population at hand than when the direct estimator and simple random sampling are used. Still, as indicated in Example 3.8 of Commandeur (2012, page 45-46), required sample sizes may be up to 70% smaller when stratified random sampling is used instead of simple random sampling.

In naturalistic driving study designs, the sampling technique of choice will also first of all depend on whether a centralised national sampling frame of car drivers is available or not. In the Netherlands, for example, it seems obvious that the database containing all Dutch licensed vehicles of the “RDW”' (Vehicle Technology and Information Center) is the most appropriate frame from which to sample passenger cars. The database contains all registered motor vehicles in the Netherlands, including several technical specifications of each vehicle. The latter specifications can be very useful for the stratification of the vehicle population. The Dutch Vehicle Technology and Information Center also has a database containing all driver licences issued in the Netherlands, including background variables of the drivers like age and gender. These demographic characteristics can be used for the stratification of the driver population. In the Dutch situation the available sampling frames imply that the units to be sampled and then observed should be the licensed drivers since they are the ones who give informed consent to participate in the study.

However, if the sampling frame happens to be decentralised and municipal, for example, then a two-stage sampling design would typically be called for. A nice illustration of the latter approach to survey sampling is presented in Rofique, Humphrey, Pickering, and Tipping (2010) who discuss the methodology used in the National Travel Survey in Great Britain. The methodology of this travel survey covers and combines many of the aspects of sampling discussed in Commandeur (2012), and we therefore discuss it here in some detail. In order to obtain estimates of personal travel of the total population within Great Britain, a stratified two-stage random probability sample was used of private households in Great Britain. The sampling frame is the ‘small user’ Postcode Address File (PAF), a list of all addresses (delivery points) in the country. The sample was drawn firstly by selecting the Primary Sampling Units (PSUs) in the first stage, and then by selecting addresses within PSUs in the second stage. The sample design employs postcode sectors as PSUs. There were 684 PSUs in 2010. In order to reduce the variance of estimates of year-on-year change, half the PSUs in a given year's sample are retained for the next year's sample and the other half are replaced. Hence 342 of the PSUs selected for the 2009 sample were retained for the 2010 sample, supplemented with 342 new PSUs. The PSUs carried over from the 2009 sample for inclusion in 2010 were excluded from the 2010 sample frame, so they could not appear twice in the sample. The dropped PSUs from 2009 were included in the sample frame.

While the same PSU sectors might appear in different survey years, no single addresses were allowed to be included in three consecutive years. Each year, the National Center for Social Research provided the sampling company with a list of the addresses selected for the previous three survey years. These addresses were excluded from the sampling frame before the addresses for 2010 were selected. This meant respondents to the previous year's survey in the carried over PSUs could not be contacted again.

The list of postcode sectors in Great Britain was stratified using a regional variable, car ownership and population density. This was done in order to increase the precision of the sample and to ensure that the different strata in the population are correctly represented. Random samples of PSUs were then selected within each stratum. Forty regional strata were used, and within each region, postcode sectors were listed in increasing order of the proportion of households with no car (according to the 2001 Census). Cut-off points were then drawn approximately one third and two thirds (in terms of delivery points) down the ordered list, to create three roughly equal-sized bands. Within each of the 120 bands thus created (40 times 3), sectors were listed in order of population density (people per hectare). Then 342 postcode sectors were systematically selected with probability proportional to delivery point count. Differential sampling fractions were used in Inner London, Outer London and the rest of Great Britain in order to oversample London, as response rates tend to be much lower in London compared with the rest of Great Britain. These sectors were then added to the 342 sectors carried over from the previous year’s survey to make the final sample of 684 sectors for each year.

Next, within each selected sector, 22 addresses (the secondary or second-stage house-hold units) were sampled systematically, giving a sample of 15,048 addresses (684 postcodes times 22). More details of the sampling methodology used in this survey can be found in Rofique, Humphrey, Pickering, and Tipping (2010).

Besides the just mentioned considerations concerning the types of sampling frame available, based on the material presented in Commandeur (2012) we end with the following specific conclusions and recommendations for the selection of a probabilistic sample of car drivers in a naturalistic driving study design:

1. All sample size estimation methods have in common that they require an a priori specified degree of precision with an a priori specified probability; this therefore applies to sampling methods for naturalistic driving studies as well. The degree of precision simply specifies how close we want the sample estimate (of the mean, the total, or a proportion of a RED/SPI) to be to its actual population value; this can be expressed in absolute terms (i.e., I want the sample estimate of the total number of kilometres travelled to deviate no more than 10 million from the actual total number of kilometres travelled) or in relative terms (i.e., I want the sample estimate of the total number of kilometres travelled to deviate no more than 1% of the actual total number of kilometres travelled). For sample size estimation we also have to specify how certain we want to be of obtaining the desired degree of precision with a sample.

2. All sample size estimation methods have in common that they require some knowledge of, or an estimate of, the dispersion/variation of the variable(s) of interest in simple random sampling, of the population dispersion/variation in the different strata in stratified random sampling, and of the dispersion/variation of the primary and secondary units in two-stage sampling. When sample size is estimated for proportions or percentages the situation is easier because a conservative estimate can always be obtained by assuming the population proportion to be equal to 0.5.

3. When the objective is to measure changes in the population over time, as is the case in naturalistic driving studies, the required precision should be established by considering the minimal difference in parameter estimates between consecutive time points that we want to detect with certainty, as mentioned earlier in this section.

4. When information on additional variables in the population is available that are highly correlated with the variable of interest this opens up the possibility of improving the precision of the parameter estimates obtained with simple random sampling by using stratified random sampling.

5. When several items in the car driver population need to be estimated, then this requires sample size estimations for each of these items separately. If costs are not an issue, the largest estimated sample size should be used in order to guarantee the required precision for all items. In naturalistic driving studies where several RED and SPI items are estimated, e.g., passenger car kilometres travelled, speed, and seat belt use, sample size estimations should be made for each of these items also, and the largest estimated sample size should be used in order to guarantee the required precision for all RED and SPI items. If the budget is fixed, it is also still possible to determine the optimal sample size in stratified random sampling and two-stage sampling, see Commandeur (2012) for details

6. Since national naturalistic driving studies are expected to extend over a number of years, the best sampling strategy for measuring change is to use a rotating sample where one half, three-quarter, or even four-fifth of the sample is retained and the remaining part of the sample is replaced after some fixed period of time.

7. The length of this fixed period of time should also take into consideration the costs and time required for the installation and de-installation in each sampled car of the chosen recording device(s).

8. In order to control for seasonal fluctuations (e.g., due to holidays) it seems that the ideal consecutive period to observe the sample units with the recording device would be one year. This could be combined with the just mentioned rotating sampling procedure, as follows. All cars in the selected sample are equipped with the recording device on time point 1, say. Half of this sample is replaced after half a year, and the replacements are then observed during one year. The other half of the sample is observed the whole first year, and then replaced with a new sample, et cetera. In this way none of the sampled cars are in the sample for more than one year, while still being rotated on a fifty percent basis.

9. The continuous nature of the measurements obtained in a naturalistic driving study implies that the ratio and/or regression estimators discussed in Commandeur (2012) are natural and well-suited candidates for improving the precision of the population parameter estimates: the sample observations obtained for the previous time point or time period can be used to statistically increase the precision of the sample estimates in the next time point or time period. However, these estimators do require knowledge of (or estimates of) the population total or mean of the corresponding RED/SPI variable.

10. When estimates for sub-populations of the total passenger car population in a country are required, it is recommended to use these sub-populations as strata in a stratified random sampling design because this yields more precise estimates than when the sub-populations cut through the strata.

11. The estimation of the required sample size for a pre-specified precision should always take the problem of non-response into account, and the estimated sample size should be increased accordingly.

12. In some countries at least, it should be possible to get information on the characteristics of the non-respondents by using the double sampling for non-response approach discussed in Commandeur (2012). This can be applied in two ways: either by obtaining a random sub-sample of the non-respondents and then make sure that they participate in the study after all, or by obtaining a random sub-sample of the non-respondents and then consulting a second frame also containing (estimates of) the required information.

13. Whenever possible, selection bias as a result of non-response should be corrected for by poststratification based on 1) demographic information of the driver population; 2) technical characteristics of the passenger car population; and/or 3) odometer readings of passenger cars as registered during roadworthiness checks (see Commandeur, 2012, for details). If available this last source of information is to be preferred since it is the best indicator of the actual distance travelled by passenger cars in a country.

14. Should it not be possible to install the chosen recording device in all the sampled passenger cars due to technical restrictions, then these cars should be treated the same as non-response.

4. INDICATORS FOR RISK EXPOSURE MEASURE FROM NATURALISTIC DRIVING DATA

4.1. Introduction

This chapter presents Risk Exposure Data (RED) that can be computed using naturalistic driving data. The first subchapter presents general principles for the RED estimation, and then the following subchapters give the detailed procedures to compute 5 relevant RED. This “procedure” chapter has been created to give as much information as possible to permit the successful computation of the indicators: It aims at addressing all the possible issues that may rise at the different stages of the RED computation.

4.2. General description

4.2.1. Context and definition

Risk Exposure Data (RED) are used to calculate road safety risk indicators, which enable comparisons over time and countries relative to the amount of exposure. In other words, risk (road safety risk indicator) can be defined as a rate [ERSO, 2010]:

$$\text{risk} = \frac{\text{road safety outcome}}{\text{amount of exposure}}$$

Figure 2 - Road safety risk indicator equation

Among the Risk Exposure Data, we can distinguish 2 categories of RED, the ones focusing on traffic and the ones focusing on mobility. The EC project SafetyNet has identified 4 RED of major interest for Road Safety, their definition is given below [Yannis et al., 2005; Lejeune et al., 2007; Duchamp et al., 2008].

1. Vehicle kilometres of a country is defined as “the total number of kilometres travelled within the borders of the country by road motor vehicles”. The according unit is “vehicle km”.
2. Person kilometres of a country is defined as “the total number of kilometres travelled within the borders of the country by persons, regardless of their age”. The according unit is “person km”.
3. Number of trips of a country is defined as “the total number of trips made by persons, regardless their age, in the country.” A return trip counts as two.
4. Time in traffic of a country is defined as “the total time spent travelling by persons, regardless their age or their mode or means of transport in the country”. The according unit is a unit of time (hours, minutes, and seconds).

SafetyNet project proposes to base RED estimation in a data collection framework including both travel surveys and traffic counts elements, each method presenting different features and advantages. Travel surveys have the major advantage of providing exposure data combined per person, vehicle and road characteristics. On the other hand, traffic count systems are the only method, which practically can provide continuous exposure measurements over time.

Naturalistic driving studies involve the observation in naturalistic settings of a sample of drivers. The vehicle of each driver is instrumented in order to record during his/her everyday mobility, information on his/her behaviour, vehicle position and dynamics and driving context.

Compared to the global framework proposed by SafetyNet, computing RED using Naturalistic Driving Data requires a more focused approach. Indeed, the limitations of the NDS, for the estimation of the RED, are the following,

- Only passenger vehicles are included in the NDS.
- The participants of the NDS are only drivers of a passenger car, excluding the part of the country population which doesn't drive.
- Only the journeys made as driver of the instrumented car are considered, even though the person may travel also as passenger or as driver of another car.
- Only passenger car journeys are considered excluding travel made with other modes of road transport.

So NDS design forces a focus on the individual mobility of the drivers of passenger cars. In balance, NDS provides the opportunity to have access to the number of kilometre driven and the time spent driving according to the driving context that can be described in terms of road type, period of the day, period of the week, period of the year, weather conditions, presence or not of passengers… We have also access to descriptive statistics of the trips, in terms of average number of trip by year, mean duration and length of a trip, distribution of the trip duration and length.

Using NDS data to estimate RED assumes that both the driver sample and the instrumented vehicle sample can be weighted up to obtain a representative sample of the driver population of the country and a representative sample of the vehicle fleet of the country. It assumes also that mobility data are collected during long period to disregard fluctuation between season, work and holidays period.

We propose to calculate the five following RED from the NDS data:

- Total number of kilometres driven by passenger vehicles during one year in the country
- Total number of kilometres driven by drivers at the wheel of their main vehicle during one year in the country
- Total amount of time spent by drivers at the wheel of their main vehicle during one year in the country
- Total number of trips made by drivers at the wheel of their main vehicle during one year in the country
- Characteristics of trips made by drivers at the wheel of their main vehicle during one year in the country: mean and standard deviation, length, duration and speed

4.2.2. Measure requirements

The calculation of RED requires basically the continuous measurement of a set of naturalistic driving data including time and date and GPS position. The difficulty raised by the estimation of the RED is that we need to be exhaustive in the record of the trips made by the instrumented vehicle. This means that the data acquisition systems (DAS) must be always present in the vehicle which favours the installation of an embedded on-board system rather than a nomadic system that may be left at home by the participant. This means also that the DAS must be robust to limit the occurrence of breakdown. The RED estimation is dependent on the GPS receiver that gives the position change of the vehicle. The unavailability and the inaccuracy of the GPS coordinates, due to a lack or an insufficient number of satellites visible, will impact negatively on their estimation.

The calculation of some RED needs to deal with the concept of a trip. We consider that a trip starts once the ignition is engaged and finishes when the ignition is disengaged, disregarding the technical related issues. The situations when the car is stopped and the engine is still running, such as some situations of parking, are considered as part of the trip. On the other hand, engine stalls and engines switched off in traffic jams or at traffic lights will be considered as a trip end. These issues can be addressed in post-processing by joining two successive trips or by cutting out a trip in two different trips [Wolf et al., 2004].

The readers are invited to refer to the session 2.7 of the document for more detailed presentation and discussion of the concept of trips in NDS.

Specific databases are necessary for the disaggregation of the RED according to the driving situation characteristics:

- a geographic information system (GIS) for map matching of GPS coordinates to infer the road type and the country identification.
- a weather database that can be used to obtain local weather conditions on a day by day basis that will be analysed conjointly with sensor data (please refer to chapter 2. 7.2.4 for more details).
- a database of sunrise and sunset times to infer dawn, daytime, dusk, night-time conditions (please refer to chapter 2. 7.2.3 for more details).

The calculation of the RED needs to have an identification of the driver to keep only the trips where the NDS participant is the driver of the instrumented vehicle. It will be also interesting to have an indication of the presence of passengers in the vehicle, to disaggregate the number of kilometres driven and time spent at the wheel when the driver is alone or when there are some passengers in the car.

Lastly, the disaggregation per driver and per vehicle needs a set of data describing the participants sample in terms of driver characteristics and vehicle characteristics

4.2.3. Filtering of the naturalistic data

Two filters have to be applied to the NDS data for the calculation of the RED.

The first filter concerns the identification of the driver. The four RED that describe the mobility of persons in terms of number of kilometres driven and time spent at the wheel or in terms of number and characteristics of the trips need to keep only the trips where the instrumented vehicle is driven by the participant of the study and to exclude all the trips where the vehicle is driven by the secondary drivers of the car. In the case of the RED that estimates the total mileage of the vehicle, no filter has to be applied according to the driver identification.

The second filter aims to include, for the calculation of the RED, only the kilometres travelled within the borders of the country. For that, we propose for the calculation of the number of kilometres driven and time spent at the wheel of the vehicle to remove the part of the trips outside the borders of the country. For the calculation of the trip number and characteristics, we propose to include only the trips which in their entirety remain within the borders of the country.

4.2.4. Disaggregation of the RED

We propose four lists of clustering variables for the disaggregation of the RED, according to the driving situation characteristics, the trip characteristics, the vehicle characteristics and the driver characteristics. The two last lists of clustering variables are dependent of the number of participants in the NDS and the criteria used to build up the sample of participants (driver + vehicle). Adjustments will be certainly necessary to finalize these two lists.

Driving situation characteristics	• Road type (urban outside urban area, motorway) • Hour and period of the day (dawn, daytime, dusk, night-time) • Day and period of the week (week, week-end) • Month and period of the year (spring, summer, autumn, winter) • Weather condition (clement, adverse) • Presence or not of passengers
Trips characteristics	• Duration of the trip (less than 20 minutes, between 20 minutes and 60 minutes, greater than to 60 minutes) • Local mobility or long distance mobility (trips included or not in a 80km area around the participant home) • Regularity of the trip (done more than 10 times a year)
Vehicle characteristics	• Vehicle type = passenger car • Vehicle age • Vehicle engine size
Driver characteristics	• Age • Gender • Driving experience • Occupation[1] • Home location[2] • Country

Table 2 - Clustering variables used for the disaggregation of RED per driving situations, trips, vehicles and drivers.

These four sets of clustering variables will be used for both univariate and bivariate analysis of RED, including RED distribution and cross-tabulation.

Risk exposure data	Distribution of RED	Cross tabulation of RED
Total amount of kilometres driven by passengers vehicle during one year in the country	Driving situation characteristics Vehicle characteristics	Yes
Total amount of kilometres driven by drivers at the wheel of their main vehicle during one year in the country	Driving situation characteristics Driver characteristics	Yes
Total amount of time spent by drivers at the wheel of their main vehicle during one year in the country	Driving situation characteristics Driver characteristics	Yes
Total number of trips made by a drivers at the wheel of their main vehicle during	Trip Characteristics	Yes

[1] The occupation and more precisely the fact to be part of the working or non-working population, has a strong impact on vehicle mileage due to the part of professional trips among the trips made by car.

[2] The urban density of the home location has a strong impact on the motorization of household and on the vehicle mileage.

one year in the country	Drivers Characteristics	
Characteristics of trips made by drivers at the wheel of their main vehicle during one year in the country	Driver Characteristics	No

Table 3 – Summary of the univariate and bivariate analysis of RED.

4.2.5. Aggregation of the RED at the level of the country

According to the categories of RED, traffic or mobility, the values obtained for a given sample of vehicles / persons need to be weighted to obtain a value describing the general exposure at the level of the whole fleet of motor vehicles or at the level of the whole population of the country.

4.3. Vehicle Kilometre RED

4.3.1. RED definition

This RED gives the total yearly mileage of a passenger vehicle, whoever the driver. Vehicle kilometre is described as the ”Total amount of kilometres driven by passenger vehicles during one year in the country”. The according unit is km per year.

4.3.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: time and date, GPS position, trip number, driver identifier, vehicle identifier, detection of wipers and fog lamps use, passengers presence or not, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer the road type and the country; a weather database that can be used to obtain local weather conditions on a day by day basis; a database of sunrise and sunset times to infer daylight and night conditions.
3. a set of sample characteristics, including driver and vehicle characteristics for country level aggregation

4.3.3. Data filtering

As explained in chapter 4.2.3, the data will be filtered to remove the part of the driving data collected outside the borders of the country.

4.3.4. Data disaggregation

As explained in chapter 4.2.4, two sets of clustering variables will be used for the disaggregation of the RED:

Driving situation characteristics:

- Road type (urban outside urban area, motorway)
- Hour and period of the day (dawn, daytime, dusk, night-time)
- Day and period of the week (week, week-end)

- Month and period of the year (spring, summer, autumn, winter)
- Weather condition (clement, adverse)
- Presence or not of passengers

Vehicle characteristics

- Vehicle age
- Vehicle engine size

4.3.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, a vehicle identifier, a driver identifier, a trip number, a timestamp (date + time), the driving context (road type: outside urban area, urban, motorway), the country identifier, the presence of passenger, the weather conditions.

The first step will be to apply the filter in order to obtain only the driving data collected with the vehicle on the country territory. Once this filter has been applied, the remaining dataset contains all the driving data that are relevant for the RED clustering.

Then, the second step to compute this RED will be to produce an aggregation of the data at the level of the vehicle taking into account the required clustering classes. This clustering will be done according to the different possibilities discussed above. For this purpose, it will be necessary to browse the filtered data and to identify in which cluster the driving data should be taken into account. The following list describes the variables that have to be used to identify the driving situations corresponding to the clusters. This step should be done cautiously has it will be necessary to cluster according to almost 50 classes:

- 3 road types
- 4 periods of the day
- 24 hours of the day
- 7 days
- 2 periods of the week
- 12 months in the year
- 4 periods of the year
- 2 weather conditions
- 2 presence of passengers conditions

Once these clusters have been applied, there are as many subsets of data as clustering class.

The third step will be to compute, from these data subsets containing the filtered and clustered data, the final value of the RED. Thus, it will consist in computing the kilometres driven for each cluster.

The outcome will be an aggregated database, presenting information at the level of the vehicles and containing the following information: Vehicle ID, country ID, total km driven, km driven in {each of the cluster}.

The following figure aims to illustrate the calculation principles and show the different steps: filtering, dispatching the data in the different clusters, computing RED on target cluster subset.

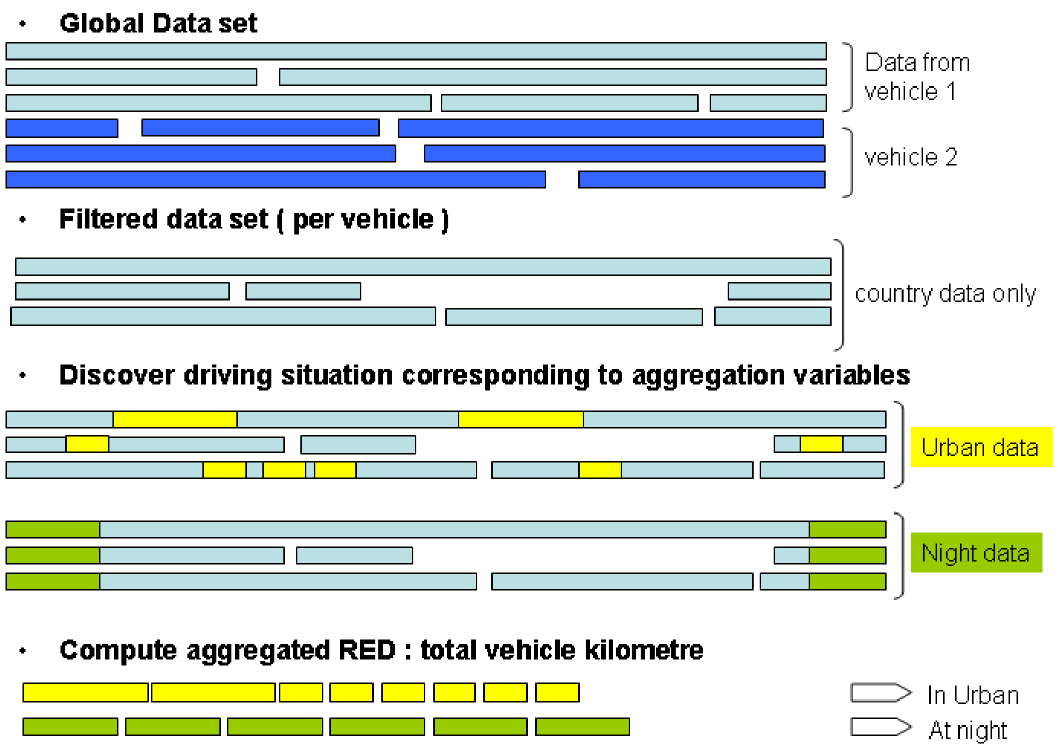


Figure 3 - Approach for Vehicle Kilometre RED processing

4.3.6. Reporting to the ERSO

The RED values obtained for each vehicle need to be weighted up to obtain a global value representative of the exposure at the level of the whole fleet of passenger vehicles of the country. The weighting factors will be defined by comparing the vehicle distribution in the sample to the vehicle distribution in the country.

Once the RED values have been corrected to match with the country vehicle fleet, different RED values can be also cross-tabulated according to the vehicle characteristics, such as age and engine size.

4.4. Driver Kilometre RED

4.4.1. RED definition

This RED gives the total yearly mileage of a driver at the wheel of his/her main passenger vehicle. Driver kilometre is described as the "total amount of kilometres driven by drivers at the wheel of their main vehicle during one year in the country". The according unit is km per year.

4.4.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: time and date, GPS position, trip number, driver identifier, vehicle identifier, detection of wipers and fog lamps use, passengers presence or not.
2. a set of static data: a geographic information system (GIS) for map matching to infer the road type and the country, a weather database that can be used to

obtain local weather conditions on a day by day basis; a database of sunrise and sunset times to infer daylight and night conditions.

3. a set of sample characteristics, including driver and vehicle characteristics for country level aggregation

4.4.3. Data filtering

As explained in chapter 4.2.3, the data will be filtered to remove the part of the driving data collected outside the borders of the country. Only the driving data collected where the driver of the vehicle is the participant of the NDS will be kept.

4.4.4. Data disaggregation

As explained in chapter 4.2.4, two sets of clustering variables will be used for the disaggregation of the RED:

Driving situation characteristics:

- Road type (urban outside urban area, motorway)
- Hour and period of the day (dawn, daytime, dusk, night-time)
- Day and period of the week (week, week-end)
- Month and period of the year (spring, summer, autumn, winter)
- Weather condition (clement, adverse)
- Presence or no of passengers

Driver characteristics

- Age
- Gender
- driving experience
- Occupation
- Home location

4.4.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, a driver identifier, a vehicle identifier, a trip number, a timestamp (date + time), the driving context (road type: outside urban area, urban, motorway), the country identifier, the presence of passenger, the weather conditions.

The first step will be to apply the filters in order to obtain only the driving data collected with the vehicle on the country territory and with the participant as a driver. Once these filters have been applied, the remaining dataset contains all the driving data that are relevant for the RED clustering.

Then, the second step to compute this RED will be to produce an aggregation of the data at the level of the participant driver taking into account the required clustering classes. This clustering will be done according to the different possibilities discussed above. For this purpose, it will be necessary to parse the filtered data and to identify in which cluster the driving data should be taken into account. The following list describes the variables that have to be used to identify the driving situations corresponding to the clusters. This step should be done cautiously has it will be necessary to cluster according to almost 60 classes:

- 3 road types
- 4 periods of the day
- 24 hours of the day

- 7 days
- 2 periods of the week
- 12 months in the year
- 4 periods of the year
- 2 weather conditions
- 2 presence of passengers conditions

Once these clusters have been applied, there are as many subsets of data as clustering class.

The third step will be to compute, from these data subsets containing the filtered and clustered data, the final value of the RED. Thus, it will consist in computing the kilometre driven for each cluster.

The outcome will be an aggregated database, presenting information at the level of the drivers and containing the following information: driver ID, Vehicle ID, country ID, total km driven, km driven in {each of the cluster}.

The following figure aims to illustrate the calculation principles and show the different steps: filtering, dispatching the data in the different clusters, computing RED on target cluster subset.

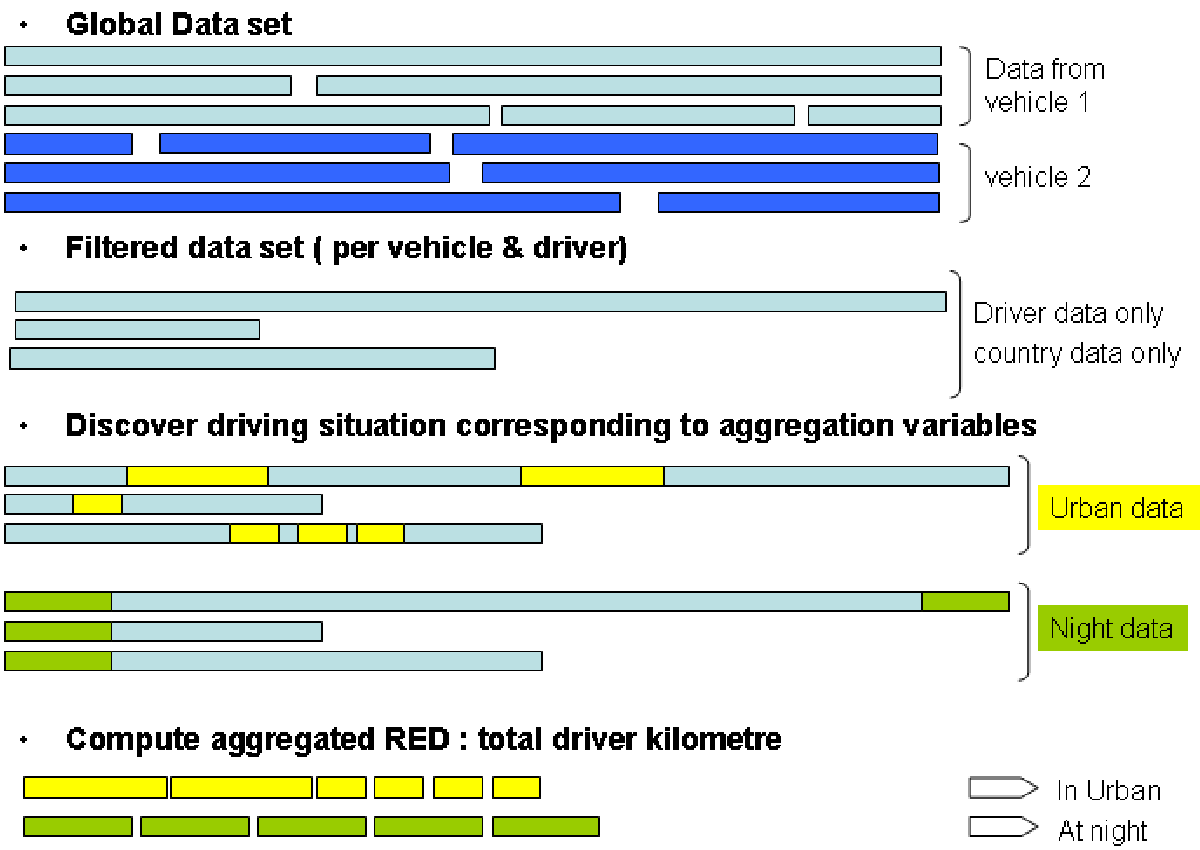


Figure 4 - Approach for Driver Kilometre RED processing

4.4.6. Reporting to the ERSO

The RED values obtained for each participant driver need to be weighted up to obtain a global value representative of the exposure at the level of the whole driver population of the country The weighting factors will be defined by comparing the driver distribution in the sample to the driver distribution in the country.

Once the RED values have been corrected to match with the country driver population, different RED values can be also cross-tabulated according to the driver characteristics, such as age, gender, driving experience.

4.5. Driver Time in Traffic RED

4.5.1. RED definition

This RED gives the total time spent in the traffic by a driver at the wheel of their main passenger vehicles. Driver Time in Traffic is described as the ”total amount of time spent by a driver at the wheel of his/her main vehicle during one year in the country”. The according unit is unit of time by year.

4.5.2. Data collection requirement

This RED is very close to the previous RED: output values expressed in term of time instead of kilometre. The data collection requirements are the same as above.

4.5.3. Data filtering

This RED is very close to the previous RED: output values expressed in term of time instead of kilometre. The data filtering is the same as above.

4.5.4. Data disaggregation

This RED is very close to the previous RED: output values expressed in term of time instead of kilometre. The data disaggregation is the same as above.

4.5.5. Data processing

This RED is very close to the previous RED: output values expressed in term of time instead of kilometre. The data processing is almost the same as above.

The difference is in the third step, where it will be necessary to compute, from the data subsets containing the filtered and clustered data, the time driven in each cluster.

The outcome will be an aggregated database, presenting information at the level of the drivers and containing the following information: driver ID, vehicle ID, country ID, total time spent in traffic, total time spent in traffic in {each of the cluster}.

4.5.6. Reporting to the ERSO

This RED is very close to the previous RED: output values expressed in term of time instead of kilometre. The reporting is the same as above.

4.6. Trip Number RED

4.6.1.1.1. RED definition

This RED gives the total number of trips that a driver will accomplish yearly (cf 2.7. for more details about trip definition). Trip number is described as the "total number of trips made by drivers at the wheel of their main vehicle during one year in the country".

4.6.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: time and date, GPS position, trip number, driver identifier, vehicle identifier, detection of wipers and fog lamps use, passengers presence or not.
2. a set of static data: a geographic information system (GIS) for map matching to infer the road type and the country, a weather database that can be used to obtain local weather conditions on a day by day basis; a database of sunrise and sunset times to infer daylight and night conditions.
3. a set of sample characteristics, including driver and vehicle characteristics for country level aggregation

4.6.3. Data filtering

As explained in chapter 4.2.3, the data will be filtered to remove from the analysis every trip that contains driving data collected outside of the borders of the country and every trip where the vehicle driver is not the participant of the NDS

4.6.4. Data disaggregation

As explained in chapter 4.2.4, two sets of clustering variables will be used for the disaggregation of the RED:

Trips characteristics:

- Duration of the trip (less than 20 minutes, between 20 minutes and 60 minutes, greater than 60 minutes)
- Local mobility or far distance mobility (trips included or not in a 80km area around the participant home, whatever the trip duration)
- Regularity of the trip (done more than 10 times a year)

Driver characteristics

- Age
- Gender
- driving experience
- Occupation
- Home location

4.6.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, a driver identifier, a vehicle identifier, a trip number, a timestamp (date + time), the driving context (road type: outside urban area, urban, motorway), the country identifier, the presence of passenger, the weather conditions.

The first step will be to apply the filters in order to keep only the trips where the driver is the participant of the NDS and in order to obtain only the trips collected with the vehicle on the country territory: as soon as the trip contains data collected outside of the country, the trip is discarded. Once these filters have been applied, the remaining dataset contains all the driving data of the trips that are relevant for the RED clustering.

Then, the second step to compute this RED will be to produce an aggregation of the data at the level of the driver, taking into account the required clustering classes. This clustering will be done according to the different possibilities discussed above. For this purpose, it will be necessary to parse the filtered data trip by trip and to identify in which cluster the trips should be taken into account. The following list describes the variables that have to be used to identify the trip characteristic corresponding to the clusters.

- 3 durations
- 2 mobility patterns
- 2 regularity possibilities

Once these clusters have been applied, there are as many subsets of trips as clustering class.

The third step will be to compute, from these trip subsets containing the filtered and clustered trips, the final value of the RED. Thus, it will consist in computing the sum for each cluster.

The outcome will be an aggregated database, presenting information at the level of the drivers and containing the following information: Driver ID, Vehicle ID, country ID, total number of trips, number of trip driven with characteristic {each of the cluster}.

The following figure aims to illustrate the calculation principles and show the different steps: filtering, dispatching the trips in the different clusters, computing RED on target cluster subset.

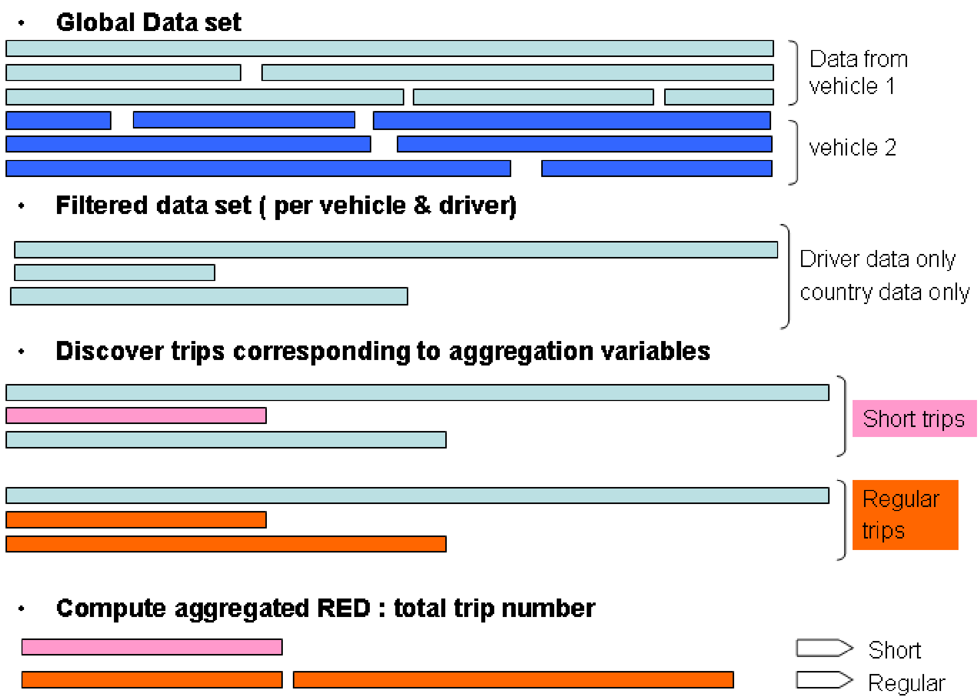


Figure 5 - Approach for Driver Time in traffic RED processing

4.6.6. Reporting to the ERSO

The RED values obtained for each participant driver need to be weighted up to obtain a global value representative of the exposure at the level of the whole driver population of the country The weighting factors will be defined by comparing the driver distribution in the sample to the driver distribution in the country.

Once the RED values have been corrected to match with the country driver population, different RED values can be also cross-tabulated according to the driver characteristics, such as age, gender, driving experience.

4.7. Trips Characteristics RED

4.7.1. RED definition

For this RED, the objective is to produce a complete logbook of the drivers "trip" mobility. For this purpose, the output will be a table describing each trip, with the variables mentioned below. Indeed, this RED aims to give a better understanding of driver mobility and propose to compute aggregate measures about trips that a driver will accomplish yearly (cf 2.7. for more details about trip definition).

For each trip, the main variables that can be listed in the logbook are listed below:

- trip length in kilometre
- trip duration in seconds
- Mean speed during trip in km/h
- Standard deviation of speed
- Number of passengers
- Period of the week
- Month

This list is not complete and it possible to extend the list to new variables that can measure other aspect of the trips (for example, dispatching of road context…).

The trips characteristics are described as "An aggregated measure (percentage, mean, standard deviation…) of a variable on trips made by drivers at the wheel of their main vehicle during one year in the country". The according unit is the unit of the variable. For example, "mean speed and standard deviation of speed on trips made by a driver at the wheel of his/her main vehicle during one year in the country".

4.7.2. Data collection requirement

This RED is very close to the previous RED: output values propose measures computed on the trips instead of a trip count. The data collection requirements are the same as above.

4.7.3. Data filtering

This RED is very close to the previous RED: output values propose measures computed on the trips instead of a trip count. The data filtering conditions are the same as above.

4.7.4. Data disaggregation

For this RED, there is no necessity to make specific clustering before the data processing. However, the value of the variables describing the trips can be used to create classes that will permit average value, standard deviation or other aggregated indicators. Following the same logic, driver characteristic will also be useable to create clustering classing.

4.7.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, a driver identifier, a vehicle identifier, a trip number, a timestamp (date + time), the driving context (road type: outside urban area, urban, motorway), the country identifier, the presence of passenger, the weather conditions.

The first step will be to apply the filters in order to keep only the trips where the driver is the participant of the NDS and in order to obtain only the trips collected with the vehicle on the country territory: as soon as the trip contains data collected outside of the country, the trip is discarded. Once these filters have been applied, the remaining dataset contains all the driving data of the trips that are relevant for the RED clustering.

Then, the second step to compute this RED will be to parse of the filtered trips and to compute the variables associated to each trip:

- trip length in kilometre
- trip duration in seconds
- Mean speed during trips in km/h
- Standard deviation of speed
- Number of passengers
- Period of the week
- Month

The outcome will be an aggregated database, presenting information at the level of the trips and containing the following information: Trip ID, Driver ID, Vehicle ID, country ID, variables describing the trip {each of the variable presented above}.

This database does not give results with a high level of aggregation but it offers the raw material to perform several aggregations, depending on the available variables. For example, the final step will consist in the calculation of mean speed and standard deviation of speed (expressed in km/h), mean length and standard deviation of length (expressed in km), mean duration and standard deviation of duration (expressed in minutes).

4.7.6. Reporting to the ERSO

The RED values obtained for each participant driver need to be weighted up to obtain a global value representative of the exposure at the level of the whole driver population of the country The weighting factors will be defined by comparing the driver distribution in the sample to the driver distribution in the country.

Once the RED values have been corrected to match with the country driver population, different RED values can be also cross-tabulated according to the driver characteristics, such as age, gender, driving experience.

4.8. Synthesis

This last chapter aims to provide a high level overview of the RED that have been proposed to be monitored using a Naturalistic Driving database. Even if most of them are technically feasible without too many constraints, the limits of this feasibility are described in detail in the previous chapters. Their added value and the considerations to keep in mind when interpreting the results are also described in detail in the previous chapters.

RED	RED definition
Vehicle Kilometre	Total amount of kilometres driven by passenger vehicles during one year in the country
Driver Kilometre	Total amount of kilometres driven by drivers at the wheel of their main vehicle during one year in the country
Driver Time in traffic	Total amount of time spent by drivers at the wheel of their main vehicle during one year in the country
Trip Number	Total number of trips made by drivers at the wheel of their main vehicles during one year in the country
Trips Characteristics	Characteristics of trips made by drivers at the wheel of their main vehicle during one year in the country

Table 4 – Proposition of five RED issued from NDS data.

5. INDICATORS FOR SAFETY PERFORMANCE MEASURES FROM NATURALISTIC DRIVING DATA

5.1. Introduction

This chapter presents safety performance indicators (SPI) that can be computed using naturalistic driving data. For each category of SPI, the first subchapter presents the general description of the family, and then the following subchapters give the detailed procedures to compute the possible SPI. These “procedure” chapters have been created to give as much information as possible to permit the successful computation of the indicators: It aims at addressing all the possible issues that may rise at the different stages of the SPI computation.

The following table gives an overview of the SPI categories and the proposed SPI

SPI category	Behavioural SPI	Descriptive SP
Excessive speed	Mean speed and standard deviation of speed in free flowing traffic conditions V85 in free flowing traffic conditions Percentage of driving time over the legal speed limit in free flowing traffic conditions Percentage of driving time 10 km/h over the legal speed limit in free flowing traffic conditions	Percentage of driving time over the legal speed limit Percentage of driving time 10 km/h over the legal speed limit
Seat belt use	Percentage of trips without seat belt use, with partial seat belt use, with total seat belt use Systematic use of seat belt: percentage of trips with immediate seat belt fastening	Percentage of driving time with seat belt fastened for drivers, front passengers and rear passengers.
Daytime running light use	Percentage of trips without DRL use, with partial DRL use, with total DRL use during daytime and clement weather conditions Systematic use of DRL: percentage of trips with immediate DRL switching on during daytime and clement weather conditions	Percentage of driving time with DRL switched on during daytime and clement weather conditions
Short headway	15th percentile of the headway in vehicle following situations Percentage of driving time with headway greater than 2 seconds, between 1 and 2 seconds, , between 0.5 and 1 second and less	Percentage of driving time with headway greater than 2 seconds, between 1 and 2 seconds, , between 0.5 and 1 second and less than 0.5 second

	than 0.5 second in vehicle following situations Frequency of occurrences of short headway epochs(headways less than 0.5 second during at least 0,2 seconds) in vehicle following situations per hour driven	Frequency of occurrences of short headway epochs (headways less than 0.5 second during at least 0,2 seconds) per hour driven
Strong deceleration	15th and 85th percentile of the vehicle in deceleration situation Percentage of deceleration time with deceleration greater than -0.25g, between -0.25g and -0.50 g and less than - 0.50 g, in deceleration situation	Frequency of occurrences of strong decelerations per hours driven (deceleration less than -0.5 g during at least 0,2 seconds)
Safety Systems use		Frequency of occurrences of safety system (Anti-lock braking system and Electronic stability control system…) activation per hours driven

Table 5 – Overview of behavioural and descriptive SPI from NDS

Inside the "procedure" chapters, the processing description part, even if detailed and technical, aims to propose a tangible solution to compute the SPI. It also aims to resolve all possible ambiguities that are linked to classical written description.

This part has been written to act as an operational handbook for SPI implementation and therefore, the document was designed to provide a direct access to the description of each specific SPI, rather than optimised for a sequential reading of all the SPI. We assumed that readers would rather want to access directly to the definition of 1 of the SPI and would be glad to find all the related information available at the same place. When reading each SPI sequentially, the reader will notice that the content are repetitive.

5.2. Excessive speed SPI

5.2.1. General description

5.2.1.1. Context and definitions

Speed is one of the main causes of road crash. Speed has been shown as a major contributory factor in 10% of all crashes and in 30% of fatal crashes [TRB, 1998]. Beyond its role in crash occurrence, speed has a direct influence on accident severity. This explains the road authorities' interest in implementing various safety interventions to reduce speeding behaviour. However, to achieve this goal, they need SPIs that give a realistic evaluation of drivers' behaviour related to the compliance with the legal speed limits.

The methods commonly used through European countries to collect the data and to estimate the speed SPI have been analysed by SafetyNet consortium and recommendations have been elaborated based on the best European practices to favour comparisons between European countries [Hakkert and Gitelman, 2007]. Speeds SPI are based on the instantaneous speed measures of vehicles observed in a restricted set of locations that are selected for their representativity of the road network of a country. They include the mean speed, the standard deviation, the 85th percentile speed and the percentage of drivers exceeding the speed limit. The estimation of the speed SPI takes into account the road type, the periods of day and week of the speed data collection, and the selected vehicle type.

In order to be able to make the link between speed measurements and speeding behaviour, speed data are only collected when traffic can be considered as "free flowing traffic", i.e. when the speed of the vehicle is freely chosen by driver and is not constrained by the driving context. Reasonably free flowing traffic conditions are obtained through the selection of appropriate locations and periods to measure vehicle instantaneous speed. More precisely, it is reached by selecting straight and flat roads, avoiding proximity with intersection, avoiding proximity with pedestrian crossings, avoiding proximity with enforcement radar, avoiding proximity with roadwork, avoiding proximity with local events (market days, sports events, ...), excluding morning and evening peak hours (eg 7h30-9h30 and 16h00-19h00) and avoiding adverse weather conditions (rain, snow, freezing, fog, strong wind).

Within a naturalistic driving observation, speed data are provided on a continuous basis and the SPI must be inferred from the speed variations over time of a restricted set of drivers. The characteristics of the data collection method, observing, in an unobtrusive way, drivers' behaviour within their everyday mobility offer the possibility to assess unsafe drivers' behaviour such as speeding. Nevertheless, the lack of experimental control induces a set of methodological constraints: data gathers together speed measures done in different traffic conditions where the vehicle speed is either freely chosen by driver or is constrained by the driving context.

We propose to distinguish two families of excessive speed SPI, the behavioural SPI and the descriptive SPI, whether the naturalistic driving data will be filtered or not to keep only free flowing traffic conditions.

- In the first case, the behavioural SPI will highlight the propensity of drivers to drive over the legal speed limit by excluding driving situations that can induce a drastic reduction of the vehicle speed. The calculation of the 4 following speed behavioural SPI will be detailed in the section 5.1.2.
    1. Mean speed and standard deviation of speed in free flowing traffic conditions
    2. V85 in free flowing traffic conditions, which is the 85^{th} percentile.
    3. Percentage of driving time over the legal speed limit in free flowing traffic conditions
    4. Percentage of driving time 10 km/h over the legal speed limit in free flowing traffic conditions
- In the second case, the descriptive SPI will highlight the exposure of drivers to excessive speeds situations during their everyday mobility by considering all the data collected. The calculation of the 2 following speed descriptive SPI will be detailed in the section 5.1.3.
    1. Percentage of driving time over the legal speed limit

2. Percentage of driving time 10 km/h over the legal speed limit

5.2.1.2. Measurement requirements

The calculation of Excessive Speed SPI requires firstly the measure of the vehicle speed. This measure can be issued from the CAN bus of the car that gives the value of the vehicle speed displayed by the speedometer or from a GPS receiver that gives a speed estimated from position change of the vehicle. Generally, the dashboard speedometer overestimates the speed of the vehicle and the difference between the real speed and the dashboard indications can greatly vary according to the car model. Some drivers are aware of the overestimation of the speedometer of their car and take into account this margin of error to choose their speed. Thus, the identification of the speeding situations will have to take into account the specifications and the accuracy of the sensors that will be used to estimate the vehicle speed.

In order to be able to disaggregate Excessive Speed SPI according to the road characteristics, it is necessary to know the GPS positions of the vehicle and to have access to a geographic information system (GIS) in order to infer, through map matching, information such as road type and legal speed limit. The access to the GIS data can be done in real-time, during driving, so that the collected data directly contains the relevant information, or can be post processed, using raw GPS coordinate and enriching the data set with required information.

The availability of the GPS coordinates and the GIS database, the accuracy of the two sources and the quality of the map matching algorithm might impact the estimation of the SPI. In some specific driving environments such as tunnels or narrow streets edged by high buildings, the lack or an insufficient number of satellites visible can result in unavailable or erroneous GPS coordinates. This can induce an erroneous estimation, by the map matching algorithm, of the road or street taken by the vehicle and then an erroneous inference of the legal speed limit. Moreover, the legal speed limits that are essential information for the Excessive Speed SPI calculation might not be available in all the geographic information system, and if they are available they can be erroneous. The accuracy of the data can greatly vary between different countries or geographic areas and according to the road type and the duration of the speed restrictions (for example restriction of short duration like highway entrance and exit might not be indicated at all). Nevertheless, the accuracy of GIS is very hard to control. We can expect that due to the extensive periods of data collection, the amount of invalid data remains rather negligible.

5.2.1.3. Identification of reasonably free flowing traffic conditions: principles for the data filtering

In order to make the link between speed measurements and speeding behaviour and to calculate speed SPI that could be compared to the SafetyNet SPI, the analysis of drivers' speeding behaviours requires the identification, among the huge volume of data, of the driving situations during which it is highly probable that the vehicle speed is freely chosen by the driver and not constrained by the driving context. These driving situations, where the driver can freely choose the speed, can be defined as "reasonably free flowing traffic conditions". If SafetyNet gives a lot of recommendations to perform road-side speed observations with free flowing traffic conditions, it is more difficult to point out these specific conditions in a large set of naturalistic driving data. However, focusing on these situations is very important as it necessary to understand and interpret correctly the results of the speed SPI (e.g. if the continuous speed observation shows that a driver never goes above the legal speed limit, is it because he/she has a very safe driving and deliberately choose to stay under the legal speed limit at all time or is it because he/she only drives in traffic jams, during the peak hours and can never go above the legal speed limit?). Determining the free flowing condition is a key issue, as it is far from trivial to determine automatically and reliably these specific situations [Brusque 2012].

Several characteristics of the driving situations can limit the driver's possibility to freely choose the speed of his/her vehicle.

- The traffic conditions (traffic jam, surrounding traffic affecting vehicles' speed)
- The geometric characteristics of the road (presence of bends, slopes, intersections, pedestrian crossings, damaged pavement surface, …)
- The presence of specific events (presence of speed controls, roadworks, local events, …)
- The adverse weather conditions (presence of rain, snow, freezing, fog, strong wind)

We identified two manners to filter data to select reasonably free flowing traffic conditions by excluding traffic congestion situations.

A first solution, directly inspired from SafetyNet, consists in excluding data collected during the morning and evening peak hours (7h30-9h30 and 16h00-19h00). The issue raised by this hour based filter solution is that we can exclude a lot of data and have no longer a sufficient amount of data to calculate speed with a sufficient accuracy. This issue is discussed in detail in chapter 5.2.1.4.

A second solution consists in inferring congestion situations from the analysis of the distributions of vehicle's variables such as speed or headway and from knowledge of traffic engineers on traffic flow characteristics. In the 100 car study, the level of service scale has been used as a measure of traffic density to be coded from the video by the data analysts [Dingus et al., 2006]. The Level of service is a 6-level scale that offer a qualitative measure of a road's operating conditions from free-flow being rated as LOS-A to congested conditions rated as LOS-F [TRB, 2010]. The LOS estimation are based on a set of measures such as speed, headway, travel time, freedom to maneuver, traffic interruptions, comfort, and convenience… The concept of LOS is interesting because it can be used on different driving situations (freeways, highways, signalized or signalized intersections, etc.) and different modes (car, pedestrian, bicycle, buses, etc.), despite that the drivers seem to perceive less than six categories of LOS [Papadimitriou et al., 2010] [Choocharukul et al., 2004]. Nevertheless, the development of filtering algorithms of road's operating conditions for naturalistic driving observations that can be run on an automatic way without the human assistance of a data analyst is still a topic of research that will need further investigations.

The solution of data filtering based on the time of the day seems nowadays the more operational and relevant solution to filter naturalistic driving data according to the traffic conditions.

We can assume that due to the longitudinal characteristic of the data collected, there is no need of specific filtering to exclude from the indicators computation punctual characteristics of the driving environment such as presence of intersection, enforcement radars, roadworks. However, in order to make sure that we are in free flowing conditions, we identified a second criterion: to filter all data where speed is below 5 km/h. In urban areas, it will remove all situations where driver is waiting at a traffic light or at any intersection and it will also remove potential traffic jams that might occurs outside of the peak hours. On a highway, it will remove stops at toll gates or traffic jams. This will contribute to make the data that are kept more homogeneous.

The cases of adverse weather, snowy or foggy situations are specific and it should be also a good idea to remove them from the data set, as then tend to imply bad traffic conditions. Two solutions are possible: in the case of scenario 2, using CAN data and combining several signals (lights, windscreen wipers, temperature…) one can build a filter to remove adverse conditions. In the case of scenario 1, without CAN data, one must find a weather forecast database that provide rain information for different GPS positions, in order to be able to rebuild, in post processing, the weather condition information.

Finally, as generally traffic conditions and travel patterns are very heterogeneous during the weekend, with an even bigger difference between Saturdays and Sundays, it is important to separate week ends from week days. For the sake of homogeneity, it might be possible to filter out the data collected during the weekends and to keep only the data of the week days.

To investigate drivers' speeding behaviour, it is important to use this set of filters that will guarantee the good quality of the data for the estimation of speed behavioural SPI. For the remaining set of data, we can assume that the conditions are controlled and homogeneous and that they can be considered as reasonably free flowing traffic conditions. However, the amount of data that have been filtered out has to be quantified and compared to the amount of raw data, in order to control the accuracy of the SPI estimations that will be linked to the number of measures used for the calculation.

5.2.1.4. Principles for the data clustering and the time window selection

The usefulness of speed SPI will depend of the possibilities they will offer to evaluate the changes over time of speeding behaviour and to compare compliance with legal speed limit in different driving contexts (legal speed limit, type of road, period of the week, period of the day, …) and for different populations (drivers and vehicles). The selection of the time window and the selection of clustering criteria and classes will have to been done by taking into account the compatibility of the chosen filtering principles (for example, filter out peak hours and select a time window for a SPI between 8h and 9h in the morning, or filter out weekends and compare SPI between week days and weekends).

In order to highlight individual behaviour and not to hide it according to the mileage of the participant, speed data will be first aggregated at the participant level before doing the aggregation at the country level. Thus, the accuracy should be evaluated at the level of the participant. The choice of the time windows and the choice of clustering criteria and classes have a direct link on the number of speed measurements available for the SPI calculation and so on the accuracy obtained at the level of each participant.

Authors want to point out that accuracy considerations have to be taken into account for the choice of the time window and for the choice of clustering criteria and classes. It is mainly the case for speed behavioural SPI where about 20% of the raw data remain for the SPI estimation after the filtering phase to keep only reasonably free flowing traffic conditions. This is even truer when we need to combine the cluster.

To ensure the quality of data, we must take into account two important inputs:

- the global amount of data for the clustering,

- the amount of data brought by each driver.

The time window selected must be sufficient to collect driving data in various driving contexts in terms of road type, legal speed limit, period of the day and of the week, traffic conditions and weather conditions. On the other hand, the time window must permit the impact overtime of safety interventions to be investigated. A time window of one month seems a good compromise to address these two requirements.

The issue related to the choice of the criteria for data clustering and the choice of the number of clustering classes is linked to the travel patterns of the participants and that the driving time in some road contexts can be very low for one part of the participants.

To evaluate the impact of the number of data collected at the level of the participant, we consider a driver who drivers about 15 000 km per year (this value is considered to be a mean value which is representative of the driver population even, if it is possible to include in the observation participants with far less or far more km), thus 1 250 km per month. Assuming that their mean speed is 50 km/h (which is probably above the real value, but puts a higher constraint on the following calculation), 1 250 km represent 25 hours of driving per month.

We make the hypothesis that the speed is measured with a GPS which gives 1 measure per second (1Hz). The variation of speed is such that it does not require more frequent measurement. 25 hours of driving will bring 90 000 speed measure for the month.

If we consider that only 20% of the data happen during free flowing traffic conditions, we keep around 18 000 measures per month per driver in the case of speed behavioural SPI (this threshold has been set according to the findings of task 6.3) [Pilgerstorfer et al., 2011].

To evaluate speed behaviour in relation to the legal speed limit, for example, we might need to break down the measurements for each driving situation in different legal speed limits. Assuming that 6 classes may exist in a country (limits at 30, 50, 70, 90, 110 or 130 km/h) we will be able to evaluate the number of speed measurements for all the classes and to assess if all participants bring data for all the classes. In the case of a homogeneous repartition (which is very unlikely, especially for some values, like 30 km/h areas, where the probability that drivers run through these depends on the mobility pattern and road network environment), we would obtain 3 000 measures per class per driver for speed behavioural SPI. Thus, we can expect that for each speed limit class and for each driver, the calculation of the speed SPI will be done with near 3000 speed measurements.

If we need to consider other clustering possibilities, the process will be exactly the same. If we need to break down by context (urban, motorway, outside of urban), the classes will be larger, we can expect to have about 6000 values per class.

If we want to break down by the lighting condition (day vs. night) and we assume that 10% (before filtering) of the data are collected during the night, we can expect 9 000 measures per month per driver in night conditions and 16 000 measures during day (the 81 000 remaining * 20% remaining after peak hour filter).

If we need to combine the cluster and to look simultaneously at legal speed limit and light conditions, we can expect to obtain around 1 500 measures by legal speed limit class in night conditions (9 000 measures / 6 classes). On the opposite, if we plan to combine the clustering per legal speed limit classes and per hours of the day, and if we need to make 17 classes of hour (24 hours – 7 hours in peak hours) in a day for clustering, and if we assume that the drivers will have a homogeneous dispatching of driving time (which is really unrealistic), we will obtain 18 000 / 17 = 1060 measures per class per month. It seems difficult to cluster according to the speed limit class as it would result in 180 values per speed limit per hour per month, in the case of speed behavioural SPI. This would make it impossible to draw reliable conclusions with so little data.

As a conclusion, the reduction of the data set, through data clustering process and the time window selection, should be monitored in order to be able to provide feedbacks on the amount of data used for the final calculation both at the level of the drivers and at the level of the country. For this purpose, chapter 2.7.1 introduces the concept of “sub sample characteristic” which can be helpful to do so.

5.2.1.5. Principles for the aggregation of the speed SPI at the country level

In the above simulations, we make the assumption that the drivers will have a homogeneous dispatching of driving time according to the different clustering classes. But the reality will be certainly different; and we can also expected strong differences amongst the drivers of the sample. The information of number of measures available for each participant in each clustering class will be useful to handle the situation where a driver only brings too few data in a clustering class for the estimation of the SPI value related to this class. When it happens, the recorded data correspond to a too specific situation or a rare one that cannot be used as an estimation of a regular behaviour of the driver. So we propose to exclude the data of this participant for the calculation of the SPI at the country level for the concerned class

In order to implement this principle, it has been decided to compute and to provide, in addition to the SPI value, the SPI subsample characteristics for each cluster, first at a participant level and then at the country level: number of measurements used for the calculation at both levels and number of drivers at the country level

At the participant level, the SPI subsample characteristic can be used as followed to aggregate the SPI at the country level: the data from a participant will be ignored in a given cluster if he/she has less than 1000 measurements over a month, which represent less than 17 minutes per month of aggregated driving time in the given situation.

For some legal speed limits that are underrepresented in the road network, for example 30km/h area, the threshold of 1000 measurements by month might be excessive because these areas tends to be very short and drivers will never spend a lot of time driving in these conditions. Thus, the recommendation would be to lower the threshold for participant in country aggregation to 500 measurements by month in such conditions. If the SPI is computed in a year time window, we suggest the threshold is raised to 10 000 measurements.

We recommend that the data provided by each county at the ERSO include the SPI values for each clustering class and the characteristics of the subsample used for the calculation of each SPI value. These SPI subsample characteristics given at country level should give information about the number of drivers considered and the cumulative driving time used for the SPI calculation after data filtering, clustering and selection. To disregard the possible differences between countries in terms of sampling frequency used for the measures of the speed measurements, we propose to give the cumulative driving time instead of the cumulative number of measures.

5.2.1.6. Synthesis of the recommendations for the estimation of the speed SPI

In the case of speed behavioural SPI, we recommend to apply the following filters to obtain homogeneous data by keeping only reasonably free flowing traffic conditions.

- Remove data during peak hours
- Remove data from weekends
- Remove data where car drives less than 5 km/h
- Remove data during bad weather conditions

For SPI accuracy considerations, we recommend to choose a 1-month time window and to restrain the number of classes while clustering to the following ones.

- Classes defined with the legal speed limits: 30 km/h, 50 km/h, 70 km/h, 80 km/h, 90 km/h, 110 km/h, 120 km/h, and 130 km/h to cover the majority of legal speed limits in Europe. For some specific country, it might be relevant to add a class if a given road type has a specific speed limitation.
- Classes defined with the driving context: (urban / outside urban area / motorway)
- Classes defined according to the lighting conditions: day and night conditions. Day time is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour. (.See 2.7.3)
- Classes defined according to the period of the week: week days and weekends in the case of speed descriptive SPI.

For SPI reliability considerations, we recommend to provide in addition to SPI values, SPI subsample characteristics (number of drivers and cumulative driving time) for each clustering class. We recommend to exclude, from the class subsample, participants who drive less than 17 min over the month in the situation described by the class.

5.2.2. Detailed procedure to compute Speed behavioural SPI

5.2.2.1. Mean speed and standard deviation of speed in free flowing traffic conditions

5.2.2.1.1. Choice of meaningful SPI indicators

The relevance of this indicator is to highlight specific and remarkable speed behaviour in the participant sample: the speed generally selected according to the legal speed limit.

In order to be meaningful, it is important to compute the mean speed with its standard deviation only where it is relevant: in reasonably free flowing traffic conditions excluding traffic jam situations. It is also important to split the computation of mean speed and its standard deviation, according to the legal speed limit of the roads, so that we can monitor the final SPI value and that we can compare it to the legal value.

5.2.2.1.2. SPI definition

This SPI characterise the safety behaviour of a driver and highlight the mean speed he/she goes and how close to this mean he/she keeps, according to the current legal speed limit and only in free flowing traffic conditions.

5.2.2.1.3. Data collection requirement

To compute this indicator with all filtering and clustering possibilities, 3 kinds of data must be available.

1. a set of naturalistic driving data: vehicle speed, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road legal speed limit, a weather database that can be used to obtain local weather conditions on a day by day basis, a database of sunrise and sunset times to infer daylight and night conditions.
3. a set of participant data, for country level aggregation

5.2.2.1.4. Data filtering

As explained in chapter 5.1.1.4, the filters will be the following:

- Remove data during peak hours
- Remove data week ends
- Remove data where car drives less than 5km/h
- Remove data during bad weather conditions

5.2.2.1.5. Data clustering conditions

As explained in chapter 5.1.1.4, the clusters will be the following:

- Classes defined with the legal speed limits: 30 km/h, 50 km/h, 70 km/h, 80 km/h, 90km/h, 110km/h, 120 km/h, and 130 km/h to cover the majority of legal speed limits in Europe. For some specific country, it might be relevant to add a class if a given road type has a specific speed limitation.
- Classes defined according to the lighting conditions: day and night conditions. Day time is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour. (.See 2.7.3)

5.2.2.1.6. Data processing

The data from the vehicles must be inserted in a database. The database must contain, for each line, the raw speed data, associated with a driver identifier, a trip number, a timestamp (date + time), and legal speed limit.

First step: the filters must be applied on this data set to build a second "filtered dataset". The first filter, for optimisation reasons, should be the removal of bad weather conditions. Depending on the method used to obtain "good weather conditions" (i.e. through sensors, through a third party weather database or both), this steps aims to obtain the information on all the data that have to be copied to the filtered dataset. Then, only data collected during the week days have to be copied to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

We use this filtered raw database to build 3 new participant level aggregated databases, useful for the final analyses. The 3 aggregated databases have the same structure and contain the values of the mean speed/standard deviation of speed for all speed limit conditions (8 columns in total: 30, 50, 70, 80, 90, 110, 120, 130) and for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level)

The following list describes the use of the 3 aggregated databases

1. Store mean speed/standard deviation of speed independently of the time of the day. Store the number of measurements used to provide subsample characteristics.

2. Store mean speed/standard deviation of speed observed during the day. Store the number of measurements used to provide subsample characteristics.

3. Store mean speed/standard deviation of speed observed during the night. Store the number of measurements used to provide subsample characteristics.

Data from the filtered database are aggregated to fill in the first aggregated database: limiting sequentially to each driver, selection of all samples where speed limit is {30, 50, 70, 80, 90, 110, 120, 130} and calculation of the mean and standard deviation. The time spent by the driver in each class is also computed: it should be equal to the number of speed measure kept in the condition if the data collection is performed at 1Hz. This value will be the subsample characteristic.

Data from the filtered database are aggregated to fill in the second aggregated database: limiting sequentially to each driver and limiting to time windows “daylight conditions” as defined in chapter 2. Selection of all samples where speed limit is {30, 50, 70, 80, 90, 110, 120, 130} and calculation of the mean and standard deviation. The time spent by the driver in each of the class is also computed for the subsample characteristic.

Data from the filtered database are aggregated to fill in the third aggregated database: limiting sequentially to each driver and limiting to time windows “night conditions” as define in chapter 2. Selection of all samples where speed limit is {30, 50, 70, 80, 90, 110, 120, 130} and calculation of the mean and standard deviation. The time spent by the driver in each of the class is also computed for the subsample characteristic.

The following illustration gives an overview of the basic table at the participant level. It only includes filtering to obtain free flowing traffic condition and no clustering other than speed limits.

	30 km/h	50 km/h	70 km/h	80 km/h	90 km/h	110 km/h	120 km/h	130 km/h
Driver 1	mean speed = 35,2 stdev = 5,23 SSC = 7	mean speed = 55,4 stdev = 6,23 SSC = 45	mean speed = 86,4 stdev = 7,23 SSC = 28	...	...	...	...	...
Driver 2	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	

SPI : Mean speed and standard deviation of speed in free flowing traffic conditions in march 2012*

* Filters provoke the removal of data collected during
Peak hours
Week ends driving
Car speed is less than 5km/h
Weather conditions are bad

SSC = sub sample characteristics (total aggregated driving time in cluster in minutes)

Figure 6 - Possible country reporting at participant level

5.2.2.1.7. Reporting to the ERSO and data analysis

It is possible, in addition to the clusters proposed previously to prepare some specific comparison between driver groups. Of example, the mean speeds/standard deviation can be compared by creating drivers groups:

- Male drivers vs. Female drivers
- Age groups

For each cluster or comparison, it will be possible, at the country level to obtain the information that will be necessary to contribute to the SPI general table.

It is possible to follow the following process to aggregate the participant data:

For each class (according to the clustering: legal speed limit + constraint on the time of the day)

- for each participant, assess if the sub sample characteristic (SSC) is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000s of data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, the remaining participant averages can be used to compute the weighted average and the standard deviation at the country level. The weighting factors have to be selected to match with the sample composition. At last, it is required to sum up the measurement brought by all the participants and the total number of participants used for the calculation to provide the country level subsample characteristics.

The following illustration gives an overview of the basic table that only includes filtering to obtain free flowing traffic condition and no clustering others than speed limits.

	30 km/h	50 km/h	70 km/h	80 km/h	90 km/h	110 km/h	120 km/h	130 km/h
Country 1	mean speed = 32,4 stdev = 1,23 SSC = 12 / 34	mean speed = 56,4 stdev = 2,23 SSC = 26 / 89	mean speed = 76,4 stdev = 5,12 SSC = 35 / 115	...	...	...	...	...
Country 2	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	

SPI : Mean speed and standard deviation of speed in free flowing traffic conditions in march 2012*

* Filters provoke the removal of data collected during
Peak hours
Week ends driving
Car speed is less than 5km/h
Weather conditions are bad

SSC = sub sample characteristics (number of drivers included / total aggregated driving time in cluster in minutes)

Figure 7 - Possible ERSO reporting at country level

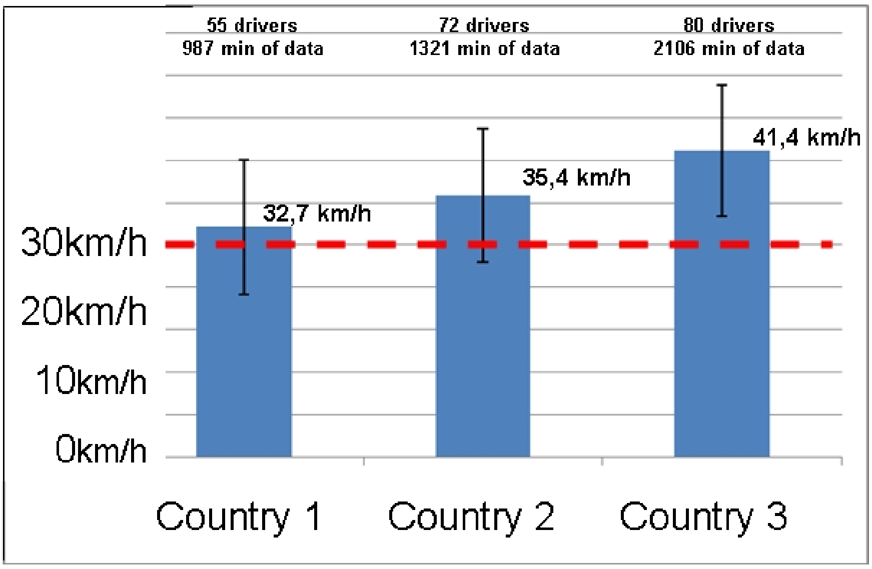
The table with the other clustering or comparisons will have the same aspect but the results will vary according to the additional conditions applied for each class.

There is a set of issues raised by the aggregation of speed data according to the legal speed limit that can limit the possibility of comparison between countries.

For the same type of road, several legal speed limits can be associated (e.g. 110 km/h or 130 km/h for motorways) and the legal speed limits can vary between countries.

Some countries have special rules in terms of speed regulation. For example countries can have specific speed limits for some categories of drivers or some categories of vehicle, specific speed limits according to the weather conditions (e.g. in France), specific speed limits according to the day time (e.g. in Austria) and specific speed limits for traffic regulation purpose.

It will be possible, using these tables, to produce graphs that can describe country differences in terms of speed behaviour.



Excessive speed SPI in free flowing traffic condition in march 2012, limited to 30km/h legal speed zones.

Figure 8 - Possible illustration using country level SPI

5.2.2.2. V85 in free flowing traffic conditions

5.2.2.2.1. Choice of meaningful SPI indicators

The relevance of this indicator is to highlight specific and remarkable speed behaviour in the participant sample. V85 correspond to the 85th percentile of the speed: the V85 value split the data in two parts with 85% of the speed measures below and 15% above.

In order to be meaningful, it is important to compute the compute the V85 only where it is relevant: in reasonably free flowing traffic conditions excluding traffic jam situations. It is also important to split the computation of the V85, according to the legal speed limit of the roads, so that we can monitor the final SPI value and that we can compare it to the legal value.

5.2.2.2.2. SPI definition

This SPI characterise the safety behaviour of a driver and highlight the speed below which he/she goes 85% of the time, grouped by different legal speed limit and only in free flowing traffic conditions.

5.2.2.2.3. Data collection requirement

In order to produce homogeneous SPI, it is preferable to use the same raw database. The collected data will be the same as what is described in 5.1.2.1.3

5.2.2.2.4. Data filtering

As explained in chapter 5.1.1.4, the filters will be the following:

- Remove data during peak hours
- Remove data week ends
- Remove data where car drives less than 5km/h
- Remove data during bad weather conditions

5.2.2.2.5. Data clustering conditions

As explained in chapter 5.1.1.4, the clusters will be the following:

- Classes defined with the legal speed limits: 30 km/h, 50 km/h, 70 km/h, 80 km/h, 90km/h, 110km/h, 120 km/h, and 130 km/h to cover the majority of legal speed limits in Europe. For some specific country, it might be relevant to add a class if a given road type has a specific speed limitation.
- Classes defined according to the lighting conditions: day and night conditions. Day time is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour. (See 2.7.3)

5.2.2.2.6. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the raw speed data, associated with a driver identifier, a trip number, a timestamp (date + time), and legal speed limit.

First step: the filters must be applied on this data set to build a second "filtered dataset". The first filter, for optimisation reasons, should be the removal of bad weather conditions. The remote database should give the information on all the date to copy to the filtered dataset. Then, only data collected during the week days have to be copied to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

We use this filtered raw database to build 3 new aggregated databases, useful for the final analyses. The 3 aggregated databases have the same structure and contains the values of the V85 of speed for all speed limit conditions (8 columns in total: 30, 50, 70, 80, 90, 110, 120, 130) and for all the participants (one per line).

The following list describes the 3 aggregated databases

1. Store V85 of speed independently of the time of the day.
2. Store V85 of speed observed during the day.
3. Store V85 deviation of speed observed during the night.

Data from the filtered database are aggregated to fill in the first aggregated database: limiting sequentially to each driver, selection of all samples where speed limit is {30, 50, 70, 80, 90, 110, 120, 130}. All the selected values are then sorted by ascending order and the number of sample is counted. The value of the speed that let 85% of the sample below and 15% of the sample above is the V85. This value is stored. The total number of values in each speed limit class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters)

Data from the filtered database are aggregated to fill in the second aggregated database: limiting sequentially to each driver and limiting to time window “daylight period” as defined in chapter 2. Selection of all samples where speed limit is {30, 50, 70, 80, 90, 110, 120, 130}. All the selected values are then sorted by ascending order and the number of sample is counted. The value of the speed that let 85% of the sample below and 15% of the sample above is the V85. This value is stored. The total number of values in each speed limit class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters)

Data from the filtered database are aggregated to fill in the third aggregated database: limiting sequentially to each driver and limiting to time “night period” as defined in chapter 2. Selection of all samples where speed limit is {30, 50, 70, 80, 90, 110, 120, 130}. All the selected values are then sorted by ascending order and the number of sample is counted. The value of the speed that let 85% of the sample below and 15% of the sample above is the V85. This value is stored. The total number of values in each speed limit class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters)

5.2.2.2.7. Reporting to the ERSO and data analysis

See 5.1.2.1.7 as the data can be aggregated in the same way and the same tables and graphs can be created.

5.2.2.3. Percentage of driving time over the legal speed limit in free flowing traffic conditions

5.2.2.3.1. Choice of meaningful SPI indicators

The relevance of this indicator is to highlight specific and remarkable speed behaviour in the participant sample: the ratio of time spent over the legal speed limit.

In order to be meaningful, it is important to compute the over speed situations only where it is relevant: in reasonably free flowing traffic conditions excluding traffic jam situations. It is also important to distinguish for the computation of time above speed limit between the road context in terms of driving environment (urban / outside urban area / motorway).

5.2.2.3.2. SPI definition

This SPI characterise the safety behaviour of a driver and highlight the time drivers spend travelling at speeds greater than the speed limit grouped by to each driving environment and only in free flowing traffic conditions

5.2.2.3.3. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: vehicle speed, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road classification in term of driving context (urban/outside urban area/motorway) and in term of legal speed limit, a weather database that can be used to obtain local weather conditions on a day by day basis. A database of sunrise and sunset times to infer daylight and night conditions.
3. a set of participant data, for country level aggregation

5.2.2.3.4. Data filtering conditions

As explained in chapter 5.1.1.4, the filters will be the following:

- Remove data during peak hours
- Remove data week ends
- Remove data where car drives less than 5km/h
- Remove data during bad weather conditions

5.2.2.3.5. Data clustering conditions

As explained in chapter 5.1.1.4, the clusters will be the following:

- Classes defined with the driving context: urban / outside urban area / motorway)
- Classes defined according to the lighting conditions: day and night conditions. Day time is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour. (See 2.7.3)

5.2.2.3.6. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the raw speed data, associated with a driver identifier, a trip number, a timestamp (date + time), the driving context (road type: outside urban area, urban, motorway), the legal speed limit

First step: the filters must be applied on this data set to build a second “filtered dataset”. The first filter, for optimisation reasons, should be the removal of bad weather conditions. The remote database should give the information on all the date to copy to the filtered dataset. Then, only data collected during the week days have to be copied to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

We use this filtered raw database to build 3 new aggregated databases, useful for the final analyses. The 3 aggregated databases have the same structure and contains the values of the time over speed limit of speed for all driving context conditions (3 columns in total: urban, outside urban area, motorway) and for all the participants (one per line).

The following list describes the used of the 3 aggregated databases

1. Store the time over speed limit independently of the time of the day.
2. Store the time over speed limit observed during the day.
3. Store the time over speed limit observed during the night.

Data from the filtered database are aggregated to fill in the first aggregated database: limiting sequentially to each driver, selection of all samples where driving context is { urban area, outside of urban area, motorway}. Compute the ratio of samples where driver speed is greater than the legal speed limit, whatever the value of the legal speed limit. This value is stored. The total number of values in each road environment class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters).

Data from the filtered database are aggregated to fill in the second aggregated database: limiting sequentially to each driver and limiting to time windows “daylight” conditions as defined in chapter 2. Selection of all samples where driving context is { urban area, outside of urban area, motorway}. Compute the ratio of samples where driver speed is greater than the legal speed limit, whatever the value of the legal speed limit. This value is stored. The total number of values in each road environment class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters). The total number of values in each road environment class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters).

Data from the filtered database are aggregated to fill in the third aggregated database: limiting sequentially to each driver and limiting to time windows “night condition” as defined in chapter 2. Selection of all samples where driving context is { urban area, outside urban area, motorway}. Compute the ratio of samples where driver speed is greater than the legal speed limit, whatever the value of the legal speed limit. This value is stored. The total number of values in each road environment class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters).

5.2.2.3.7. Reporting to the ERSO and data analysis

See 5.1.2.1.7 as the data can be aggregated in the same way and the same tables and graphs can be created.

5.2.2.4. Percentage of driving time 10 km/h over the legal speed limit in free flowing traffic conditions

5.2.2.4.1. Choice of meaningful SPI indicators

The relevance of this indicator is to highlight specific and remarkable speed behaviour in the participant sample: the ratio of time spent 10km/h over the legal speed limit.

In order to be meaningful, it is important to compute the over speed situations only where it is relevant: in reasonably free flowing traffic conditions excluding traffic jam situations. It is also important to distinguish for the computation of time above speed limit between the road context in terms of driving environment (urban / outside urban area / motorway).

5.2.2.4.2. SPI definition

This SPI characterise the safety behaviour of a driver and highlight the time drivers spend 10km/h over the speed limit according to each driving environment and only in free flowing traffic conditions.

5.2.2.4.3. Data collection requirement

See 5.1.2.3.3

5.2.2.4.4. Data filtering

See 5.1.2.4.4

5.2.2.4.5. Data clustering conditions

See 5.1.2.3.5

5.2.2.4.6. Data processing

See 5.1.2.3.6

5.2.2.4.7. Reporting to the ERSO and data analysis

See 5.1.2.3.7

5.2.3. Detailed procedure to estimate Speed descriptive SPI

5.2.3.1. Percentage of driving time over the legal speed limit

5.2.3.1.1. Choice of meaningful SPI indicators

The relevance of this indicator is to highlight specific and remarkable speed behaviour in the participant sample: the ratio of time spent over the speed limit. This value is not exactly linked to the behaviour of a driver, as it includes all external factors (traffic, weather…) that may occur. Indeed, on the contrary to the indicator presented in chapter 5.1.2.1 in order to be meaningful, it is important to compute this indicator in all possible driving situations in order to gain an overview of the driver speed exposure.

Note that it is important to distinguish for the computation of time above speed limit between the road context in terms of driving environment (urban / outside urban area / motorway).

External factors may have an impact on the time spent over the speed limit: the period of day (night / day) and the period of week (week day / weekends), and they can be taken into account for comparisons.

5.2.3.1.2. SPI definition

This SPI characterise the safety behaviour of a driver and highlight the time drivers spend over the speed limit according to each driving environment.

5.2.3.1.3. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: vehicle speed, time and date, GPS position, driver identification
2. a set of static data: a geographic information system (GIS) for map matching to infer road classification in term of driving context (urban/outside urban area/motorway) and in term of legal speed limit. A database of sunrise and sunset times to infer daylight and night conditions
3. a set of participant data, for country level aggregation

5.2.3.1.4. Data filtering

As explained in chapter 5.1.1, no filter will be used:

5.2.3.1.5. Data clustering conditions

The clusters will be the following:

- Classes defined with the driving context: urban / outside urban area / motorway.
- Classes defined according to the lighting conditions: day and night conditions. Day time is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour. (.See 2.7.3)
- Classes defined according to the period of week: week day / weekend.

5.2.3.1.6. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the raw speed data, associated with a driver identifier, a trip number, a timestamp (date + time), the driving context (road type: outside urban area, urban, motorway), the legal speed limit

For this indicator, the calculation will be made directly with the raw data set.

We use this raw database to build 5 new aggregated databases, useful for the final analyses. The 3 aggregated databases have the same structure and contains the values of the time over speed limit of speed for all driving context conditions (3 columns in total: urban, outside urban area, motorway) and for all the participants (one per line).

The following list describes the used of the 3 aggregated databases

1. Store the time over speed limit independently of the time of the day.

2. Store the time over speed limit observed during the day.
3. Store the time over speed limit observed during the night.
4. Store the time over speed limit observed during week days
5. Store the time over speed limit observed during weekends.

Data from the database are aggregated to fill in the first aggregated database: limiting sequentially to each driver, selection of all samples where driving context is {outside urban area, interurban, motorway}. Compute the ratio of samples where driver speed is greater than the legal speed limit. This value is stored. The total number of values has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters).

Data from the filtered database are aggregated to fill in the second aggregated database: limiting sequentially to each driver and limiting to time windows “daylight conditions” as defined in chapter 2. Selection of all samples where driving context is {outside urban area, interurban, motorway}. Compute the ratio of samples where driver speed is greater than the legal speed limit. This value is stored. The total number of values in each class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters).

Data from the filtered database are aggregated to fill in the third aggregated database: limiting sequentially to each driver and limiting to time windows [23:00-5:30], selection of all samples where driving context is {outside urban area, interurban, motorway}. Compute the ratio of samples where driver speed is greater than the legal speed limit. This value is stored. The total number of values in each class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters).

Data from the filtered database are aggregated to fill in the fourth aggregated database: limiting sequentially to each driver and limiting to week days, selection of all samples where driving context is {outside urban area, interurban, motorway}. Compute the ratio of samples where driver speed is greater than the legal speed limit. This value is stored. The total number of values in each class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters).

Data from the filtered database are aggregated to fill in the fifth aggregated database: limiting sequentially to each driver and limiting to weekends, selection of all samples where driving context is {outside urban area, interurban, motorway}. Compute the ratio of samples where driver speed is greater than the legal speed limit. This value is stored. The total number of values in each class has to be stored to provide information on the SPI subsample characteristic (driving time in given clusters).

5.2.3.1.7. Reporting to the ERSO and data analysis

See 5.1.2.1.7.

5.2.3.2. Percentage of driving time 10 km/h over the legal speed limit

5.2.3.2.1. Choice of meaningful SPI indicators

The relevance of this indicator is to highlight specific and remarkable speed behaviour in the participant sample: the ratio of time spent 10km/h over the legal speed limit. This value is not exactly linked to the behaviour of a driver, as it includes all external factors (traffic, weather…) that may occur. Indeed, on the contrary to the indicator presented in chapter 5.1.2.1 in order to be meaningful, it is important to compute this indicator in all possible driving situations in order to gain an overview of the driver speed exposure.

The relevance of this indicator is to highlight specific and remarkable speed behaviour in the participant sample: the ratio of time spent 10km/h over the speed limit. Note that it is important to distinguish for the computation of time 10km/h over speed limit between the road context in terms of driving environment (urban / outside urban area / motorway).

External factors may have an impact on the time spent 10km/h over the speed limit: the period of day (night / day) and the period of week (week day / weekends), and they can be taken into account for comparisons.

5.2.3.2.2. SPI definition

This SPI characterise the safety behaviour of a driver and highlight the time drivers spend 10km/h over the speed limit according to each driving environment.

5.2.3.2.3. Data collection requirement

See 5.1.3.1.3.

5.2.3.2.4. Data filtering

See 5.1.3.1.4.

5.2.3.2.5. Data clustering conditions

See 5.1.3.1.5.

5.2.3.2.6. Data processing

See 5.1.3.1.6.

5.2.3.2.7. Comparisons

See 5.1.3.1.7.

5.2.3.2.8. Generalisation and dissemination to ERSO

See 5.1.3.1.8.

5.3. Seat belt use SPI

5.3.1. General description

5.3.1.1. Context and definition

Increasing the prevalence of belt use is a major goal among traffic safety in many countries. The emphasis on these efforts exists because of the proven effectiveness of seatbelt use in saving lives and reducing injuries. The National Highway Traffic Safety Administration [Pickrell, T. M., & Ye, J. Y, 2011] estimated that for front seat riders of passenger cars, proper seatbelt use reduces the risk of death from crashes by 45%. In 2009, wearing a seatbelt saved the lives of approximately 13,000 passenger vehicle occupants in the United States. In the USA, a recent road side observations estimates reaching 84% belt use rate [Pickrell, T. M., & Ye, J. Y, 2011].

The success of efforts to increase use is measured by both road side observations and self-report questionnaires. Seatbelt use rates can be derived by completing observational surveys, in which trained observers record seatbelt status for drivers and passengers while vehicles are on the roadways. As the use rates vary in time and space, it is recommended in order to produce accurate estimation, to employ a sampling procedure to determine the optimal set of road types across and to use a random assignment of observation sites to different selected days of week/ time of day time slots. A limitation of the method is that it is a single observation of one driver at one point in time during daytime. Given the method, observers cannot possibly know how the seatbelt use pattern of a particular driver varies over time and driving context. Another way to estimate rates of automobile seat belt fastening is to use self-report measures. The well-known shortcoming of this method is the overestimation of belt use rates compared to observational surveys of the same population.

Safetynet recommends to use, as seat belt use SPIs, the daytime wearing rates of seat belts in front seats and in rear seats for passenger cars and vans under 3.5 tons, classified according to the main road types, such as motorways, other outside urban area roads and urban roads. For this SPI estimation, Safetynet recommends to rely exclusively on independent observational surveys of protective systems' use in traffic instead of survey done with questionnaire.

Using naturalistic driving data permits to observe individuals repeatedly over time, in different driving contexts [Reagan, 2012]. It makes it possible to estimate the rate of seat belts use for drivers and passengers according to the road type, like it is recommended by Safetynet, but also by distinguishing daytime and night-time. In addition, naturalistic driving data enable to see if the seat belt is fastened when the driver set the vehicle in motion, and if there are changes in seatbelt use later in the trip (fastening it or unfastening it). Moreover, seatbelt use habit can be investigated according to the characteristics of drivers (education level, age, gender…). The accuracy of the information will be helpful to increase the efficiency of prevention messages to encourage people to fasten their seat belt.

We propose to distinguish two families of seat belt use SPI, the behavioural SPI and the descriptive SPI.

- In the first case, the behavioural SPI will highlight the propensity of drivers to fasten their seat belt according to the trip characteristics. The calculation of the 2 following seat belt use behavioural SPI will be detailed in the section 5.2.2.
    - Percentage of trips without seat belt use, with partial seat belt use, with total seat belt use
    - Systematic use of seat belt: percentage of trips with immediate seat belt fastening
- In the second case, the descriptive SPI will give exposure data of seat belt use for both drivers and passengers. The calculation of the following seat belt use descriptive SPI will be detailed in the section 5.2.3.
    - Percentage of driving time with seat belt fastened for drivers, front passengers and rear passengers.

5.3.1.2. Measure requirements

First, the calculation of seat belt SPI requires the information about the fastening of the belt. In newer vehicles, this measure can be directly issued from the CAN bus of the car that gives the information of the fastening of the belt when there is a passenger on the seat. Indeed, these sensors exist as they are used to give a warning if the car starts but the driver and the passengers are unfastened. The warnings are different for each type of seat (driver seat, front passenger seat, rear passenger seats). For the driver and front passenger seats, a sound is broadcast when the belt is not fastened. For rear passenger seats, there is only a light indication on the dashboard.

If these sensors are useful, perhaps some drivers who do not want to fasten the belt (for example taxi drivers in specific roads type like town) can develop a strategy to fool them in order to prevent the alarm. They just have to buy and install a belt loop. The CAN computer detects a fastened belt and the alarm stops. In this case, there is no way to detect the real use of the belt.

These sensors can also bring false positive. Generally, the car computer makes the difference between a passenger and a bag placed on the seat, but when the bag is heavy, the confusion can be done. When the bag is on the passenger car, driver can put the bag down in order to stop the noisy alarm, there is no false detection. But if the bag is on the rear seat, with no alarm, if the driver does not pay attention to it, there is no way on the data, to make the distinction between a bag placed on a seat and a child with the seat belt not engaged.

The measure of seat belt use SPI will be easy in the case of new and premium vehicles as the vehicles are equipped with a seat belt alarm and associated sensors. However, Swedish and American studies have shown that the presence of seat belt reminders impacts positively the behaviour of the drivers in terms of seat belt use [ETSC, 2006]. The population of the drivers of equipped cars will probably tend to comply more with this rule. In such conditions, it will be difficult to generalize the result to the whole drivers' population.

If we would like to have a vehicle sample more representative of the vehicle fleet, specific development will be necessary to design a sensor that gives the needed information. A cost-benefit analysis will be required to determine the seat positions to instrument taking into account that for a majority of the trips the driver will be the only occupant.

Seat Belt SPI cannot be used to focus on child restraints. For the youngest children, a specific "young child" seat should be fixed to the car. The seat has its own seat belts to attach the child. There is no way with the automatic sensors to detect if a young child is properly restrained or not.

In order to be able to disaggregate Seat Belt SPI according to the road characteristics, it is necessary to know the GPS positions of the vehicle and to have access to a geographic information system (GIS) in order to infer, through map matching, information such as road type and legal speed limit. Accessing GIS data leads to several constraints that are already discusses in detail in chapter 5.1.1.2. Please refer to this chapter for additional information on GIS data.

5.3.1.3. Filtering, Clustering and time window

We have made the decision not to apply any filter on the data, considering all the trips performed by the driver. The readers are invited to refer to the session 2.7 for a definition of the trip and the issues related. We have decided to keep for the SPI estimation, the situations when the car is stopped and the engine is still running, considering the situations in traffic jam where it is important to see if drivers keep wearing their belt or not. We are aware that without filtering, we take in account situations of long breaks where the car is parked with the engine running and drivers can take off their belt, but it appears difficult to define a threshold.

The usefulness of Seat Belt SPI, both behaviour and descriptive, will depend on the possibilities they will offer to evaluate the changes over time of seat belt use in different driving contexts (type of road, duration of the trip, length of the trip, period of the week, period of the day, during peak hours or not…).

In order to ensure sufficient data for clustering, the choice of the time windows will be at the level of a month, as for the other SPI.

5.3.1.4. Aggregation

For behavioral seat belt use SPI the first level of aggregation will be the trip. Then we can compute the percentage of trips with total, partial or without seat belt use, and systematic use of seat belt.

A second aggregation will be performed at a participant level to allowed comparisons of seat belt use between drivers' groups at the country level:

- Males drivers vs. female drivers
- Between age groups
- Between commuters and professional drivers
- …

For descriptive SPI, we compute the percentage of driving time with seat belt fastened; there is no interest to aggregate data at a trip level. Exposure data for drivers will be directly aggregated at an individual level before doing the aggregation at the country level. Exposure data for passengers will be directly aggregated at a country level.

5.3.2. Detailed procedure to estimate Seat belt behavioural SPI

5.3.2.1. Percentage of trips without seat belt use, with partial seat belt use, with total seat belt use

5.3.2.1.1. SPI definition

This SPI characterizes the safety behaviour of a driver and highlight the percentage of the trips he/she chooses to fasten his/her seat belt and in case of fastening, if it is done during all the trip or only a part of the trip. The identification of the characteristics of the trip that can affect drivers' choice to fasten their seat belt is crucial to have a better understanding of the behaviour of the occasional seat belt users [Reagan, 2012].

5.3.2.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if the seat belt of the driver is used or not, speed of the vehicle, time and date, GPS position, driver identification

2. a set of static data: a geographic information system (GIS) for map matching to infer road type

3. a set of participant data, for country level aggregation

5.3.2.1.3. Data filtering

There is no specific filter to be applied here as it is important to consider all the trips performed by the driver.

The first level of aggregation for this indicator is the trip: each time the driver start the engine and move from 1 origin toward 1 destination and then shut down the engine.

5.3.2.1.4. Data clustering conditions

The first clustering aims to highlight the different seat belt uses on long trips vs. short trips in terms of the trip duration. If a trip last more than 20 minutes, it can be considered as a long trip.

The second clustering aims to highlight the different seat belt uses on close trips vs. far trips in terms of straight line trip distance (as the crow flies). When all the locations of the trip positions are within a 3km radius from the start point, it can be considered as a close trip. Otherwise it is a far trip.

A third possible clustering concerns the main type of road met during the trip: if driving time is spent more than 80% on a given road type, it can be considered as a trip “mainly on this given road type”. The three road type considered will be urban / outside urban area / motorway.

5.3.2.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the seat belt fastening, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area , motorway).

First step: to compute this SPI, it is necessary to have an aggregation of the data at the level of the trips and to obtain trip level information about the seat belt use. The target “trip dataset” that has to be created must contain the following information as primary key: driver identifier, trip identifier. Then it should also provide relevant information about the trip both for the SPI and the clustering: percentage of time with seat belt on, duration of trip in term of time driven, straight line distance between the origin position and the arrival position, percentage of time on urban roads, percentage of time on motorways, percentage of time on ‘outside of urban’ roads. All these data can be easily computed trip by trip by making the proper ratios.

We use this trip database to build new aggregated databases at the level of the participant, useful for the final analyses and aggregation. The aggregated databases contains, for all the participants (one per line), 3 values (one per column): the percentage of trips dispatched in each of the three conditions

1. “trip without seat belt” when the rate of use is below 5%,

2. “trip with partial use of seat belt” when the rate of use is greater than 5% but less than 95%,

3. "trip with total use of seat belt" when the rate of use is greater than 95%.

Then the following list describes the different aggregated databases to be produced according to the clustering variable

1. Database without clustering: dispatch all the trips in each of the 3 conditions and at the end compute the 3 ratios (on the basis of the total number of the trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.
2. database with short vs long trips in terms of time :

- Calculation with short trips in terms of time: include only the trips that last less than 20 minutes and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the short trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.
- Calculation with long trips in terms of time: include only the trips that last more than 20 minutes and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the long trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.

3. database with close vs far trips in terms of straight line distance (as the crow flies)

- Calculation with close trips in terms of straight line distance: include only the trips where all the trip locations stay within a 3km radius from the start point and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the close distance trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.
- Calculation with far trips in terms of straight line distance: include only the trips where part of the trip are outside a 3km radius from the start point and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the far distance trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.

4. database with outside urban area vs urban vs motorway trips :

- Calculation with "mainly outside urban area " trips : include only the trips that are more than 80% of time on outside urban area roads and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the "mainly outside urban area" trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.
- Calculation with "mainly urban" trips : include only the trips that are more than 80% of time on urban roads and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the "mainly urban" trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.

- Calculation with "mainly motorway" trips: include only the trips that are more than 80% of time on motorways and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the "mainly motorway" trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.

5.3.2.1.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. For example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- Between commuters and professional drivers

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, the remaining participant trip % can be used to compute the weighted % and the standard deviation at the country level, in each condition (mean % of no use, mean % of partial use, mean % of total use). The weighting factors have to be selected to match with the sample composition. At last, it is required to compute the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.3.2.2. Systematic use of seat belt: percentage of trips with immediate fastening of the seat belt

5.3.2.2.1. SPI definition

This SPI characterise the safety behaviour of a driver and gives information on the percentage of trips for which the driver immediately fasten his/her seat belt when he/she starts a new trip. The time window that will be investigated for the "immediate" fastening is between the moment when the driver start the engine (beginning of the trip) and the moment when the vehicle start moving (speed > 5 km/h, beginning of the driving).

Malenfant and Van Houten's have observed that most drivers waited to buckle their seatbelt until after they started their vehicle or placed it into gear, with a substantial proportion buckling after placing the vehicle in motion. 99% of the drivers who buckled their seatbelts did so within the first 30 s of placing the vehicle in gear. [Malenfant and Van Houten's, 2008]

5.3.2.2.2. Data collection requirement

To compute this indicator, 2 kinds of data must be available.

1. a set of naturalistic driving data: detection if the seat belt of the driver is used or not, speed of the vehicle, time and date, driver identification
2. a set of participant data, for country level aggregation

5.3.2.2.3. Data filtering

There is no specific filter to be applied here as it is important to consider all the trips performed by the driver.

5.3.2.2.4. Data clustering conditions

No clustering process is planned. The percentage of trips with immediate fastening of the seat belt is not investigated according to the trip characteristic. It is considered as a general behaviour of the driver that will be only investigated according to the drivers' characteristics.

5.3.2.2.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the seat belt fastening, the speed of the vehicle associated with a driver identifier, a trip identifier and a unique timestamp (date + time).

To compute this SPI, it is necessary to have an aggregation of the data at the level of the participant. The aggregated database contains, for each participant the percentage of trips with immediate fastening, i.e. fastening of the seat belt by the driver before the speed of the vehicle reaches 5 km/h. The database includes also the Sub Sample Characteristics, which is here the number of trips used for the calculation and the total time spent driving in these trips.

5.3.2.2.6. Reporting to the ERSO and data analysis

The mean / standard deviation of the percentage of tips with immediate fastening can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

In order to obtain relevant comparison, it is crucial to assess the balance of the participant sample and to make sure that there are enough participants within the subgroups used for comparison.

For each comparison, the process based on SSC, described in section 5.2.2.1.6, will be used to aggregate the participant data and to produce a table at the level of the country:

5.3.3. Detailed procedure to estimate Seat belt descriptive SPI

5.3.3.1. Percentage of driving time with seat belt fastened

5.3.3.1.1. SPI definition

This SPI provides exposure data of seat belt use of both drivers and passengers. I characterises, for the whole sample, the ratio of time driven with seat belt fastened by distinguishing the driver, the front passengers and the rear passengers.

5.3.3.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: presence of passengers, detection of seat belts used for the front and rear seats, speed of the vehicle, time and date, GPS position, driver identification
2. a set of static data: a geographic information system (GIS) for map matching to infer road type
3. a set of participant data, for country level aggregation

5.3.3.1.3. Data filtering

There is no specific filter to be applied here as it is important to consider all the trips performed by the driver.

5.3.3.1.4. Data clustering conditions

The first clustering aims to highlight the different seat belt used according to the driving context in terms of road types (urban roads, outside urban area roads or motorways).

The second clustering aims to highlight the different use of seat belt on daytime vs night-time.

The third clustering aims to highlight the different use of seat belt on week days vs week-ends days.

The fourth clustering aims to highlight the different use of seat belt on peak hours vs non-peak hours.

5.3.3.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the seat belt fastening for the driver, the presence of passengers, the seat belt fastening for the front and rear passengers, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

To compute this SPI for drivers, it is necessary to have an aggregation of the data at the level of the participant. The following list describes the different aggregated databases to be produced according to the clustering variable:

1. Database according to the road type: compute the seat belt use rate of the driver for the 3 types of road (urban, outside urban area, motorway). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving for these 3 types of road.
2. Database with day-time vs night-time conditions: compute the seat belt use rate of the driver for the 2 periods of the day. It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving for these 2 periods of the day.

3. Database with week days vs week-end days: compute the seat belt use rate of the driver for the 2 periods of the week. It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving for these 2 periods of the week.
4. Database with peak hours vs non-peak hours: compute the seat belt use rate of the driver for the 2 types of hours. It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving for these 2 types of hours.

To compute this SPI for passengers, the aggregation of the data is made directly at the level of the country. The following list describes the different aggregated databases to be produced according to the clustering variable:

1. Database according to the road type: compute the seat belt use rate of front and rear passengers for the 3 types of road (urban, outside urban area, motorway). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the cumulate time spent in the vehicle for the 2 kinds of passengers and for these 3 types of road.
2. Database with day-time vs night-time conditions: compute the seat belt use rate of front and rear passengers for the 2 periods of the day. It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the cumulate time spent in the vehicle for the 2 kinds of passengers and for these 2 periods of the day.
3. Database with week days vs week-end days: compute the seat belt use rate of front and rear passengers for the 2 periods of the week. It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the cumulate time spent in the vehicle for the 2 kinds of passengers and for these 2 periods of the week.
4. Database with peak hours vs non-peak hours: compute the seat belt use rate of front and rear passengers for the 2 types of hours. It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the cumulate time spent in the vehicle for the 2 kinds of passengers and for these 2 types of hours.

5.3.3.1.6. Reporting to the ERSO and data analysis

The mean / standard deviation of seat belt use rates can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- …

For each comparison, the process based on SSC, described in section 5.2.2.1.6, will be used to aggregate the participant data and to produce a table at the level of the country:

5.4. Daytime running light use SPI

5.4.1. General description

5.4.1.1. Context and definition

Daytime running light (DRL) use has a high potential to increase road safety by helping road users to better and earlier detect, recognize and identify vehicles [DRL, 2006]. DRL can also support drivers in their estimation of distance, speed and moving direction of others vehicles [Koornstra et al, 1997]. The life-saving potential of DRL has been estimated about 3 to 5% of the yearly number of road fatalities. This led in 2008 the European Commission to introduce dedicated Daytime Running Light (DRL) on all new types of motor vehicles from the year 2011 onwards by amending the Directive 76/756/EEC. In the long term this SPI will be deprecated but at this stage it is still relevant due to the latency of the renewal of the vehicle fleet.

SafetyNet recommends to use as DRL SPI, the percentage of vehicles using daytime running lights, classified according to the main road types and the vehicle types (cars, heavy good vehicles, motorcycles and mopeds). Observational surveys of DRL use in traffic permit to estimate this SPI. Surveys have to be made during daytime and under clear weather conditions, in order to prevent the effect of the weather and perception circumstances influencing the usage rate of the DRL.

Using naturalistic driving data will permit to observe individual repeatedly over time, in different driving context and to investigate the different factors that can impact the use of DRL by drivers.

We propose to distinguish two families of daytime running light use SPI, the behavioural SPI and the descriptive SPI.

- In the first case, the behavioural SPI will highlight the propensity of drivers to switch on the daytime running light of their vehicle according to the trip characteristics. The calculation of the 2 following DRL behavioural SPI will be detailed in the section 5.3.2.
    - Percentage of trips without DRL use, with partial DRL use, with total DRL use
    - Systematic use of DRL: percentage of trips with immediate DRL switching on.
- In the second case, the descriptive SPI will give exposure data of DRL use. The calculation of the following DRL descriptive SPI will be detailed in the section 5.3.3.
    - Percentage of driving time with DRL switched on.

5.4.1.2. Measure requirements

First, the calculation of DRL SPI requires the information about the switching on of the DRL. In newer vehicles, this measure can be issued from the CAN bus of the car.

Some vehicles are equipped with systems that automatically switch on DRL when the car is moving. It is not relevant to include, in the participant sample, drivers of these models of vehicles.

As SPI have to be evaluated during daytime and under clear weather conditions, see 2.7.3 and 2.7.4 for more details on definition of day time and weather conditions

In order to be able to disaggregate DRL SPI according to the road characteristics, it is necessary to know the GPS positions of the vehicle and to have access to a geographic information system (GIS) in order to infer, through map matching, information such as road type. Accessing GIS data leads to several constraints that are already discusses in detail in chapter 5.1.1.2. Please refer to this chapter for additional information on GIS data.

5.4.1.3. Filtering, Clustering and time window

Data will be filtered in order to keep only data collected during daytime.

Data will also be filtered in order to keep only data coming from vehicles that are not equipped with automatic DRL.

The usefulness of DRL SPI, both behaviour and descriptive, will depend of the possibilities they will offer to evaluate the changes over time of the DRL use in different driving contexts (type of road, duration of the trip, length of the trip, period of the week, during peak hours or not…).

In order to ensure sufficient data for clustering, the choice of the time windows will be at the level of a month, as for the others SPI.

5.4.1.4. Aggregation

For behavioural DRL use SPI the first level of aggregation will be the trip. Then we can compute the percentage of trips with total, partial or without DRL use, and systematic use of DRL.

A second aggregation will be performed at a participant level to allowed comparisons of DRL use between drivers' groups at the country level:

- Males drivers vs. female drivers
- Between age groups
- …

For descriptive SPI, we compute the percentage of driving time with DRL switched on; there is no interest to aggregate data at a trip level. Exposure data for drivers will be directly aggregated at an individual level before doing the aggregation at the country level.

5.4.2. Detailed procedure to estimate Daytime running light use behavioural SPI

5.4.2.1. Percentage of trips without DRL use, with partial DRL use, with total DRL use

5.4.2.1.1. SPI definition

This SPI characterizes the safety behaviour of a driver and highlight the percentage of the trips he/she chooses to switch on the daytime running lights of his/her vehicle., and in case of DRL use, if it is made during all the trip or only a part of the trip.

5.4.2.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if DRL are switched on, detection of wipers and fog lamps use, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road type, a database of sunrise and sunset time, a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.4.2.1.3. Data filtering

Data will be filtered in order to keep only data collected during daytime. Daytime is defined from sunrise plus 1 hour until sunset minus 1 hour. Data will be also filtered to keep only clement weather conditions. The data coming from vehicles equipped with automatic DRL will also be filtered out.

The first level of aggregation for this indicator is the trip: each time the driver start the engine and move from 1 origin toward 1 destination and then shut down the engine.

5.4.2.1.4. Data clustering conditions

The first clustering aims to highlight the different DRL uses on long trips vs. short trips in terms of the trip duration. If a trip last more than 20 minutes, it can be considered as a long trip.

The second clustering aims to highlight the different seat belt uses on close trips vs. far trips in terms of straight line trip distance (as the crow flies). When all the locations of the trip positions are within a 3km radius from the start point, it can be considered as a close trip. Otherwise it is a far trip.

A third possible clustering concerns the main type of road met during the trip: if driving time is spent more than 80% on a given road type, it can be considered as a trip “mainly on this given road type”. The three road type considered will be urban / outside urban area / motorway.

5.4.2.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the DRL use, associated with a driver identifier, a trip identifier, a unique timestamp (date + time), the driving context (road type: urban, outside urban area, motorway), the daytime and the clement weather information.

First step: to compute this SPI, it is necessary to have an aggregation of the data at the level of the trips and to obtain trip level information about the DRL use. The target “trip dataset” that has to be created must contain the following information as primary key: driver identifier, trip identifier. Then it should also provide relevant information about the trip both for the SPI and the clustering: percentage of time with DRL switched on, duration of trip in term of time driven, straight line distance between the origin position and the arrival position, percentage of time on urban roads, percentage of time on motorways, percentage of time on ‘outside of urban’ roads. All these data can be easily computed trip by trip by making the proper ratios. Only trips driven during the daytime and in clement weather will be kept in the database.

We use this trip database to build new aggregated databases at the level of the participant, useful for the final analyses and aggregation. The aggregated databases contains, for all the participants (one per line), 3 values (one per column): the percentage of trips dispatched in each of the three conditions

1. "trip without DRL" when the rate of use is below 5%,
2. "trip with partial use of DRL" when the rate of use is greater than 5% but less than 95%,
3. "trip with total use of DRL" when the rate of use is greater to 95%.

Then the following list describes the different aggregated databases to be produced according to the clustering variable

1. Database without clustering: dispatch all the trips in each of the 3 conditions and at the end compute the 3 ratios (on the basis of the total number of the trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.
2. database with short vs long trips in terms of time :

- Calculation with short trips in terms of time: include only the trips that last less than 20 minutes and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the short trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.
- Calculation with long trips in terms of time: include only the trips that last more than 20 minutes and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the long trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.

3. database with close vs far trips in terms of straight line distance (as the crow flies):

- Calculation with close trips in terms of straight line distance: include only the trips where all the trip locations stay within a 3km radius from the start point and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the close distance trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.
- Calculation with far trips in terms of straight line distance: include only the trips where part of the trip are outside a 3km radius from the start point and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the far distance trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.

4. database with outside urban area vs urban vs motorway trips :

- Calculation with "mainly outside urban area" trips : include only the trips that are more than 80% of time on outside urban area roads and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the "mainly outside urban area" trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.

- Calculation with "mainly urban" trips : include only the trips that are more than 80% of time on urban roads and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the "mainly urban" trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.
- Calculation with "mainly motorway" trips: include only the trips that are more than 80% of time on motorways and dispatch them in each of the 3 conditions and at the end, compute the 3 ratios (on the basis of the number of the "mainly motorway" trips). It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips.

5.4.2.1.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the mean weighted percentage of trips in each condition (mean % of no use, mean % of partial use, mean % of total use) for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.4.2.2. Systematic use of Daytime running light: percentage of trips with immediate DRL switching on

5.4.2.2.1. SPI definition

This SPI characterise the safety behaviour of a driver and gives information on the percentage of trips for which the driver immediately switches on when he/she starts a new trip. The time window that will be investigated for the "immediate" fastening is between the moment when the driver start the engine (beginning of the trip) and the moment when the vehicle start moving (speed > 5km/h, beginning of the driving).

5.4.2.2.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if DRL are used or not, detection of wipers and fog lamps use, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a database of sunrise and sunset time, a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.4.2.2.3. Data filtering

Data will be filtered in order to keep only data collected during daytime. Daytime is defined from sunrise plus 1 hour until sunset minus 1 hour. Data will be also filtered to keep only clement weather conditions. The data coming from vehicles equipped with automatic DRL will also be filtered out.

5.4.2.2.4. Data clustering conditions

No clustering process is planned. The percentage of trips with immediate switching on of the DRL is not investigated according to the trip characteristic. It is considered as a general behaviour of the driver that will be only investigated according to the drivers' characteristics.

5.4.2.2.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the DRL switching on, the speed of the vehicle associated with a driver identifier, a trip identifier, a unique timestamp (date + time), the daytime and the clement weather information.

To compute this SPI, it is necessary to have an aggregation of the data at the level of the participant. The aggregated database contains, for each participant the percentage of trips with immediate switching on, i.e. switching on of the DRL by the driver before the speed of the vehicle reaches 5 km/h. The database includes also the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving in these trips. Only trip driven during daytime and with a clement weather will be kept in the database.

5.4.2.2.6. Reporting to the ERSO and data analysis

The mean / standard deviation of the percentage of tips with immediate switching on of the DRL can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

In order to obtain relevant comparison, it is crucial to assess the balance of the participant sample and to make sure that there are enough participants within the subgroups used for comparison.

For each comparison, the process based on SSC, described in section 5.2.2.1.6, will be used to aggregate the participant data and to produce a table at the level of the country:

5.4.3. Detailed procedure to estimate Daytime running light descriptive SPI

5.4.3.1. Percentage of driving time with DRL switched on

5.4.3.1.1. SPI definition

This SPI provides exposure data of DRL use of both drivers and passengers by the ratio of time driven with Daytime running lights switched on.

5.4.3.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if DRL are switched on, detection of wipers and fog lamps use, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road type, a database of sunrise and sunset time; a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.4.3.1.3. Data filtering

Data will be filtered in order to keep only data collected during daytime. Daytime is defined from sunrise plus 1 hour until sunset minus 1 hour. Data will be also filtered to keep only clement weather conditions. The data coming from vehicles equipped with automatic DRL will also be filtered out.

5.4.3.1.4. Data clustering conditions

The first clustering aims to highlight the different DRL used according to the driving context in terms of road types (urban roads, outside urban area roads or motorways).

The second clustering aims to highlight the different use of DRL on week days vs week-ends days.

The third clustering aims to highlight the different use of DRL on peak hours vs non-peak hours.

5.4.3.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the DRL switching on, associated with a driver identifier, a trip identifier, a unique timestamp (date + time), the driving context (road type: urban, outside urban area, motorway), the daytime and the clement weather information.

Only driving data collected during daytime and with a clement weather will be kept in the database. To compute this SPI for drivers, it is necessary to have an aggregation of the data at the level of the participant. The following list describes the different aggregated databases to be produced according to the clustering variable:

1. Database according to the road type: compute the DRL use rate of the driver for the 3 types of road (urban, outside urban area, motorway). It is important

to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving for these 3 types of road.

2. Database with week days vs week-end days: compute the DRL use rate of the driver for the 2 periods of the week. It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving for these 2 periods of the week.
3. Database with peak hours vs non-peak hours: compute the DRL use rate of the driver for the 2 types of hours. It is important to add the Sub Sample Characteristic, which is here the number of trips used for the calculation and the total time spent driving for these 2 types of hours.

5.4.3.1.6. Reporting to the ERSO and data analysis

The mean / standard deviation of DRL use rates can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- …

For each comparison, the process based on SSC, described in section 5.2.2.1.6, will be used to aggregate the participant data and to produce a table at the level of the country:

5.5. Short Headway SPI

5.5.1. General description

5.5.1.1. Context and definition

Headway is the distance between two vehicles, expressed as the time it will take for the trailing vehicle to cover that distance. Maintaining a safe headway while driving is considered as a determinant key to prevent rear-end collisions. A too short headway does not give the driver sufficient time to start emergency breaking if necessary. It is considered a significant contributor in road accidents, mainly on motorways and main roads. Safe headway distance has recently been introduced in traffic engineering research as a new crash risk predictor (for example, in statistical crash prediction models), to estimate traffic crash likelihood in a given location, at a given time, under various traffic conditions [Hojun et al., 2008]. A headway time of two seconds is sufficient for the vast majority of drivers to prevent a rear-end collision with the vehicle in front, particularly on motorways where the traffic situation is not very complex. It gives the driver sufficient time to start emergency braking if necessary. If the headway time is considerably less than one second, this is called tailgating [SWOV, 2007].

The phenomenon of following distances is quite complex to analyse. The safety level of headway depends on the location and on the traffic conditions. The variability of the situations makes difficult to indicate appropriate safety levels in all conditions. In light traffic conditions, following is somehow rare as there is sufficient opportunity for drivers to move into adjacent lanes to maintain their speed. In high traffic flow, Brackstone and Mc. Donalds have highlighted that there are many reasons that can affect the driver’s motivation and willingness to respect the headways such as the duration of the following or the distance to the destination. [Brackstone and Mc. Donalds, 2007]

In addition to the issues of determining safe versus unsafe headway linked to the context, several methodological difficulties exist. They concern the difficulties of measuring the required information on the dynamics inherent to the following process. Roadside and static studies are unable to reflect the dynamics inherent to the process, like during overtaking, for example, where the vehicle reference to compute the headway is changing.

The naturalistic driving studies with instrumented vehicles allowed examining the complexity of the phenomena in details and also the relation with intrinsic variables. Brackstone and McDonald (2007) have pointed out specific driver profiles that typically drive closer than others. They have shown that the frequency and severity of this behaviour is influenced by education, desire, driving regulations and enforcement [Brackstone and McDonald, 2007].

We propose to distinguish two families of short headway SPI, the behavioural SPI and the descriptive SPI.

- In the first case, the behavioural SPI will highlight the propensity of drivers to respect or not a safe headway. The calculation of the 2 following behavioural SPI will be detailed in the section 5.4.2.
    - o 15th percentile of the headway in vehicle following situations
    - o Percentage of driving time with headway greater than 2 seconds, between 1 and 2 seconds, between 0.5 and 1 second and less than 0.5 second in vehicle following situations
    - o Frequency of occurrences of short headways epochs (headways less than 0.5 second during at least 0,2 seconds) in vehicle following situations
- In the second case, the descriptive SPI will give exposure to short headway. The calculation of the following short headway descriptive SPI will be detailed in the section 5.3.3.
    - o Percentage of driving time with headway greater than 2 seconds, between 1 and 2 seconds, between 0.5 and 1 second and less than 0.5 second
    - o Frequency of occurrences of short headway episodes (headways less than 0.5 second during at least 0,2 seconds)

5.5.1.2. Measure requirements

First, the calculation of short headway SPI requires the information about following distance to the next vehicle. In newer vehicles, this measure can be issued from the CAN bus of the car equipped with a radar. In order to compute the SPI, it adds a constraint on the participant sample as it requires to make sure that the sample is composed of a sufficient number of vehicles equipped with radars so that the results can be significant. The driver population equipped with radars should also be assessed as it is probably a specific sub part of the general driver sample.

As SPI have to be evaluated during daytime conditions, it is necessary to have access to a table giving for each latitude, longitude and day of the year, the time of sunrise and the time of sunset. Please refer to 2.7.3 for additional information.

To distinguish the good and bad weather conditions, please refer to 2.7.4.

In order to be able to disaggregate short headway SPI according to the road characteristics, it is necessary to know the GPS positions of the vehicle and to have access to a geographic information system (GIS) in order to infer, through map matching, information such as road type. Accessing GIS data leads to several constraints that are already discusses in detail in chapter 5.1.1.2. Please refer to this chapter for additional information on GIS data.

5.5.1.3. Filtering, Clustering and time window

Data will be filtered in order to keep only data collected when the car speed is above 20 km/h.

For behavioural SPI, the computation requires to filter data to keep only following situations, that is with headway greater than 10 seconds.

The usefulness of short headway SPI, both behaviour and descriptive, will depend of the possibilities they will offer to evaluate the changes over time of the distance headway in different driving contexts (type of road, period of the week, during peak hours or not…).

In order to ensure sufficient data for clustering, the choice of the time windows will be at the level of a month, as for the others SPI.

5.5.1.4. Aggregation

For behavioural and descriptive headway SPI, the first level of aggregation will be the participant level. There is no interest to aggregate data at a trip level. This aggregation at an individual level will allow comparisons of headway values between drivers' groups at the country level:

- Males drivers vs. female drivers
- Between age groups
- …

5.5.2. Detailed procedure to estimate Short headway behavioural SPI

5.5.2.1. 15thpercentile of the headway in vehicle following situations

5.5.2.1.1. SPI definition

This SPI characterizes the safety behaviour of a driver and highlight the shorter headways.

5.5.2.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if the situation is a following one with the radar, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)

2. a set of static data: a geographic information system (GIS) for map matching to infer road type; a weather database that can be used to obtain local weather conditions on a day by day basis;

3. a set of participant data, for country level aggregation

5.5.2.1.3. Data filtering

Data will be filtered in order to keep only data collected when the car speed is above 20 km/h.

The computation requires to filter data to keep only following situations, that is with a headway greater than 10 seconds.

5.5.2.1.4. Data clustering conditions

The first clustering aims to highlight the different headway chosen according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering is defined, for each road type, the clusters classes will be the following:

- Classes defined according to the lighting conditions: day and night conditions. Daytime is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour (See 2.7.3)
- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours
- Classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4

5.5.2.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the headway, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second “filtered dataset”. The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

We use this filtered raw database to build 4 new participant level aggregated databases, useful for the final analyses.

The first database contains the values of the 15th percentile of headway for all road conditions (3 columns in total: urban / outside urban area / motorway) and for all the participants (one per line).

The 3 last aggregated databases have the same structure, one database per road type. They contain the values of the 15th percentile of headway for one road conditions cross with each class of the 3 others clusters (The total number of columns is sum of the class number of the clusters, ie 2+2+2=6). Example : database on urban roads contains the 6 following columns:

- the values of the 15th percentile of headway for clement weather
- the values of the 15th percentile of headway for rainy weather
- the values of the 15th percentile of headway for daylight condition
- the values of the 15th percentile of headway for night time condition
- the values of the 15th percentile of headway for peak hours
- the values of the 15th percentile of headway for no-peak hours

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.5.2.1.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the 15th percentage of headway in each condition for all the participants. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.5.2.2. Percentage of driving time with headway greater than 2 seconds, between 1 and 2 seconds, between 0.5 and 1 second and less than 0.5 second in vehicle following situations

This SPI characterise the safety behaviour of a driver and gives information driving profile to know if drivers respect safe headways or not. We compute the percentage of driving time with headway greater than 2 s, which can be considered as safe, between 1 and 2 seconds, 0.5 and 1 second and less than 0.5 second in vehicle following situations.

5.5.2.2.1. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if the situation is a following one with the radar, speed of the vehicle, time and date, GPS position, driver

identification sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)

2. a set of static data: a geographic information system (GIS) for map matching to infer road type; a weather database that can be used to obtain local weather conditions on a day by day basis;

3. a set of participant data, for country level aggregation

5.5.2.2.2. Data filtering

Data will be filtered in order to keep only data collected when the car speed is above 20 km/h.

The computation requires to filter data to keep only following situations, that is with a headway greater than 10s.

5.5.2.2.3. Data clustering conditions

The first clustering aims to highlight the different headway chosen according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the lighting conditions: day and night conditions. Daytime is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour.(.See 2.7.3)
- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours.
- Classes defined according to the weather conditions: clement weather / rainy weather. See 2.74

5.5.2.2.4. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the headway, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second “filtered dataset”. The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

The first aggregated database contains the values of the percentage of driving time with headway greater than 2 s, between 1 and 2 seconds and less than 0.5 second for all road conditions (3*4=12 columns in total) and for all the participants (one per line).

The 3 last aggregated databases have the same structure, one database per road type. They contain the values of the percentage of driving time with headway greater than 2 s, between 1 and 2 seconds and less than 0.5 second one road conditions cross with each class of the 3 others clusters (The total number of columns is sum of the class number of the clusters (6) * the 4 ratios to compute, ie 24 columns)

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.5.2.2.5. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the weighted percentage of driving time in each condition for all the participants. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.5.2.3. Frequency of occurrences of short headways epochs (headways less than 0.5 second during at least 0,2 seconds) in vehicle following situations

This SPI characterise the safety behaviour of a driver and gives information on the frequency of very short headway epochs in vehicle following situations. The short headway epoch begins when headway is less than 0.5 seconds during at least 0.2 seconds. The frequency will be given in terms of number of occurrence per hour driven.

5.5.2.3.1. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if the situation is a following one with the radar, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)

2. a set of static data: a geographic information system (GIS) for map matching to infer road type; a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.5.2.3.2. Data filtering

Data will be first filtered in order to keep only data collected when the car speed is above 20 km/h.

The computation requires filtering data to keep only following situations, that is with a headway greater than 10s.

5.5.2.3.3. Data clustering conditions

The first clustering aims to highlight the different headway chosen according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the lighting conditions: day and night conditions. Daytime is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour (See 2.7.3).
- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours.
- Classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4

5.5.2.3.4. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the headway, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second "filtered dataset". The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

We use this filtered raw database to build 4 new participant level aggregated databases, useful for the final analyses.

The first database contains the values of the frequency of occurrence of short headways for all road conditions (3 columns in total: urban / outside urban area / motorway) and for all the participants (one per line).

The last aggregated databases have the same structure, one database per road type. They contain the values of the frequency of occurrence of short headways for one road conditions cross with each class of the 3 others clusters (The total number of columns is sum of the class number of the clusters, ie 2+2+2=6). Example: database on urban roads contains the 6 following columns:

- the Frequency of occurrences per hour of short headways episodes for clement weather
- the Frequency of occurrences per hour of short headways episodes for rainy weather
- the Frequency of occurrences per hour of short headways epochs for daylight condition
- the Frequency of occurrences per hour of short headways episodes for night time condition
- the Frequency of occurrences per hour of short headways episodes for peak hours
- the Frequency of occurrences per hour of short headways episodes for no-peak hours

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.5.2.3.5. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the frequency of occurrence of short headways in each condition for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.5.3. Detailed procedure to estimate Short Headway descriptive SPI

5.5.3.1.1. Percentage of driving time with headway greater than 2 seconds, between 1 and 2 seconds, between 0.5 and 1 second and less than 0.5 second SPI definition

This SPI provides exposure data of driving time in situation described by the length of headway.

5.5.3.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if the situation is a following one with the radar, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…).
2. a set of static data: a geographic information system (GIS) for map matching to infer road type; a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.5.3.1.3. Data filtering

Data will be first filtered in order to keep only data collected when the car speed is above 20 km/h.

5.5.3.1.4. Data clustering conditions

The first clustering aims to highlight the different headway chosen according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the lighting conditions: day and night conditions. Daytime is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour (See 2.7.3).
- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours
- Classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4

5.5.3.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the headway, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second “filtered dataset”. The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

We use this filtered raw database to build 4 new participant level aggregated databases, useful for the final analyses.

The aggregated databases contains, for all the participants (one per line), 4 values (one per column): the percentage of driving time dispatched in each of the three conditions

1. Driving time with headway greater than 2s

2. Driving time with headway greater than 1s and less than to 2s
3. Driving time with headway greater than 0.5s and less than 1s
4. Driving time with headway less than 1s

The first aggregated database contains the values of the four ratios of driving time by length of headway for all road conditions (3 columns for each ratio: urban / outside urban area / motorway) and for all the participants (one per line).

The others aggregated databases have the same structure, one database per road type*class of the second cluster. They contain the four percentages of driving time of headway for one road conditions cross with each class of the 3 others clusters. In total, in each table, there are 24 ratios computed for each participant.

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.5.3.1.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the weighted frequency of driving time in each condition for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.5.3.2. Frequency of occurrences of short headways epochs (headways less than 0.5 second during at least 0,2 seconds)

5.5.3.2.1. SPI definition

This SPI characterizes the safety behaviour of a driver and highlight the frequency of short headways epochs, giving an idea of his driving style. The frequency is given in terms of number of occurrence per hour driven.

5.5.3.2.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: detection if the situation is a following one with the radar, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road type; a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.5.3.2.3. Data filtering

Data will be first filtered in order to keep only data collected when the car speed is above 20 km/h.

5.5.3.2.4. Data clustering conditions

The first clustering aims to highlight the different headway chosen according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the lighting conditions: day and night conditions. Daytime is defined from sunrise plus 1 hour to sunset minus 1 hour. Night time is defined from sunset plus 1 hour to sunrise minus 1 hour (See 2.7.3).
- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours.
- Classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4

5.5.3.2.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the headway, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second “filtered dataset”. The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

The first aggregated database contains the values of the frequency of short headway epochs for each road conditions.

The others aggregated databases have the same structure, one database per road type. They contain the values of the frequency of short headway epochs for each class of the 3 others clusters (The total number of columns is sum of the class number of the clusters (6) * the ratio to compute, i.e. 6 columns)

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.5.3.2.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the weighted frequency of occurrence of short headways in each condition for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.6. Strong deceleration SPI

5.6.1. General description

5.6.1.1. Context and definition

Drivers who rapidly change speed while driving may be more at risk for a crash. Making strong decelerations, they may put strain on drivers behind them, and appear to be more at risk for rear-crashs. Simulator studies have shown that sudden stops are particularly predictive of rear-end collisions (Harb et al., 2007). Driving simulator experiments in right turn lanes show that higher deceleration rates were associated with higher rear-end crash history (Yan et al., 2008).

Nevertheless, deceleration patterns have been investigated not only as an indicator of a ‘near crash’ (Dingus et al., 2006) but also as a measure of appropriate speed management (Baldwin et al., 2004).

There are few data on characteristics of drivers who make rapid decelerations. Younger subjects (ages 20–29 years) have been shown to have a shorter deceleration distance and time, compared to older drivers, and tend to drive faster (Porter and Whitton, 2002). Moreover, rear end crashes tend to occur more commonly in younger age groups and among males (Yan and Radwan, 2006).

Naturalistic driving studies do not allow the whole process of braking to be analysed, only the last period when drivers press the brake. The response time and the pressure build-up time are not taking into account. Braking is defined as a strong deceleration when it is less than -0.5g. (As the deceleration cannot be increased infinitely, a limit is set by the acceleration due to gravity (g) at g=9.81 m/s²).These include situations where the driver needed to rapidly decelerate to complete a turn safely, stop at a signal or avoid another vehicle.

Naturalistic driving studies with instrumented vehicles allow the complexity of the phenomena to be examined in detail and also the relation with intrinsic variables, to investigate braking use according to the characteristics of drivers (education level, age, gender…).

We propose to distinguish two families of strong deceleration SPI, the behavioural SPI and the descriptive SPI.

- In the first case, the behavioural SPI will highlight the propensity of drivers to brake heavily. The calculation of the 2 following behavioural SPI will be detailed in section 5.5.2.
    - 15th and 85thpercentile of the decelerations
    - Percentage of deceleration time with deceleration greater than -0.25g, between -0.25g and -0.5g seconds, and less than 0.5g
- In the second case, the descriptive SPI will give exposure to strong deceleration. The calculation of the following strong deceleration descriptive SPI will be detailed in the section 5.3.3.
    - Frequency of occurrences of strong decelerations per hours driven (deceleration less than -0.5 g during at least 0,2 seconds)

5.6.1.2. Measure requirements

First, the calculation of strong deceleration SPI requires information about braking. In newer vehicles, this measure can be issued from the CAN bus of the car.

To distinguish good and bad weather conditions, please refer to 2.7.4 for information about the process.

In order to be able to disaggregate strong deceleration SPI according to the road characteristics, it is necessary to know the GPS positions of the vehicle and to have access to a geographic information system (GIS) in order to infer, through map matching, information such as road type. Accessing GIS data leads to several constraints that are already discusses in detail in chapter 5.1.1.2. Please refer to this chapter for additional information on GIS data.

5.6.1.3. Filtering, Clustering and time window

For behavioural SPI, data will be filtered in order to keep only data collected when the car deceleration is under -10^{-3}g.

For descriptive SPI, the computation requires to remove data where car drives less than 5km/h as we don't want to include in the exposure basis all the driving situations where the car is stopped and will not be exposed to any deceleration.

The usefulness of strong deceleration SPI, both behaviour and descriptive, will depend of the possibilities they will offer to evaluate the changes over time of the deceleration in different driving contexts (type of road, period of the week, during peak hours or not…).

In order to ensure sufficient data for clustering, the choice of the time windows will be at the level of a month, as for the others SPI.

5.6.1.4. Aggregation

For behavioural and descriptive strong deceleration SPI, the first level of aggregation will be the participant level. There is no interest to aggregate data at a trip level. This aggregation at an individual level will allow comparisons of braking and acceleration behaviour between drivers' groups at the country level:

- Males drivers vs. female drivers
- Between age groups
- …

5.6.2. Detailed procedure to estimate Strong deceleration behavioural SPI

5.6.2.1. 15thand 85th percentile of the deceleration

5.6.2.1.1. SPI definition

This SPI try to define the values and profile of strong deceleration during braking situations.

5.6.2.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: the value of deceleration,, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road type; a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.6.2.1.3. Data filtering

The computation requires to filter data to keep only braking situations, that is with a deceleration less than -10^{-3}g.

5.6.2.1.4. Data clustering conditions

The first clustering aims to highlight the different braking profile according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and none-peaks hours.
- Classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4.

5.6.2.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the deceleration, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second "filtered dataset". The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

We use this filtered raw database to build 3 new participant level aggregated databases, useful for the final analyses.

The first database contains the values of the 15thand 85thpercentile of deceleration for all road conditions (3 columns in total: urban / outside urban area / motorway) and for all the participants (one per line).

The 2 last aggregated databases have the same structure, one database per road type. They contain the values of the 15thand 85thpercentile of deceleration for one road conditions cross with each class of the 2 others. Example : database on urban roads contains the 8 following columns:

- the values of the 15th percentile of deceleration for clement weather
- the values of the 15th percentile of deceleration for rainy weather
- the values of the 15th percentile of deceleration for peak hours
- the values of the 15th percentile of deceleration for no-peak hours
- the values of the 85th percentile of deceleration for clement weather
- the values of the 85th percentile of deceleration for rainy weather
- the values of the 85th percentile of deceleration for peak hours
- the values of the 85th percentile of deceleration for no-peak hours

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.6.2.1.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. For example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).

- Once all the participants have been assessed and correctly included, compute the 15^{th} and 85^{th} percentiles of deceleration in each condition for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.6.2.2. Percentage of deceleration time with deceleration greater than -0.25g, between -0.25g and -0.50 g and less than - 0.50 g.

This SPI characterise the profile of braking behaviour of a driver. We compute the percentage of driving time with deceleration greater than to -0.25 s, between -0.25 and -0.5 seconds and less than -0.5 g.

5.6.2.2.1. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: value of the deceleration, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road type, a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.6.2.2.2. Data filtering

The computation requires filtering data to keep only braking situations, that is with a deceleration less than -10^{-3}g.

5.6.2.2.3. Data clustering conditions

The first clustering aims to highlight the different braking profile according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours
- Classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4

5.6.2.2.4. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the deceleration, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second “filtered dataset”. The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

The first aggregated database contains the values of the percentage of driving time with deceleration greater than -0.25 g, between -0.5 and -0.25 g and less than -0.5 g for all road conditions (3*4=12 columns in total) and for all the participants (one per line).

The 3 last aggregated databases have the same structure, one database per road type. They contain the values of the percentage of driving time with deceleration greater than -0.25g, between -0.25g and -0.5g, less than -0.5 g in one road conditions cross with each class of the 2 others clusters (The total number of columns is sum of the class number of the clusters (4) * the 3 or 4 ratios to compute, ie 12 or 16 columns)

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.6.2.2.5. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. For example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the weighted percentages of deceleration time in each condition for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics.

5.6.3. Detailed procedure to estimate Strong deceleration descriptive SPI

5.6.3.1. Frequency of occurrences of strong decelerations per hours driven (deceleration less than -0.5 g during at least 0,2 seconds)

5.6.3.1.1. SPI definition

This SPI characterize the prevalence of strong deceleration. A deceleration is considered as strong when it is less than -0.5g and must last more than 0.2 seconds. The frequency is given in terms of number of occurrence per hour driven.

5.6.3.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: value of the deceleration, speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road type, a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.6.3.1.3. Data filtering

The computation of the SPI requires to remove data where cars drive less than 5 km/h.

5.6.3.1.4. Data clustering conditions

The first clustering aims to highlight the different braking profile according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours.
- Classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4

5.6.3.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the deceleration, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second "filtered dataset". The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

The aggregated database contains in a first column the values of the frequency of occurrences of strong decelerations per hour driven for all the participants (one per line). The 4 next columns contain the frequency of occurrence of strong deceleration in each situation (peak hours, no peak hours, clement weather, no clement weather situations)

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.6.3.1.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the weighted frequency of occurrence of strong deceleration in each condition for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics

5.7. Safety System use SPI

5.7.1. General description

5.7.1.1. Context and definition

In today's vehicles, active safety systems are introduced addressing a large variety of safety issues such as providing optimal braking effect, preventing spins and rollover, collision avoidance to mention just a few. In addition the number of these systems is expected to grow. Active safety systems, in contrast to passive safety systems, interact with the driver and environment.

With the introduction of active safety systems arises the need for methods that evaluate the safety performance of these systems. Indeed, the influence of the system activation on an accident has to be studied in detail by experts to judge whether the accident may have been prevented if the cars had such a safety system. If such an evaluation is complex, little is know about the real use of these systems in every day driving situations. In this chapter, we will focus our investigations on *Anti-lock Braking* System, also known as ABS, and *Electronic stability control system,* also known as ESP, and especially to learn about the situations when they are activated.

As a short reminder, there are a few different manufacturers of ABS systems on the market but their fundamental functions are similar. The ABS controller basically prevents the braking wheels from skidding on the road surface. This is based on the knowledge that a skidding or spinning wheel has less traction and side stability than a rolling wheel [Demel and Hemming, 1989]. Under ideal road conditions it usually takes a few seconds of braking for a car to stop, but less than one second to lock-up a wheel. The electronic control unit (ECU) is thus programmed to decelerate each wheel near its peak slip condition without locking the wheel. By pulsating the brake pressure, up to 15 times per second, the controller allows the wheel to alternate between free rolling and braking during the pulse cycle. This controlled pulsing thereby preserves the ability to steer the vehicle in the desired direction while braking in a slippery road [Gillespie, 1992].

The stability systems referred to in this section is for directional stability under slippery road conditions. These systems have been developed for more advanced wheel control [van Zanten et al., 1995]. Today, these systems offer holistic control of each individual wheel of the car. By comparing the steering input with the yaw motion and lateral acceleration of the vehicle the system identifies whether the car is about to lose directional control. To avoid loss of control and to offer correction of control, each of the wheels that are about to spin or to slide can be individually controlled.

Although the work is limited to ABS and ESP, we assume that the principles can be used to investigate other active safety systems, for example Collision Avoidance Systems (CAS), blind spot information system…However, the work has not be extended to cover the use of informative systems and other in-vehicle information system IVIS which requires driver interactions, as it bring complex methodological issues [Bonnard, 2008].

We propose only one family of Safety System use SPI: descriptive SPI.

- In this case, the descriptive SPI will give exposure to system activation
    - Frequency of occurrences of *Anti-lock braking* system activation per hours driven
    - Frequency of occurrences of *Electronic stability control system* activation per hours driven

5.7.1.2. Measure requirements

First, the calculation of safety system use SPI requires that the vehicles are equipped with the systems and that the information about the functioning status of these systems is available. In newer vehicles, this measure can be issued from the CAN bus of the car.

To distinguish good and bad weather conditions, please refer to 2.7.4 for information about the process.

In order to be able to disaggregate safety system activation SPI according to the road characteristics, it is necessary to know the GPS positions of the vehicle and to have access to a geographic information system (GIS) in order to infer, through map matching, information such as road type. Accessing GIS data leads to several constraints that are already discusses in detail in chapter 5.1.1.2. Please refer to this chapter for additional information on GIS data.

5.7.1.3. Filtering, Clustering and time window

For descriptive SPI, the computation requires to remove data where car drives less than 5km/h. Indeed we don't want to include in the exposure basis all the driving situations where the car is stopped and will not be exposed to any system activation.

The usefulness of Safety System use SPI, will depend of the possibilities they will offer to evaluate the changes over time of the deceleration in different driving contexts (type of road, period of the week, during peak hours or not…).

In order to ensure sufficient data for clustering, the choice of the time windows will be at the level of a month, as for the others SPI.

5.7.1.4. Aggregation

For safety system use SPI, the first level of aggregation will be the participant level. There is no interest to aggregate data at a trip level. This aggregation at an individual level will allow comparisons of braking and acceleration behaviour between drivers' groups at the country level:

- Males drivers vs. female drivers
- Between age groups
- …

5.7.2. Detailed procedure to estimate Safety System use SPI

5.7.2.1. Frequency of occurrences of *Anti-lock braking system* activation per hours driven

5.7.2.1.1. SPI definition

This SPI describes the occurrence of Anti-lock braking system activation, when car drives more than 5km/h. The frequency is given in term of number of occurrence per hour driven.

5.7.2.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: safety system use speed of the vehicle, time and date, GPS position, driver identification, sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road type, a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.7.2.1.3. Data filtering

The computation of the SPI requires to remove data where cars drive less than 5 km/h.

5.7.2.1.4. Data clustering conditions

The first clustering aims to highlight the safety system use according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours, classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4

5.7.2.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the information about the frequency of occurrence of ABS, the use of ABS, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second “filtered dataset”. The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

The first aggregated database contains the values of the frequency of occurrence of ABS use per hour and for all the participants (one per line).

The 3 last aggregated databases have the same structure, one database per road type. They contain the values of the frequency of occurrence of ABS use per hour in one road conditions cross with each class of the 2 others clusters (The total number of columns is sum of the class number of the clusters (4) * the ratio to compute, i.e. 4 columns)

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.7.2.1.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the weighted frequency of occurrence of ABS activation per hour driven in each condition for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics

5.7.2.1. Frequency of *Electronic stability control system* activation per hours driven

5.7.2.1.1. SPI definition

This SPI describes the occurrence Electronic stability control system activation, when car drives more than 5km/h. The frequency is given in term of number of occurrence per hour driven.

5.7.2.1.2. Data collection requirement

To compute this indicator, 3 kinds of data must be available.

1. a set of naturalistic driving data: frequency of Electronic stability control system per hours driven, speed of the vehicle, time and date, GPS position, driver identification sensors available in the vehicle to determinate the weather (like the screen wipers activation, or the luminosity sensor used for automatic light activation…)
2. a set of static data: a geographic information system (GIS) for map matching to infer road type, a weather database that can be used to obtain local weather conditions on a day by day basis;
3. a set of participant data, for country level aggregation

5.7.2.1.3. Data filtering

The computation of the SPI requires to remove data where cars drive less than 5 km/h.

5.7.2.1.4. Data clustering conditions

The first clustering aims to highlight the safety system use according to the driving context: (urban / outside urban area / motorway).

Once this first level of clustering defined, for each road type, the clusters will be the following:

- Classes defined according to the peak hours: peak hours (7h30-9h30 and 16h00-19h00) and no-peaks hours. Classes defined according to the weather conditions: clement weather / rainy weather. See 2.7.4

5.7.2.1.5. Data processing

The data from the vehicles must be inserted in a database. The database must contain, at each line, the use of ESCS, associated with a driver identifier, a trip identifier, a unique timestamp (date + time) and the driving context (road type: urban, outside urban area, motorway).

First step: the filters must be applied on this data set to build a second “filtered dataset”. The remote database should give the information on all the date to copy to the filtered dataset. At last, the data inside of the observation times have to be copied.

At this stage, we have built a new data set, containing controlled data. All the indicators will be calculated on this database.

The first aggregated database contains the values of the frequency of activation of ESCS per hour and for all the participants (one per line).

The 3 last aggregated databases have the same structure, one database per road type. They contain the values of the frequency of occurrence of ESCS use per hour in one road conditions cross with each class of the 2 others clusters (The total number of columns is sum of the class number of the clusters (4) * the ratio to compute, i.e. 4 columns)

The values are computed for all the participants (one per line). It also provides information of the SPI subsample characteristic (driving time in given cluster at this level).

5.7.2.1.6. Reporting to the ERSO and data analysis

It is possible, in addition of the clusters proposed beforehand to prepare some specific comparison between drivers groups. Of example, the mean and the standard deviation of each percentage of trips can be compared by creating drivers groups:

- Males drivers vs. female drivers
- Between age groups
- ..

For each cluster or comparison, it is proposed to follow the following process to aggregate the participant data and to produce a table at the level of the country:

For each database

- for each participant, assess if the Sub Sample Characteristics (SSC) in term of total time spent driving is high enough for the data to be considered relevant (i.e. if SSC > 16 minutes of driving time, it means that 1000 data have been collected for the participant so the participant can be included for this class).
- Once all the participants have been assessed and correctly included, compute the weighted frequency of safety system use in each condition for all the participants and the standard deviation. Then, for the subsample characteristic sum up the total time spent driving by all the participants, the total number of trips used and the total number of participants used for the calculation to provide the subsample characteristics

5.8. Situational SPI

5.8.1. Lane behaviour / turning indicators use / inappropriate speed SPI

5.8.1.1. Context and propositions

In addition to Behavioural Safety Performance Indicators and Descriptive Safety Performance Indicators, as presented so far in this document, it is important to mention that naturalistic driving data could be used to produce even more detailed indicators that could give a measure of the driver's performance in predefined and specific driving situations.

In order to assess lane behaviour, a lane keeping performance could be computed for each driver in order to record each driver incursion in the right or left adjacent lines (triggered by two successive line crosses) and to distinguish the incursions linked to an overtaking manoeuvre or obstacle avoidance and the incursions linked to an impairment of trajectory control.

In order to assess inappropriate speed, performance indicators could consist of the distribution of speed in the entrance of a bend according to the radius of curvature and the banking of the bend and according to the weather conditions. It would be useful to analyse speed not only according to the legal speed limit but also according to more localised speed constraints that are dictated by the road infrastructures or other external factors. It would highlight the adequacy of drivers' speed choice to the driving situations or manoeuvres.

In order to assess turning indicators, a use rate could be computed in order to obtain the percentage of time when the driver activated the right or left turning indicators when the situation required them to (for example, when turning at an intersection or when over taking…). It would be useful to assess the potential interactions between the driver and the other road users, which is a key factor to road safety.

5.8.1.2. Situation identification

Unlike the behavioural and descriptive SPI that can be computed systematically on large amount of data, these situational SPI requires a more accurate interpretation of the collected data stream in order to isolate driving situations for which the contextual description corresponds to the requirement of the analysis (for example, a pedestrian avoidance situation, an overtaking manoeuvre…)

In the literature, different approaches based on advanced "knowledge discovery", "data mining" and "pattern matching" have been used to identify, among the huge volume of data, the parameters that are the most relevant to differentiate specific driving situations and to find the matching situations automatically. However, these approaches still remain at the level of research investigations in relation to the understanding of drivers' behaviour.

5.9. Synthesis

5.9.1. Behavioural and descriptive SPI

This last chapter aims to provide a high level overview of the SPI that have been proposed to be monitored using a Naturalistic Driving database. Even if most of them are technically feasible without too many constraints, the limits of this feasibility are described in detail in the previous chapters. Their added value and the considerations to keep in mind when interpreting the results are also described in detail in the previous chapters.

	Behavioural SPI	Descriptive SP
Excessive speed	Mean speed and standard deviation of speed in free flowing traffic conditions V85 in free flowing traffic conditions Percentage of driving time over the legal speed limit in free flowing traffic conditions Percentage of driving time 10 km/h over the legal speed limit in free flowing traffic conditions	Percentage of driving time over the legal speed limit Percentage of driving time 10 km/h over the legal speed limit
Seat belt use	Percentage of trips without seat belt use, with partial seat belt use, with total seat belt use Systematic use of seat belt: percentage of trips with immediate seat belt fastening	Percentage of driving time with seat belt fastened for drivers, front passengers and rear passengers.
Daytime running light use	Percentage of trips without DRL use, with partial DRL use, with total DRL use during daytime and clement weather conditions Systematic use of DRL: percentage of trips with immediate DRL switching on during daytime and clement weather conditions	Percentage of driving time with DRL switched on during daytime and clement weather conditions
Short headway	15th percentile of the headway in vehicle following situations Percentage of driving time with headway greater than 2 seconds, between 1 and 2 seconds, , between 0.5 and 1 second and less than 0.5 second in vehicle following situations Frequency of occurrences of short headway epochs(headways less than 0.5 second during at least 0,2 seconds) in vehicle following situations per hour driven	Percentage of driving time with headway greater than 2 seconds, between 1 and 2 seconds, , between 0.5 and 1 second and less than 0.5 second Frequency of occurrences of short headway epochs (headways less than 0.5 second during at least 0,2 seconds) per hour driven
Strong deceleration	15th and 85th percentile of the vehicle in deceleration situation Percentage of deceleration time with deceleration greater than -0.25g, between -0.25g and -0.50 g and less than - 0.50 g, in deceleration situation	Frequency of occurrences of strong decelerations per hours driven (deceleration less than -0.5 g during at least 0,2 seconds)
Safety		Frequency of occurrences of

Systems use		safety system (Anti-lock braking system and Electronic stability control system…) activation per hours driven

Table 5 – Overview of behavioural and descriptive SPI

5.9.2. Situational SPI

The situational SPI are suggested as future perspectives of naturalistic data analysis, as for the moment, the knowledge on the best way to identify specific driving situation inside a naturalistic driving database is still limited. However, with the development of research projects dealing with ND data analysis, we can safely assume that it will be possible at some point.

- Lane behaviour (% of adequacy of lane crossing to driving situation)
- Turning indicators use (% of adequacy of indicator activation to driving situation)
- Inappropriate speed (% of adequacy of speed to driving situation)

6. LEGAL AND ETHICAL ISSUES

6.1. Introduction

Monitoring Safety Performance Indicators (SPI) and Risk Exposure Data (RED) by gathering Naturalistic Driving data can give rise to a considerable amount of legal and ethical issues. This ranges from data protection in the vehicle where it is collected, to access to the data kept in databases at the (international) institutes. In this Chapter an overview of legal and ethical issues will be given that should be considered when conducting monitoring trials such as designed in the DaCoTa Project.

The FESTA consortium produced an extensive handbook (FESTA-consortium, 2011) on conducting Field Operational Tests and Naturalistic Driving trials. In the FESTA-handbook, a Chapter has been dedicated to the Legal and Ethical issues that rise when conducting these trials. The overview of Legal and Ethical issues in this Chapter will be largely based on issues highlighted in the FESTA-Handbook but will also be based on knowledge produced in recent Naturalist Driving projects (e.g. PROLOGUE (Groenewoud et al., 2010) and INTERACTION). It is therefore advised to also consult the FESTA-handbook legal and Ethical issues Chapter when identifying legal and ethical issues for a naturalistic driving study. The FESTA-handbook also contains an Annex in which a worked example (with contributions from a lawyer) of legal and ethical issues in the execution of FOTs.

6.2. Legal requirements

6.2.1. Legal requirements at the European level

At the European level there are at least two directives relevant when working with personal data such as is done by performing a naturalistic driving trial: Directive 95/46/EC and 2002/58/EC. EU directives lay down certain end results that must be achieved in every Member State. National authorities have to adapt their laws to meet these goals, but are free to decide how to do so (European Commission, 2011).

Directive 95/46/EC concerns the protection of individuals with regard to the processing of personal data and the free movement of such data. Directive 2002/58/EC concerns the processing of personal data and the protection of privacy in the electronic communications sector.

<u>Key issues raised by Directive 95/46/EC</u>

- Personal data must be processed fairly and lawfully, and collected for specified, explicit and legitimate purposes;
- They must also be accurate and, where necessary, kept up to date;
- Personal data may be processed only if the data subject has unambiguously given his/her consent;
- The controller must provide the data subject from whom data are collected with certain information relating to himself/herself (the identity of the controller, the purposes of the processing, recipients of the data etc.);
- The data subject should have the right to object, on legitimate grounds, to the processing of data relating to him/her;

- Any person acting under the authority of the controller or of the processor, including the processor himself, who has access to personal data must not process them except on instructions from the controller. In addition, the controller must implement appropriate measures to protect personal data against accidental or unlawful destruction or accidental loss, alteration, unauthorized disclosure or access;
- The notification of processing to a supervisory authority: the controller must notify the national supervisory authority before carrying out any processing operation. Prior checks to determine specific risks to the rights and freedoms of data subjects are to be carried out by the supervisory authority following receipt of the notification. Measures are to be taken to ensure that processing operations are publicised and the supervisory authorities must keep a register of the processing operations notified.

<u>Key issues raised by Directive 2002/58/EC</u>

- Ensuring personal data is accessed by authorised persons only;
- Ensuring the implementation of a security policy on the processing of personal data;
- In the case of an infringement of personal data, the service provider must inform the person concerned, as well as the National Regulatory Authority (NRA).

6.2.2. Legal requirements at a National level

In addition to the legal requirements at a European level, member states of the European union often have national Acts, Regulations, Directives and requirements relevant when conduction a study that involves gathering personal data. The scope of Legal requirements at a National level is too broad to address in this chapter, but the national legislation of EU-member states often (but not exclusively) include National Data Protection Acts and Ethical committee approval requirements.

In Europe, the minimal standard of data protection is stipulated in the already mentioned Directive 95/46/EC. National laws often extend this data protection directive with National Data Protection Acts. In these acts, the restrictions and obligations when gathering and storing personal data are described. Before conducting a trial that involves gathering personal data, the national data protection acts (and related legal requirements) should be examined closely and proper actions should be taken to be able to conduct the trials within the these legal requirements.

In some European countries, Ethical committee approval is required when conducting a study with human subjects. Some research institutes have their own Ethical committees whereas in other countries the Ethical committees operate on a national level. As stated in the FESTA handbook, the procedures for ethical approval can be very time consuming and should therefore be well considered in the project plan.

6.3. Participant Recruitment

In participant recruitment it is important to ensure that participants hold valid driving permits (for the duration of the trial). If the participants will drive their own vehicle, insurance coverage needs to be checked, in particular if participating in the trial does not invalidate the insurance.

6.4. Participant Agreement

In the participant agreement, all agreements between the participant and research organisation and the responsibilities of both parties are stipulated. When setting up the participant agreement, it is advised to consult a lawyer that could support in identifying legal issues. There are a few main topics that should at least be covered by the participant agreement:

- Costs; Who is responsible for certain costs (e.g. vehicle maintenance, damage to vehicle, insurance excess, traffic penalties)
- Benefits; what is the allowance the participant will receive and are there possible other benefits (e.g. use of instrumented vehicle, fuel cost reimbursements)
- Risks; Is the participant exposed to increased risks (of involvement in crashes or of theft or burglary of the vehicle or ND-devices) by participating in the trial and if so, what has been done to minimise the risks?
- Withdrawal; is the participant free to withdraw his/her participation to the trial at any moment and how will this affect the agreed participant allowance.
- Confidentiality of recorded data; how is the participants privacy protected? What will and what will not be done with the data gathered? Which parties will have access to the recorded data? Who owns the data (during and after the trial)?
- Who is allowed to drive the vehicle, how will the data records of non-participating drivers be dealt with (in case non-participating drivers are allowed to drive)?

Candidate participants should be given enough time to read and understand all agreements described in the participant agreement and should be offered the opportunity to ask questions. The participant agreement should be signed by both the research conducting party as the participant and both parties should receive a signed copy of the agreement.

6.5. Data protection and ownership

Data acquired by means of Naturalistic Driving monitoring will often contain privacy sensitive data. It is therefore important to determine what privacy sensitive data is gathered and how this data will be protected.

Personal data and contact data, often gathered to communicate with the participants and to describe the participant population for scientific purposes, should be stored separate from other data gathered. All other data gathered should be properly anonymized. In case the data contains video recordings or GPS locations, anonymization of the data is not always possible. In any case, data that could lead to identification of the participant should never be released to other parties than those described in the participant agreement, without prior consent of the participant.

In the process of collecting data to building a database which could be used for analyses, often several operations with the data are required (see Welsh et al. (2010) for an overview of data storage and management methods). First the data has to be transferred from the vehicle to the research institute. There are several ways to achieve this, for example: direct transfer from in-vehicle storage device to institutes servers, transfer by means of portable storage device as intermediate step, wireless transfer (cellular networks or Wi-Fi networks) etcetera. In every step of the process it is important that data access is regulated and data is stored secured in a way the unauthorized access to the data is impossible. This implies that in-vehicle stored data, should be secured (or encrypted) to avoid unauthorized access (e.g. in case of burglary). Data transfer from the vehicle to the research institute should be a secured process. In case data is transferred wirelessly, proper encryption methods should be used and unauthorized access to the data by operators of the wireless networks should be prevented. If intermediate storage devices are used, after the transfer to the final storage device has been done, the data on the intermediate storage devices should be properly deleted such that recovery of the data from this device is not possible.

Also once the data is stored on the final storage device, data should be stored properly secured and access to the data should be regulated. All 'users' of the data should be briefed in case the data contains privacy sensitive information and confidentiality agreements should be signed by the users of the data.

6.6. Vehicle instrumentation and approval

While instrumenting vehicles with observation equipment, the vehicle type approval could be invalidated. Appropriate authorities should be consulted in order to affirm that the instrumented vehicles approval for on-road use is not invalidated.

Observation equipment shouldn't interfere with the normal functioning of the vehicle and vehicle systems. Special attention should be paid to ensure the observation equipment doesn't interfere with (the proper functioning of) vehicle's safety systems such as airbags and that the observation equipment doesn't introduce additional risks in case of a crash (e.g. unsecured objects that could injure car occupants in a crash).

Vehicles should be instrumented by professionals that are authorised or licenced to perform the installation and make the necessary adjustments.

6.7. Risk assessment

A comprehensive risk assessment plan should be prepared that demonstrates that the subsequently identified risks have been properly managed. The plan should contain all identified risks and describe how each specific risk is approached. A lawyer could be consulted to help identifying potential risks and could give advise in managing these risks.

7. CONCLUSION

This document proposes accurate guidelines for the design of a “naturalistic driving study” to investigate road safety, in the perspective of the European Road Safety Observatory. It covers 3 dimensions:

- The experimental design, as the definition of the sample size and characteristic will have a strong impact both on the operational recruitment of the drivers and on the possibilities to exploit the final SPI and RED results and their accuracies.
- The procedures to RED and SPI estimation, as the definition of the calculation and requirements in terms of raw data / filtering / clustering will strongly constraint the data collection and the technical backend that will be necessary for the exploitation of the vehicle data.
- The legal, ethical and privacy requirements, as it is important to make sure at all time during the preparation of the study that the designed solutions are compatible with the local regulations which can add additional constraints.

These guidelines have been developed to propose an overview of innovative RED and SPI that could be computed thanks to naturalistic driving data and to show the limits and methodological considerations that have to be kept in mind when using such data. One of the most innovative propositions beyond the indicators already defined in SafetyNET is to propose 3 kinds of SPI:

  - Behavioural SPI refers to SPI that describe drivers’ behaviour toward a specific safety issue and permit to identify some of its determinants,
  - Descriptive SPI refers to SPI that quantify the occurrence of a phenomenon and can be useful to assess if a safety policy is followed or not,
  - Situational SPI refers to SPI that describe driver behaviour in very specific situation which are relevant in term of road safety issues. They require a very accurate assessment of the driving situation and current manoeuvre in order to be relevant.

The question of implementation issues has been evocated in different parts of the guidelines, but in the end, the available budget will be a decisive factor that will shape all the details of the study. When implementing a naturalistic driving study, one should dimension carefully (at least) 3 major budgets allocations:

- For the data collection systems,
- For the sample recruitment,
- For the SPI & RED calculations development.

For instance, if two scenarios of data collection systems were proposed (scenario 1: GPS/GIS, accelerometers, gyrometers, driver ID and scenario 2: GPS/GIS, accelerometers, gyrometers, driver ID, CAN data), it appears clearly that scenario 2 offers far more possibilities in terms of SPI calculation. Scenario 1 only enables Excessive speed SPI and strong deceleration and braking SPI, with limited clustering. In the scope of scenario 2, the added values of the RED and SPI calculation is very clear but if scenario 1 is favoured, the standard SafetyNet solutions should be preferred as the added value of naturalistic driving data is not obvious. From the authors’ point of view, the part of the budget of the study dedicated to data collection systems should be significant enough to permit the purchase of a device corresponding to the scenario 2 specifications.

In the same state of mind, if several variables can be used to build the study sample (number of countries in which the study is done, number of participant to recruit and number of cars to equip…), it appears clearly that large samples permit to obtain accurate results at the country level and permit relevant comparisons. From the authors' point of view, the budget of the study dedicated to the sample should be spent by favouring the size of the sample over the number of countries that performs the study. This will permit immediately results to be obtained that are meaningful for the country and that can be compared in a relevant way to the other country results. It will also decrease the time necessary to investigate in detail the legal and ethical requirements. Once the first countries are operational, it will be possible to extend the study in a second step to other new countries, which will also permit the experience obtained during the first implementation to be drawn upon.

Finally, if several SPI seem to be interesting and could be implemented, the time required for the technical development (from database infrastructure, algorithms and data export…) should not be underestimated. From the authors' point of view, the budget of the study dedicated to the SPI & RED development should be spent by favouring the RED development and the SPI linked to excessive speed, as they can be compared to classical SPI and act as a way to evaluate the methodology and the results, and the SPI that have a clear added value compared to classical methods (Short Headways SPI, Strong deceleration and braking SPI, Safety System use SPI…). Once the first SPI are operational, it will be possible to extend the study in a second step to other SPI, which will also permit the experience obtained during the first implementation to be drawn upon.

As a final word, authors want to stress that this work was completed in 2012 and tried to take maximum advantage of the technological and methodological development of the period. In the light of the latest research outcomes in the field of Naturalistic Driving and Field Operational Test, it can be safely assumed that new and innovative computation approaches, developed specifically to analyse large quantity of driving data (for example like the "Chunking" method [Dozza M., 2012]), will be useful to create new RED and SPI. Furthermore, research progresses in vehicle dynamics and driver behaviour analysis will also permit to understand better the link between naturalistic driving data and unsafe behaviours will also permit to create more complex SPI that will focus on very specific aspects of road safety (for example like fatigue detection, unsafe manoeuvre detection…). Finally, the enrichment of the data available in Geographic Information Systems and the generalisation of their use for research studies in the field of mobility will also provide promising elements for the creation of new RED and SPI and will be very interesting for ERSO.

The field of naturalistic driving studies is booming and the development of innovative indicators for exposure and safety performance measures should be part of a background and long-term effort.

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