Investigating the effects of sleepiness in truck drivers on their headway: An instrumental variable model with grouped random parameters and heterogeneity in their means

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Highlights:

- Driver's heart rate data are collected using sensors on the steering wheel
- Heart rate data are correlated with sleepiness by support vector machine algorithm
- Instrumental variable modelling is used to address endogeneity in sleepiness
- Age, experience, road type, and exposure are among determinants of sleepiness
- Night-time shift is associated with varied effects of sleepiness on headway

Abstract

Sleepiness is a common human factor among truck drivers resulting from sleep loss or time of day and causing impairment in vigilance, attention, and driving performance. While driver sleepiness may be associated with increased risk on the road, sleepy drivers may drive more cautiously as a result of risk-compensating behaviour. This endogeneity has been overlooked in the previous driver behaviour studies and may provide new insight into the effects of sleepiness on driving performance. In addition, the Karolinska Sleepiness Scale (KSS) has been widely used to quantify sleepiness. However, the KSS is a subjective self-reported measure and is reliant on honest reporting and understanding of the scale. An alternative way of quantifying sleepiness is using drivers' heart rate and correlating it with their sleepiness. While recent advances in data collection technologies have made it possible to collect heart rate data in real-time and in an unobtrusive way, their application in measuring sleepiness particularly among truck drivers has been unexplored.

This study aims to address these gaps and contribute to analytic methods in road safety research by collecting truck drivers' heart rate data in real-time, measuring sleepiness from those data, and using it in an instrumental variable modelling framework to investigate its effect on driving performance. To this end, a driving simulator experiment was conducted in Belgium and heart rate data were collected for 35 truck drivers via sensors installed on the steering wheel of the simulator. Additional demographic data were collected using a questionnaire before the experiment. An instrumental variable model consisting of a discrete binary logit and a continuous generalized linear model with grouped random parameters and heterogeneity in their means was then developed to study the effects of driver sleepiness on headway. Results indicate that age, years of holding driver licence, road type, type of truck transport, and weekly distance travelled are significantly associated with sleepiness among the participants of this study. Sleepy driving is associated with reduced headway for 30.5% of the drivers and increased headway for the other 69.5%, and night-time shift is associated with such varied effects. These findings indicate that there may be group- or context-specific risk patterns which cannot be explicitly addressed by hours of service regulations and therefore, transport operators, driver trainers and fleet managers should identify and handle such context-specific high risk patterns in order to ensure safe operations.

Keywords: sleepiness, heart rate, safety, endogeneity, instrumental variable model, machine learning

1. Introduction

Driver sleepiness is an important safety hazard within the truck transport industry (Philip and Åkerstedt, 2006), which is often used interchangeably with fatigue in road safety research. Fatigue is defined as the need for taking a break from a task that has been continuing for too long and is due to either extended time on task (Bartley and Chute, 2009) or work under- or over-load (May and Baldwin, 2009). Sleepiness is defined as the physiological urge to fall asleep and is resulted from either sleep loss or time of day (Dement and Carskadon, 1982). Previous studies have shown that driver sleepiness is significantly associated with increased risk on the roads (Bioulac et al., 2017) and is a major cause of truck crashes (Morrow and Crum, 2004). It can result in decrements in driving performance, including simple and complex tasks, slower reaction times, impaired attention and even loss of consciousness behind the wheel (Williamson et al., 2011). It can also result in a higher frequency of lane departures and dangerous manoeuvres (Hallvig et al., 2014). Therefore, it is essential to understand sleepiness in truck drivers, find its contributing factors, and determine its effects on driving performance in order to reduce the risk. This exercise, however, is confronted with the following important challenges.

Firstly, quantification of sleepiness is not straightforward. While the Karolinska Sleepiness Scale (KSS) (Åkerstedt and Gillberg, 1990) has been widely used to quantify sleepiness in previous empirical investigations (Shahid et al., 2011), the scale is self-reported and subjective. Therefore, individuals may not be accurate in judging their level of sleepiness due to many reasons such as understanding of the scale, pressure of work and schedules, fear of reporting and so forth. In addition, KSS scores vary depending on earlier sleep, time of day, and many other psychological and physiological factors (Shahid et al., 2011). Meanwhile, there has been an increase in the use of driver state detection technology, with commercially available in-vehicle systems (such as steering wheel sensors) and wearable devices (such as smartwatches) (Koesdwiady et al., 2017; Melnicuk et al., 2016). On the one hand, these technologies can be used to collect heart rate measurements of drivers and determine their alertness or sleepiness in real-time. On the other hand, they can enhance the communication between drivers and operators, providing further insight into truck drivers sleep patterns and sleepiness levels, and ultimately mitigate the risk associated with sleepiness. However, the application of these technologies in capturing and quantifying sleepiness has remained relatively unexplored.

Secondly, finding a relationship between sleepiness and driving performance is not straightforward because these two variables may be endogenous. While sleepiness can result in decrements in driving performance, the behaviour of sleepy drivers may well be influenced by driving performance (or driving conditions) too. *Headway* –defined as the difference (in terms of time or distance) between any two successive vehicles when they cross a given point– is one of these driving performance measures that may be influenced by sleepiness and fatigue (Belz et al., 2004; Zhang et al., 2016). However, reduced headway may cause drivers to drive more cautiously as a result of risk-compensating behaviour (Oviedo-Trespalacios et al., 2020). This behaviour may arise due to the difficulty and complexity of controlling the vehicle in shorter headways (Reimer, 2009) and hence may increase the driver's situational awareness (Endsley, 1995). In fact, sleepiness is relatively static from a driver's perspective but it may be inter-related with several dynamic factors during the drive such as overtaking, lane-changing, braking, and crossing behaviour of other road users. This inter-relationship between sleepiness and driving behaviour has been, by and large, overlooked in the literature and is even more acute noting that it may vary among individuals due to various unobserved factors. This variation which is referred to as unobserved heterogeneity (Mannering et al., 2016) must be taken into account when defining the relationship between sleepiness and driving performance. One way of addressing the above challenges is to create a statistical model with special enhancements for capturing endogeneity and unobserved heterogeneity. However, such a model does not exist in driver behaviour research.

This study aims to contribute to analytic methods in road safety research by addressing the above gaps. The study is a part of the European funded Horizon 2020 *i*-DREAMS project, aiming to develop, test and validate a context aware safe driving platform, taking into account driver related background factors, risk related real-time physiological indicators and driving task complexity, to determine if a driver is within the boundaries of safe operation. The *i*-DREAMS project takes a holistic approach in driver monitoring, and one aspect considered is driver sleepiness (Pilkington-Cheney et al., 2021).

2. Literature Review

2.1 Prevalence of Sleepiness in Truck Drivers

Insufficient sleep is a prevalent issue among truck drivers and has been found to be the leading cause of sleepiness in this cohort of drivers (Onninen et al., 2021a) which can further accumulate when working irregular shifts (Onninen et al., 2021b). Previous studies have investigated the risk associated with insufficient sleep and have found that truck drivers who are reporting significantly less sleep before duty, are more likely to be involved in safety critical events, such as crashes and near-misses (Hanowski et al., 2007). In addition, shorter sleep hours, sleeping in the early part of the non-work periods and less sleep between 1:00am and 5:00am have been found to be associated with the highest rate of safety critical events among truck drivers (Chen et al., 2016). Some studies have shown that duty schedules can be incompatible with circadian sleep need (for example driving at night or early in the morning), which can result in increased sleepiness and fatigue (Satterfield and van Dongen, 2013). Finally, an important modulator of sleepiness in truck drivers was found to be hours-of-service regulations in relation to time on duty or drive duration (Hanowski et al., 2003). While these regulations aim to mitigate driver sleepiness, they are mainly effective on fatigue and thus they do not completely eliminate sleepiness. The above studies have shown that truck drivers experience the effects of both sleepiness and fatigue, combining the impact of sleep loss, shift work, time of day, and extended time on task.

2.2 Quantification of Sleepiness

Sleepiness has been commonly quantified by the KSS (Shahid et al., 2011) which is a subjective self-reported 9-point scale (1=extremely alert, 3=alert, 5=neither alert nor sleepy, 7=sleepy – but no difficulty remaining awake, and 9=extremely sleepy – fighting sleep) and has been verified and validated with drivers' electroencephalography activity (Åkerstedt and Gillberg, 1990) and correlated with their lapses (Kaida et al., 2006). Apart from the KSS, a few recent studies have shown that individuals' heart rate measurements such as electrocardiogram and heart rate variability are well correlated with their sleepiness (Awais et al., 2017; Martensson et al., 2019). They have shown that with the recent advances in data collection technologies, it is possible to collect these heart rate measurements in an unobtrusive way and in real-time, and subsequently correlate them with drivers' KSS scores (Rodrigues, 2021). However, the reliability of such quantification of KSS scores and its effects on driving performance have been unexplored.

2.3 Effects of Sleepiness on Driving Performance

Numerous studies have shown that sleepiness can result in driver impairment in vigilance, attention, and driving performance (Anund et al., 2008a, 2008b; Caponecchia and Williamson, 2018; Jackson et al., 2016; Soares et al., 2020). The majority of literature exploring the effects of driver sleepiness on driving performance have focused on the lateral position of the vehicle, with a recent review of driver sleepiness simulator studies reporting that the most commonly measured driving performance variables were lateral lane position and deviation, and speed (Soares et al., 2020). Research shows that driving when sleepy results in increased lane crossings and deviations (Anund et al., 2008a; Caponecchia and Williamson, 2018; Hallvig et al., 2014) and increased lateral variability of the vehicle (Anund et al., 2008b; Jackson et al., 2016; Otmani et al., 2005). More importantly, previous studies have shown that fatigued and sleepy drivers adopt shorter headways (Mahajan and Velaga, 2021; Zhang et al., 2016), which can have serious safety implications particularly when coupled with slowed reaction times and lapses in attention. However, none of these studies have considered the inter-relationship between sleepiness and driving performance which may provide new insight into the interactions between these two variables.

2.4 Addressing Endogeneity and Unobserved Heterogeneity

Simultaneous equation models have been largely used in the statistical literature to address endogeneity between two variables (Washington et al., 2020). These models are divided into two general categories of single-equation methods (indirect least squares, instrumental variables, two-stage least squares and limited information maximum likelihood) and system equation methods (three-stage least square and full information maximum likelihood) with the latter providing consistent and more efficient estimates, albeit with higher computational cost and identification problems (Kim and Washington, 2006; Afghari et al., 2021). Bayesian hierarchical (Oviedo-Trespalacios et al., 2020) and joint econometric models (Bhat et al., 2014; Afghari et al., 2018) have been introduced as alternative methods for addressing endogeneity.

In addition, latent class and random parameters modelling specifications have been widely used to capture unobserved heterogeneity in data (Mannering et al., 2016). The former specification assumes that observations may belong to a finite number of classes in the population, and the effects of independent variables on the dependent variable (e.g. the inter-relationship between sleepiness and driving behaviour) may vary across these classes (Heydari et al., 2017; Afghari et al., 2020). The latter specification assumes that model parameters vary across the population implying that the effects of independent variables on the dependent variable may vary across observations (Coruh et al., 2015). Many advanced variants of both specifications have been proposed in road safety research including latent class with random parameters (Chang et al., 2021), grouped random parameters (Ali et al., 2022), correlated random parameters (Saeed et al., 2019), and random parameters with heterogeneity in means and variances (Behnood and Mannering, 2017a,b). Despite these advancements, there is no model that can adequately capture the complexities (endogeneity and unobserved heterogeneity) underlying the relationship between sleepiness and driving performance.

2.5 Study Scope

The objective of this study is to address the above gaps and contribute to analytic methods in road safety research by collecting truck drivers' heart rate data in real-time, measuring sleepiness from those data, and using it in an instrumental variable modelling framework to investigate its effect on driving performance. To this end, a wide range of data (including heart rate measurements, driving kinematics, and sociodemographic data) are collected for 35 truck drivers in a driving simulator in Belgium. The heart rate data are then linked with driver sleepiness using a support vector machine algorithm and the result is transformed into a binary variable representing alert/sleepy driving. An instrumental variable model consisting of a discrete binary logit and a continuous generalized linear model is then developed to study the endogenous effect of drivers' sleepiness on their headway among the sample of truck drivers. The models are specified by random parameters with heterogeneity in their means to account for unobserved heterogeneity. Moreover, the random parameters are grouped across repeated observations to account for the panel structure of the data.

3. Methodology

Data collection and data analysis are two pivotal elements of the methodology in this study. First, heart rate measurements of drivers are collected and correlated with their sleepiness levels using a pre-validated algorithm. The resulting data are then analysed to understand the determinants of driver sleepiness and ultimately the effects of sleepiness on headway. The following sub-sections describe these two elements of the methodology.

3.1 Heart Rate Data Collection

Driver's physiological data are collected using the CardioWheel (Lourenço et al., 2015), an off-the-person electrocardiogram sensor that uses conductive fabric electrodes as a steering wheel cover (Figure 1). Such an unobtrusive sensor results in a lower signal to noise ratio, and at the same time, brings a seamless integration within the vehicle and provides insight into the driver's heart dynamics without compromising their normal interaction with the vehicle control. The CardioWheel system collects electrocardiogram and lead on detection signals (a binary variable indicating whether both hands are placed on the steering wheel) directly from the electrodes.

Figure 1. CardioWheel for collecting drivers' electrocardiogram and lead on detection signals

After filtering and windowing the electrocardiogram signal in time periods where the lead on detection signals indicate contact, the peaks within QRS complexes (the combination of three graphical deflections seen on a typical electrocardiogram) are located and the heart rate measurement is obtained from the time elapsed between successive pairs. The sequence of successive time intervals between heart beats – the Inter Beat Interval (IBI) – is then used to compute heart rate variability features at two-minute intervals of the collected data. This feature set contains time, frequency and non-linear domain heart rate variability variables, from simple means and standard deviations of heart rate and IBI values, to spectral power in very low, low and high bands, and Poincare plot axis lengths. Heart rate variability features are then used in a support vector machine (SVM) for further analysis. SVM is a machine learning algorithm that splits the data into two classes by finding a hyper-plane separating those two classes and maximizing the distance between that hyper-plane and the closest data points from each class. These data points are called *support vectors* and their position ultimately define the classification decision. The selection of support vectors is achieved by minimizing the below cost function:

$$\min_{w,b,\zeta}\left(\frac{1}{2}\,\vec{w}\cdot\vec{w}\;+C\sum_{i=1}^{n}\zeta_i\right) \qquad \text{Equation (1)}$$

Subject to the following constraints:

$$y_i(\vec{w}\cdot\phi(x_i)+b)\geq 1-\zeta_i \qquad \text{Equation (2)}$$

In the above equations, $\vec{w}$ is the vector defining the hyper-plane, b is the bias vector, (x_i, y_i) represents a data point with independent variable (or feature) x and the binary dependent variable (or label) y, and *C* is the regularization term. ζ_i is a positive slack term that is zero if the data point is correctly classified and falls outside of the margin area; it is between zero and one if the data point falls inside the margin area ($\zeta_i \leq 1$); and it is more than one if the data point is totally misclassified ($\zeta_i > 1$). $\phi(\cdot)$ is a space transformation that is set to the identity function in this study. A radial basis kernel is also used for the inner product of the feature vectors in the transformed space after application of $\phi(\cdot)$. This SVM algorithm is then applied on the collected heart rate data in order to classify each 2-minute driving episode into one of two states: alert or sleepy. A flowchart describing the steps for such a classification is presented in Figure 2. The interested readers can refer to Scholkopf and Smola (2018) for more details about SVM specification.

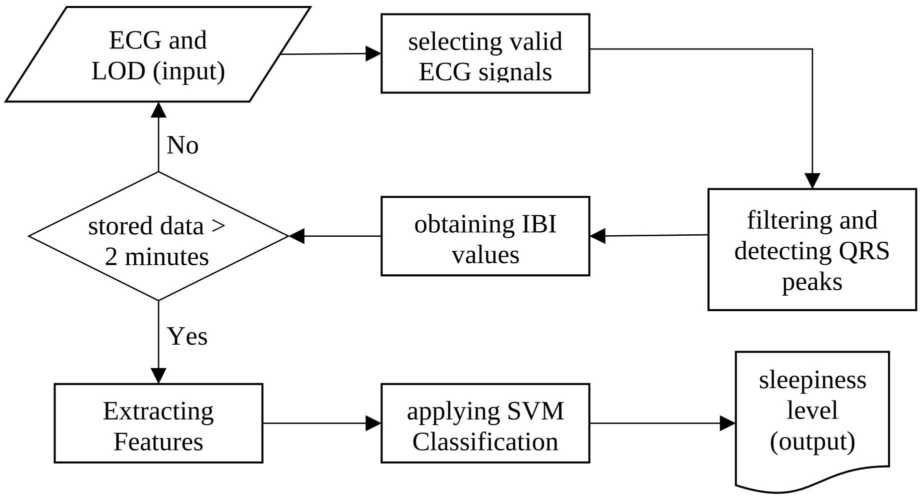

Figure 2. Flowchart of sleepiness classification using heart rate data and support vector machine (**ECG**: electrocardiogram, **LOD**: lead on detection, **QRS**: the combination of three graphical deflections seen on a typical electrocardiogram, **IBI**: Inter beat intervals, **SVM**: support vector machine)

The use of a binary classification for sleepiness is justified by the need to represent this information in a format that conveys driving capability impairment, instead of a higher resolution definition of the driver state. Thus by classifying a driver's state into an alert and a sleepy range, the risk that any given state implies is directly described in the two-level indicator. Another important reason supporting such binary classification is that grouping wide ranges of sleepiness values into two broader levels mitigates the consequences of measurement error.

3.2 Data Analysis – Instrumental Variable Model

An instrumental variable modelling approach (Washington et al., 2020) is used in this study to investigate the endogenous effect of the binary sleepiness indicator on headway. In this approach, the endogenous variable (the binary sleepiness indicator) is replaced with an instrumental variable —a variable that is highly correlated with the endogenous variable it replaces, and is not correlated to the disturbance term of the dependent variable (headway). As such, the proposed modelling exercise in this context has two stages: (1) obtaining the predicted probability of being sleepy from a binary choice model using one or more instruments, and (2) regressing headway on the predicted probability of being sleepy obtained from the first stage in addition to other exogenous covariates. The details of these two stages are described in the following.

3.2.1 Stage 1 – Grouped Random Parameters Binary Logit Model

Binary logit discrete choice models have been widely used to correlate a binary dependent variable with explanatory variables (Hensher et al., 2005). These models assume that effects of explanatory variables are fixed across the sample. However, this assumption may not always hold and the effects of explanatory variables may vary across individuals due to unobserved heterogeneity (Hensher and Greene, 2003). In addition, the empirical data in this study contain multiple observations for each driver (multiple episodes of sleepiness per drive for each participant) creating several panels in the data. The *grouped random parameters logit model* has been used in the literature to address the above limitations of the simple binary logit model (Fountas et al., 2018) and thus is used in this study to model the binary sleepiness indicator. The specification of this model is briefly presented in the following.

Let Y_{it} be a binary dependent variable representing sleepiness (Y_{it}=0: alert , Y_{it}=1: sleepy) of the i^{th} driver at time *t*. Assuming a random utility theory (Hensher et al., 2005), the utility of sleepiness for this driver (U_{it}) is stated as:

$$U_{it} = \beta_i X_{it} + \varepsilon_{it} \qquad \text{Equation (3)}$$

where β_i are estimable parameters (including the intercept), X_{it} are explanatory variables and ε_{it} is the random error term assumed to be identically and independently distributed across observations and describing the random part of the utility. Assuming that ε_{it} is generalized extreme value distributed (Mcfadden, 1980), the probability of driving while sleepy can be presented as:

$$P(Y_{it} = 1) = \frac{1}{1+e^{-(\beta_i X_{it})}} \qquad \text{Equation (4)}$$

Note that the estimable parameters are allowed to vary across individuals to account for unobserved heterogeneity in the data. However, the parameters are fixed across multiple observations of the same individual, accounting for the panel nature of the data. This model is referred to as the *grouped random parameters model* in the literature (Oviedo-Trespalacios et al., 2020). The likelihood of driving while sleepy across all individuals can then be determined by the product of the above equation over the entire observations.

3.2.2 Stage 2 – Grouped Random Parameters Generalized Linear Model with Heterogeneity-in-the-Means

The predicted probability of being sleepy obtained from the first stage is now used in addition to other explanatory variables to create a generalized linear model of headway. Let $Y_{it\bullet}$ be a non-negative continuous dependent variable representing headway of driver *i* at time *t*. This dependent variable is now linked with a number of covariates using a log-linear function:

$$\log(Y_{it\bullet}) = \lambda_i\, Z_{it} + \alpha_i P(Y_{it}) + \tau_{it} \qquad \text{Equation (5)}$$

where λ_i and α_i are estimable parameters, Z_{it} are exogenous explanatory variables and τ_{it} is the random error term. $P(Y_{it})$ is the predicted probability of being sleepy that is inferred in the first stage from a set of explanatory variables (X_{it}) with at least one variable that is exogenous to the set explanatory variables in the second stage (Z_{it}). Such a specification addresses the endogeneity problem (Washington et al., 2020). Similar to the first stage, the estimable parameters are allowed to vary across individuals (to account for unobserved heterogeneity) but are fixed across multiple observations of the same individual (to account for the panel nature of the data).

In addition and to shed more light on the factors behind such unobserved heterogeneity, the means of the random parameters are also correlated with explanatory variables in this second stage:

$$\lambda_i = \bar{\lambda} + \gamma_i m_i + \eta_i \qquad \text{Equation (6)}$$

Where $\bar{\lambda}$ is the mean of the random parameter across all individuals, γ_i are estimable parameters, m_i are explanatory variables, and η_i is a random error term defined based on the distributional assumption of the random parameter. Such a specification is referred to as the random parameters model with heterogeneity-in-the-means (Mannering et al., 2016; Behnood and Mannering, 2017a, 2017b; Fountas et al., 2021; Seraneeprakarn et al., 2017; Venkataraman et al., 2014) and the overall model in the second stage is referred to as the *grouped random parameters generalized linear model with heterogeneity-in-the-means* in this manuscript. The probability density function of the dependent variable in this complex model depends on the distributional assumption for τ_{it} which, of course, must be consistent with the nature of the dependent variable –it should be continuous and non-negative. Assuming an exponential distribution for τ_{it}, the probability density function of the dependent variable can be obtained by:

$$\mathrm{P}(y_{it\bullet} = Y_{it\bullet}) = \frac{1}{\lambda_i\, Z_{it}} e^{-\frac{1}{\lambda_i\, Z_{it}} y_{it\bullet}} \qquad \text{Equation (7)}$$

where the notation are as stated previously. The likelihood of the dependent variable can be determined by the product of this density function over the entire observations.

3.2.3 Model Estimation

While a simultaneous estimation of the two stages in the instrumental variable model may result in more efficient parameter estimates (Afghari et al., 2018; Afghari et al., 2021), it also brings additional complexity and computational cost. Therefore, these two stages are estimated separately in this study. Neither of the likelihood functions in the proposed instrumental variable model has closed form and thus the models in each stage are estimated using maximum simulated likelihood estimation (Bhat, 2001).

3.2.4 Statistical Fit and Predictive Accuracy

Statistical fit of the models is assessed using McFadden pseudo-rho squared (ρ^2) for the grouped random parameters binary logit model (McFadden, 1973), and using Likelihood Ratio (LR) test for the generalized linear model (Washington et al., 2020). The McFadden pseudo-rho squared can be calculated as:

$$\rho^2 = 1 - \left[{}^{LL_m}/_{LL_0}\right] \qquad \text{Equation (8)}$$

where LL_m and LL_0 are the log-likelihoods of the full and the null models, respectively. ρ^2 is analogous to R^2 in linear models and so a higher ρ^2 indicates improved statistical fit. Similarly, the likelihood ratio test statistic can be calculated as:

$$LR = -2[LL_0 - LL_m] \qquad \text{Equation (9)}$$

where the notations are as previously stated. LR follows a chi-squared distribution with P degrees of freedom (P being the number of estimated parameters in the full model) and so the chi-squared statistical test is used to check whether the full model has improved fit than the null model.

In addition, Mean Absolute Deviance (MAD) and Mean Squared Predictive Error (MSPE) are used to assess the predictive accuracy of the grouped random parameters logit model as the probability of sleepiness predicted from this model is directly used as an independent variable in the grouped random parameters generalized linear model. These measures of predicative accuracy can be calculated as:

$$MAD = \frac{1}{N}\sum_{i=1}^{N}|Y_{it} - P(Y_{it})| \qquad \text{Equation (10)}$$

$$MSPE = \frac{1}{N-P}\sum_{i=1}^{N}(Y_{it} - P(Y_{it}))^2 \qquad \text{Equation (11)}$$

where N is the sample size and the rest of notations are as previously stated. Lower (closer to zero) MAD and MSPE indicate improved predictive accuracy.

4. Empirical Data

While the *i*-DREAMS project intends to detect sleepiness and provide appropriate interventions in a naturalistic driving environment, a driving simulator experiment is first conducted to test the applicability of driver state monitoring technologies, which forms the basis of the current paper. A brief description of the driving simulator experimental design and some specifications of the Belgian truck driving simulator are provided in this section, followed by implementation details of the SVM algorithm and extraction of sleepiness from heart rate measurements. Descriptive statistics of the data that are used in this study are then presented, paving the way to the results and discussions in the next section.

4.1 Experimental Design

The simulator experiment in this study was designed based on several principles including definition of outcomes, predictors and hypotheses, selection of sample size and statistical power, selection of design type, distribution of risk scenarios among participants, selection of drive durations to avoid simulator sickness and learning effects, and consideration of confounding effects (Fisher et al., 2011). In line with these design principles, the design of simulator experiment for sleepiness in this study is as follows: (i) the outcome was sleepiness and the predictors were driving characteristics; the hypothesis was defined as whether the binary sleepiness variable can be detected using participants heart rate and how it influences driving headway; (ii) the sample size was pre-defined due to practical constraints; (iii) the experiment was a fractional factorial design; (iv) the experiment was a within-participant design; (v) the experiment included two practice drives prior to the trials; (vi) the order of events within the trials were randomized among the participants and during the trials and (vii) the maximum duration of each trial was 15 minutes.

Participants were recruited via social media (closed groups from truck organizations) and via e-mails to truck companies within the Dutch speaking part of Belgium (Flanders). Truck drivers who were interested in this study needed to complete a recruitment questionnaire, consisting of items related to their demographic information such as gender, age, and driving experience, and also about their employment such as night-time or daytime driving shifts. The experiments were conducted throughout the day (from 8:00 until 21:15) to fit the participants' availability. Simulator lighting was kept on consistently to ensure all participants experienced the same lighting conditions throughout the experiment.

The simulator scenarios had a total distance of approximately 16.5 km - 18 km, consisting of rural roads and motorway segments. These different types of road layouts were distinguished by speed limit. Rural roads with two lanes (one in each direction) were set with the speed limit of 70 km/h for cars (60 km/h for trucks); rural roads with four lanes (two in each direction) were set with the speed limit of 90 km/h for cars (90 km/h for trucks); and motorway segments were set with the speed limit of 120 km/h for cars (90 km/h with motorway sign for trucks). The above road layouts are illustrated in Table 1.

Table 1. Illustration of different road layouts in the experimental scenarios

Road layout	Description	Illustration	Speed sign	Speed limit for trucks (>3.5T)
A	Rural road with 2 lanes (1x1)		70 km/h	60 km/h
B	Rural road with 4 lanes (2x2) and a narrow shoulder, divided by median section		90 km/h	90 km/h
C	Rural road with 4 lanes (2x2) and a wide shoulder, divided by median section		Motorway sign	90 km/h

Three experimental scenarios were then designed (according to the fractional factorial design principles) based on a combination of the above road layouts (Table 2) and were evenly assigned (based on random selection) among the participants.

Table 2. Experimental scenarios designed based on the combination of road layouts

Scenario	Total length of drive	Order of road layouts
1	16.5 km	A, B, C
2	18.0 km	B, C, A
3	17.0 km	C, B, A

In addition, several events (e.g. overtaking, lane changing, pedestrian crossing) with the lead vehicle suddenly braking were included in the scenario to investigate headway. These events occurred at a predefined location for each driver. Please refer to De Vos et al. (2022) for a detailed description of these events. It is important to note that the aim of this study is not to evaluate the differential effects of these events on sleepiness or headway, but to find the determinants of sleepiness and its effects on headway in common situations of day-to-day driving where these events do take place; hence, the inclusion of the events in the simulator trial scenario.

Finally, due to study restrictions and practical constraints of recruiting shift working truck drivers (e.g. availability for work after participation, insurance etc.), sleepiness was not experimentally induced. However, the recruited participants were all truck drivers currently working shifts. Sleepiness is prevalent within shift working populations, including truck drivers (Onninen et al., 2021a). Therefore, there is potential for the drivers to experience underlying sleepiness at the time of the experiment as a result of their working schedules and the impact on their sleep.

4.2 Driving Simulator Specifications

The driving simulator that was used for the experiment was a custom truck simulator by DriveSimSolutions. It was built to recreate the experience of driving a heavy vehicle, but also to provide the option of hardware-in-the-loop simulation through serial interfaces and a programmable controller. Original Equipment Manufacturer (OEM) parts, including the steering wheel, an adjustable driver seat and the turn indicator lever were incorporated into the simulator. A custom digital instrument cluster was used to display vehicle speed and engine speed. Although a manual shifter mechanism was also installed, the simulator was set to automatic gearbox mode for all participants. The OEM steering wheel was modified and connected to a CardioWheel module in order to collect cardiovascular data through the steering wheel. As graphical setup, three 4K 42-inch monitors, was used to provide a 135° horizontal field of view. The Belgian truck simulator is shown in Figure 3. It is worth mentioning that auditory simulation (sound of the engine) was also created during the simulator experiments in order to recreate a real truck driving experience.

Figure 3. DriveSimSolutions truck simulator in Hasselt University, Belgium

As for the virtual environment, the STISIM Drive 3 software was used in combination with its Open Module extension. This extension works as a plugin where custom code is executed at every simulation frame. Within Open Module, a software was developed to interface in real-time with the *i*-DREAMS intervention algorithms and external *i*-DREAMS hardware. At each simulation frame, simulation variables were combined with data from external sensors and stored to a log file, thus data sampling rate was identical to the simulator frame rate at a frequency of around 30Hz. To account for small variations in frame rate, timestamps (with 0.1μs precision) were included in the log file. Externally, an *i*-DREAMS gateway was used to interface with the driving simulator and forward sensor data from the CardioWheel.

4.3 Heart Rate Measurements and Sleepiness

The support vector machine was applied on the participants' heart rate data collected by the CardioWheel and a binary variable for sleepiness was created accordingly. This machine learning algorithm was previously trained and validated by a separate dataset from an on-road experiment with prolonged drives along open road courses and constant workload. In that experiment, drivers reported their KSS and had their electrocardiogram measured using a Holter Monitor. The machine learning algorithm was trained to correlate the drivers' self-reported sleepiness scale with their heart rate measurements. The trained and validated machine learning algorithm was then adopted and applied to the drivers' heart-rate measurements in this study in order to predict their sleepiness (please refer to Rodrigues (2021) for more details about this process). The results of implementing the SVM machine learning algorithm on the heart rate data collected in our study show that the episodes of alert and sleepy driving constitute 86.2% and 13.8% of the drives from all participants, respectively. The average ($\pm$standard deviation) collected heart rate of the participants during these episodes are 87.2 ($\pm$3.6) and 82.6 ($\pm$1.8), respectively. Previous studies have also found that heart rate values in alert and sleepy states are within these same ranges (Jo et al., 2019; Buendia et al., 2019).

4.4 Descriptive Statistics of Data

The data were collected from two main sources: (i) driving data collected through the driving simulator (headway, speed, speed limit) and the CardioWheel (episodes of sleepiness while driving), and (ii) driver demographic data (age, gender, years of holding driving licence) and individual characteristics (weekly distance travelled per week, type of truck transport, working shift). The collected sample consists of 35 truck drivers aged between 22 and 61 years old, and who were mostly male. Table 3 presents descriptive statistics of the variables that are used in this study.

Table 3. Descriptive statistics of the data used in this study

Variable	Mean	Standard deviation	Minimum	Maximum	Sample share
Participants characteristics					
Age (years)	41.967	9.821	22	61	
Age categories					
< 30 years old					0.162
≥ 30 years old but < 40 years old					0.199
≥ 40 years old but < 50 years old					0.404
≥ 50 years old					0.235
Gender:					
male					0.827
female					0.173
Weekly distance travelled per week: (1=less than 500 km, 2=between 500 and 1000 km, 3=between 1000 and 2000 km, and 4=more than 2000 km)	2.899	1.005	1	4	
Years of holding driving licence	17.588	10.379	1	42	
Type of truck transport:					
heavy transport					0.119
construction transport					0.173
distributing transport					0.144
other types of transport					0.564
Driver working shift					
day time shift					0.505
night time shift					0.090
day time and night time shift					0.405
Experimental setup characteristics					
Road type:					
two-lane rural road (speed limit 60 km/h for trucks)					0.450
four-lane rural road (speed limit 90 km/h for trucks)					0.270
motorway (speed limit 90 km/h with motorway sign for trucks)					0.280
Dependent variables in the instrumental variable model					
Sleepiness					
0: alert					0.862
1: sleepy					0.138
Headway (seconds)	472.312	1255.527	2.930	7589.641	

5. Results and Discussion

Many of the variables in the simulator experiment are collected on an event basis, which means that their data are only available when the data collection technology within the simulator detects the event associated with those variables (e.g. when the sensors on the steering wheel detect the heart rate measurement). Such an event-based data collection results in blank data entries for the time intervals with no event. As a result, it is necessary to pre-process the data prior to the analysis. To fill in the blank entries, an algorithm is designed to look back into the data, search for the last valid entry, and replace the preceding blank entries by that valid entry. Moreover, a flagged event is recorded when no hand is detected on the steering wheel and all the data produced during the time of flagged events are discarded. This mechanism ensures that noisy data resulting from hand movements on the steering wheel or other excess motions are not used for classification. In addition, as the data are recorded in small time intervals (sampling frequency of around 30Hz) and to simplify the analysis, the data were aggregated across two minutes during the drives. In doing so, the aggregation method varied depending on the variable of interest: arithmetic mean was used for continuous variables (e.g. headway) and median was used for discrete variables (e.g. sleepiness indicator). Aggregating the data across two minutes resulted in a final dataset consisting of 277 observations for 35 participants (7 to 9 panels depending on the total duration of the drivers for each participant).

5.1 Determinants of Sleepiness

Within the first stage of the instrumental variable modelling approach, the grouped random parameters binary logit model was first estimated against the empirical data. Explanatory variables were selected using a stepwise variable selection criterion. In addition, explanatory variables were tested for multicollinearity by computing the Pearson or Spearman correlation coefficients, and the variables with unacceptably high (>0.7) correlation coefficients were not jointly introduced into the model. The parameters of all variables were tested for random parameters specification and normal distribution was used as the distribution for all of the random parameters. The parameters were considered random only if their standard deviations are statistically significant. The model was estimated using the maximum simulated likelihood approach with 500 Halton draws. The required number of Halton draws was selected so that further increasing the number of draws does not change the estimates significantly. The results of the grouped random parameters logit model are presented in Table 4. According to these results, age, years of experience, type of road, type of truck transport, and weekly distance travelled are statistically significant at 5% significance level (with 95% certainty) among the sample of truck drivers.

Table 4. Results of grouped random parameters logit model of drivers' sleepiness

Variable	Mean	Standard Error	Z Score	p-Value	95% Confidence Interval	
Constant	3.068	2.664	1.150	0.250	-2.154	8.291
Standard deviation of constant	0.096	0.266	0.360	0.717	-0.425	0.619
Driver demographics						
Age	-0.176	0.073	-2.400	0.016	-0.320	-0.032
Operational characteristics						
Years of holding driving licence	0.479	0.112	4.270	0.000	0.259	0.698
Weekly distance travelled	-2.129	0.465	-4.580	0.000	-3.040	-1.218
Standard deviation of weekly distance travelled	1.419	0.292	4.860	0.000	0.846	1.992
Type of truck: heavy transport	-2.186	0.788	-2.770	0.006	-3.730	-0.642
Type of truck: distributing transport	-3.217	0.918	-3.510	0.001	-5.015	-1.418
Road environment						
Road type: four-lane rural road (speed limit 90 km/h for trucks)	1.119	0.582	1.920	0.055	-0.022	2.259
Interaction effects						
Years of holding driving licence in 40+ years old drivers	-0.141	0.074	-1.900	0.058	-0.287	0.004
Measures of statistical fit and predictive accuracy						
Log-likelihood of null model (LL_0)	-110.750					
Log-likelihood of full model (LL_m)	-64.090					
McFadden rho squared (ρ^2)	0.421					
MAD	0.105					
MSPE	0.052					

The negative parameter of age (-0.176) indicates that older truck drivers are less likely to be involved in episodes of sleepiness. The same finding has been reported in the literature suggesting that younger drivers are more likely to suffer from sleep deprivation (Otmani et al., 2005) and continue to drive when sleepy because they have lower risk perception of sleepy driving (Watling et al., 2014). Another study has shown that factors such as 'trip preparations' and 'social gatherings and parties before departure' result in higher sleep deprivation among younger drivers (Philip et al., 1996).

Years of holding a driving licence, on the contrary, has a positive parameter (0.479) implying that drivers with more driving experience are more likely to be involved in episodes of sleepiness. While this finding may be in contrast with the effect of age on sleepiness, the interaction between age groups[1] and years of holding a driving licence clarifies this contrast. The parameter of this interaction term (-0.141) indicates

[1]During model estimation and based on the stepwise variable selection criterion, the last two age categories (≥ 40 years old but < 50 years old, and ≥ 50 years old) were combined to better capture the effect of age groups.

that driving experience is associated with lower likelihood of sleepiness among drivers who are 40 years old or above, and higher likelihoods of sleepiness among drivers who are less than 40 years old. This finding may be due to over-confidence among younger and more experienced professional drivers (Arnold et al., 1997) or the pressure of continuing with their job (McCartt et al., 2000). Road safety research has also shown that years of driving experience is a significant predictor of involvement of sleep or fatigue as a contributing factor in roadway crashes (Sagberg, 1999).

Four-lane rural roads (with speed limit 90 km/h for trucks) has also a positive parameter (1.119) indicating that, in comparison with the other two types of roads, it has increasing effect on the likelihood of being involved in episodes of sleepiness. This finding is intuitive and may be due to monotony and lower cognitive workload (May and Baldwin, 2009) along this type of roads in comparison with roads with lower speed limits (but fewer lanes) and motorways (higher speed limits). Previous research has also shown the adverse effects of monotonous driving and speed limit on cognitive workload suggesting that cognitive workload is lower in a rural environment with a medium speed limit compared to an urban environment with lower speed limits (Son et al., 2011) or motorways with very high speed limits (Piechulla et al., 2003).

In terms of the type of truck transport, the results show that drivers of heavy and distributing transport trucks are less likely to be involved in episodes of sleepiness. This finding may be due to the regular monitoring and heavy enforcement of sleepiness among these groups of professional drivers. Such enforcement may have resulted in a long term sustainable behavioural change among drivers of these two types of truck transport, which in turn may have affected the behaviour of these drivers even when driving the truck simulator.

The parameter of weekly distance travelled is random, indicating that this variable has varying effects on sleepiness across participants. The negative parameter of weekly distance travelled (-2.129) indicates that participants who drive more regularly during the week are, on average, less likely to be involved in episodes of sleepiness. However, the standard deviation of this parameter (1.419) indicates that the effect of weekly distance travelled is decreasing for 93.3% of participants and increasing for 6.7% of the participants. Bearing in mind that weekly distance travelled is a measure of exposure, the mixed effects of this variable might be due to gaining more experience or becoming less alert/attentive due to high exposure. Additional research is needed to unravel the reasons underlying differences in the effects of this variable on sleepiness.

Neither the mean nor the standard deviation of the constant term are statistically significant. However, these non-significant estimates are retained in the model because they determine the probability of sleepiness when no external factors are accounted for but also because they keep the panel setting in the model (please refer to the grouped random parameters specification in section *3.2.1*).

Finally, the McFadden pseudo-rho squared (ρ^2=0.421), mean absolute deviance (MAD=0.105) and mean squared predictive error (MSPE=0.052) of the model show that the model has acceptable statistical fit and predictive accuracy.

5.2 Effect of Sleepiness on Headway

Within the second stage of the instrumental variable modelling approach, the grouped random parameters generalized linear model was estimated using the predicted probabilities of sleepiness obtained from the previous stage and the rest of the empirical data. All of the considerations in the first stage (variable selection criteria, multicollinearity checks, distributional assumptions for the random parameters, and the number of Halton draws) were made for estimating the model in the second stage too. In addition, all of the explanatory variables were considered within the heterogeneity in the means function for random parameters. The results of the grouped random parameters generalized linear model with heterogeneity in their means are presented in Table 5. According to these results, gender, age, weekly distance travelled, and the instrumented sleepiness are statistically significant at 5% significance level (with 95% certainty) among the sample of truck drivers. In addition, night-time shift is significantly (5% significance level) associated with the mean of random parameters in this model.

Table 5. Results of grouped random parameters generalized linear model of drivers' headway

Variable	Mean	Standard Error	Z Score	p-Value	95% Confidence Interval	
Constant	-5.628	0.419	-13.43	0.000	-6.449	-4.806
Driver demographics						
Gender: male	-0.654	0.194	-3.37	0.001	-1.035	-0.274
Age	0.002	0.007	0.34	0.734	-0.011	0.016
Standard deviation of age	0.005	0.001	3.36	0.001	0.002	0.008
Night-time shift for heterogeneity in the mean of age	-0.171	0.055	-3.12	0.002	-0.280	-0.064
Operational characteristics						
Weekly distance travelled	0.019	0.062	0.31	0.758	-0.103	0.141
Standard deviation of weekly distance travelled	0.095	0.021	4.48	0.000	0.054	0.137
Night-time shift for heterogeneity in the mean of weekly distance travelled	2.473	0.885	2.79	0.005	0.737	4.208
Sleepiness						
Instrumented (probability of) sleepiness	0.399	0.265	1.51	0.132	-0.119	0.917
Standard deviation of instrumented (probability of) sleepiness	0.784	0.228	3.44	0.001	0.337	1.230
Night-time shift for heterogeneity in the mean of instrumented (probability of) sleepiness	7.191	2.073	3.47	0.000	3.127	11.255
Measures of statistical fit						
Log-likelihood of null model (LL_0)	-1982.67					
Log-likelihood of full model (LL_m)	-1953.11					
LR statistic	59.12					

The negative parameter of gender (-0.654) indicates that male truck drivers maintain shorter headways. This is in line with the findings from a recent review of gender differences in various driving behaviour metrics, showing that female drivers exhibit higher longitudinal distance than males (Rezaei et al., 2021); it is noted however that no study was found explicitly examining the impact of gender on truck drivers' headways in particular. While the parameters of age, weekly distance travelled, and instrumented sleepiness (0.002, 0.019, and 0.399, respectively) are not statistically significant at 5% significance level, the standard deviation of these parameters (0.005, 0.095, and 0.784 respectively) are statistically significant at this level.

These findings indicate that the effects of age, weekly distance travelled, and instrumented sleepiness on headway are decreasing for a proportion (34.5%, 42.1% and 30.5%, respectively) of the truck drivers, and increasing for the others. The parameters of night-time shift shows that this variable is underlying such varied effects. The negative parameter of night-time shift for age (-0.171) indicates that it decreases the mean effect of age on headway and implies that the majority of older drivers who work night-time shifts maintain shorter headways. This finding may be indicative of the reduced ability to drive during the night for this cohort of drivers. On the contrary, the positive parameters of night-time shift for weekly distance travelled and sleepiness (2.473 and 7.191, respectively) indicate that night-time shift increases the mean effects of these two variables on headway. These findings imply that, for the majority of drivers, higher weekly distance travelled and sleepy driving are associated with increased headway if they work night-time shifts. The former could be a sign that that more experienced truck drivers maintain safer driving behaviour during the night, and the latter could be a sign that sleepy truck drivers initiate risk-compensating behaviour during the night. It is noteworthy that this additional information is a direct benefit of using a heterogeneity-in-the-means specification for the random parameters in that it reveals the underlying factors (night-time shift) for the heterogeneous effects of independent variables (age, weekly distance travelled, and sleepiness) on the dependent variable (headway).

Finally, the likelihood ratio test statistic associated with the grouped random parameters generalized linear model (LR= 59.12) is much larger than the critical chi-squared value for 5% significance level and 11 degrees of freedom ($\chi^2_{0.05,11}$ =19.68) indicating that the model has substantially improved statistical fit relative to the null model.

6. Conclusions

Sleepiness is a common human factor among truck drivers which is mainly due to sleep loss and time of day. Previous studies have shown that sleepiness is significantly associated with increased risk and thus it is very important to detect sleepiness, understand its underlying contributing factors and assess its effects on driving performance. Although the KSS has been traditionally used to quantify sleepiness, this self-reported metric is subjective and is reliant on honest reporting and understanding of the scale. Recent advances in data collection technologies have made it possible to collect heart rate measurements of drivers in real-time and in an unobtrusive way. However, the application of such technologies in measuring sleepiness among truck drivers has remained unexplored. The endogeneity between sleepiness and driving behaviour has been overlooked too. As such, this study aimed to investigate the applicability of sensors installed on the steering wheel of trucks for measuring sleepiness in truck drivers, and use the measured sleepiness in a proper methodological framework to understand its effect on driving performance.

The findings from our experiment indicated that heart rate data can be used to identify driving episodes into one of two states: alert or sleepy. These binary episodes can then be used along with other driving data to investigate determinants of sleepiness and its effect on headway as a measure of driving performance. An instrumental variable model consisting of a grouped random parameters binary logit and a grouped random parameters generalized linear model with heterogeneity in the means were estimated against data collected for 35 truck drivers in a driving simulator study. Results indicated that younger drivers and drivers with more driving experience are more likely to be involved in episodes of sleepiness. In addition, four-lane rural roads with speed limit 90 km/h contribute to higher chances of being involved in sleepiness. On the contrary, drivers of heavy and distributing truck transports are less likely to be involved in episodes of sleepiness compared to drivers of other types of truck transport. Weekly distance travelled is also associated with sleepiness among the sample truck drivers in this study. However, the effect of this factor varies across the participants. Moreover, gender, age, weekly distance travelled, and sleepiness are significantly associated with driving headway. Out of these factors, age, weekly distance travelled, and sleepiness have mixed effects among truck drivers. Our findings indicate that night-time shift is the factor underlying these mixed effects. Future research should be dedicated to better understand driving behaviour mechanisms during different times of day.

This study is not without limitations. From the empirical perspective, the findings from this study are based on a driving simulator experiment which is a confined environment and may not be completely the same as the real driving environment. As sleepiness was not experimentally induced, the observed episodes of sleepy driving (which only constituted around 14% of all driving instances) in this study are most likely due to an underlying level of sleepiness as a result of shift work, poor sleep, or personal or social commitments. Future research should validate our findings using real driving data from a much larger sample (such as data obtained from naturalistic driving studies) with sleep restriction protocols. In addition, the time of day at which experiments are conducted should be standardised, with further considerations given to lighting and duration of driving. In doing so, additional data about sleeping patterns of truck drivers should also be collected for use in the analysis. In addition, the binary sleepiness variable was not directly observed but approximated by the support vector machine in this study. However, such an approximation can lead to some biases such as measurement errors, which are carried to the grouped random parameters logit model of sleepiness too. As such, the results of this model should be interpreted with caution. Finally, mild and extreme levels of sleepiness were not distinguished from one another in this study. Future research should disentangle the effects of these two levels of sleepiness on driving performance.

From the methodological perspective, the two stages of the instrumental variable model were estimated separately in this study. Future research may be dedicated to estimating the model simultaneously and comparing the results with those of this study. In addition, only one type of distribution was used for the error term of the generalized linear model in the second stage of the instrumental variable model. Employing alternative types of non-negative distributions, testing their goodness of fit and comparing the results with those from this study is a worthy research exercise. While a grouped random parameters approach was adopted to address unobserved heterogeneity and panel data setting, the correlations between random parameters were not considered in this study. Future research may be dedicated to extend the proposed model to a correlated random parameters variant (Ali et al., 2022) in order to better understand the interaction effects of independent variables on the dependent variable. Finally, temporal variations were not considered in the effects of explanatory variables on sleepiness or headway due to the very short duration of the simulator experiment. However, in real driving conditions and over long periods of time, such temporal instability may exist due to the availability bias in the external factors such as changes in truck industry regulations and/or global experiences of truck drivers over time (Mannering, 2018) and may alter the effects of the aforementioned explanatory variables.

This study, although exploratory, contributes a number of insights to the truck transport industry and policy makers. A key finding is that, despite the important developments in hours of service regulations (see Goldenbeld (2017) for a review), the prevalence of sleepiness among professional truck drivers is still non-negligible, and therefore fleet managers and authorities should not only rigorously implement and enforce these regulations, but also stay aware of their limitations. Moreover, there may be group- or context-specific risk patterns which cannot be explicitly addressed by regulations. For instance, in our study the combination of young age with sufficient experience is associated with higher probability of sleepiness. The impact of external factors on fatigue may be heterogeneous; night shifts have positive effects on the headways of sleepy drivers when combined with exposure, but negative effects when combined with older age. Therefore, transport operators, driver trainers and fleet managers should identify and handle such context-specific high risk patterns in order to ensure safe operations.

There are two main directions for policy and management interventions in this respect: (i) through real-time interventions with emerging technologies that allow continuous unobtrusive monitoring of sleepiness-related physiological indicators, and (ii) through post-trip interventions by means of personalized feedback, re-training and incentives. In the next steps of the *i*-DREAMS project, both types of interventions on truck drivers will be tested and evaluated (Pilkington-Cheney et al., 2021).

7. Authors Statement

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