Subjective sleepiness and accident risk avoiding the ecological fallacy

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SUMMARY The present study of sleepiness and accident risk in a HI-FI car simulator aimed to provide subject-level relative risks (RR) with 95% confidence intervals (CI) for different levels of subjective sleepiness measured with the Karolinska Sleepiness Scale (KSS), 1 = very alert, 9 = very sleepy, fighting sleep, an effort to staying awake. Five male and five female shift workers, mean age 37 years, participated with a 2-h drive (08:00–10:00 hours) in a dynamic high-fidelity moving base driving simulator, after a night of work and after a night of sleep. Subjective sleepiness was measured with KSS every 5 min and events of incidents (two wheels outside the right lane), accidents (two wheels off the road or four wheels in opposite lane) and crashes (four wheels off the road) were recorded. The probability of an accident was modelled with a Generalized Linear Mixed Model approach to estimate subject-specific effects, rather than group average effects, to avoid the ecological fallacy. The results showed that sleepiness was strongly related to accident risk. An average subject was estimated at 28.2 times (95% CI RR = 10.7–74.1) increased risk at KSS = 8 and at 185 times (95% CI RR = 42–316) at KSS = 9 compared with KSS = 5. There were large individual differences in event propensity that complicates the prediction of absolute accident risk for individual subjects.

KEYWORDS generalized linear mixed models

INTRODUCTION

Sleepiness and fatigue have been identified as major risk factors in the transport sector and are suggested to account for a large proportion of the road accidents (Dinges, 1995). Recently, road crash investigations have demonstrated that subjective sleepiness is frequently increased before the crash (Connor et al., 2002). Sleepiness because of sleep deprivation and prolonged wakefulness have also been suggested to increase the risk of road accidents during the drive home after a night shift (Gold et al., 1992; Ohayon et al., 2002; Stutts et al., 2003). Circadian regulation also plays an important role and further increases the risk of sleepiness-related accidents in the early mornings (Horne and Reyner, 1995). Furthermore, the early morning hours have been associated with a five- to sixfold increase in the risk of having a highway accident of any kind – sleepiness related or not (Åkerstedt et al., 2001).

An easy assessment of sleepiness states combined with knowledge about the risk involved in driving could be a very potent safety measure, i.e. if it could be used to change the behaviour of sleepy drivers to use effective counter measures such as napping and caffeine or to completely avoid driving (Horne and Reyner, 1996).

The most feasible assessment of sleepiness states is the subjective introspection and the two most used methods are the visual analogue scale (100 mm line with ‘very alert’ and ‘very sleepy’ indicating the extremes (Monk, 1989) and the Stanford Sleepiness Scale using Likert technique with seven
labelled steps from 1 = ‘Feeling active and vital; alert; wide awake’ to 7 = ‘Almost in reverie; sleep onset soon; lost struggle to remain awake’ (Hoddes et al., 1973). In addition, the Karolinska Sleepiness Scale (KSS) was developed to obtain a simple, one-dimensional, sleepiness scale for easy assessment in the field (or laboratory) and uses a nine-level Likert scale from ‘very alert’ to ‘very sleepy, fighting sleep/an effort to keep awake’ (Åkerstedt and Gillberg, 1990).

Subjective sleepiness is a potent predictor of performance (Dorrian et al., 2000; Gillberg et al., 1994) but it has also been pointed out that the correlation is far from perfect (Rogers and Dinges, 2003). This raises the question of what a subjective rating of sleepiness really means. To be of practical value, one would need to be able to interpret scale values in relation to the risk of serious performance impairment. Reyner and Horne (1998) used the KSS in a driving simulator experiment and related incidents (two wheels outside the lane) or accidents (four wheels outside the lane) to ratings of subjective sleepiness made every 200 s. The results showed that accidents and incidents were rare below level 7 on the scale but started to increase at that level and reached very high numbers for level 9. In all cases, the drivers were aware of increased sleepiness before driving off the road, although the time driven at high sleepiness before the crash varied. The latter finding indicates a certain amount of individual differences in accident propensity independent of sleepiness.

In the presence of individual differences in event propensity, the traditional approach to average effects over a group of subjects will be biased compared with subject-specific estimates (Lindsey and Lambert, 1998; Neuhaus, 1992). This has also been recognized in some studies. For example, Hanowski et al. (2003) reported that 5% of the subjects accounted for 26% of the incidents in a study of truck drivers. Similarly, Mitler et al. (1997) reported that 10% of the drivers accounted for 54% of the video recorded segments of drowsiness. Making inferences about individuals from group data is sometimes called ‘the ecological fallacy’ and while group average estimates on the above reported data provide sound estimates of effects at the group (or population) level, they refer to no individual subject in the population, i.e. leading to the ecological fallacy if they are used to infer effects in individuals.

The present study of sleepiness in a driving simulator was designed to carry the study by Reyner and Horne (1998) one step further by estimating the risk of having an accident as a function of sleepiness and calculate relative risks (RR) for different levels of the KSS. Severe events like accidents are relatively rare observations, at least in realistic settings, and this makes it impossible to get reliable estimates unless the data set is very large. To overcome this problem, a statistical model was developed that ‘borrowed strength’ from more frequent events. To avoid the ecological fallacy, a Generalized Linear Mixed Model (GLMMM) approach was used to provide conditional estimates at the subject level. Conditional estimates were also compared with group average estimates to assess the influence of the ecological fallacy. Data was obtained from an earlier study on the effect of driving home after the night shift on sleepiness and driving performance (Åkerstedt et al., 2005)

METHOD

The overall design of the study was a within-subject experimental design with two conditions: a ‘Night sleep’ condition when subjects had a normal night sleep and a ‘Night work’ condition where the subjects had stayed up all night working. In both conditions, subjects drove in a high-fidelity car simulator between 08:00 and 10:00 hours. The subjects participated in the two conditions in a counter-balanced order with at least three days between conditions.

Five male and five female shift workers were recruited through advertisements in local companies with night work. Most came from hospitals, newspapers and an energy plant. They had a mean age of 37 years (SD = 12), drove annually an average of 9500 km (SD = 6800) and had 5–9 years experience as shift workers. Three participants worked only at night while the rest alternated between night and day work. They received a monetary compensation of approximately €110. The study was carried out by the Swedish National Road and Transport Research Institute, under their study guidelines, including the Declaration of Helsinki.

The subjects were instructed to maintain their normal work sleep pattern and behaviour in connection with night and day work during experiment. Before the study began, the subjects had a practice drive in the simulator for 20 min and practice at using the rating scale (described below), which had been sent out beforehand. They arrived at approximately 07:00–07:30 hours, directly after night work or rising. After the drive, the subjects were debriefed and sent home. In the night work condition the drivers were brought to and from the test centre by taxi.

A dynamic, high-fidelity, moving base driving simulator was used. The car cab was a Volvo 850 and the system simulated acceleration in three dimensions through roll, pitch and linear lateral motion. The visual system presented the scenario on a 120° wide screen 2.5 m in front of the driver. The sound system generated noise and infrasound that resembles the internal environment in a modern passenger car. The vibration system simulated the sensations the driver experience from the contact between the road surface and the vehicle. The driving scenario was a rural two-lane road with lanes 3.6 m wide with a 0.5 m hard shoulder. The conditions were ‘summer’ with a slightly hazy sky. Signed speed limit was 90 km h⁻¹ and there was sparse oncoming traffic or cars to follow or pass.

Several measures were recorded from the simulator at a frequency of 12 Hz, e.g. speed (mean + variability), lateral position (mean + variability), time to Line Crossing (TLC) and steering wheel angle (mean and variability). In addition, electro-occulogram (EOG) was used to record blink duration and blink frequency of the driver.

Sleepiness was rated every 5 min prompted by an instruction displayed on the windshield, with the response given orally, using the scale pasted to the steering wheel. The scale used was
the KSS ranging from 1 to 9 where 1 = very alert, 3 = alert, 5 = neither sleepy nor alert, 7 = sleepy but no effort to remain awake, and 9 = very sleepy, fighting sleep, difficulty staying awake (Akerstedt and Gillberg, 1990). The scale was modified to have labels on all nine steps (Reynier and Horne, 1998) and subjects were also allowed to rate intermediate steps with half points yielding a highest possible rating of 9.5 and a total of 18 categories on the scale. The modifications of the scale were motivated by a high rating frequency in a highly controlled environment where the subjects had continuous access to the scale at the steering wheel.

The present study focused only on events related to accident risk and subjective sleepiness (KSS). Three types of events were identified. The most severe event, a ‘Crash’, was scored if the ‘car’ left the road with all four wheels. The event indicates a very high probability for a crash if there would be objects close to the road edge. The second most severe event, an ‘Accident’, was scored if the car went off the right side of the road with two wheels or crossed into the left lane with all four wheels. This event indicates a very high probability for an accident, either by driving completely off the road on the right side or through a frontal collision with a meeting car in the left lane. An ‘Incident’, was scored if the car had two wheels on the wrong side of the right lane marker. Because subjects were instructed to maintain a position inside the lane markers, an incident indicated an error, but with a low accident risk. A complete record of the obtained data for every subject is presented in Fig. 1.

**Statistical analyses**

Data was analysed with a multilevel GLMM approach using a software for Generalized Linear Latent and Mixed Models (GLLAMM) called *gllamm* version 2.3.9 (Rabe-Hesketh et al., 2001, 2002) running in the statistical package Stata 8.2 for the Macintosh (StataCorp, 2003). The software comes with a link function that makes it possible to fit non-linear responses (such as binary and ordinal responses using a logit/logistic link function and a binomial error family) and allows for explanatory variables (i.e. fixed effects) and for unobserved heterogeneity between subjects to be estimated as latent variables (i.e. random effects) and included in the model. In our context the random effects relate to an individual’s ‘driving accuracy’ not explained by the fixed effects. The fixed effect estimates reported by *gllamm* are conditional on the random effects and describe an ‘average’ subject, i.e. all random effects are set to zero. Empirical Bayes predictions that take into account both fixed and random effects are available for individual subjects as well as for any hypothetical subject with an optional level of the random effect(s), making it possible to evaluate individual differences.

In addition to conditional estimates, *gllamm* also has the ability to provide the more commonly used marginal (or population/group average) effect. For comparison, marginal effects are also plotted and differences discussed. The *gllamm* software uses maximum likelihood estimation with adaptive quadrature and provides valid estimates in the presence of missing data if the mechanism can be assumed to be missing at random (MAR).

The probability of an event during a subsequent 5 min segment of driving was modelled as a function of rated sleepiness levels (KSS) using a logit link function for the dependent variable (events) with total driving time and condition (night work/night sleep) as additional covariates. An ordinal logistic link function was used to estimate event-specific effects. The model assumes that the different event types form an ordered scale of severity (i.e. from incidents to accidents to crashes) and that the coefficients for the log-odds of events above or below any specified level of severity are the same for all events – the proportional odds assumption. One could say that the coefficients and cut point for a specific event ‘borrows strength’ from other events. The proportional odds assumption was tested and relaxed in a third set of models where the threshold for a specific event was allowed to depend on covariates to estimate event-specific coefficients.

Constraints were also imposed on the model so that the coefficients were only relaxed for a subset of events and a likelihood ratio test was used to assess changes in model fit.

Previous research has suggested that the effect of sleepiness might follow a curvilinear function (Åkerstedt and Gillberg, 1990). To test this assumption, a set of models was estimated with the KSS raised to the power of exponents ranging from one to four in 0.1 steps. The best-fitted model was then tested for significance with a one-degree-of-freedom likelihood ratio test against the model with the linear transform of KSS. A random intercept was added to the model to control for individual differences in the propensity for an event (‘driving accuracy’) and because this propensity might vary between conditions (because of practice/order effects or other situation factors not related to sleepiness such as mood or just having a ‘bad day’) a random effect of condition (night work/night sleep) was also included. A heuristic equation describing the overall model (excluding the link function) is presented below with subscripts for subjects (i) and measurement occasions (j) and latent variables (η) indicating the random effects where (ε) represents the stochastic variability associated with event occurrence within a segment of time.

\[
event_{ij} = \beta_0 + \beta_1 \text{condition}_{ij} + \beta_2 \text{time}_{ij} + \beta_3 \text{KSS}_{ij} + \eta_{ij} + \varepsilon_{ij}
\]

Sleepiness-related RR and 95% confidence intervals (CI) were calculated from the parameter vector of the final model by means of the ‘delta method’ on the natural logarithm of the ratio between accident probabilities (i.e. absolute risk) at different levels of the KSS, using the Stata procedure `nlcom` (StataCorp, 2003). The point estimates ± 1.96 standard error were exponentiated to describe RRs and 95% CI. We can obtain estimates marginal to random effects as shown in Pickles (1998). The coefficient from the final model was multiplied by a factor lambda to give adjusted estimates that were marginal to the random effect of condition and thus conditional on only the stable part of the individual differences.

\[
\lambda = \sqrt{\text{var}(\eta_0) + \text{var}(\varepsilon)} / \sqrt{\text{var}(\eta_0) + \text{var}(\eta_1) + \text{var}(\varepsilon)}
\]

\[\text{var}(\varepsilon) = \pi^2 / 3\] for a model with logistic link. The intraclass correlation coefficient (ICC) was calculated to describe the stable part of the intercept across conditions.

\[
\text{ICC} = \frac{\text{var}(\eta_0)}{\text{var}(\eta_0) + \text{var}(\eta_1)}
\]

A technical and comprehensive review of GLMM within a unified generalized latent variable modelling framework is provided by Skrondal and Rabe-Hesketh (2004) and a more hands-on introduction can be found in Skrondal and Rabe-Hesketh (2003). A review of logistic regression for longitudinal data is provided in Neuhaus (1992). For a discussion of efficient handling of missing data, see Schafer and Graham (2002). For an introduction to linear mixed models in the context of sleep research, see Van Dongen et al. (2004a). The GLMM approach used in the present paper have previously been used to model variation in sleepiness during early morning shifts (Ingre et al., 2004).

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**RESULT**

There were 20 crashes, 36 accidents and 69 incidents, a total of 125 events, recorded from a total of 446 observations of 10 subjects. There were large individual differences in event rate. Two subjects accounted for only two incidents (no. 2 and 10) while two other subjects (no. 3 and 4) accounted for a total of 35 incidents, 17 accidents and eight crashes. Four subjects (no 3, 4, 7 and 8) have missing data because they were too sleepy to continue driving at the end of the night work condition (Fig. 1).

An ordinal logistic model was fitted to the data with only condition and time as covariates. The results indicate that the log-odds of an event increased during the night work condition (coefficient, coef = 1.29, standard error, SE = 0.50, \( P = 0.010 \)) and with driving time in minutes (coef = 0.009, SE = 0.003, \( P = 0.009 \)). The overall log-likelihood was estimated at ~332.6. When rated sleepiness (KSS) was added to the model, a significant improvement of model fit was observed (\( \chi^2 = 114, \text{ df} = 1, P < 0.001 \)). The proportional odds assumption was tested by allowing the coefficient of KSS to vary across the different events. A model with two sets of coefficients, one for incidents and one for accidents and crashes, proved to provide the best fit to data with a log-likelihood of ~261.5 (\( \chi^2 = 28, \text{ df} = 1, P < 0.001 \)). Finally, applying a set of non-linear transformations of the KSS indicated that the best-fitted model included the KSS raised to the power of 3.2 (\( \chi^2 = 14, \text{ df} = 1, P < 0.001 \)).

**Table 1 Summary of results**

<table>
<thead>
<tr>
<th>GLMM parameters</th>
<th>Estimates</th>
<th>SE</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Condition (night work)</td>
<td>-0.15329</td>
<td>0.6446</td>
<td>0.812</td>
</tr>
<tr>
<td>Time (min)</td>
<td>0.00871</td>
<td>0.0053</td>
<td>0.100</td>
</tr>
<tr>
<td>KSS3.2 incident</td>
<td>0.00352</td>
<td>0.0007</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>KSS3.2 accident</td>
<td>0.00597</td>
<td>0.0009</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>KSS3.2 crash</td>
<td>0.00597</td>
<td>0.0009</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Constant incident</td>
<td>-4.42740</td>
<td>0.9085</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Constant accident</td>
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<td>1.1356</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Constant crash</td>
<td>-10.4320</td>
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<td>&lt;0.001</td>
</tr>
<tr>
<td>var</td>
<td></td>
<td>0.795</td>
<td>P-value</td>
</tr>
<tr>
<td><strong>Random effects</strong></td>
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<td></td>
</tr>
<tr>
<td>Intercept</td>
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<td>2.715</td>
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</tr>
<tr>
<td>Condition</td>
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<td>0.002</td>
</tr>
<tr>
<td>lambda</td>
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<tr>
<td>ICC</td>
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<td></td>
<td></td>
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<tr>
<td><strong>Model fit</strong></td>
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<tr>
<td>Constant only</td>
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<td></td>
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<tr>
<td>+ Random intercept</td>
<td>-356.1</td>
<td>0.105</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>+ Time and condition</td>
<td>-332.6</td>
<td>0.164</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Proportional odds</td>
<td>-267.2</td>
<td>0.329</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Full model</td>
<td>-255.8</td>
<td>0.357</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

coef, log-odds ratio; SE, standard error; var, variance. A Wald test was used to test the significance of the fixed effects and a likelihood ratio test was used to test the significance of the random effects.
The results from the final model are summarized in Table 1 and indicate that once sleepiness as reported by the KSS was included, time and condition were no longer significant predictors of events. The results also indicate substantial heterogeneity between subjects in overall accident propensity as indicated by the significant random effect variance of the intercept. The significant random effect of condition suggests that this propensity was not completely stable. The ICC estimate indicates that 79% of the variance in the intercept was stable across conditions.

Fig. 2 illustrates the effect of KSS on incidents and accidents. There are two main differences between the two events; incidents have a higher overall probability and accidents show a stronger (relative) increase with increased sleepiness. The plots for individual subjects illustrate the magnitude of the individual differences; two subjects already showed a very high probability for incidents at low sleepiness levels. The marginal estimates illustrate the group average effect, and are attenuated compared with the conditional and adjusted estimates for an average subject calculated from the coefficients of the final model.

DISCUSSION

The results showed that subjective sleepiness measured with the KSS was strongly related to accident risk. There was also evidence of differential effects between minor mistakes (incidents) and more severe events (accident and crash). KSS was more strongly related to severe events than incidents. There were also a large heterogeneity between subjects in event propensity and the marginal (group average) estimate was attenuated compared with the conditional estimate. The results also suggest a curvilinear relation between KSS and the log-odds of event rate, which enhanced the rise in risk at high sleepiness levels. The finding is in accordance with previous research of KSS and physiological signs of sleepiness (Åkerstedt and Gillberg, 1990).

The results showed that total driving time and condition were related to event risk. However, the huge increase in model fit ($\chi^2 = 114$, df = 1) when sleepiness was added to the model and the fact that neither time nor condition remained significant suggest that the effects of driving time and condition were mediated through sleepiness.

There were only 20 crashes and 36 accidents recorded and these events were very unevenly distributed between subjects. This makes it impossible to get reliable estimates from a model based on only crashes or accidents. However, it was possible to capitalize on the fact that incidents, accidents and crashes can be ordered in severity and simultaneously estimate a model using all events. The results suggest that the proportional odds assumption did not hold completely. Sleepiness was a more important predictor for the more severe events.

Making inferences about individuals from group data is sometimes called the 'ecological fallacy' and is particularly problematic with non-linear (e.g. logit/logistic) models (Lindsey and Lambert, 1998; Neuhaus, 1992) like the ones estimated in the present study. In such models, there is a fundamental difference in the interpretation of marginal or population/group average estimates on one hand and conditional models on the other. The former describe the average effect between two randomly sampled subjects in the group and the latter the within-subject effect for an average subject. In the presence of individual differences in event propensity, the marginal estimate will be attenuated compared with conditional estimates and the difference between the two approaches will increase with the variance of the random effect (i.e. individual differences).

In a similar study, Reyner and Horne (1998) averaged the effect over a group of subjects and found that increased sleepiness increased the risk for accidents. It is possible to
calculate a RR from the text between KSS = 5 (three minor incidents) and KSS = 8 (11 minor incidents) which indicates an increased risk of accidents of RR = 3.7. This estimate is similar to the marginal estimate of incident risk in the present study. However, the (adjusted) estimate for an average subject in the present study shows a much steeper risk increase at high sleepiness level and a lower absolute risk at low sleepiness levels. To illustrate our findings and compare it with the estimates reported by Reyner and Horne, a set of RRs with 95% CIs have been calculated from the final model and summarized in Table 2. The results show that the risk increase for an average subject is much higher than the group average and was estimated at RR = 28. The difference between the two estimates is striking and can be explained by individual differences in event propensity. Reyner and Horne report that the duration of driving with sleepiness (KSS ≥ 7) before an accident was estimated at 43.5 min with a standard error of 13.8 min for 12 subjects, i.e. a standard deviation of about 48 min, indicating considerable differences between subjects in incident propensity.

The findings of individual differences in event propensity are similar to previous findings of truck driver sleepiness and incidents (Hanowski et al., 2003; Mitler et al., 1997). An important question is whether this heterogeneity should be considered a trait (Van Dongen et al., 2004b). The present study does not allow for any strong conclusions about trait-propensity because it only covered two ‘snapshots’ in time and it is possible that the propensity estimated in the present study may vary over longer periods of time. However, the ICC estimate suggests that approximately 80% of the variance in overall propensity was stable across the two conditions indicating a possible trait component in event propensity. These findings are consistent with recent reports of individual differences in performance (Van Dongen et al., 2004b) and many other areas within the files of sleep research (Van Dongen et al., 2005).

The major practical implication of the present study is that the sleepiness-related increase in accident risk is much higher than has been suggested by earlier studies. The results suggest a 185 times risk increase from KSS = 5–9 and that it would be possible to reduce accident risk of an individual by ≈96.5% if sleepiness could be reduced from a level of 9–7. Even if the lower 95% confidence limit is used, the difference is almost three times what has been reported earlier (10.7 vs. 3.7). The large risk increase compared with previous findings (Reyner and Horne, 1998) is mainly because of a lower risk estimate at low sleepiness levels. This finding seems to be more ecologically valid because one would not expect a high risk for accidents in alert subjects. As far as we know, these are the first estimates of conditional (within-subject) RRs and they were based on a relatively small data set with 446 observations and 69 accidents (including crash events). Further research with more subjects is needed to confirm our RR estimates. However, our findings suggest that group average effects will underestimate the effect in individual subjects thus, leading to the ecological fallacy if they are used to infer effects in individual subjects.

Finally, whereas a simulator comes rather close to real life driving in some ways (Törnros, 1998) it is likely that the accident rate is higher in a simulator compared with real life driving because of a lower level of stimulation and effort. This might have inflated the estimate of absolute event risk in the present study, but it is less likely that it had an effect on the association between KSS and events. The study only included 10 subjects and all of them were shift workers, which may limit the population to which the result can be generalized.

In conclusion, the present study has shown that subjective sleepiness measured with the KSS was strongly related to accident risk in a HI-FI car simulator with a rural two-lane-road driving scenario. For an average subject, the risk of an accident was estimated to increase 28 times if sleepiness increased from 5 to 8 on the KSS and another 6.5 times between 8 and 9.

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