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Effects of partially automated driving on the development of driver sleepiness

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ABSTRACT

The objective of this study was to compare the development of sleepiness during manual driving versus level 2 partially automated driving, when driving on a motorway in Sweden. The hypothesis was that partially automated driving will lead to higher levels of fatigue due to underload. Eighty-nine drivers were included in the study using a 2 × 2 design with the conditions manual versus partially automated driving and daytime (full sleep) versus night-time (sleep deprived). The results showed that night-time driving led to markedly increased levels of sleepiness in terms of subjective sleepiness ratings, blink durations, PERCLOS, pupil diameter and heart rate. Partially automated driving led to slightly higher subjective sleepiness ratings, longer blink durations, decreased pupil diameter, slower heart rate, and higher EEG alpha and theta activity. However, elevated levels of sleepiness mainly arose from the night-time drives when the sleep pressure was high. During daytime, when the drivers were alert, partially automated driving had little or no detrimental effects on driver fatigue. Whether the negative effects of increased sleepiness during partially automated driving can be compensated by the positive effects of lateral and longitudinal driving support needs to be investigated in further studies.

1. Introduction

Fatigued drivers show slower visual processing, loss of selective attention, poor distractor inhibition, reduced peripheral processing capacity as well as lapses and wake state instability (Chee, 2015; Krause et al., 2017; Van Dongen et al., 2011). This leads to worsened decision making, slower reaction times, reduced attention to the forward roadway and driving performance incapability (Anderson and Horne, 2013; MacLean, 2019). As such, sleepiness and fatigue are contributing factors in 5–50 % of all crashes (cf. Dawson et al., 2018), with median values usually falling between 15–25 % (Åkerstedt, 2000), and elevating the crash risk with 1.29–1.34 times compared to driving without fatigue (Moradi et al., 2019). These fatigue related crashes typically occur during night-time or in the early morning hours, after too many uninterrupted hours behind the wheel, or after extended periods of high or low workload (Williamson et al., 2011). In this paper, fatigue is defined as the biological drive for recuperative rest, with sleepiness as a special case referring to accumulated sleep debt, prolonged wakefulness, or troughs in the circadian rhythm.

A range of countermeasures can be implemented to address fatigue-related issues in transport, including public awareness campaigns, legal approaches, roadside initiatives, and in-vehicle technologies (Anund and Kecklund, 2011; Fletcher et al., 2005; Phillips et al., 2017). Some of these countermeasures aim to reduce the likelihood of fatigue-related driving whereas others aim to reduce the consequences of driving while fatigued. Driver support and intervention systems is a relatively new countermeasure that belongs to the latter category. These systems aim to prevent or reduce the impact of crashes in general, and as such they may also alleviate fatigue-related crashes. For example, lane departure warnings and lane keeping assistance reduce single-vehicle, sideswipe, and head-on injury crash rates (Cicchino, 2018; Sternlund et al., 2017; Wang et al., 2020). These crash types are often associated

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with driver fatigue and inattention. If these positive effects carry over to even more advanced systems, such as the partially automated functions with combined lateral and longitudinal support, is not known.

According to the taxonomy of the Society of Automotive Engineering (SAE, 2018), in level 2-type partial automation, the driver is responsible and obliged to monitor traffic, while at the same time being relieved from the actual driving task (steering and using the pedals). This transformation of the driving task from active driving to active monitoring may lead to increased levels of fatigue due to boredom and under-stimulation. For example, Körber et al. (2015) found indications of passive fatigue in terms of decreased pupil diameter, increased blink frequency, longer blink durations and increased mind wandering during partially automated driving in a simulator study where 20 participants drove on a six-lane motorway for 42.5 min (note that the study did not include a baseline comparison with manual driving). Similarly, Hjälmdahl et al. (2017) found higher levels of subjective sleepiness in partially automated truck platooning compared to a baseline condition. Research on fatigue, sleepiness and sleep during automated driving has otherwise mostly examined higher levels of automation that are not yet available on the market.

With automation levels where the driver no longer need to supervise the automation at all times, higher levels of fatigue has been found compared to manual driving (Jamson et al., 2013; Omae et al., 2005), especially if the drivers are sleep-deprived (Vogelpohl et al., 2019) or if they are not engaged in non-driving related tasks while on the move (Jarosch et al., 2019a, 2019b; Naujoks et al., 2018; Schömig et al., 2015; Vogelpohl et al., 2019; Wu et al., 2020). A fatigued state is typically reached within 20–40 min of highly automated driving (Feldhütter et al., 2019; Jarosch et al., 2017), and after 50 min, this affects take-over performance (Jarosch et al., 2019a, 2019b). The elevated levels of fatigue that arise in highly automated driving have been found to decrease when switching from automated to manual driving, but the alerting effect of 10 min of manual driving only lasts for 4–6 min after control is handed back to the vehicle (Wu et al., 2019).

The purpose of the present study was to compare the effects of manual versus level 2 partially automated driving on subjective and objective indicators of sleepiness. This was done by comparing the development of driver sleepiness while driving on a motorway with real traffic during both daytime (full sleep) and night-time (sleep deprived). The hypothesis was that partially automated driving will lead to higher levels of fatigue due to underload. A secondary objective was to collect video data for the development of driver fatigue monitoring systems, a topic that will not be explored in the present paper.

2. Methods

2.1. Participants

Eighty-nine drivers (36 women and 53 men) participated in the study. Selection criteria were experience with advanced driving assistance systems such as adaptive cruise control, lane keep assist and similar, a body mass index below 30 (to reduce the risk of sleepiness due to undiagnosed obstructive sleep disorders), no sleep disorders, no disabilities that prevented the participant from driving an ordinary car, and no problems with motion sickness. The participants' mean age was 38 years (SD = 11 years, range = 20–59 years). The experience requirement had to be made less strict in the end of the data collection period since these advanced systems are still quite rare and it is difficult to recruit experienced drivers, especially on short notice in case of drop-outs. An extension of the data collection period was not an option, partly for budget and practical reasons, but mostly due to the outbreak of COVID-19. The last slots were therefore made available to drivers with less experience of advanced driving assistance systems. The final study population consisted of 54 drivers experienced with adaptive cruise control, 44 experienced with lane keeping assistance, 48 with parking assistance, and 19 with level 2 assistance. Seventeen drivers did not have any experience with advanced driving assistance systems. Each participant received 4000 SEK (≈400 USD) for participation to compensate for loss of income. The Swedish government approved the experiment with sleepy drivers on real roads (N2007/5326/TR), and the study was approved by the Swedish Ethical Review Authority (Dnr 2019−04813).

2.2. Design and procedure

The study has a within-subject 2 × 2 design, with factors for *condition* (daytime versus night-time driving) and for *automation mode* (manual versus partially automated level 2 driving). Sixteen 10 km segments were extracted from the 180 km drives to analyse changes over *time on task*. An approximately equal number of women and men was strived for to account for gender differences. Two instrumented *vehicles* were used in the trials, allowing 4 drivers to participate each experiment day. Each participant first drove in the afternoon (daytime, alert condition) and again during night-time (sleep deprived condition). The afternoon drive started at 15.00 h (drivers A and C) or 17.00 h (drivers B and D) and the night drive started at 01.00 h (drivers A and C) or 03.00 h (drivers B and D).

The manual and automated driving sessions took place on different days, thus requiring two visits to the laboratory. Automation mode was counterbalanced, but since the government approval to use sleepy drivers on real roads was restricted to night-time hours, the daytime (alert) condition will always precede the night-time (sleep deprived) condition.

The participants were instructed to sleep for at least 7 h during the three days before the trials, to go to bed no later than 24.00 h, and to get up no later than 09.00 h. Before arrival, they were also asked to fill in a background questionnaire with background information and a sleep diary covering the three nights before the experiment day. Upon arrival to the laboratory, the participant received further instructions, both concerning the experiment itself and the automated vehicle, and signed an informed consent form. After that, electrodes for the physiological measurements were posed (see Section "Measurements" below). Before and after each drive the participants did a 10-minute psychomotor vigilance task (PVT; Dinges and Powell, 1985). A post-drive questionnaire was filled in after each drive. The participants were not allowed to bring their own food or beverages but were offered dinner, fruits, rice cakes, water, red tea, or decaffeinated coffee during the evening. The participants were aware that the coffee and tea did not contain caffeine. The calorie intake was not logged. The dinner was served at 18.00 h (drivers A and C) or at 19.30 h (drivers B and D) and consisted of traditional Swedish home cooked food with an estimated calorie content of 600–800 calories.

The test route comprised a 90-km section of a dual-lane motorway (road E4, Sweden) where the participants drove from exit 111 (Linköping) to exit 104 (Gränna) and back, resulting in a 180 km drive. The posted speed limit was 120 km/h on the whole section, and the annual average daily traffic for this road section is about 8000–15000 vehicles according to the Swedish Transport Administration. The participants were always accompanied by a test leader ready to intervene using dual-command if the drivers were too sleepy to continue or if they showed signs of inappropriate or dangerous driving. The test leader did not talk to the driver during the data acquisition.

2.3. Measurements

The tests were carried out in two different test vehicles, a 2015 Volvo XC90 and a 2020 Volvo V60. Note that each participant drove the same vehicle on both visits, either with or without partially automated functions activated. Both vehicles were instrumented with ODB-II loggers to log GPS and vehicle kinematics, eye tracking systems, and video logging of the forward roadway, the drivers' face, and the drivers' upper body. Respiration and an electrocardiogram (ECG) were also recorded in both vehicles, and in addition, an electrooculogram (EOG) and a 64-channel electroencephalogram (EEG) were recorded in the Volvo XC90. The reason for not including EOG and EEG in both vehicles is that the obstructing electrodes in the face and on the head may limit the generalisability of the dataset. For example, the electrodes may interfere when developing computer vision algorithms for driver fatigue monitoring, which is a future objective with the present dataset.

Of the 356 planned trials, 2 were cancelled due to bad weather, 1 was cancelled due to technical issues with the logging equipment, 4 were cancelled due to hazardous drivers, and 18 were cancelled due to scheduling and availability issues, leaving 333 trials for analysis.

2.3.1. Test vehicles and partially automated functions

The tests were carried out in two different instrumented vehicles, a 2015 Volvo XC90 and a 2020 Volvo V60. Both vehicles were equipped with the second version of the Volvo Pilot Assist system. Pilot Assist consists of the combined operation of adaptive cruise control and lane keeping assistance. The driver may remove the hands from the steering wheel for no longer than approximately 15 s. The status of the system is indicated by a symbol representing a steering wheel, which is integrated in the speedometer. When the system is active and Pilot Assist is providing steering assistance, the symbol is represented in green. However, if the detection of the lane markings is temporarily interrupted (e.g. degraded lane markings), the system enters a stand-by mode, and the symbol turns grey. Then, only adaptive cruise control is active until the detection of the lane markings is resumed. The change from active to stand-by mode is only informed by the change in the symbol colour, and no other auditory or haptic warning is presented. When the system is turned off completely, the symbol is not shown. In this experiment, adaptive cruise control was available and activated 98.96 ± 2.04 % of the time during partially automated driving in the Volvo XC90. The corresponding availability for lane keeping assistance was 94.14 ± 3.72 %, which was also the availability for the Pilot Assist system. The availability of the Pilot Assist system in the present experiment is not known for the Volvo V60. Both cars were equipped with dual command to allow the test leader to intervene if needed.

2.3.2. Vehicle kinematics

Both cars were equipped with a GPS module and OBD-II logger (AutoPi.io ApS, Aalborg, Denmark) that logged latitude, longitude, speed, engine speed, lateral and longitudinal acceleration and throttle positon.

2.3.3. Eye tracking and video recordings

Both cars were equipped with a remote Blackbird3 3-camera eye tracking system (Smart Eye AB, Gothenburg, Sweden), an interior camera (acA1300−75gm, Basler AG, Ahrensburg, Germany) and a forward view camera (acA1300−75gc, Basler AG, Ahrensburg, Germany). A monitor showing the camera view from the Blackbird3 cameras was in front of the glove compartment, granting the test leader high-resolution videos of the driver's face. The gaze direction was calibrated using 13 calibration points distributed throughout the cockpit. Raw videos from the three eye tracking cameras was stored and eye tracking was carried out in a post-processing procedure using the Smart Eye TrackingSW SDK version 0.9.0 (Smart Eye AB, Gothenburg, Sweden).

2.3.4. Physiological measurements

Electrophysiological data were recorded with bio-amplifiers (Vitaport 2, Temec Instruments BV, the Netherlands in the Volvo V60 and eego sports, ANT Neuro, Hengelo, the Netherlands in the Volvo XC90). An electrocardiogram (ECG, lead II) and respiration (chest strap) were recorded in both vehicles, and in addition, a vertical electrooculogram (EOG) and a 64-channel electroencephalogram (EEG) were recorded in the Volvo XC90. Before each drive, the impedance was checked, and the electrodes were adjusted and filled with more conductive gel if needed.

Physiological data were acquired with a sampling rate of 512 Hz but later down-sampled to 256 Hz. The ECG was band-pass filtered between 0.3 and 30 Hz, the respiration signal was high-pass filtered at 1 Hz, and the EOG was band-pass filtered between 0.3 and 11.5 Hz. All filtering was carried out with zero-phase 5th order Butterworth filters. The EEG data was pre-processed in EEGLAB version 2019.1 (Delorme and Makeig, 2004) by high-pass filtering the data at 1 Hz, removing line noise by adaptively estimating and removing sinusoidal components, removing bad channels and transient or large-amplitude artifacts using artifact subspace reconstruction (Chang et al., 2020), and interpolation of missing or removed channels. Independent component analysis was used to suppress ocular and movement artifacts according to Pion-Tonachini et al. (2019). In total, 75.9 ± 10.9 % of the EEG data were deemed as useful for further analyses after suppression of ocular artifacts and removal of movement artifacts. Only data from the ECG and the Fz-T7 (frontal), Cz-T8 (central) and Pz-Oz (parietal) derivations will be presented here.

2.4. Sleepiness indicators

Subjective and physiological measures related to sleepiness were calculated in 10 km segments along the route. The segment surrounding the turning point in Gränna was excluded in the analyses. The reason for defining the segments based on distance rather than time was to facilitate comparisons across drives and to reduce the impact of environmental differences.

2.4.1. Subjective sleepiness ratings

The Karolinska Sleepiness Scale (KSS; Åkerstedt and Gillberg, 1990) was used to acquire self-reported sleepiness every fifth minute during the drives. KSS has nine anchored levels: 1 – extremely alert, 2 – very alert, 3 – alert, 4 – rather alert, 5 – neither alert nor sleepy, 6 – some signs of sleepiness, 7 –sleepy, no effort to stay awake, 8 – sleepy, some effort to stay awake, and 9 – very sleepy, great effort to keep awake, fighting sleep. The reported value corresponds to the average feeling during the last 5 min. The KSS ratings were upsampled to 1 Hz by retrospectively copying each KSS rating backwards in time. Subjective sleepiness was then calculated as the mode of the KSS ratings in each segment.

2.4.2. EEG measures

The total power in the 5–9 Hz theta frequency range and in the 8–14 Hz alpha frequency range was calculated for the three EEG derivations using Welch's power spectral density estimate (time window of 4 s and 75 % overlap). These two frequency bands were selected since an increase in the 5–9 Hz frequency range has been put forward as a sign of sleep need (e.g. Aeschbach et al., 1997; Cajochen et al., 1995) and an increase in alpha content has been found to be a robust indicator of sleepiness in a driving setting (Kecklund and Åkerstedt, 1993; Simon et al., 2011). Note that EEG-based measures suffer from noise in naturalistic settings, large inter-individual variability, and the fact that some individuals do not respond despite being clearly sleepy (Sandberg et al., 2011; Sparrow et al., 2018; Åkerstedt et al., 2010).

2.4.3. Eye and blink related measures

Mean blink durations, percentage of closed eyes over time (PERCLOS), and pupil diameter, were obtained from the Smart Eye system. In this experiment, the availability of eyelid tracking was 99.91 ± 0.37 % and the availability of pupil tracking was 91.84 ± 8.12 % (using a quality threshold of 0.2). Note that the SmartEye system defines PERCLOS as the percentage of time where the eyes are fully closed, but despite this difference, the term PERCLOS will still be used here. Increased PERCLOS is often cited to be the most reliable and valid ocular sleepiness parameter (e.g. Sparrow et al., 2018; van Loon et al., 2015) while blink durations has been found for increasing levels of driver sleepiness in essentially all studies were blink duration has been measured (e.g. Schleicher et al., 2008; Åkerstedt et al., 2005). The effect size may however be small and both parameters have difficulties in predicting sleepiness on an individual level in a specific time epoch

(Ingre et al., 2006; Jimenez-Pinto and Torres-Torriti, 2012; Wierwille et al., 1996).

A decreases in pupil diameter is also associated with fatigue (Morad et al., 2000; Schmidt et al., 2017). Note that changes in overall luminance cause large fluctuations in pupil diameter (Lohani et al., 2019), which has to be kept in mind when interpreting the results, especially if comparisons are made between the daytime versus night-time conditions.

2.4.4. Heart rate measures

Heart beats (R-peaks) were extracted from the ECG using a filter-bank approach (Afonso et al., 1999) and an RR time-series was derived as the time difference between heart beats. The corresponding normal to normal (NN) time series was obtained by a recursive procedure where RR intervals were removed if they differed from the mean of the surrounding RR intervals with more than 30 % (Karlsson et al., 2012). A lowered heart rate gives more room for variability between successive heartbeats allowing higher heart rate variability. This is typically seen during sleepiness when the body is winding down to prepare for sleep (e.g. Buendia et al., 2019). As with most sleepiness indicators, heart rate and heart rate variability usually give clear results on a group level, but results vary between individuals and over time within individuals, depending on both internal and external factors (Persson et al., 2020). Heart rate was here expressed as the mean NN-interval in each segment and heart rate variability was quantified as the root mean square of successive differences (RMSSD) between normal heartbeats (Shaffer and Ginsberg, 2017).

2.4.5. Driving performance

Driving performance metrics such as speed, variability in lateral position and line crossings are commonly used in driver sleepiness research (e.g. Hallvig et al., 2014; McDonald et al., 2014; Mårtensson et al., 2019; Sikander and Anwar, 2018). However, since both longitudinal and lateral behaviour are influenced by the automated functions under scrutiny in this experiment, it was decided to not include any driving performance metrics in this paper (c.f. Gonçalves and Bengler, 2015).

2.4.6. Psychomotor vigilance task

The PVT was set up according to Loh et al. (2004), with random stimuli onsets with an interval of 2–10 s between stimuli, a maximum stimulus duration of 2 s, and a total test duration of 10 min. The PVT is a widely used test of vigilant attention, with high reliability and predictive validity and lack of aptitude and learning effects (Basner et al., 2018, 2020). Increased sleepiness levels typically result in longer mean reaction times and higher percentages of lapses/misses (here defined as reaction times >500 ms). However, the test is sensitive to confounds from loss of motivation or presence of distractions during testing (Sparrow et al., 2018).

2.5. Statistical analyses

The sleepiness indicators were analysed by deriving analyses of variance (ANOVA) tables from mixed linear regression models. Separate regression models were created using each of the sleepiness indicators as dependent variables. *Condition* (daytime versus night-time driving), *automation mode* (manual versus partially automated) and *time on task* (10 km segment) were used as within-subjects independent variables while *vehicle* (Volvo V60 versus Volvo XC90) and *gender* (male versus female) were used as between-subjects variables. *Participant* was modelled as a factor with random slope and intercept for condition and time on task, nested within gender and vehicle. Note that the factor time on task relates to distance driven rather than time. The factor vehicle was included to account for confounding effects due to vehicle type (cross-country versus sport utility vehicle).

The PVT results were analysed using a mixed-model five-factor ANOVA. *Condition* (daytime versus night-time driving), *automation mode* (manual versus partially automated) and *time* (before versus after the driving task) were used as within-subjects independent variables while *vehicle* (Volvo V60 versus Volvo XC90) and *gender* (male versus female) were used as between-subjects variables. *Participant* was included as a random factor. Two-way interactions between condition, automation mode and time on task were included. Two different dependent variables were analyses, mean reaction times and minor lapses.

The significance level was set to 0.05 and Bonferroni correction was used to compensate for multiple comparisons.

3. Results

Night-time driving expectedly led to increased sleepiness levels in KSS, blink duration, PERCLOS, pupil diameter and interbeat interval (Fig. 1 and Table 1). Significant time on task effects were found in KSS, pupil diameter and interbeat interval, and as interaction effects between night-time and time on task in KSS, blink duration, PERCLOS, pupil diameter and in EEG parietal alpha and theta power. In general, the development of sleepiness showed a faster increase with time on task during night-time. Note that the main changes in pupil diameter between daytime and night-time is likely due to changes in light condition rather than sleepiness.

Partially automated driving, as compared to manual driving, led to a significant but small increase in sleepiness levels for KSS, blink duration, pupil diameter, interbeat interval, EEG central alpha, EEG frontal theta and EEG central theta (Fig. 1 and Table 1). In partially automated driving the reported KSS values were 0.07 units higher, blink durations were 4.5 ms longer, the pupil diameter was 0.1 mm narrower, the interbeat interval was 9.22 ms longer, EEG central alpha was 0.16 dB/Hz higher, EEG frontal theta was 0.04 dB/Hz higher and EEG central theta was 0.36 dB/Hz higher (Table 2). The drivers reported lower KSS levels for partially automated driving during daytime and higher KSS levels for partially automated driving during night-time, compared to manual driving. Blink duration showed a steeper increase with time on task during night-time compared to daytime, especially during partially automated driving (Fig. 1).

Note that the proportion of variability explained by the models was considerably lower for the EEG metrics compared to the other sleepiness indicators (R^2 in Table 1). Even though there was an interaction effect between night-time and time on task in parietal EEG alpha and theta power, and even though the general trend in Fig. 1 indicate higher alpha and theta content in the EEG indicators during night-time and with increased time on task, there were no significant main effects of night-time driving nor time on task in any of the EEG indicators. For these reasons, it is difficult to interpret the effects of partially automated driving on the EEG sleepiness indicators.

Male participants showed slightly higher levels of subjective sleepiness and frontal theta power, but except from these findings, there were no significant differences in relation to gender. No significant differences were found for vehicle type.

PVT results only showed minor differences with respect to the analysed factors. The marginal mean reaction time was 10.69 ms longer ($F_{(1,557)} = 149.3$, $p < 0.001$) for the night-time condition compared to the daytime condition, 6.81 ms longer ($F_{(1,557)} = 80.6$, $p < 0.001$) after the driving session compared to before, and 0.96 ms shorter ($F_{(1,557)} = 9.3$, $p = 0.002$) when driving with partial automation. A significant interaction effect indicated slower reaction times after the night-time drive compared to after the daytime drive ($F_{(1,557)} = 18.4$, $p < 0.001$). The number of minor lapses increased with 0.48 ($F_{(1,557)} = 39.9$, $p < 0.001$) at night-time, with 0.38 ($F_{(1,557)} = 28.9$, $p < 0.001$) after the driving session compared to before driving. Partial automation did not significantly change the number of minor lapses. The factor participant was significant for both variables, indicating large interindividual differences.

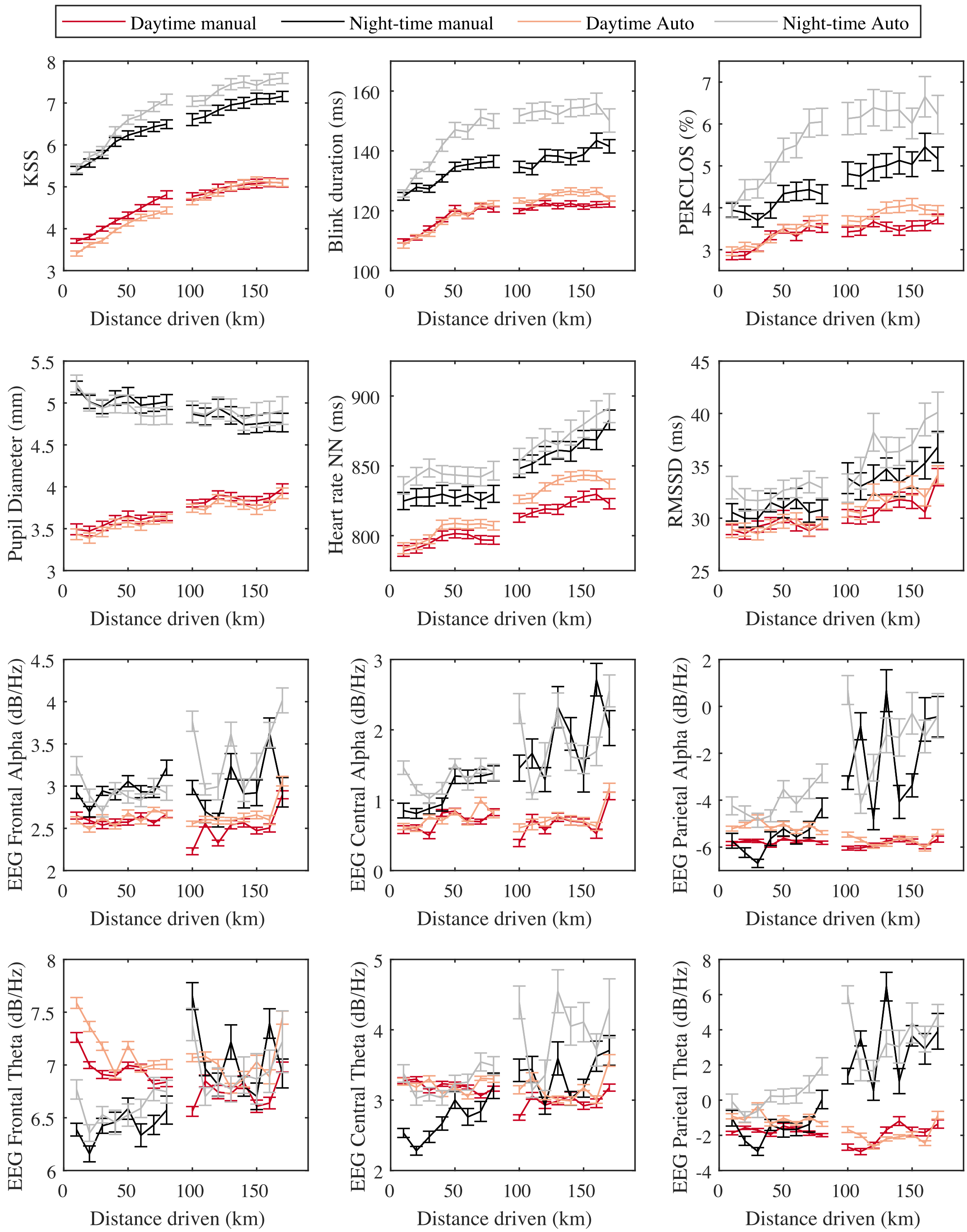

Fig. 1. The mean values of each sleepiness indicator computed every 10 km along the test route (time on task) for the day/night condition during manual versus partially automated driving. The error bars represent the standard error of mean.

4. Discussion

This paper set out to investigate the effects of partially automated driving on subjective and objective indicators of sleepiness. The hypothesis was that partially automated driving will lead to higher levels of sleepiness and fatigue due to underload. The results showed that partially automated driving led to slightly higher KSS values, longer blink durations, decreased pupil diameter, longer interbeat intervals, and higher central alpha, frontal theta, and central theta power. However, elevated levels of sleepiness mainly arose from the night-time drives when the sleep pressure was high. During daytime, when the drivers were alert, partially automated driving had little or no detrimental effects on driver fatigue. The KSS results even indicated a small alerting effect of partial automation during the first half of the drive (Fig. 1, top left, red and orange curves).

During the night-time drives, partial automation led to increased driver sleepiness. This was seen in eye related metrics, heart rate-based metrics as well as subjective sleepiness, either as main effects or as

Table 1
Coefficient of determination (R^2), model fit (-2LL) and ANOVA results (F-values) for the linear regression models. Degrees of freedom are df1 = 1 in all cases, df2 according to the table. Significant differences at the 0.01 level (0.0005 after Bonferroni correction) are marked in green (**), at the 0.05 level (0.0025 after correction) in green/yellow (*) and higher levels in shades from yellow/orange to red. The factor Vehicle was excluded in the EEG analyses since EEG data were only available in one of the vehicles.

	R2	Model fit (−2LL)	df2	Intercept	Condition (daytime vs night-time)	Automation mode (manual vs partially automated)	Time on Task (10 – 180 km)	Vehicle (XC90 vs V60)	Gender (Female vs male)	Cond*Auto	Cond*ToT	Auto*ToT
KSS	85.9%	9308	4405	10.3*	231.7**	83.7**	29.1**	0.2	10.1*	71.0**	90.0**	24.1**
Blink duration (ms)	86.0%	31160	4113	121.5**	52.9**	41.7**	0.6	2.2	7.5	60.5**	90.1**	61.4**
PERCLOS (%)	90.4%	22752	4113	3.5	11.0*	3.9	1.1	0.2	0.9	10.6*	51.1**	14.4**
Pupil Diameter (mm)	86.7%	6094	4113	17.1**	272.5**	9.3*	175.2**	0.0	0.1	15.9**	255.1**	0.1
Interbeat interval NN (ms)	92.7%	37087	4084	180.1**	28.6**	24.0**	42.5**	0.4	1.0	15.2**	0.5	0.0
RMSSD (ms)	85.2%	26061	4084	1.7	2.5	1.4	2.5	5.6	0.2	3.5	4.9	0.1
EEG Frontal Alpha (dB/Hz)	60.7%	10011	2115	6.2	0.4	1.0	0.0		2.8	3.0	0.7	3.8
EEG Central Alpha (dB/Hz)	74.4%	8830	2115	2.7	1.1	39.4**	0.6		0.1	39.1**	0.2	5.8
EEG Parietal Alpha (dB/Hz)	53.4%	11595	2115	0.0	0.3	7.0	5.1		2.9	21.9**	13.1**	0.8
EEG Frontal Theta (dB/Hz)	82.7%	7720	2115	46.2**	3.4	19.7**	5.7		11.1*	34.2**	4.8	1.3
EEG Central Theta (dB/Hz)	68.8%	8862	2115	14.7**	2.7	18.8**	2.5		1.2	26.5**	5.6	0.1
EEG Parietal Theta (dB/Hz)	54.8%	11416	2115	0.0	0.0	0.4	4.5		0.4	6.0	15.2**	2.3

Table 2
Mean change in a sleepiness indicator per factor in the linear regression models. Significant differences at the 0.01 level (0.0005 after Bonferroni correction) are marked in green (**), at the 0.05 level (0.0025 after correction) in yellow (*) and higher levels in shades from orange to red. The factor Vehicle was excluded in the EEG analyses since EEG data were only available in one of the vehicles.

	Condition (daytime → night-time)	Automation (manual → automated)	Time on Task (10km → 180 km)	Vehicle (XC90 → V60)	Gender (Female → Male)
KSS	2.13**	0.07**	1.84**	-0.05	0.30*
Blink duration (ms)	17.67**	4.48**	16.55	0.74	1.35
PERCLOS (%)	0.87*	0.28	1.05	0.28	-0.19
Pupil Diameter (mm)	1.13**	-0.10*	0.14**	-0.02	-0.13
Interbeat interval NN (ms)	37.12**	9.22**	51.40**	6.15	5.72
RMSSD (ms)	2.16	0.79	4.80	0.30	0.67
EEG Frontal Alpha (dB/Hz)	0.54	-0.09	0.30		0.17
EEG Central Alpha (dB/Hz)	0.54	0.16**	0.44		0.22
EEG Parietal Alpha (dB/Hz)	0.46	0.61	0.33		1.33
EEG Frontal Theta (dB/Hz)	-0.22	0.04**	0.07		0.16*
EEG Central Theta (dB/Hz)	-0.11	0.36**	0.22		0.60
EEG Parietal Theta (dB/Hz)	2.33	0.64	2.05		0.74

interaction effects (Fig. 1 and Table 1). In other words, when both the circadian and the homeostatic sleep pressure is high, a sleepy driver will become even sleepier when driving with partial automation. These results support earlier findings that drivers will become more fatigued when the active driving task is replaced by a passive monitoring task (e.g. Hjälmdahl et al., 2017; Jamson et al., 2013; Körber et al., 2015; Omae et al., 2005; Vogelpohl et al., 2019). It also supports earlier findings on task-dependent time-on-task effects on fatigue, showing that the execution of monotonous vigilance tasks lead to higher fatigue scores than the more motivating task of driving a simulator (Richter et al., 2005).

Most sleepiness indicators expectedly showed higher sleepiness levels during night-time compared to daytime. There were also differences in the interaction effect of time on task during daytime versus night-time, with a steeper increase in sleepiness during night-time. These results are supported by previous studies (e.g. Hallvig et al., 2014; Philip et al., 2005; Åkerstedt et al., 2013). Exceptions are the EEG parameters that did not show a significant effect of night-time driving. The central and parietal alpha power as well as the parietal theta power showed (non-significant) tendencies of higher alpha and theta frequency content with increasing time on task during night-time (Fig. 1), something that also showed up as significant interactions between night-time driving and time on task. This lack of significance between daytime and night-time driving was unexpected.

In terms of automation, there were significant main effects of partially automated driving on central alpha power, frontal theta power and central theta power. There were also significant interaction effects between partial automation and night-time driving for several EEG parameters. However, given the lack of effect between daytime versus night-time driving, the differences in EEG power due to partially automated driving are most likely not driven by sleepiness. Driving with adaptive cruise control (Acerra et al., 2019) and with partial automation (Stapel et al., 2019) has been associated with increased cognitive load, which is characterised by increases in frontal theta and parietal alpha (Di Flumeri et al., 2019). This could be one reason for the observed changes in the EEG during partially automated driving.

The PVT results after two hours of partially automated driving showed a slight but significant reduction in mean reaction time (but not in the number of minor lapses), which may suggest that drivers recuperated faster from the time on task effect after driving with partial automation compared to manual driving. This is however very speculative and needs further investigations.

The distinction between fatigue due to underload and the physiological drive to fall asleep is important for how the level of fatigue should be brought back to normal levels. Fatigue due to underload can be countered by doing something else for a while, fatigue due to overload can be remedied by a short break, whereas fatigue caused physiological sleepiness (homeostatic and circadian effects) can only be countered by actual sleep (Matthews et al., 2019; May and Baldwin, 2009). Given the results from the present study, activation of partial automation will not be an effective sleepiness countermeasure. It is difficult to speculate on the impact of partial automation on fatigue-related crashes though. On the one hand, sleepiness levels seem to increase, which would lead to more crashes, but at the same time, automated functionalities such as lane and distance keeping systems may prevent these crashes from happening. Adapting safety margins/thresholds to the current state of the driver in combination with preventive and corrective driver fatigue countermeasures and warnings may be a way to further improve the safety of automated vehicles. This would however require new and more accurate driver state detection algorithms since today's vehicles' driver alertness assessment systems are indirect (based on driving performance). Such measures are of little or no use when driving with automation. This means that direct, robust, and accurate camera- or physiology-based detection systems needs to be developed.

Previous studies on fatigue and sleepiness during assisted or automated driving have been carried out in driving simulators or in Wizard of Oz vehicles. While such studies are important, it is also important to note that there are clear differences in how sleepiness and fatigue develops in driving simulators compared to on real roads in real traffic (Fors et al., 2018; Hallvig et al., 2013). One reason is that it quickly becomes boring to participate in monotonous driving simulator experiments. Another reason is that there is no real threat in a simulator. Without real consequences of a potential crash, drivers tend to fight less hard to remain awake. This motivates studies with sleepy drivers in real traffic at high speed.

There are several limitations to this study, the most important being the limited experience with partially automated driving; 19 participants were experienced with partially automated driving, 44 had experience with lane keeping assistance and 54 drivers had experience with adaptive cruise control, while 17 drivers did not have any experience with advanced driving assistance systems. A second limitation is the varying traffic density and lighting conditions between the day- and night-time drives. As already mentioned, changes in overall luminance cause profound fluctuations in pupil diameter (Lohani et al., 2019). It is therefore difficult to know if a change in pupil diameter is due to lighting conditions, sleepiness, or both. The decrease in pupil diameter with time on task during night-time (Fig. 1, black and grey curves), when it was dark throughout the drive, is probably due to increasing levels of sleepiness. In contrast, the increase in pupil diameter with time on task during daytime (Fig. 1, red and orange curves) is probably a consequence of the setting sun. Thirdly, the two vehicles used in the study had different vehicle characteristics and partly different physiological measurement setups. Vehicle type would probably have caused differences in driving performance indicators, but such indicators were not used in this investigation. Differences in physiological measurements relates to the absence of EEG in one setup and different bio-amplifiers for the collection of the ECG data. The different brands of bio-amplifiers did however not affect the R-peak detection, and consequently not the ECG-based sleepiness indicators. Lastly, the experimental design established when the partially automated function was activated and when it was disengaged. In reality, the drivers will decide for themselves when to activate the system (Hardman et al., 2019). Some drivers may then deactivate the system when they are feeling fatigued, in order to keep alert. Others may activate the system when severely fatigued, to get help to stay on the road. Future naturalistic driving studies are needed to assess how driver fatigue and partially automated function usage interact, and how this impact crash risk.

5. Conclusions

Driving with partial automation leads to higher levels of sleepiness, especially during night-time driving when the sleep pressure is high. During daytime, when the drivers in the study were alert, partially automated driving had little or no detrimental effects on driver fatigue. This may have an impact on evaluation and enforcement of driver monitoring regulations/assessments such as UNECE GSR 2022 and Euro NCAP 2024.

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CRediT authorship contribution statement

Christer Ahlström: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization, Project administration. **Raimondas Zemblys:** Resources, Writing - review & editing. **Herman Jansson:** Resources, Data curation. **Christian Forsberg:** Resources, Data curation. **Johan Karlsson:** Resources, Writing - review & editing. **Anna Anund:** Conceptualization, Methodology, Writing - review & editing, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that there is no conflict of interest.

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