THE PREDICTION OF THREE DRIVING QUALITY STATES OF SIMULATED DRIVING BY PSYCHOPHYSIOLOGICAL VARIABLES WITH SLEEP-DEPRIVED SUBJECTS

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ABSTRACT

The aim of this study was to examine whether the quality of driving performance could be predicted by psychophysiological variables. The study was conducted with sleep deprived subjects (n = 9) performing a simulated driving task for three hours. Driving performance was analyzed in 15.5 s epochs. Epochs were classified to represent accurate, unstable or deficient states of driving. These states of driving formed the dependent variable. Delta, theta, alpha, sigma and beta EEG band powers, eye blink rate and amplitude, and heart rate were each examined at four epochs before the epoch defined according to the driving quality, and formed the independent variables (altogether $8 \times 4 = 32$ variables). Differences in the averages of the variables in the driving quality states were analyzed across subjects with MANOVAs. The variable beta_{-4} differentiated significantly the quality states ($p = 0.015 < 0.05$), but in further analysis with paired samples t-tests it did not differentiated the states significantly. Logistic regression analyses were carried out at the subject level when accurate and unstable driving and accurate and deficient driving formed the dependent variable. Most of the independent variables (delta, alpha and sigma power, blink rate and amplitude, heart rate) predicted according to the hypotheses the change of driving from accurate to unstable or deficient states. The changes in theta and beta were, however, contrary to the hypotheses. The accurate classifications of correct driving quality states changed individually and were quite low for some subjects. The results show that further studies of the power of psychophysiological variables to predict changes in driving quality with validity and generalizability are needed.

Keywords: Driver Fatigue, Driving Performance, Sleepiness, EEG power spectrum, Eye Blink, Heart Rate

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TIIVISTELMÄ

Tämän tutkimuksen tarkoituksena oli tutkia, voiko ajosuorituksen laatua ennustaa psykofysiologisilla muuttujilla. Valvoneet koehenkilöt ($n = 9$) ajoivat tutkimuksessa kolme tuntia ajosimulaattorilla. Ajosuoritusvideot analysoitiin ajovirheiden osalta 15,5 s pituisissa epokeissa. Epokit luokiteltiin edustamaan joko virheetöntä, epävakaata tai vajaata ajolaatua. Nämä ajolaadun tilat muodostivat riippuvan muuttujan. Riippumattomat muuttujat olivat EEG:n tehospektrit delta, theta, alfa, sigma ja beeta, sekä silmän räpytystiheys, räpytyksen amplitudi ja sydämen syke tarkasteltuna ajolaadun mukaan määriteltyä epokkia edeltävältä neljältä epokilta (yhteensä 8 x 4 = 32 muuttujaa). Riippumattomien muuttujien keskiarvojen eroja eri ajolaatutiloissa vertailtiin yli koehenkilöiden MANOVAlla. Beta$_{-4}$ oli ainoa merkitsevästi ajolaadun mukaan erotteleva muuttuja ($p = 0{,}015 < 0{,}05$), mutta riippuvien otosten t-testin mukaan se ei kuitenkaan erotellut enää merkitsevästi yksittäisiä ajolaatutilanteita toisistaan. Logistinen regressioanalyysi tehtiin jokaiselle koehenkilölle siten, että virheetön ja epävakainen tai virheetön ja vajaa ajolaatu muodostivat riippumattoman muuttujan kaksi luokkaa. Riippumattomista muuttujista suurin osa (deltan, alfan ja sigman tehospektrit, räpytystiheys ja amplitudi, syke) ennusti pääasiassa hypoteesien mukaisesti ajolaadun muuttumista virheettömästä ajamisesta epävakaaseen tai vajavaiseen. Theetan ja beetan tehospektrit kuitenkin ennustivat useammin hypoteesien vastaisesti kuin niiden mukaisesti. Oikean ajolaatutilan ennustamisprosentit vaihtelivat koehenkilöittäin ja olivat joillakin koehenkilöillä melko matalia. Tulokset osoittavat, että lisätutkimukset ovat tarpeen psykofysiologisten muuttujien kyvystä ennustaa validisti ja yleistettävästi ajolaadun muutoksia.

Avainsanat: Ajoväsymys, Ajosuoritus, Uneliaisuus, EEG:n tehospektri, Silmänräpytys, Syke

CONTENTS

LIST OF TERMS

accurate driving = accurate driving quality, one of three *driving quality* states defined in this study on the basis of the driving performance of the subjects, includes not more than one minor error during the time unit of one *epoch*

alpha band power = EEG (electroencephalographic) power (μV^2) of alpha frequency. In this study the frequency of 8.0-12.0 Hz measured at the Oz-channel (occipital area), the independent variables of alpha are $alpha_{-4}$, $alpha_{-3}$, $alpha_{-2}$ and $alpha_{-1}$

BA = blink amplitude, measured on the vertical EOG channel

beta band power = EEG power (μV^2) of beta frequency, in this study the frequency of 14.0-30.0 Hz measured at the Oz-channel (occipital area), the independent variables of beta are $beta_{-4}$, $beta_{-3}$, $beta_{-2}$ and $beta_{-1}$

crash = when the simulated car touched the wall on the right side of the road

deficient driving = deficient driving quality, one of the three *driving quality* states formed in this study on the basis of the driving performance of the subjects, includes several large *driving errors* during the time unit of one *epoch*

delta band power = EEG power (μV^2) of delta frequency. In this study the frequency of 0.5-4.0 Hz measured at the Oz-channel (occipital area), the independent variables of alpha are $alpha_{-4}$, $alpha_{-3}$, $alpha_{-2}$ and $alpha_{-1}$

dependent variable = formed of the three categories of *driving quality*

driving error = types of errors observed in this simulated driving study. Four different types were distinguished: *two wheels out of the road*, *near crash*, *four wheels out of the road* and *crash*

driving quality = quality of the driving performance, three states/categories of driving quality for each epoch were defined: *accurate*, *unstable* and *deficient driving* on the basis of the *summed variable*

EOGH = horizontal EOG; EOG (electro-oculography) channel, which is measured in this study from the corner of the left eye

EOGV = vertical EOG; EOG channel, which is measured in this study above the left eye

epoch = the time unit of this study; 15.5 ± 0.5 s.

four wheels out of the road = when the whole car in the simulated driving had crossed the line marking on the left side of the road

HR = heart rate in beats per minute

impaired driving/driving impairment = reduced driving quality, in this study refers also to *unstable* and *deficient* states of driving

independent variable = the variables of delta, theta, alpha, sigma and beta band power, blink rate and amplitude and heart rate

near crash = when the car in the simulated driving was near the wall on the right side of the road

sigma band power = EEG (electroencephalographic) power (μV^2) of sigma and sleep spindle frequency, in this study the frequency of 12.0-4.0 Hz measured at Oz-channel (on occipital area), the independent variables of sigma are $sigma_{-4}$, $sigma_{-3}$, $sigma_{-2}$ and $sigma_{-1}$

SO = in this study, sleep onset refers to the onset of Stage 2 (Ogilvie, Simons, Kuderian, MacDonald & Rustenburg, 1991)

St 1/St 2 = Stage 1 or Stage 2 according to the sleep scale of Retschaffen and Kales (1968)

subscript $_{0}/_{-1}/_{-2}/_{-3}/_{-4}$ = in the name of a variable (for example $alpha_{-1}$) or epoch ($epoch_{0}$), signifies how many epochs before the *dependent variable* (*driving quality*) the value of the independent variable is averaged

summed variable = a methodological way to summarize the four types of driving errors during one *epoch*

theta band power = EEG power (μV^2) of theta frequency, in this study the frequency of 4.0-8.0 Hz measured at the Oz-channel (occipital area), the independent variables of theta are $theta_{-4}$, $theta_{-3}$, $theta_{-2}$ and $theta_{-1}$

two wheels out of the road = when the wheels on the left side of the car in the simulated driving crossed the line marking on the left side of the road

unstable driving = unstable driving quality, middle category of the three *driving quality* states, includes moderate errors during the time of one *epoch*

variable type = refers to the types of independent variables, for example to variables of alpha

1. INTRODUCTION

The increase in the amount of road-traffic fatalities in the world during the last decades has been primarily due to low- and middle-income countries (Peden et al., 2004). After 1960s and 1970s there has been decrease in a number of road-traffic fatalities in high-income countries (Peden et al., 2004). In Finland, the amount of accidents has slightly decreased from 1980s to 2002 with growing number of vehicles (Statistics Finland, 2004).

Different factors contribute to the occurrence of the accidents. According to the study of Powell, Schechtman, Riley, Li and Guilleminau (2002) some factors, which were found to be significantly associated with the increased number of accidents, were younger age, alcohol use, driving at night, or a night/irregular work shifts. Sleepiness was also among those factors (Powell et al. 2002).

Reports of the amount of accidents due to sleepiness vary. Italian police officers have ascribed that amount to be 3.2 % of all accidents (Garbarino, Nobili, Beelke, De Carli, & Ferrillo, 2001), which is similar with the percent based on the questionnaire for Norwegian accident-involved drivers, where sleep or drowsiness was reported to be a contributing factor in 3.9 % of all accidents (Sagberg, 1999). Also rates as high as 20 % have been brought up by the research based on police databases and spot interviews (16 % in major roads and over 20 % in motorways; Horne & Reyner, 1995) or as an estimation, which is based on real accident rates (21.9 %; Garbarino et al, 2001). The reported rate of sleepiness as a contributing factor in accidents is higher within accidents occurring at night-time (Sagberg, 1999). Optimal driving performance requires a certain level of attention and alertness. The qualifications and subparts of adequate driving are presented clearly by MacLean, Davies and Thiele (2003).

> The perception of relevant cues; the making of appropriate decisions; the performance of necessary control movements; and the maintenance of a sufficient level of attention both to deal with the normal demands of driving as well as to respond to emergency situations. Clearly, most, if not all, of these functions are compromised under conditions of drowsiness. (MacLean et al., 2003, pp. 509)

As performance varies in attention tasks (Kraemer et al., 2000) or in simulator driving (Lenné, Triggs, & Redman, 1998) according to the time of the day, it is evident that the time of the day has a significant effect on the number of accidents too. There are more sleep-related accidents in the night and in the mid-afternoon (Horne & Reyner, 1995; Pack et al., 1995; Garbarino et al, 2001). This circadian effect can also result in falling asleep in the beginning of the trip (Horne & Reyner, 1995), but often longer trips induce sleepiness (Sagberg, 1999) more likely as does the monotony of the road (Thiffault & Bergeron, 2003b).

Changes of alertness can be modelled to reflect the amount of hours been awake and the length of prior sleep in addition to the circadian rhythms (Åkerstedt & Folkard, 1994). According to this model and other studies, sleep deprivation reduces alertness and sleep latency (latency: Carskadon & Dement, 1979; Helmus et al., 1996). Sleep deprivation has been found to affect driving performance on a simulator (Lenné et al., 1998). And, prior sleep loss has been found to be one of the contributing factors of accidents (Fell & Black, 1997), even though in the study with truck drivers, prior time awake and prior sleep length were not related to sleepiness during the evening and at night-time (Kecklund & Åkerstedt, 1993).

Alertness changes can be perceived subjectively as well as objectively. Drivers report as different subjective fatigue feelings as muscles going numb, pain in the eyes, difficulties in focusing and in speaking, increased blinking, hallucinations, apathy, lack of attention, incoherent memory and stomach pain (Summala, Häkkänen, Mikkola, & Sinkkonen, 1999). In spite of this variety of subjective symptoms, the problem with subjective evaluations of alertness is that it is not always concurrent with objective ones or reliable. Drivers may have knowledge of their sleepiness (Horne & Baulk, 2004), but the person’s own evaluations of sleepiness are not necessarily concurrent with behavioural ones (Risser, Ware, & Freeman, 2000) or do not predict well the driving impairments (Verwey & Zaidel, 2000). Also if the feelings of sleepiness precede the sleep in the driving situation, the driving impairment can be worse than the driver realizes (Horne & Reyner, 2001).

The dilemma of defining sleepiness is not only the discrepancy between subjective evaluation and behavioural capability. There are also variations between the different objective variables in reflecting sleepiness. The accuracy with which alertness is defined has been found to increase by using several measuring indices (Numata, Kitajima, Goi & Yamamoto, 1998). For that reason, a multiparametric approach seems to be the most effective method for examining the alertness of a driver (Heitmann, Guttkuhn, Aguirre, Trutschel, & Moore-Ede, 2001). Different methods consist of performance measures during driving, vigilance tasks (reaction time tasks), physiological measures, video image of the driver's face, behavioural signs of sleepiness and subjective evaluations (Heitmann et al., 2001; Rimini-Doering, Manstetten, Altmueller, Ladstaetter, & Mahler, 2001). In addition, analyses of eye-movement or different measures of the pupil are used (Heitmann et al., 2001; Velichovsky, Rothert, Kopf, Dornhöfer, & Joos, 2002). Physiological measures include electroencephalographic measures (EEG), event-related potentials (ERP), electro-oculography (EOG), electromyography (EMG), heart rate (HR), skin impedance and respiration. Despite of the variety of methods, the issue of detection and prevention of driver fatigue is still vague. According to MacLean et al. (2003), especially the prediction of impaired driving by EEG and heart rate in simulated settings needs further investigation.

In this research driver drowsiness was studied in a simulated driving environment. The main task of this research was to examine whether it is possible to predict driving performance based on the psychophysiological variables. Driving performance was observed among sleep deprived subjects in the simulated driving. The predicative occurrence of behavioural alertness was studied within the variables of electroencephalographic (EEG) band powers, blink rate, blink amplitude and heart rate.

In the next chapters some research results of those variables are introduced in different alertness levels starting from basic sleep studies to sleep deprivation studies and continuing to studies with task performance including driving studies. The process of falling asleep is assumed to be always similar (e.g. independent of the sleep deprivation or circadian variation), which makes it possible to study the results through the whole field of sleepiness studies with the variables used in this research. The specific sleepiness studies with driving or similar situations are however the focus of the introduction and form the basis of the whole research.

1.1. The variables and diminishing of alertness

1.1.1. Background

At rest

The diminishing of alertness towards sleep is often measured with scale based on electrophysiological variables at normal resting (relaxed wakefulness) situation with closed eyes. The scale most often used is the one of Retschaffen & Kales (1968). According to this scale, the EEG contains alpha (8-13 Hz) activity during the stage of wakefulness, while in the stage 1, the activity of 2-7 Hz is dominant and the amount of alpha activity is less than in the stage of wakefulness. Sleep spindles and K-complexes in the frequency of the sigma band occur in the stage 2 (Retschaffen and Kales, 1968). This process of falling asleep is quite similar with the process presented in the scale of Hori (Hori, Hayashi, & Morikawa, 1994). Instead, Santamaria & Chiappa (1987) describe the reduction of alertness more accurately with some additions to the process mentioned above. Fronto-central beta can appear at the time of the bursts at slow activities and is attenuated by arousing stimuli. On the other hand, centro-frontal beta is mentioned as a sign of arousal either alone or together with a return to alpha (Santamaria & Chiappa, 1987).

EEG can be examined during sleep deprivation and it seems that sleepiness is directly represented in the awake EEG (Strijkstra, Beersma, Drayer, Halbesma, & Daan, 2003). The effect of sleep deprivation is a natural one: according to the study of Rogé et al. the episodes of sleep were more frequent after sleep deprivation than after a normal night of sleep (Rogé, Pébayle, El Hannachi, & Muzet, 2003). Thus, sleep deprivation is often used to induce episodes of falling asleep. Then the process of sleep onset is thought to be comparable with normal and sleep deprived states.

The term ’at rest’ refers, in this study, to the state of sleep deprivation in addition to the normal sleep onset process, starting with relaxed wakefulness with closed eyes. Exceptions are blink variables, which are examined shortly during a normal work-day.

At task performance

The process of diminishing alertness can be studied also while performing a task. This is done for studying the behavioural sleep onset (Ogilvie & Wilkinson, 1984; Ogilvie, Wilkinson, & Allison, 1989; Ogilvie, Simons, Kuderian, MacDonald, & Rustenburg, 1991) or for finding out whether task performance interferes with or effects on the natural sleep onset process (Casagrande, De Gennaro, Violani, Braibanti, & Bertini, 1997). Task performance with diminishing alertness is often studied with sleep deprived subjects. The effect of sleep deprivation on the EEG during task performance is brought out by the study of Corsi-Cabrera, Arce, Ramos, Lorenzo and Guevara (40 h deprivation; 1996). The effect was more pronounced during the reaction time (RT) task than during the relaxed wakefulness. Also the number of omissions in RT task increased during hours of deprivation (Corsi-Carbera et al., 1996) as did RT (Corsi-Carbera et al., 1996; Lorenzo et al., 1995).

Additionally, task performance can refer to reaction time, vigilance, or motor tasks. In this study, task performance refers also to driving or similar tasks such as train driving or piloting. In studies of driver fatigue, the performance measures can refer to driver's performance (Lemke, 1982) or driving performance. Driving performance is examined in this study. The time on task effects and performance impairments are considered in the context of each variable.

Driving or piloting tests can be carried out as field or simulator studies. The reliability of simulator studies is examined in many other studies. According to the review of George (2003), simulators can detect the driving performance in sleepy subjects. In the study of Contardi, Pizza, Sancisi, Mondini and Cirignotta (2004), the driving performances with a simulator reflected the circadian variations of alertness; the conclusion being that simulator was reliable in measuring driver fatigue. The reliability of a simulator is increased by the fact that the tunnel vision phenomenon is found to occur with time on task also in simulator with monotonous driving task (Rogé, Pébayle, Kiehn, & Muzet, 2002). Also the relative energy parameter [(alpha + theta)/beta], which is found to increase with time on task (2.5 h) in a daytime field study of car drivers (Brookhuis & de Waard , 1993), increased in simulated driving task with sleep deprived subjects (Eoh, Chung, & Kim, in press).

1.1.2. EEG alpha band power

At rest

When the eyes are closed, the alpha rhythm (8-13 Hz) is at its greatest (Cantero, Atienza, Gomez, & Salas, 1999) in the posterior regions of the brain (Tolonen and Lehtinen, 1994; Lang and Krause, 1996; Benca et al., 1999).

During pre-sleep wakefulness, alpha activity has been found to slow between 0.5 and 1.5 Hz and diffuse to anterior from posterior regions (Broughton & Hasan, 1995). It can vanish progressively during pre-sleep wakefulness and return to more focally distributed in awakenings from drowsiness and sleep (Hasan & Broughton, 1994; Broughton & Hasan, 1995). More specifically, this rhythm has been found to spread from occipital-central to fronto-polar areas during drowsiness (Cantero et al., 1999).

The anterior diffusion of this rhythm (8-11 Hz) is denoted to happen also at sleep onset (SO) in stage 2 (St 2) (De Gennaro, Ferrara, Curcio, & Cristiani, 2001b). Distributional changes of alpha are visible in power too. The vanishing of alpha (8-11 Hz) power in the occipital area ends with SO (St 2), when power starts to increase (De Gennaro, Ferrara, & Bertini, 2001a; De Gennaro et al., 2001b). Also in an auditory RT task alpha (8-12 Hz) power has been found to decrease when behavioural SO (St 2) closed and to increase at SO (Ogilvie et al., 1991).

In sleep deprivation studies the power of alpha has been found to decrease. With 40 h of sleep deprivation, alpha (8-12 Hz) decreased with time awake in all scalp locations (Strijkstra et al., 2003). In the other study of sleep deprivation (40h), a decrease of alpha power (7.5-9.5 Hz) was found with time on task when eyes were closed (Lorenzo et al., 1995). Similarly, in the study of Barabato et al (1995), relative alpha EEG power (8-12 Hz) increased after sleep deprivation (23 h), mainly because of the alpha 1 component (8-10 Hz).

At task performance

The increment of alpha 1 (7.5-9.5 Hz) power with time on task in a sleep deprivation study (40 h) was greater during RT task performance than during rest (Corsi-Carbera et al., 1996). In the study of Åkerstedt, Kecklund & Knutsson (1991) with shift workers an increased amount of alpha power (8-11.9 Hz) was found before and during sleep episodes. The alpha power increased also with time on task (Åkerstedt et al., 1991). Also within the more driving-specific field-study (4.5 h) with train drivers at night-time the increased amount of alpha power was found with time on task; power started to increase after 75 min of driving (Torsvall & Åkerstedt, 1987). Instead, in the field-study (500 km) with truck drivers composed of evening and night groups, mean alpha power density (8-11.9 Hz) did not increase significantly with hours of driving (Kecklund & Åkerstedt, 1993). But the increase of alpha power (8-12 Hz) along with driving time has been found also in a simulated night-time driving task (350 km; Campagne et al, 2004) and in a simulated driving (8-13 Hz; 50 min), performed in the morning after the night of sleep deprivation (Eoh et al., in press). In another simulator study, it was found that after two hours of driving, slower alpha appeared when the drivers closed their eyes (Shiozawa et al., 1995). In a daytime simulator study (60 min) it was found that attention lapses defined as, at least, 3 seconds duration of EEG alpha activity (8-12 Hz) correlated in frequency and duration with lane position variability and crash frequency

(Risser, Ware & Freeman, 2000). As a conclusion, alpha power increases in falling asleep episodes and with driving time and it seems possible that it also accompanies inadequate driving in driving simulator tasks.

1.1.3. EEG delta, theta and sigma band powers

At rest

Theta activities (3-7 Hz) seem to be largest in amplitude at frontal and central scalp sites during drowsiness (Broughton & Hasan, 1995). The power of delta-theta activity (1-3 and 4-7 Hz) has been found to increase in all areas after St 1 onset, only occipital delta increased more slowly (Hori, 1995). In addition to the increase in St 1, the power of delta/theta/sigma frequencies (1-7, 12-16 Hz) has been found to increase in St 2 (De Gennaro, 2001a). This increasing of power is also found in partly different frequency ranges (0.3-3 Hz, 3-8 Hz, 12-15 Hz) when behavioural SO (St 2) closed and at onset (Ogilvie et al., 1991). In the study of De Gennaro et al. (2001b), the increase was higher at central sites than at other sites about 1 min before SO (St 2). After SO, the increase was found at all sites, but mostly at Cz for the frequencies delta, theta, and sigma (1-7, 12-15 Hz; De Gennaro et al., 2001b).

The main location of the sigma band (13-15 Hz) is reported to change from parieto-occipital to fronto-centro-parietal 0.6 min before St 2 (Morikawa, Hayashi, & Hori, 2002). Also the power of sigma frequencies (12-16 Hz) increased at centro-parietal sites after SO (St 2) (De Gennaro, 2001b).

In a sleep deprivation study (40 h), the power of theta (4-8 Hz) was found to increase at fronto-central locations with time at wake (Strijkstra et al., 2003). Similar results were found also in another study (Lorenzo et al., 1995). Theta power (4-7.5 Hz) increased at all locations with time of sleep deprivation (Lorenzo et al., 1995). Instead in the study of Barbato et al. (1995), the relative theta (3.0-7.5 Hz) EEG power did not vary before, nor after sleep deprivation (23 h).

At task performance

The increment of power in the theta band (4-7.5 Hz) with time on task was greater during task performance than at rest in a sleep deprivation study (40 h) (Corsi-Carbera et al., 1996). In a study with shift workers (Åkerstedt, 1991), the amount of theta power was found during sleep episodes among night-shift workers. Theta power (4-7.9 Hz) did not increase with time on task (Åkerstedt et al., 1991).

Instead increases in the theta and delta power (0.5-3.9 Hz; 4-7.9 HZ) were found in a night-time field-study of train drivers in real surroundings along with driving time (4.5 h; $n = 11$; $p < 0.01$), but despite the delta power was actually significant with alert subjects, it was not so with sleepy ones (Torsvall & Åkerstedt, 1987).

In a field-study with truck drivers (500 km), neither delta nor theta (0.5-3.9; 4-7.9 Hz) power density/hour changed significantly with hours of driving (Kecklund & Åkerstedt, 1993). Similar results to the study of train-drivers were found in driving simulator studies. The power of theta (4-8 Hz) was found to increase with driving time in a simulated night-time driving task (350 km) (Campagne et al, 2004). In another simulator study (2 h), continuous theta persisted and sleep spindles appeared with driving time (Shiozawa et al., 1995). As a sum, the increase in power of delta, theta and sigma occur with diminishing alertness, when falling asleep or with increased driving time. On the basis of this, it seems possible that the increase in power accompanies also the occurrence of driving impairments in a simulator task.

1.1.4. EEG beta band power

At rest

Only small amounts of beta with very low amplitude have been found during drowsiness (Broughton & Hasan, 1995). The power of beta (17-28 Hz) has been found to decrease during the transition from wakefulness to sleep (De Gennaro, 2001a). Also, according to another study, beta power (15-25 Hz) decreased when the behavioural SO (St 2) closed, but at SO it increased (Ogilvie et al.,1991).

In a sleep deprivation study of 40 hours, the increase in beta power with hours of wakefulness was found in central locations when eyes were closed (Lorenzo et al., 1995). Similar results were obtained in another research of sleep deprivation (40 h): the power of beta band (20-32 Hz) was found to increase at fronto-central locations with hours of sleep deprivation (Strijkstra et al., 2003). Also in another study, the relative amount of beta power (12.25-16.0 Hz) was increased after 23 h of sleep deprivation (Barabato et al., 1995).

At task performance

In task performance it was found that the increment of beta 1 power (13-20 Hz) with time on task was greater at task performance than at rest in a study of sleep deprivation (40 h; Corsi-Carbera et al., 1996). More specific results of task performance were obtained in a field-study with truck drivers (500 km) with evening group (n= 11) and night group (n=7) of Kecklund and Åkerstedt (1993). In that study the mean power density per hour of beta band (12-14.9 Hz) did not change significantly with driven hours (Kecklund, 1993). Contrary results were obtained in a simulator study performed in the morning after one night of sleep deprivation: beta power (13-22 Hz) decreased with time on task (50 min) (Eoh et al., in press). As a conclusion, falling asleep and increased driving time seems to be accompanying the diminishing power of beta. It seems possible that in a driving simulator task, the occurrence of impaired driving co-occurs with diminishing in beta power.

1.1.5. Blink rate and amplitude

At rest

Eye blink can be measured by different methods, for example video, EMG or EOG while blink amplitude (BA) is measured as potential changes in the vertical EOG channel (BA: Stern, Walrath, & Goldstein, 1984).

According to the study of Caffier, Erdmann and Ullsperger (2003), the blink rate (BR) of spontaneous blinks decreased after one working day. Instead, the proportion of long blinks increased after one working day (Caffier et al., 2003). After 23 h of sleep deprivation, blink rate has been found to increase (14 ± 8/min vs. 30 ± 20/min; Barbato et al, 1995). Also in another study, the spontaneous blink rate during voluntary and reflexive saccade tasks was increased after sleep deprivation (20 h) (Crevits, Simons, & Wildenbeest, 2003).

At task performance

Blink frequency increased with time in a viewing task (5h) at a visual display terminal after 2 hours of viewing in the study of Kaneko and Sakamoto (2001). Also blink amplitude increased as a function of time (5h) (Kaneko & Sakamoto, 2001).

With more driving specific tasks, in a night-time field-study of driving (1200 km; Summala, 1999), the blink rate was found to be higher with a more demanding task; blink rate was higher while driving than while being a passenger (30.96 vs. 19.77). Blink rate increased as a function of time on task (Summala et al, 1999). Similar results were found in a daytime field study of Brookhuis and de Waard (1993) with car drivers (2.5 h). BR increased with time on task, but more with task performance than at rest (driver compared to passenger; Brookhuis & de Waard, 1993).

In a simulated setting, blinking has been found to increase in a driving study (2h) during day- and night-time (Shiozawa et al., 1995). In the daytime simulated driving-task, the rate (/30 s) of long blinking (110 % of standard) has been found to represent changes in behavioural sleepiness with sleep deprived (24 h) subjects. (Numata et al., 1998) Also in the night-time simulated driving task it was found that the frequency of long eye-blinks (closure >1 s.) was one of the best predicting measures of poor driving (Verwey & Zaidel, 2000).

Blink amplitude was found to predict drowsiness in a simulated flight in the study of Morris and Miller (1996). They assumed that the decrease in blink amplitude could be due to a lower starting position of the eyelid while being sleepy. Thus, the changes in the lid position could reflect changes in attention or arousal and further predict performance decrements (Morris & Miller, 1996).

As a sum, the change in both blink variables seems to co-occur with diminishing alertness and with task performance. In simulator study, the occurrence of impaired driving could accompany the increase in blink rate and the decrease in blink amplitude.

1.1.6. Heart rate

At rest

Variations of EEG alertness are found to influence cardiac autonomic activity (Ferini-Strambi et al., 2000). In a study with preadolescents, the heart rate (HR) measured from the beat-to-beat interval decreased significantly 30 s before the onset of stage 1 and 30 s after the onset of stage 2 (Pivik & Busby, 1996). Also, according to other studies, HR decreased from transitions to stage 2 sleep (Burgess, Kleiman, & Trinder, 1999) and it was lower (6.64 beats /min) in stable stage 2 sleep than during wakefulness (Burgess et al., 1999) or pre-sleep wakefulness (Trinder et al., 2001). In a delayed sleep onset study of 3 h, HR was found to fall at sleep onset, though prominently influenced by the circadian rhythm (Carrington, Walsh, Stambas, Kleiman, & Trinder, 2003).

At task performance

In a study with shift workers during the nightshift, the HR did not increase with time on task (Åkerstedt et al., 1991). With more driving specific tasks in a field-study of train drivers (4.5 h) (Torsvall & Åkerstedt, 1987), HR was found to be lower in the night-time study than in the daytime study. Apart from that, HR did not change with time on task in the night-time study (Torsvall & Åkerstedt, 1987). Similar results were obtained in highway driving (340 km), where HR did not change along with the distance driven (Egelund, 1982). Instead in a daytime field-study of driving (2.5 h), inter-beat-interval (IBI) increased significantly after 150 min of driving and co-occurred with behavioural changes as the deviation of the lateral position of the car (Brookhuis & de Waard, 1993). Thus the diminishing of alertness and also the occurrence of impaired driving could accompany HR increases.

1.2. Hypotheses

In this research the quality of the driving performance was evaluated in a simulated driving task to identify changes in the psychophysiological variables preceding compromised driving. Errors in driving were assumed to be preceded by changes in vigilance level and the change of the alertness state towards drowsiness (Risser et al., 2000; Campagne et al, 2004, Horne & Baulk, 2004). Driving performance was observed by analysing the driving videos in 15.5 s epochs. Driving errors were combined into one variable. The dependent variable, the quality of the driving performance, represented an ordinal-scale variable. The first category of this dependent variable denoted accurate driving. Not more than one minor driving error; crossing the lane marking or near crash situation was accepted. Unstable driving consisted of two to three smaller incidents or one larger one; driving out of the road and crash, and formed the second category of the quality of driving. The third category, deficient driving performance, included several larger driving errors in addition to smaller ones. The averages of power of delta, theta, alpha, sigma and beta bands, blink rate and amplitude, and heart rate at four time segments (epoch; 15.5 s) preceding each of the three driving quality states formed the independent variables.

The research question was, whether the quality of the driving performance could be predicted by psychophysiological changes occurring during a time window covering one minute before an event in the driving behaviour, or more specifically during the four previous 15.5 s observation epochs analysed separately from this time.

The stated hypotheses are that the following changes of the psychophysiological variables are detectable before driving impairments occur:

1. increase in delta power
2. increase in theta power
3. increase in alpha power
4. increase in sigma power
5. decrease in beta power
6. increase in blink rate
7. decrease in amplitude of eye-blink
8. decrease in heart rate

Also research questions concerning the linearity of changes through the three categories of driving (stable, unstable and deficient) and the contribution of each preceding epoch in predicting the states of impaired driving are examined.

The differences in the averages of each psychophysiological variable among the three driving states are tested at the group level and the prediction of driving states is carried out for each individual separately.

2. METHODS

2.1. Experiment

2.1.1. Design

The purpose of this study was to investigate how electrophysiological variables could predict the quality of driving. Driving was performed continuously for three hours at night-time on a simulated environment. The driving performances of 9 subjects were analyzed on the basis of the observational data recorded on videotapes. Based on the driving errors, each 15.5 s epoch was defined to represent accurate, unstable or deficient states of driving. This categorization formed the dependent variable. Independent variables were band powers of the EEG measured at the Oz channel, blink rate and blink amplitude based on the vertical EOG channel, and heart rate. The statistical analyses were conducted with MANOVA tests across subjects and with logistic regression analysis at the subject level.

2.1.2. Participants

Participants ($n = 9$; 5 women) were recruited by an advertisement among students. Their age were 20 to 27 and average 23.7 ± 2.1 years. They all had driving licence and they were all, except one, right-handed. They were healthy and did not have any severe sleep problems according to the questionnaire of BNSQ (Basic Nordic Sleep Questionnaire; Partinen & Gislason, 1995). Others but one subject had the ESS (Epworth Sleepiness Scale; Johns, 1991) scores ($n = 8$; range 3-4; av, SD: 7 ± 3 points) in normal range ($\leq$ 10). Volunteers slept in average 8.6 ± 0.9 hours and their usual bedtime was at noon ($\approx$ 23-01) on workdays. One subject had a night work and usually he went to sleep in the early morning. Subjects drove less than once a week to 3-5 times per week. The majority (7) of them drove less than once a week, but more than once a month. Six of them drove less than 5000 km/year, the others 5000-15000 km/year.

Participants were asked to try to stay awake the night before the experiment. This was done in order to induce falling asleep events during the experimental driving.

Accordingly, the total hours of sleep in the night before the experiment were 0-3.5 h (av, SD 1.3 ± 1.4). Consumption of caffeine products were not allowed 24 h before the experiment and alcohol or drugs for 48 h before the experiment. One subject had drunk a cup of tea during the night of sleep deprivation.

The experiment was described to the participants but the purpose of inducing falling asleep episodes was not explained to them for reasons of validation. Subjects signed an informed consent and as a reward for their participation they received 23 euros.

2.1.3. Simulator

The simulator consisted of steering wheel, break and gas pedals. The seat of the driver was a comfortable office chair. The simulator software was the Nascar Racing 2002: Season (A Papyrus Racing Games Inc. Software distributed by Sierra Entertainment Inc.) and it was run under Windows 2000. The simulated driving was performed in a closed oval track, which had the form of a stadium. The direction of driving was counter clockwise. There were line markings on the left and right sides of the track. On the right side of the track there was a wall and on the left side a grass area. The steering wheel provided force feedback while driving against the wall or on the grass area. On the track, there was no other traffic and the conditions did not change during the task. This helps to make the driving monotonous and sleep inducing. A similar method has been used lately in other studies (Campagne et al., 2004; Contardi et al., 2004).

2.1.4. Setting

The game was back projected on a screen (1080 x 924 millimeters) in the front of the driver at a distance of 1.25 m. On the front right of the driver there was a camera recording his/her face. Other camera was situated behind the driver. It was directed to the view of the simulated driving environment. The images of these two cameras and the electrophysiological data from DSAMP (i.e. the Oz EEG channel, the horizontal EOG channel, and skin potential) were mixed into the same screen by a video mixer and recorded on video tape. Thus the recorded video images consisted of simultaneous information from these three different sources for the observational analysis of the driving and verification of some variables.

2.1.5. Procedure

Each participant was tested in separate nights. Participants arrived at the laboratory 2-3 hours before their usual bedtime, in the night after the night of sleep deprivation. First they signed the informed consent and filled the questionnaires concerning their sleeping (ESS, BNSQ) and driving habits. Then the heart rate, EOG and EEG electrodes, the respiration strain gauge band, and the skin potential electrodes were attached. Attaching the measuring equipment took 1.5 to 3 hours. After that, the subjects went over to the driver seat in the front of the screen where the simulated environment was projected. The video cameras directed towards their faces and to the driving environment were adjusted. Subjects were told that they could practise a little and that they were expected to drive and respond to the lights. A target driving speed (70 m/h) and the functioning of the lights of the reaction time task were explained to the subjects. Then, the participants practised as long as they felt they needed to accustom themselves to driving with the simulator and responding to the reaction time task (about 15 min).

After the practice, the sound level on the earphones was adjusted for the auditory oddball task. Then the instructions for the experimental driving session were given. The instructions indicated that the subject should react to the lights of the reaction time task as fast and accurately as possible and drive at the target speed. Subjects were explained, that the sounds of driving were turned off for the experimental purposes and they were advised not to pay attention to the sounds of the oddball task. Participants were asked to restrict the movement of the left hand to avoid artefacts. They were also encouraged to drive even if they would start to feel sleepy. The experimental session lasted as long as the subjects thought they were able to continue but the purpose was to drive for three hours. The subjects were not allowed to wear watches during the experiment and neither were they allowed to get any information about the elapsed driving time.

2.1.6. Recording

The EEG channels were recorded using the international 10-20 system (Jasper, 1958). The following EEG channels were recorded: Cz, C3, C4, Fz, F3, F4, Oz, M1 and M2. Recording was done through a monopolar connection, where the tip of the nose was used as a reference. The type of a cap was an ElectroCap and the electrodes were

Ag/AgCl. The horizontal EOG was recorded 1-2 cm from the corner of the left eye. The vertical EOG was recorded 1 cm above the left eye. These EOG channels were also referenced to the nose. The EOG electrodes were disposable Neuroline Ag/AgCl electrodes type 725 01– K and were filled with ElectroGel as a conductive. Input signal was calibrated with 100 μV and 5 Hz.

The EEG and EOG signals were amplified with a gain of 50 000 and filtered by an analogue bandpass filter with 0.3 s time constant. Passed frequencies were from 0.53 Hz to 35 Hz. The signals were further converted with a sampling rate (digitizing frequency) of 200 Hz and recorded on hard disk through the D-samp software.

For heart rate recording, the ground electrode was placed on the right side of the abdomen, just under the undermost rib. Two electrodes were placed on the left side of the upper and lower part of the chest and vertically in line. These electrodes were Blue Sensor disposable clip ECG electrodes. The heart rate signal was acquired through a cardiotachograph, sampled at 200 Hz and recorded through D-samp. Impedances of each of the electrodes (EEG and EOG) were 5 kΩ or less.

In this experiment, reaction time (RT), mismatch negativity (MMN), respiration rate and skin potential were also measured. In addition to the driving task, subjects performed continuously a visual reaction time task. In the reaction time task four diodes were placed on the sides of the screen, two on the left and two on the right side. Switching of the light varied randomly between the sides of the screen, the colours of the light, and the inter-stimulus-intervals (ISIs). Responding to this task was done by pressing two buttons placed on the steering wheel with the right thumb. The subject took part simultaneously in an auditory oddball task. In this task, the subject heard sounds for eliciting the MMN via earphones which he was wearing while driving. The MMN inducing sounds were presented as different segments, which had a duration of 31.250 s. This duration determined the basic time unit of the analysis; half of the trial named as epoch was used in the analysis. Respiration was measured around the chest and skin potential from the left index finger. The results of RT, MMN, respiration rate and skin potential are not reported here.

2.1.7. Variables

EEG-data of Oz-channel was divided off-line into the bands of delta (0.5-4.0 Hz), theta (4.0-8.0 Hz), alpha (8.0-12.0 Hz), sigma/spindle activity (12.0-14.0 Hz) and beta (14.0-30.0 Hz) (Hasan, 1994; sigma: Tolonen & Lehtinen, 1994). Spectral analysis in the frequency-domain was done with a Fast Fourier Transform (FFT) algorithm. Absolute power of the FFT for every epoch with the used bandwidths was calculated.

Eye blinks were analyzed on the basis of the vertical EOG (EOGV) channel. On the vertical channel, blinks are seen as amplitude changes (Stern et al., 1984). Correspondence in amplitude change between the vertical and horizontal channels was assured from print-outs. Then the similarity between horizontal amplitude change and the observational data of the driver's eyes via video was verified. Thus, the observational blinks coincided with the amplitude change on the EOGV channel. Direct verification of correspondence between the amplitude change of the EOGV channel and with the observational data was not possible, because only the EOGH channel was mixed into the same picture with the drivers face.

Blinks were defined by using a threshold on the vertical EOG channel in an offline computerised analysis. The number of blinks per minute was counted for every epoch on the basis of the spikes in the EOGV channel. Unfortunately blinks overloaded quite often the EOGV channel, which caused that the real amplitude of those blinks could not be calculated. Thus, blink amplitude was counted only for those blinks, which did not overload the vertical channel.

In addition, the average heart rate was counted for every epoch.

2.2. Observational measures

2.2.1. Incident types of impaired driving

Videos of the driving were analyzed by observing the quality of driving performances. Analysis was based only on the driving errors; driving impairments are often used as a measure in driver fatigue researches (George, 2003; Horne et al., 2004; Eoh et al., in press). The analyzed segment was one epoch and had the duration of 15.625 s (31.250/2) (Chapter 2.1.6). Because of the limits of the video cassette recorder the epoch had in practice the duration of 15.5 ± 0.5 s. In analyzing the quality of the driving performance, obvious driving errors which were considered at least as a sign of impaired attention unless the sleepiness of the driver, were marked. Driving impairments are defined often as the crossing of the lateral lane marking (Horne & Baulk, 2004), or more specifically crossing of the emergency line on the left or the white line on the right (Campagne et al., 2004). The obvious error incidents were chosen to be two wheels out of the road, four wheels out of the road, near crash and crash (table 1). The former two took place on the left side of the track and indicated that the driver had crossed the line marking on his left side. In the case of four wheels out of the road, the yellow line was crossed totally, before it was marked as an incident. The latter two incident types took place on the right side of the road. A crash was marked when the car seemed to touch the wall. Beside the wall, there was a shadow. When the car had crossed half of this shadow, a near crash was marked. All but one subject (6) chose to drive clearly on the left side of the road. Despite of that each of the subjects was included in the analyses.

TABLE 1. Description of driving errors observed from driving videos of the subjects in the time unit of epoch (15.5 s)
Driving errors on the left side of the road include cases when two wheels (2W) or all wheels (4W) of the car were over the left side line. Driving errors, which occur on the right side of the road, include driving errors near crash (NC) and crash (C).

Driving error	Description
Two wheels off the road (2W)	When the car had crossed the yellow line on the left side of the car so that the line is not visible until the point when the line is partly visible
Four wheels off the road (4W)	When the car had crossed the yellow line on the left side of the car, so that the yellow line was visible on the right side of the car wholly to the point when yellow line was visible only partially
Near crash (NC)	When the car was in the area from the half of the shadow before the wall to the wall on the right side of the track
Crash (C)	From the point when the car touched the wall on the right side of the track to the point when it separated from the wall

The duration of the incidents was measured. When an incident started during one epoch and continued in the next epoch, the time of the incident was measured per each epoch.

The interconnections of the driving errors were marked meaning whether the errors occurred separately or in series. This was important, for example in the cases of the 2W and NC, which can occur separately, or preceding and following 4W and C. In uncertain classification cases, the more severe category was chosen (table 1).

2.2.2. Evaluation of the incidents during epoch

After marking the quality and the duration of the driving errors, the episodes were weighted within every single epoch. 2W and NC were valued equally in severity and were combined into one category. Similarly 4W and C were combined to form another category. For both of these categories (2W/NC and 4W/C) the maximum amount of points during one epoch was decided to be three (table 2).

Some incidents of driving errors were single ones and could easily be defined to represent either one of these categories. Naturally, category 4W/C included also category 2W/NC twice as intermediate state. For avoiding overrating of error incidents, the state of 2W/NC was not valued when it occurred together with 4W/C and lasted 5 s or less.

The single incidents during one epoch were valued according to their duration. An incident that lasted 5 seconds or less was scored with one point, an incident lasting 10 s or less was scored with two points and an incident lasting 15 s or less was scored with three points. The number of points for the categories of 2W/NC and 4W/C during one epoch was also based on the occurrence rate of incidents. It was possible to get two points also from two different incidents, which lasted 5 s or less. Similarly it was possible to get three points from three or more different incidents that lasted 5 s or less. The combination of occurrence and duration was possible while evaluating the epochs. For example, a combination of longer (> 5 s) incident and shorter (< 5) incident would yield a value of three points.

An intermediate state of 4W/C is 2W/NC and it was valued when it had a duration over 5 s. This was so because 5 s or less was estimated to be the normal time in the area before or after 4W/C. Therefore, when the time in that intermediate state was over 5 s but under 10 s, the category 2W/NC was scored with one point. Similarly, when time in that area was over 10 s, the category 2W/NC yielded two points. At times there was an incident, which included both categories alternating 2W/NC and 4W/C. In those cases the time limit of the intermediate state was considered only once during the same 2W/NC, even if that 2W/NC would be between two 4W/Cs. In that case, the time was excluded from the seconds after 4W/C and not before the next 4W/C. As an example, in the case of 2W-4W-2W-4W-2W, from the duration of every 2W the time limit of the intermediate state was excluded. So from the first 2W the latest 5 s, from the middle 2W the first 5 s and the last 2W the first 5 s were not valued. If there was any seconds left after these exclusions for category 2W/NC, they were weighted according to the normal rules of category 2W/NC.

The points were given for that epoch during which parts of the incidents occurred. In cases when there was a change of epoch during the incident, the same seconds were never weighted twice to avoid overrating of time. The duration of an epoch was divided into 5 s segments and points were given to that epoch during which that 5 s (or less) segment started. An example: An incident lasted 8 s. First 2 s occurred during the previous epoch and the last 6 s during the latter epoch. The incident was segmented into five seconds' segments. The first segment had the durance of 5 s and the latter 3 s. The first segment started during the former epoch and the last segment during the latter epoch. So the both epochs yielded one point. In other cases when the epoch included four incidents with one incident continuing after an epoch change, the criteria mentioned above was followed. The former epoch got three points because of three single incidents. The fourth incident was segmented into five seconds' segments. However, because the maximum amount of points for one category during each epoch was three, the first five seconds of the incident did not increase the points of the former epoch. The latter epoch got the possible points of the next segments of 5 s.

Incidents during one epoch were evaluated by adapting the above mentioned criteria (table 2) and the segmentation of incident was considered when there was an epoch change during an incident.

TABLE 2. Criteria for evaluating the severity of the driving incidents
Driving errors were divided into two categories: two wheels out of the road/near crash (2W/NC) and four wheels out of the road/ crash (4W/C). The severity of the incident was rated according to the duration and frequency of the incidents.

Category	Rating	Description
2W/NC	1	Single incident of 2W/NC lasting 5 s or less. An intermediate state during the incident of 2W/NC preceding or following 4W/C and lasting 10 s or less.
	2	Single incident of 2W/NC lasting 10 s or less. Two incidents of 2W/NC lasting 5 s or less. An intermediate state during the incident of 2W/NC preceding or following 4W/C and lasting 15 s or less.
	3	Single incident of 2W/NC lasting 15 s or less. Three or more incidents of 2W/NC lasting 5 s or less.
4W/C	1	Incident of 4W/C lasting 5 s or less.
	2	Incident of 4W/C lasting 10 s or less. Two incidents of 4W/C lasting 5 s or less.
	3	Incident of 4W/C lasting 15 s or less. Three or more incidents of 4W/C lasting 5 s or less.

2.2.3. Categories of driving quality

A summed variable was formed from the types of driving errors (2W/NC and 4W/C) for each 15.5 s epoch. The coefficient for 4W/C was chosen to be 2.5 which means that 4W/C was estimated to be 2.5 times more severe incident type than 2W/NC. Thus the function for summing the incidents was 2.5 * 4W/C + 2W/NC. Theoretical range for the summed variable is 0-10.5, but the actual range was 0-8.5.

The division into three states of driving quality was carried out by cluster analysis. The values of the summed variable of each subject were combined into one variable. Then the number of cluster centres was set to three, and the epochs were divided into clusters which had ranges 0-1, 2-3.5 and 4.5-8.5 of the summed variable. The division of the epochs based on the cluster analysis seemed to be reasonable, so the ranges were accepted. The three formed categories of driving quality were named as accurate (state 1), unstable (state 2) and deficient stage (state 3). Cluster values were returned to the subject level. For data analysis, the first 10 minutes of data (from 41. epoch) for each subject were eliminated. This excluded the time when the subjects, despite the familiarization period, could still be getting used to drive on the simulator.

2.3. Statistical analysis

A statistical analysis was carried out across subjects to test whether the variables differed in the three states of driving quality. At the subject level, analyses were carried out to test which variables could predict the unstable and deficient states of driving. The categorisation of driving quality was defined as that of $epoch_0$. The averages of the variables during these epochs were not included in the analyses because they could contain also arousal effects caused by the incidents. The averages of variables which occurred one epoch before $epoch_0$ were used as independent variables as well as the variables which took place two, three and four epochs before $epoch_{0.}$ Those epochs were denoted as $epoch_{-1,}$ $epoch_{-2,}$ $epoch_{-3}$ and $epoch_{-4}$. The statistical analyses were carried out with the SPSS -program (v.12.0). Comparing the means of the independent variables (psychophysiological variables) among all three driving quality states (dependent variable) was carried out with MANOVA as GLM-procedure for repeated measures. Two subjects (subj. 3 and 5) did not have any epochs classified as deficient state and they were not included in the MANOVA analysis of averages in the three categories of driving. Because of that, a separate MANOVA was also carried out for all subjects between accurate and unstable states of driving. The significant or near significant variables ($p < 0.1$) within different states of driving quality were further analyzed with paired samples t-test (compared pairs: accurate vs. unstable states and accurate vs. deficient states).

The analysis for predicting the driving quality was done with logistic regression analyses. Choosing logarithmic regression as an analysis tool instead of linear regression is supported by the more liberal assumptions of logistic regression analysis for differences of variances and correlations among the dependent variables (Metsämuuronen, 2003). However, the logistic regression analysis measures only the association between dependent and independent variables; the analysis itself does not predict the dependent variable (Metsämuuronen, 2003). Instead the predicting element was captured with independent variables, which were averages of variables during epochs occurring earlier than the dependent variable.

In the logistic regression analyses, accurate driving was included either with unstable driving or with deficient driving to form the two categories of the dependent variable (table 3). The sole effect of each independent variable four epochs earlier (variables of $epoch_{-4}$) than the values of the dependent variable were tested. Two subjects (3 and 5) had not any epoch classified into the deficient state and they were not included in the analyses where deficient state of driving was used as one of both categories of the dependent variable.

The logistic regression analyses were done for both pairs of dependent variables separately. Significant variables (sig. ≤ 0.05) of $epoch_{-4}$ ($theta_{-4}$, $delta_{-4}$, $alpha_{-4}$, $sigma_{-4}$, $beta_{-4}$, BR_{-4}, BA_{-4} and HR_{-4}) for every subject were further fed one at a time into the first block of the logistic regression analysis. The other variables of $epoch_{-4}$ formed the second block. Third block consisted of values of variables at the time of $epoch_{-3}$ (similarly, $theta_{-3}$, $delta_{-3}$, $alpha_{-3}$, $sigma_{-3}$, $beta_{-3}$, BR_{-3}, BA_{-3} and HR_{-3}) 4th block of variables at time of $epoch_{-2}$ and 5th block of variables at time of $epoch_{-1}$. The variable of the first block was entered into the model; in other blocks, the variables were fed using the forward Wald method. This procedure was performed with every subject in order to find the best personal predictors for unstable and deficient states of driving. Analysis covering the minute (62.250 s; $epoch_{-1}$, $epoch_{-2}$, $epoch_{-3}$, and $epoch_{-4}$) before epoch of incident presented the averages of variables of four epochs (table 3).

The logistic analyses tested the difference of the Wald statistic from zero, with the significance level of 0.05. In tables 8 and 9, the logistic analyses with multiple variables show the final significant models which had significant step, block and model values. The significance level of the model, the Nagelkerke R^2 and the percentage of classification accuracies are presented. The variables in this final model and their significances are shown. The direction of the effect, β-coefficient, is signified as + (increased) or – (decreased) sign. The values of β-coefficients, its standard errors, the values of Wald or degrees of freedoms are not presented because the sign of the β-coefficient was considered to include sufficient information for the purposes of this study. Similarly the odds ratios are not reported.

TABLE 3. Logistic regression analyses of variables

Logistic regression analyses were initially carried out with single variables, which took place four epochs (epoch = 15.5 s) earlier than the values of the dependent variable. Those variables of epoch$_{-4}$ of each subject were entered one at a time into the analyses. Then the significant variables were entered one at time into the first block of the next logistic analyses. The rest of the variables of epoch four were fed into the next block of the analyses. Each of the variables which happened three epochs before the driving impairment were fed into the 3rd block. The 4th block contained the variables which happened two epochs earlier. And, the variables of the epoch prior to the dependent variable were fed into the 5th block. The enter method used in blocks 2 - 5, was stepwise forward Wald. The analyses were carried out for each subject.

Logistic regression analysis	**Block 1**	**Block 2**	**Block 3**	**Block 4**	**Block 5**
1. With single variables, one at a time	delta$_{-4,}$ theta$_{-4,}$ alpha$_{-4,}$ sigma$_{-4,}$ beta$_{-4,}$ BR$_{-4,}$ BA$_{4,}$ HR$_{-4}$				
2. With multiple variables	The significant* variables at time of epoch$_{-4}$, one at time	The rest of the variables at time of epoch$_{-4}$	All variables at time of epoch$_{-3}$	All variables at time of epoch$_{-2}$	All variables at time of epoch$_{-1}$

* $p \leq 0.05$

3. RESULTS

3.1. Frequencies of driving quality states

In this experiment the amount of analyzed epochs was 5398, representing 23 h 14 min (table 4). The number of epochs for most of the subjects was over 600. One subject had only 145 epochs (subject 2). The percentage of epochs classified as accurate state of driving was 70.2 %. In addition, this state was, for most of the subjects, the one which had the highest frequency of epochs. Only one subject had more epochs in unstable state than in accurate state (subject 6). The number of epochs in accurate state varied individually. Subjects 3, 5 and 8 had 94.1 % or more of the epochs in accurate state and subjects 1, 6 and 9 had fewer than 50 % of the epochs classified into this state.

Into unstable state were classified 21.5 % of all epochs. The number of epochs varied from 16 to 292 and in percents from 3.6 % to 43.8 % (subjects 8 and 6). Subjects can be divided into two different groups based on the amount of epochs classified as unstable driving. One group (subjects 1, 4, 6, 7 and 9) had over 115 epochs classified as unstable driving, while the other group (subjects 2, 3, 5 and 8) had less than 29. Subject 2 had a small amount of epochs in state of unstable driving partly because of the shorter duration of the experiment.

The total amount of epochs in deficient state was 6.9 % of all epochs. Number of epochs varied from 0 to 168, in percents from 0 to 25.2 %. Together five subjects had none (subjects 3 and 5) or less than five epochs classified as deficient (subjects 2, 4 and 8).

Three subjects had a short break during the driving; two due to technical reasons (subjects 2 and 7) and one to ergonomic ones (subject 8). Thus the amount of missing epochs was 70 (1.3 %; table 4).

TABLE 4. The frequencies and percentages of epochs in each of the three categories of driving quality
The epochs were divided into three quality states of driving performance (accurate, unstable and deficient) on the basis of cluster analysis of the summed variable. Summed variable represents the sum of the driving errors during one epoch. Ranges of the summed variable, the frequencies over and within subjects in these three driving quality states are presented. The category 'All' includes the frequencies in three driving quality states and the number of missing epochs.

	Accurate		Unstable		Deficient		Missing		All	
Range of the summed variable	0-1		2-3.5		4.5-8.5		–		0-8.5	
Subject	f	%	f	%	f	%	f	%	f	%
1	269	42.7	257	40.8	104	16.5	-	-	630	100.0
2	117	80.7	16	11.0	2	1.4	10	6.9	145	100.0
3	639	96.1	26	3.9	-	-	-	-	665	100.0
4	544	81.9	116	17.5	4	0.6	-	-	664	100.0
5	636	95.8	28	4.2	-	-	-	-	664	100.0
6	206	30.9	292	43.8	168	25.2	-	-	666	100.0
7	437	65.6	156	23.4	25	3.8	48	7.2	666	100.0
8	626	94.1	24	3.6	3	0.5	12	1.8	665	100.0
9	316	49.9	248	39.2	69	10.9	-	-	633	100.0
Total	3790	70.2	1163	21.5	375	6.9	70	1.3	5398	100.0

3.2. The driving quality with time on task

Occurrence of driving performance in states of accurate, unstable or deficient driving (respectively states 1, 2 and 3) within the subjects was basically similar (figure 1). In the beginning of the experimental driving epochs belonged most frequently to the accurate state (state 1). Usually the frequencies of unstable state (state 2) started to increase during driving. This was the case for subjects 1, 3 and 8. Subject 9 had not so obvious increase in the occurrence of unstable driving with time. For some subjects the amount of epochs in deficient state (state 3) increased while the driving task proceeded. For subjects 1 and 9 this increasing was detectable in the figures, even though with subject 9 the amount of epochs in deficient state is quite high already before the middle of the experiment (figure 1).

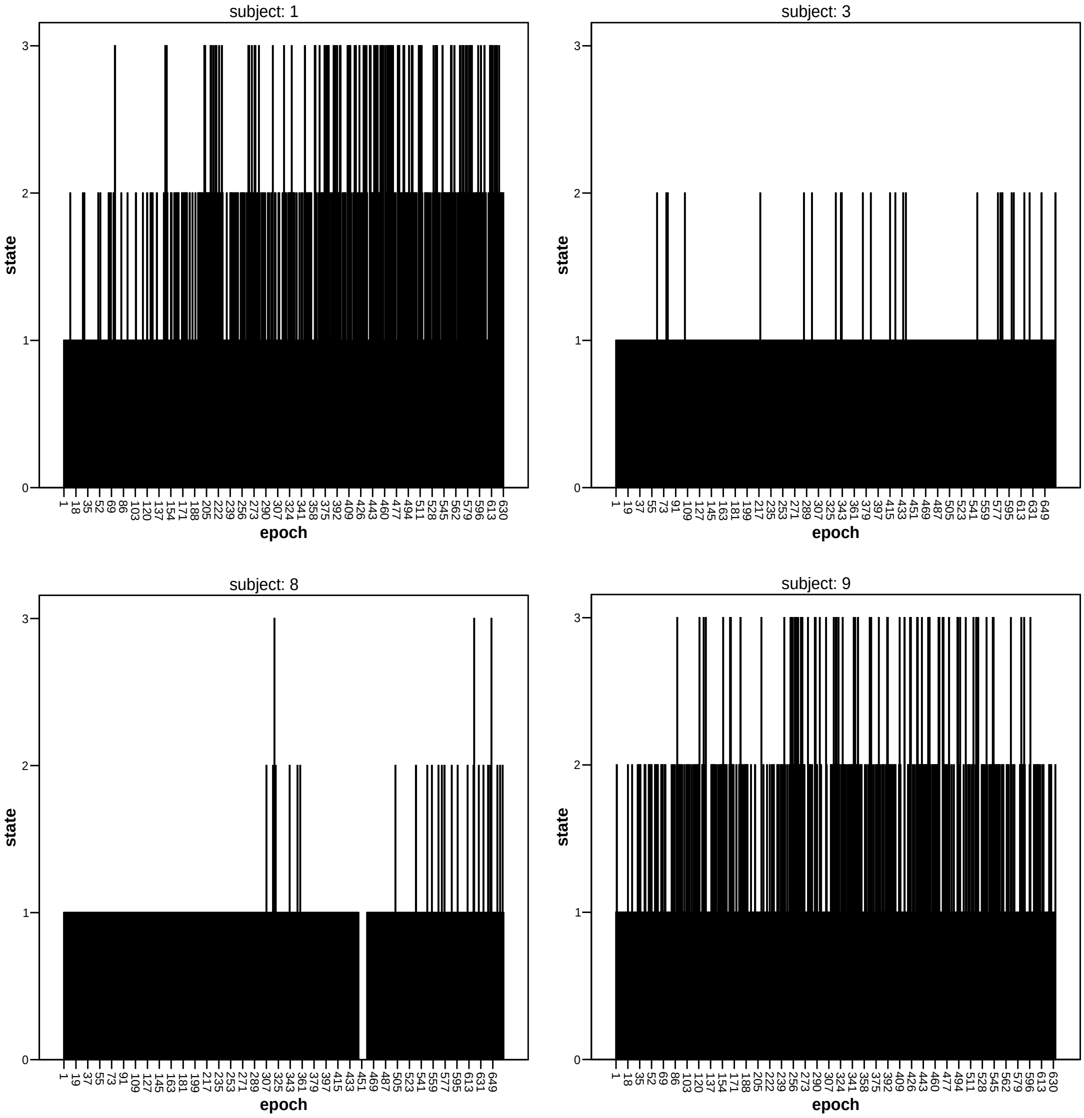

FIGURE 1. Driving quality in time
Occurrence of three different driving quality states as a function of driving time presented as epochs (15.5 s) in subjects 1, 3, 8 and 9. State 1 signifies the state of accurate driving, state 2 the unstable driving and state 3 the deficient driving. State number 0 signifies the interruptions during experiment. Numbering of the epochs starts in the beginning of the analysed driving (after 10 min 25 s of driving).

3.2.1. Averages of variables across subjects

The differences in the averages of variables across subjects through the three states of driving quality were tested with MANOVA. This analysis included 7 subjects because subjects 3 and 5 did not possess any epochs classified as deficient driving state. Beta$_{-4}$ was the variable, which reached significance ($p = 0.015$). Delta$_{-2,}$ alpha$_{-2,}$ and alpha$_{-4}$ had significance below 0.1 and they were analyzed together with $beta_{-4}$ with paired samples t-testes. None of these variables reached significances in the t-testes. A MANOVA was also carried out for accurate and unstable states of driving. This was done in order to include each subject in the analysis to increase the sample size of unstable driving quality. There were no significances in the averages of any variable across subjects.

The averages, over subjects, of the variables in the three driving quality states seem to differ in spite of insignificances in MANOVAs (table 5). The values of three of the delta increased from accurate to unstable state and further to deficient state. The EEG power in all theta variables decreased from accurate to unstable and increased from unstable to deficient in all four variables, in three variables of alpha and sigma power and in two beta variables. Concerning the BR it increased from accurate to unstable state and decreased from unstable to deficient. BA decreased in two variables from accurate to unstable and increased from accurate to deficient. HR decreases from state to state towards deficient state in two variables. The standard deviations of the EEG variables are larger than the average value. This is also true for other variables (table 5), which affects the significances of the analyses.

3.3. Logistic regression analyses on individual data

Logistic regression analyses were carried out for single independent variables at the time of $epoch_{-4}$. The dependent variable consisted of accurate state of driving either with unstable or deficient state. A separate analysis was carried out for each individual.

3.3.1. Accurate and unstable states

Logistic regression analyses were carried out with the following independent variables: $theta_{-4}$, $delta_{-4}$, $alpha_{-4}$, $sigma_{-4}$, $beta_{-4}$, BR_{-4}, BA_{-4} and HR_{-4}. The dichotomous dependent variable was driving quality state with accurate and unstable states of driving as categories (table 6). The number of significant variables at the subject level ranged from 1 to 4. For subject 1 the variables $alpha_{-4}$, $sigma_{-4}$, BA_{-4} and HR_{-4} had significant ($p \leq 0.05$) effect on predicting the accurate and unstable driving quality states. For subject 2 there was only one variable, $theta_{-4}$, which was significant. Subject 3 had $sigma_{-4}$ and

TABLE 5. Averages of the variables according to driving quality states
The averages of every variable with standard deviations are presented in three different driving quality states: accurate (St 1), unstable (St 2) and deficient (St 3). The index in the name of the variables refers to how many epochs (epoch = 15.5 s) before the driving quality definition the average of variable is counted. The unit of EEG variables (delta, theta, alpha, sigma and beta) is μV^2, with blink rate (BR) and heart rate (HR), the rate in minute and with blink amplitude (BA) μV.

	Accurate state		Unstable state		Deficient state	
Variables	Mean	SD	Mean	SD	Mean	SD
$delta_{-1}$	688 255.0	671 427.2	691 393.9	695 083.4	828 148.2	993 331.7
$delta_{-2}$	685 309.9	680 035.9	704 965.2	664 894.8	721 701.1	693 685.3
$delta_{-3}$	687 147.7	676 931.2	674 516.9	672 814.1	833 776.4	839 712.6
$delta_{-4}$	690 093.5	675 301.4	699 985.9	708 629.5	818 881.0	722 426.3
$theta_{-1}$	581 004.0	1 564 334.5	572 272.4	1 535 787.4	710 580.6	1 689 699.2
$theta_{-2}$	580 331.7	1 561 166.9	574 396.6	1 547 636.2	712 641.8	1 709 306.7
$theta_{-3}$	582 680.2	1 567 789.2	562 612.6	1 510 650.1	681 964.1	1 621 548.7
$theta_{-4}$	582 710.1	1 569 449.4	557 658.2	1 487 559.3	770 217.5	1 815 308.2
$alpha_{-1}$	224 402.3	595 389.5	222 735.1	583 450.0	282 817.8	662 184.6
$alpha_{-2}$	223 728.8	592 146.6	228 385.6	604 521.3	278 985.1	649 410.6
$alpha_{-3}$	225 009.7	596 795.7	219 097.1	574 360.4	266 646.0	618 979.6
$alpha_{-4}$	224 382.2	595 139.1	218 947.4	573 243.3	321 392.8	751 265.9
$sigma_{-1}$	79 914.0	219 957.3	76 076.5	207 984.7	97 679.2	237 993.5
$sigma_{-2}$	79 763.9	219 460.3	76 636.1	209 607.9	101 652.4	248 845.2
$sigma_{-3}$	79 993.0	220 273.1	77 423.2	211 738.3	77 397.0	185 741.2
$sigma_{-4}$	79 780.9	219 944.6	78 383.0	214 578.9	86 513.7	206 387.8
$beta_{-1}$	151 971.0	373 611.9	150 854.4	365 082.1	191 363.0	433 547.4
$beta_{-2}$	151 600.3	372 776.1	152 475.9	370 496.1	182 134.5	406 895.4
$beta_{-3}$	152 204.9	375 553.4	142 091.6	344 959.4	185 912.3	416 100.0
$beta_{-4}$	150 719.7	370 597.4	151 075.1	368 601.5	224 692.6	510 685.6
BR_{-1}	27.1	12.0	28.3	14.5	26.3	10.5
BR_{-2}	26.9	12.1	28.6	14.8	24.2	14.7
BR_{-3}	27.0	12.0	28.4	14.3	22.7	13.5
BR_{-4}	26.9	12.0	29.3	14.8	27.7	19.5
BA_{-1}	267.8	51.8	267.3	50.4	275.2	35.7
BA_{-2}	268.1	52.7	265.3	47.8	267.8	34.9
BA_{-3}	267.5	51.9	266.6	48.4	259.4	41.0
BA_{-4}	267.0	51.9	269.4	46.6	281.9	39.6
HR_{-1}	66.7	16.2	66.4	16.4	67.4	15.9
HR_{-2}	66.6	16.2	66.5	16.5	66.1	17.2
HR_{-3}	66.6	16.2	66.3	16.4	65.5	16.7
HR_{-4}	66.5	16.3	66.7	15.8	66.3	18.9

BR_{-4}, which predicted significantly the quality of driving. Subject 4 had $theta_{-4}$, $alpha_{-4}$ and BR_{-4}, and subject 5 had only BA_{-4} predicting driving quality. $Sigma_{-4}$ and $beta_{-4}$ were significant predictors for subject 6, while $theta_{-4}$, BR_{-4} and HR_{-4} predicted significantly the driving of subject 7. For subject 8, $theta_{-4}$, BR_{-4}, BA_{-4} and HR_{-4} were significant. $Sigma_{-4}$ was the only variable that predicted the driving quality for subject 9 (table 6).

TABLE 6. Logistic regression analyses of single variables with accurate and unstable driving quality states
The logistic regression analyses were carried out for independent variables $theta_{-4}$, $delta_{-4}$, $alpha_{-4}$, $sigma_{-4}$, $beta_{-4}$, BR_{-4}, HR_{-4} and BA_{-4}. Values of those variables were the averages of 15.5 sec epochs, which occurred four epochs earlier than the values of driving quality, when accurate and unstable driving states formed the dependent variable. The analyses were carried out within subjects. In the table are presented the significances of the variables entered in the logistic regression analyses.

Subject	$delta_{-4}$	$theta_{-4}$	$alpha_{-4}$	$sigma_{-4}$	$beta_{-4}$	BR_{-4}	BA_{-4}	HR_{-4}
1	0.709	0.055	0.002*	0.000*	0.132	0.834	0.001*	0.000*
2	0.299	0.018*	0.075	0.488	0.894	0.692	0.653	0.097
3	0.867	0.316	0.706	0.025*	0.864	0.038*	0.210	0.312
4	0.312	0.015*	0.002*	0.169	0.062	0.001*	0.419	0.353
5	0.226	0.458	0.270	0.937	0.634	0.068	0.015*	0.268
6	0.901	0.781	0.356	0.036*	0.034*	0.490	0.420	0.099
7	0.170	0.003*	0.116	0.272	0.298	0.008*	0.799	0.003*
8	0.989	0.001*	0.087	0.060	0.246	0.000	0.000*	0.019*
9	0.756	0.474	0.063	0.021*	0.407	0.982	0.544	0.095

* $p \leq 0.05$

3.3.2. Accurate and deficient states

Logistic regression analyses were also carried out in which accurate and deficient state formed the two categories of the dependent variable, and $theta_{-4}$, $delta_{-4}$, $alpha_{-4}$, $sigma_{-4}$, $beta_{-4}$, BR_{-4}, BA_{-4} and HR_{-4} independent variables (table 7). Two subjects (3 and 5) were excluded from the analyses because they did not possess any epochs classified as deficient driving quality.

For subject 1, the significant variables predicting accurate and deficient states were alpha$_{-4,}$ sigma$_{-4,}$ BA$_{-4}$ and HR$_{-4}$. Alpha$_{-4}$ was significant also for subject 2. Subject 4 had theta$_{-4,}$ alpha$_{-4,}$ sigma$_{-4,}$ beta$_{-4}$ and HR$_{-4}$ as significant variables. Subject 6 did not have any variable, which significantly predicted accurate and deficient driving states. For subject 7, alpha$_{-4}$ and HR$_{-4}$ were significant variables. Almost each of the variables predicted the driving quality for subject 8. These were theta$_{-4,}$ alpha$_{-4,}$ sigma$_{-4,}$ beta$_{-4,}$ BR$_{-4,}$ BA$_{-4}$ and HR$_{-4}$. Instead, subject 9 did not have any variable significantly predicting driving quality (table 7).

TABLE 7. Logistic regression analyses of single variables with accurate and deficient driving quality states
The logistic regression analyses were carried out with the independent variables theta$_{-4,}$ delta$_{-4,}$ alpha$_{-4,}$ sigma$_{-4,}$ beta$_{-4,}$ BR$_{-4,}$ HR$_{-4}$ and BA$_{-4}$. These variables were the averages of 15.5 sec epochs, which occurred four epochs earlier than the values of driving quality state. The driving quality states accurate and deficient driving formed the two categories of the dependent variable. The analyses were carried out within subjects. In the table are presented the significances of the variables entered in the logistic regression analyses.

Subject	delta$_{-4}$	theta$_{-4}$	alpha$_{-4}$	sigma$_{-4}$	beta$_{-4}$	BR$_{-4}$	BA$_{-4}$	HR$_{-4}$
1	0.230	0.630	0.001*	0.000*	0.412	0.113	0.000*	0.000*
2	0.824	0.631	0.03*	0.054	0.061	0.803	0.168	0.252
4	0.891	0.010*	0.028*	0.046*	0.049*	0.701	0.652	0.035*
6	0.596	0.207	0.253	0.703	0.624	0.151	0.631	0.761
7	0.667	0.272	0.032*	0.834	0.073	0.241	0.300	0.021*
8	0.164	0.000*	0.024*	0.006*	0.010*	0.00*	0.004*	0.008*
9	0.949	0.673	0.494	0.126	0.361	0.908	0.870	0.103

* $p \leq 0.05$

3.4. Logistic regression analyses with multiple variables

Logistic regression analyses were carried out using the significant variables of the univariate logistic regression analyses. Each of them was entered separately into the 1st block of analyses. Other variables of $epoch_{-4}$ formed the 2nd block, variables of $epoch_{-3}$ formed the 3rd block etc. until the variables of $epoch_{-1}$ and 5th block. Accurate state of driving with unstable and deficient driving formed the dependent variable. Different tests were carried out for each subject. The different models for each subject with the dependent variables are presented in the results. The models with the same dependent variable for each subject were quite similar, and hence, the significances of the models, R^2 and the percentage of correct classification of states of driving are presented in the text as representing of the different models for each subject.

3.4.1. Models including accurate and unstable states

Subject 1 had four final models with $alpha_{-4}$, $sigma_{-4}$, BA_{-4} or HR_{-4} as the entered variable in the first block of these models. From these entered variables $sigma_{-4}$ was the only significant variable in the final model. Three of these final models included the same significant variables with same direction in β-coefficient: $sigma_{-4}$ ($\beta = +$), $beta_{-3}$ ($\beta = +$), BA_{-1} ($\beta = -$) and HR_{-3} ($\beta = -$). The fourth model did not include $beta_{-3}$, but instead the variables $theta_{-4}$ ($\beta = +$) and HR_{-4} ($\beta = -$). All β-coefficients except $beta_{-3}$ showed the expected direction based on the hypotheses. The p-values of the models were quite close to each other as were the Nagelkerke R^2 and classification accuracies for accurate and unstable state ($p = 0.000$; $R^2 \approx 0.16$; classification accuracy for accurate and unstable ≈ 66 % and 62 %; table 8).

Subject 2 had $theta_{-4}$ as the entered variable in the first block of the analysis. $Theta_{-4}$ was not significant in the model. The significant variable in the model ($p = 0.05$; Nagelkerke $R^2 = 0.154$; classification accuracies 100 % and 0 %) was $beta_{-3}$ ($\beta = -$). The value of $beta_{-3}$ decreased from state accurate to unstable driving, as was expected from the hypothesis.

Subject 3 had two similar final models with $sigma_{-4}$ or BR_{-4} as variable in the first block of the analysis. $Sigma_{-4}$ was not significant in the model. The significant variables in the models ($p = 0.00$; Nagelkerke $R^2 = 0.138$; classification accuracies 100 % and 0

%) were BR_{-4} (β = +), $delta_{-3}$ (β = -) and $sigma_{-1}$ (β = -). BR_{-4} showed expected direction for β-coefficient unlike $delta_{-3}$ and $sigma_{-1}$.

Subject 4 had three different models with $theta_{-4}$, $alpha_{-4}$ or BR_{-4} as the entered variable. $Alpha_{-4}$ and BR_{-4} were significant in their final models. The significant variables in all three models (Nagelkerke $R^2 \approx 0.09$; classification accuracies ≈ 99 % and 3 %) were BR_{-4} (β = +), $theta_{-2}$ (β = -) and BA_{-2} (β = -). In addition to these, two similar models included the significant variables $alpha_{-4}$ (β = +) and BR_{-1} (β = +). Third model included also the variable $alpha_{-1}$ (β = +). Each significant variable except $theta_{-2}$ had expected changes in values from accurate to unstable driving states.

Subject 5 had one model ($p = 0.00$; Nagelkerke $R^2 = 0.163$; classification accuracies 100 % and 0 %), with BA_{-4} as the entered variable in the first block. Significant variables in the model were $theta_{-3}$ (β = -), $theta_{-2}$ (β = -) and $delta_{-2}$ (β = +). BA_{-4} was not significant in the model. The β-coefficient of $delta_{-2}$ was positive as was expected unlike the theta variables.

Subject 6 had two models with $sigma_{-4}$ or $beta_{-4}$ as the entered variable. The significant variables in both of the final models ($p = 0.00$; Nagelkerke $R^2 \approx 0.05$; classification accuracies ≈ 27 % and 87 %) were $theta_{-3}$ (β = -) and HR_{-3} (β = +). $Sigma_{-4}$ (β = +) was the significant variable in the other model. The other final model included also the variable $beta_{-4}$ (β = +). The β-coefficient had expected value for $sigma_{-4}$ unlike for other significant variables.

Subject 7 had three models ($p = 0.00$; Nagelkerke $R^2 \approx 0.100$; classification accuracies ≈ 98 % and 14 %) with $theta_{-4}$, BR_{-4} or HR_{-4} as the entered variable in the first block. Only $theta_{-4}$ was significant in the final model. All three models included significant variables $alpha_{-3}$ (β = +), $alpha_{-1}$ (β = +) and $sigma_{-1}$ (β = -). Two models were similar and did not include any other variables. The third model included also the variable $theta_{-4}$ (β = -). Values of alpha variables increased from accurate to unstable states as was expected except for the values of $theta_{-4}$ and $sigma_{-4}$ variables.

Subject 8 had only BA_{-2} (β = +) as significant variable in all four final models ($p = 0.00$; Nagelkerke $R^2 \approx 0.20$; classification accuracies = 100 % and 0 %). $Theta_{-4}$, BR_{-4}, BA_{-4} and HR_{-4}, and were fed into these models but neither of them was significant in the final models. BA_{-2} did not decrease from state accurate to unstable driving as was expected.

Subject 9 had sigma$_{-4}$ as the entered variable. In the final model (p = 0,00; Nagelkerke R^2 = 0.072; classification accuracies 74.4 % and 38.5 %; table 8) significant variables in addition to sigma$_{-4}$ (β = +) were HR$_{-4}$ (β = -), BA$_{-3}$ (β = +), HR$_{-2}$ (β = -), HR$_{-1}$ (β = -) and BA$_{-1}$ (β = +). All the other except BA variables had the direction of β-coefficient as expected.

3.4.2. Models including accurate and deficient states

Subject 1 had four final models with alpha$_{-4,}$ sigma$_{-4,}$ HR$_{-4}$ or BA$_{-4}$ as the entered variable each at turn. Sigma$_{-4}$ was the only one of these variables, which reached significance in its model. All final models had the values of Nagelkerke R^2 and classification accuracies for predicting the states accurate and deficient state quite similar (p = 0.00; Nagelkerke R^2 ≈ 0.33; classification accuracies ≈ 88 % and 40 %; table 9). The significant variables were the same in each model. These were sigma$_{-4}$ (β = +), HR$_{-3}$ (β = -), delta$_{-2}$ (β = +), HR$_{-2}$ (β = -), HR$_{-1}$ (β = -) and BA$_{-1}$ (β = -). These variables had the expected direction in their β-coefficients when comparing the states of accurate and deficient driving.

For subject 2, alpha$_{-4}$ was entered as the variable in the first block. Alpha$_{-4}$ was not significant and neither were the other variables in the model (p = 0.00; Nagelkerke R^2 = 1.00; classification accuracies 100 % and 100 %).

For subject 4, theta$_{-4}$, alpha$_{-4}$, sigma$_{-4}$, beta$_{-4}$ or HR$_{-4}$ was the entered variable in the first block of the analysis. Theta$_{-4}$ was the only significant variable. In all five final models (p ≈ 0.01; Nagelkerke R^2 ≈ 0.2; classification accuracies ≈ 100 % and 0 %) theta$_{-4}$ (β = +) was the significant variable. In addition BA$_{-3}$ (β = -) was a significant variable in one model. The directions in the β-coefficients of theta$_{-4}$ and BA$_{-3}$ were as expected.

Two final models of subject 7 (Nagelkerke R^2 ≈ 0.2; classification accuracies ≈ 100 % and 4.5 %) included alpha$_{-4}$ or HR$_{-4}$ as the entered variable. Alpha$_{-4}$ (β = +) was significant in its model. Theta$_{-3}$ (β = -), delta$_{-3}$ (β = +) and BA$_{-1}$ (β = -) were significant variables in both models. In addition to these, beta$_{-4}$ (β = +) was a significant variable in another model. The β-coefficient values of beta$_{-4}$ and theta$_{-3}$ were not in the expected direction. Instead, the other variables showed the expected direction in their β-coefficients.

For subject 8 the entered variable $theta_{-4}$, $alpha_{-4}$, $sigma_{-4}$, $beta_{-4}$, BR_{-4}, BA_{-4} or HR_{-4} was not significant in their final models (p =0.00; Nagelkerke $R^2 \approx 0.6$; classification accuracies = 100 % and 33.3 %; table 9). Two models did not include any significant variables and BR_{-4} ($\beta = +$) was the only significant variable in five models. The β-coefficient of BR_{-4} increased from accurate driving to deficient driving according to the hypotheses.

The significant variables in the models for each subject differed between both dependent variables. However, the direction of the β-coefficients of a particular variable (for example HR_{-1}) for each subject was always the same for both dependent variables (table 10). The direction of the β-coefficients for each subject was also usually the same for a particular variable type (for example variables of HR) independently of the dependent variable. Only subject 4 had a difference in the direction of the β-coefficients of the variable theta when comparing both dependent variables (table 10).

TABLE 8. Results of logistic regression analyses for accurate and unstable driving states

The analyses were carried out as logistic regression with the forward Wald method. The independent variables were fed as different blocks into the model. The entered variable is the one which was significant in the logistic regression analysis as the unique independent variable (table 6) when comparing the accurate and unstable driving categories. The entered variable is the variable of the first block. Other independent variables are fed into the four blocks of the logistic regression analysis as a method of forward Wald. Significances of final model and variables Nagelkerke R^2, classification accuracies and the sign of β-coefficients are presented. Nagelkerke R^2 signifies the predictive part of the model, classification accuracies denote the percentages of epochs (epoch = 15.5 s) rated correctly into categories of accurate (% correct 1) and unstable driving (% correct 2) based on the final models. The sign of a β-coefficient is presented as a plus or minus signifying the decrement or increment in the values of the independent variables from accurate to unstable driving. All variables of the final models are presented, despite only significant variables ($p \leq 0.05$)were accepted.

Subject	1	1	1	1	2	3	3
1st block	alpha$_{-4}$	sigma$_{-4}$	BA$_{-4}$	HR$_{-4}$	theta$_{-4}$	sigma$_{-4}$	BR$_{-4}$
Sig of variables	alpha$_{-4}$ 0.383 -	sigma$_{-4}$ 0.00 +	BA$_{-4}$ 0.782 -	HR$_{-4}$ 0.074 -	theta$_{-4}$ 0.070 -	sigma$_{-4}$ 0.075 -	BR$_{-4}$ 0.020 +
in model	sigma$_{-4}$ 0.001 +	HR$_{-4}$ 0.074 -	sigma$_{-4}$ 0.000 +	sigma$_{-4}$ 0.000 +	beta$_{-3}$ 0.048 -	BR$_{-4}$ 0.020 +	sigma$_{-4}$ 0.075 -
	HR$_{-4}$ 0.007 -	beta$_{-3}$ 0.042 +	HR$_{-4}$ 0.066 -	beta$_{-3}$ 0.042 +		delta$_{-3}$ 0.011 -	delta$_{-3}$ 0.011 -
	theta$_{-4}$ 0.015 +	HR$_{-3}$ 0.001 -	beta$_{-3}$ 0.037 +	HR$_{-3}$ 0.001 -		sigma$_{-1}$ 0.020 -	sigma$_{-1}$ 0.020 -
	HR$_{-3}$ 0.004 -	BA$_{-3}$ 0.227 -	HR$_{-3}$ 0.001 -	BA$_{-3}$ 0.227 -			
	BA$_{-3}$ 0.152 -	BA$_{-1}$ 0.006 -	BA$_{-1}$ 0.002 -	BA$_{-1}$ 0.006 -			
	BA$_{-1}$ 0.005 -						
Sig of model	0.000	0.000	0.000	0.000	0.005	0.000	0.000
Nagelkerke R^2	0.164	0.160	0.157	0.160	0.154	0.138	0.138
% correct 1	67.7	66.4	66.4	66.4	100	100	100
% correct 2	58.8	61.5	61.9	61.5	0	0	0

(continues)

TABLE 8. (continues).

Subject	4	4	4	5	6	6
1st block	theta$_{-4}$	alpha$_{-4}$	BR$_{-4}$	BA$_{-4}$	sigma$_{-4}$	beta$_{-4}$
Sig of variables	theta$_{-4}$ 0.082 +	alpha$_{-4}$ 0.028 +	BR$_{-4}$ 0.047 +	BA$_{-4}$0.084 +	sigma$_{-4}$ 0.009 +	beta$_{-4}$ 0.024 +
in model	BR$_{-4}$ 0.011 +	BR$_{-4}$ 0.047 +	alpha$_{-4}$ 0.028 +	theta$_{-3}$ 0.015 -	alpha$_{-4}$ 0.082 -	theta$_{-3}$ 0.006 -
	theta$_{-2}$ 0.005 -	theta$_{-2}$ 0.005 -	theta$_{-2}$ 0.005 -	theta$_{-2}$ 0.001 -	theta$_{-3}$ 0.015 -	HR$_{-3}$ 0.009 +
	BA$_{-2}$ 0.001 -	BA$_{-2}$ 0.001 -	BA$_{-2}$ 0.001 -	delta$_{-2}$ 0.002 +	HR$_{-3}$ 0.015 +	
	alpha$_{-1}$ 0.023 +	BR$_{-1}$ 0.036 +	BR$_{-1}$ 0.036 +			
Sig of model	0.00	0.00	0.00	0.00	0.00	0.00
Nagelkerke R^2	0.088	0.089	0.089	0.163	0.055	0.049
% correct 1	99.1	99.4	99.4	100	27.0	26.5
% correct 2	3.4	2.6	2.6	0	87.3	86.9

Subject	7	7	7	8	8	8	8	9
1st block	theta$_{-4}$	BR$_{-4}$	HR$_{-4}$	theta$_{-4}$	BR$_{-4}$	BA$_{-4}$	HR$_{-4}$	sigma$_{-4}$
Sig of variables	theta$_{-4}$ 0.011 -	BR$_{-4}$ 0.336 -	HR$_{-4}$ 0.336 -	theta$_{-4}$ 0.483 +	BR$_{-4}$ 0.190 +	BA$_{-4}$ 0.386 +	HR$_{-4}$ 0.808 +	sigma$_{-4}$ 0.031 +
in model	alpha$_{-4}$ 0.795 +	theta$_{-3}$ 0.098 -	theta$_{-3}$ 0.098 -	BR$_{-4}$ 0.266 +	BR$_{-3}$ 0.078 +	BR$_{-4}$ 0.280 +	BR$_{-4}$ 0.227 +	HR$_{-4}$ 0.048 -
	alpha$_{-3}$ 0.006 +	alpha$_{-3}$ 0.003 +	alpha$_{-3}$ 0.003 +	BR$_{-3}$ 0.078 +	BA$_{-2}$0.017 +	BR$_{-3}$ 0.095 +	BR$_{-3}$ 0.080 +	BA$_{-3}$ 0.044 +
	alpha$_{-1}$ 0.000 +	sigma$_{-1}$ 0.025 -	sigma$_{-1}$ 0.025 -	BA$_{-2}$ 0.022 +		BA$_{-2}$ 0.033 +	BA$_{-2}$ 0.018 +	HR$_{-2}$ 0.024 -
	sigma$_{-1}$ 0.028 -	alpha$_{-1}$ 0.000 +	alpha$_{-1}$ 0.000 +					HR$_{-1}$ 0.037 -
								BA$_{-1}$ 0.010 +
Sig of model	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nagelkerke R^2	0.100	0.096	0.096	0.199	0.196	0.200	0.197	0.072
% correct 1	97.9	97.9	97.9	100	100	100	100	74.4
% correct 2	12.3	14.3	14.3	0	0	0	0	38.5

TABLE 9. Results of logistic regression analyses for accurate and unstable driving states

The analyses were carried out as logistic regression with the forward Wald method. The independent variables were fed as different blocks into the model. The entered variable is the one which was significant in the logistic regression analysis as the unique independent variable (table 7) when comparing the accurate and deficient driving categories. The entered variable is the variable of the first block. Other independent variables are fed into the four blocks of the logistic regression analysis as a method of forward Wald. Significances of final model and variables Nagelkerke R^2, classification accuracies and the sign of β-coefficients are presented. Nagelkerke R^2 signifies the predictive part of the model, classification accuracies denote the percentages of epochs (epoch = 15.5 s) rated correctly into categories of accurate (% correct 1) and deficient driving (% correct 3) based on the final models. The sign of a β-coefficient is presented as a plus or minus signifying the decrement or increment in the values of the independent variables from accurate to deficient driving. All variables of the final models are presented, despite only significant variables ($p \leq 0.05$) were accpeted.

Subject	1	1	1	1	2	4	4	4
1^{st} block	alpha$_{-4}$	sigma$_{-4}$	BA$_{-4}$	HR$_{-4}$	alpha$_{-4}$	theta$_{-4}$	alpha$_{-4}$	sigma$_{-4}$
Sig of variables	alpha$_{-4}$ 0.723 -	sigma$_{-4}$ 0.000 +	BA$_{-4}$0.503+	HR$_{-4}$ 0.497 -	alpha$_{-4}$ 0.997 +	theta$_{-4}$ 0.013 +	alpha$_{-4}$ 0.113 +	sigma$_{-4}$ 0.146 +
in model	sigma$_{-4}$ 0.003 +	HR$_{-4}$ 0.497 -	sigma$_{-4}$ 0.00 +	sigma$_{-4}$ 0.00 +	sigma$_{-3}$ 0.998 -	BA$_{-3}$ 0.021 -	theta$_{-4}$ 0.019 +	theta$_{-4}$ 0.017 +
	HR$_{-4}$ 0.509 -	beta$_{-3}$ 0.116 +	HR$_{-4}$ 0.433 -	beta$_{-3}$ 0.116 +	BR$_{-1}$ 0.995 +			
	beta$_{-3}$ 0.119 +	HR$_{-3}$ 0.021 -	beta$_{-3}$ 0.118 +	HR$_{-3}$ 0.021 -				
	HR$_{-3}$ 0.021 -	delta$_{-2}$ 0.005 +	HR$_{-3}$ 0.019 -	delta$_{-2}$ 0.005 +				
	delta$_{-2}$ 0.005 +	HR$_{-2}$ 0.007 -	delta$_{-2}$ 0.004 +	HR$_{-2}$ 0.007 -				
	HR$_{-2}$ 0.007 -	BA$_{-2}$ 0.093 -	HR$_{-2}$ 0.007 -	BA$_{-2}$ 0.093 -				
	BA$_{-2}$ 0.105 -	HR$_{-1}$ 0.012 -	BA$_{-2}$ 0.075 -	HR$_{-1}$ 0.012 -				
	HR$_{-1}$ 0.012 -	BA$_{-1}$ 0.036 -	HR$_{-1}$ 0.012 -	BA$_{-1}$ 0.036 -				
	BA$_{-1}$ 0.037 -		BA$_{-1}$ 0.031 -					
Sig of model	0.00	0.00	0.00	0.00	0.00	0.004	0.01	0.014
Nagelkerke R^2	0.328	0.328	0.329	0.328	1.00	0.240	0.2	0.186
% correct 1	87.9	87.9	88.7	87.9	100	100	100	100
% correct 3	42.3	40.4	43.3	40.4	100	25.0	10	0

(continues)

TABLE 9. (continues).

Subject	4	4	7	7	8	8	8	8
1st block	beta$_{-4}$	HR$_{-4}$	alpha$_{-4}$	HR$_{-4}$	theta$_{-4}$	alpha$_{-4}$	sigma$_{-4}$	Beta$_{-4}$
Sig of variables	beta$_{-4}$ 0.063 +	HR$_{-4}$ 0.074 +	alpha$_{-4}$ 0.028 +	HR$_{-4}$ 0.072 -	theta$_{-4}$ 0.075 +	alpha$_{-4}$ 0.827 +	sigma$_{-4}$ 0.168 +	beta$_{-4}$ 0.138 +
in model	theta$_{-4}$ 0.015 +	theta$_{-4}$ 0.012 +	HR$_{-4}$ 0.194 -	beta$_{-4}$ 0.014 +	BR$_{-4}$ 0.088 +	BR$_{-4}$ 0.021 +	BR$_{-4}$ 0.033 +	BR$_{-4}$ 0.047 +
			theta$_{-3}$ 0.003 -	theta$_{-3}$ 0.002 -				
			delta$_{-3}$ 0.003 +	delta$_{-3}$ 0.004 +				
			BA$_{-1}$ 0.006 -	BA$_{-1}$ 0.007 -				
Sig of model	0.012	0.008	0.00	0.00	0.00	0.00	0.00	0.00
Nagelkerke R^2	0.193	0.211	0.201	0.213	0.637	0.543	0.577	0.587
% correct 1	100	100	99.8	99.5	100	100	100	100
% correct 3	0	0	4.5	4.5	33.3	33.3	33.3	33.3

Subject	8	8	8
1st block	BR$_{-4}$	BA$_{-4}$	HR$_{-4}$
Sig of variables	BR$_{-4}$ 0.014 +	BA$_{-4}$ 0.29 +	HR$_{-4}$ 0.301 +
in model		BR$_{-4}$ 0.039 +	theta$_{-4}$ 0.072 +
			BR$_{-4}$ 0.096 +
Sig of model	0.00	0.00	0.00
Nagelkerke R^2	0.542	0.580	0.667
% correct 1	100	100	100
% correct 3	33.3	33.3	33.3

4. DISCUSSION

In this study, the psychophysiological variables preceding the three driving quality states (accurate, unstable and deficient) from 15 s to 1 min, were examined. The study was conducted with sleep-deprived participants as a night-time simulator-study. It was found that the driving quality was impaired with time on task (figure 1). The number of epochs classified as unstable and deficient state of driving increased along the driving time. Differences in averages among the three states of driving quality and between accurate and deficient states of driving were analyzed with MANOVA tests (table 5). $Beta_{-4}$ reached significance ($p = 0.015$) in the MANOVA when comparing the three driving quality states, but not in the paired samples t-tests (accurate against unstable state and accurate against deficient state). Logistic regression analyses were carried out at the subject level (table 8 & table 9). In the final significant models, Nagelkerke R^2 ranged from 0.049 to 0.200 and from 0.186 to 0.667 and correct prediction rates of impaired driving from 0 to 87.3 % and from 0 to 43.3 % for accurate and unstable states of driving and for accurate and deficient states of driving, respectively. The significant psychophysiological variables changed often from accurate state to unstable or deficient as expected, but more often when moving from accurate to deficient state than from accurate to unstable state.

4.1. A closer look at the results

To find out how the hypotheses were supported after non-significant tests of averages, the results of the analyses made at the subject level were summarized. The signs of the β-coefficients of the significant variables for each subject and for both dependent variables were entered into the table independently of the rate of occurrence in different models. This was possible because the direction of the β-coefficient of a particular variable was always the same for each subject.

Delta power

When predicting the accurate and unstable states of driving, the values of delta increased from accurate to unstable states according to the hypothesis for one out of two subjects (table 10). When the accurate and deficient driving states were predicted, the delta variables were also significant for two subjects. For these subjects the averages increased from accurate to deficient driving as expected. The significant variables of delta were $delta_{-2}$ and $delta_{-3}$, both being significant once in predicting the accurate and unstable driving states, and accurate and deficient driving.

Increases in delta with time on task (Torsvall & Åkerstedt, 1987), before sleep onset (St 2), and during St 2 (Hori, 1995; Ogilvie et al., 1991) have been reported. The probable reason for not increasing the power of delta from accurate to unstable state of driving for both subjects in this study could be that the driver was not sleepy enough during unstable driving. Delta frequencies are however more pronounced in deeper sleep stages (Retchaffen & Kales, 1968). The increase in power from accurate state to deficient supports that notion**.**

Theta power

The variables of theta were significant for five subjects when predicting accurate and unstable driving (table 10). According to the β-coefficient values, theta increased for one of those five subjects along with the hypothesis. When predicting accurate and deficient driving, the power of theta increased, according to the hypothesis, for one of two subjects. The discrepancy with the hypothesis was also evident in the variables $theta_{-2}$ and $theta_{-3}$: contrary to the hypothesis, theta decreased from accurate to unstable state of driving for two subjects. In addition to them, $theta_{-4}$ predicted as expected for two out of thee subjects.

The power of theta has been reported to increase with time on task (Torsvall & Åkerstedt, 1987; Campagne et al., 2004) as well as before and during SO (Hori, 1995; Ogilvie et al., 1991). Theta is often treated as one of the most evident bandwidths for predicting sleepiness (Retschaffen & Kales, 1968; Hori et al., 1994; Santamaria & Chiappa, 1987). Thus, the reasons for the decrease of theta power in four subjects when predicting the states of accurate and unstable driving is unclear. Decreases of theta power towards the onset of sleep have not been found in any of the articles referred in this study. Instead, according to the study of Horne and Baulk (2004), the drifting out of the lane was accompanied with high alpha/theta power (4-11 Hz). In some sleep studies, the increase is found to be most evident in central sites (De Gennaro et al., 2001b) or slowest in occipital area (Hori, 1995), but increases of theta power should still occur at occipital sites. The discrepancy concerning theta is also found in some referred articles. According to the study of Eoh et al. (in press), the theta activity can only be found in continuous sleep, whereas according to Åkerstedt et al. (1991), theta would have occurred if the subject had been prevented from sleeping.

Alpha power

Based on the hypotheses, the values of alpha variables increased for two subjects from accurate to unstable driving as expected (table 10). The value of alpha variable also increased from state accurate to deficient driving according to hypothesis for one subject, for whom this variable was significant. The power of $alpha_{-1}$ and $alpha_{-4}$ changed also according to the hypothesis from accurate to unstable or deficient driving for these subjects, who had the any alpha variable as significant.

In addition to increases in alpha power with time on task (Torsvall & Åkerstedt, 1987; Åkerstedt et al., 1991; Shiozawa et al., 1995; Campagne et al., 2004; Eoh et al., in press) and before and during sleep episodes with shift workers (Åkerstedt et al., 1991), alpha power has been found to correlate with lane variability in simulator study of Risser et al. (2000). Thus it was interesting that it was not significant for more than two subjects in this study. One reason for this may be, that the EEG-variables were measured at Oz-channel, and alpha power has been reported to decrease before Stage 2 (Ogilvie et al., 1991) at occipital areas (De Gennaro, 2001a; 2001b), before it starts to increase at the onset of Stage 2 (De Gennaro, 2001a; 2001b). But, both of these subjects had two significant alpha variables when comparing the states of accurate and unstable driving. In addition, alpha changed always according to hypothesis. Therefore, alpha seems to be a quite reliable measure for some subjects.

Sigma power

The sigma power predicted accurate and unstable states of driving for five subjects (table 10). The power increased in three out of five subjects from accurate to unstable driving. Instead, from accurate to deficient driving states, variables of sigma were significant only for one subject. This value increased according to the hypothesis. $Sigma_{-4}$ was the variable, which was a significant predictor for four subjects. It increased from accurate to unstable or deficient driving according to the hypothesis for these four subjects. $Sigma_{-1}$ was instead the variable, which decreased for two subjects from accurate to unstable driving.

The increase in the power of sigma has been reported with time on task (Shiozawa et al., 1995) as well as in sleep studies before and during sleep onset (Hori, 1995; Ogilvie et al., 1991). The occurrence of sigma or sleep spindle occurs at Stage 2 according to the sleep scale of Retschaffen & Kales (1968). Thus, it is quite interesting that $sigma_{-4}$ showed increases in power for three subjects from accurate to unstable driving, but decreases in power of $sigma_{-1}$ for two subjects. At the individual level, sigma was one of the variables, which predicted driving impairment for most of the subjects.

Beta power

Contrary to the hypothesis, the values of beta variables increased for two out of three subjects from accurate to unstable driving (table 10). Beta power was also significant for one subject when predicting accurate and deficient driving. Also contrary the hypothesis, the power increased for this particular subject. $Beta_{-4}$ was the variable which increased as expected from accurate to unstable or deficient driving with two subjects.

The results of beta power were mostly contrary to the hypothesis. In addition to decreases in beta power with driving time (Eoh et al., in press), beta power has been reported to decrease before SO (Ogilvie et al., 1991; De Gennaro et al., 2001b) and to increase (Ogilvie et al., 1991) or decrease (De Gennaro et al., 2001) at behavioural SO. According to Santamaria & Chiappa (1987), centro-frontal beta can occur at sleep onset, but it can also be a sign of arousal. Thus, the literature is partly contradictory about the occurrence of beta power and does not explain the results of this study. One possible explanation of these contradictory results could be that the significant beta variables were either $beta_{-3}$ or $beta_{-4}$, and the possible decrease of beta power detected by Eoh et al. (in press) occurs closer in time to the moment of driving impairment.

BR

Values of BR variables increased as expected from accurate to unstable states for both subjects who showed significant BR variables (table 10). BR was significant for one subjects when comparing accurate and deficient driving. It increased according to the hypothesis. Also, BR_{-4} increased from accurate to unstable or deficient driving according to hypothesis for three subjects.

Blink rate always increased from accurate to impaired driving (unstable or deficient) according to the hypothesis. Therefore, BR was a quite reliable measure of impaired driving. In addition to increases of blink rate in driving tasks (Shiozawa et al., 1995; Summala et al., 1999), long blink rate has also been found to change with behavioural sleepiness (Verwey et al., 2000) or to predict sleepiness level during driving (Numata et al., 1998) in a driving simulator. Hence, it seems possible that significant results could have been obtained using the rate of long blinking with more subjects as a variable.

BA

When comparing the states of accurate and unstable driving, BA was significant for four subjects (table 10). It increased along with the hypothesis in two out of four subjects. For predicting the states of accurate and deficient driving, the variables of BA decreased according to the hypothesis for three subjects. Thus, the BA appeared to be a more powerful measure with increased driving impairment. BA_{-1} decreased significantly for two out of three subjects, and in general, the BA_{-4} was not significant for any subject unlike the other variables of BA.

Blink amplitude (BA) was found to be one of the best predicting variables in a simulated flight study with pilots (Morris & Miller, 1996). In the present study it was also the variable, which predicted the driving quality for more subjects than any of the other variables when predicting accurate and deficient driving states. The reason for these results, partly contrary to the hypotheses when predicting accurate and unstable states, could be that the blink detection was not perfect because the vertical EOG channel was overloaded by blinks in some occasions. This affected the calculation of blink amplitude averages, and perhaps diminished its significance and predictive power.

HR

The values of HR decreased as expected in two out of three subjects (table 10). HR was significant for three subjects when predicting accurate and unstable states and decreased for two of them as was expected. When predicting accurate and deficient states of driving, HR was significant for one subject and decreased as was expected. HR_{-4} decreased according to hypothesis for two subjects accurate to unstable driving. For these two subjects, at least two variables of HR decreased when predicting the states of from accurate and unstable driving, and accurate and deficient driving. Thus, HR seems to be a quite reliable measure predicting driving quality for those subjects.

Even though the heart rate has been reported to decrease at sleep onset (Pivik & Busby, 1996; Burgess et al., 1999), it has not been found to decrease with time on task in many studies (Egelund, 1982; Torsvall & Åkerstedt, 1987; Åkerstedt et al., 1991). In spite of this it has also been found to decrease in driving tasks (Brookhuis & de Waard, 1993) as it did in this experiment. The HR increased from accurate to unstable driving only for subject 6.

As a total 21 different variables predicted significantly the accurate and unstable states of driving quality (table 10). From these, 11 were significant for two subjects and one for three subjects. Thus the predicting variables varied widely among subjects.

In the case of accurate vs. deficient states, 13 different variables were found, which predicted significantly the driving for four subjects (table 10). These variables predicted also the states of accurate and unstable driving. Because of this there seems to be some correspondence between the results of both dependent variables.

TABLE 10. The direction of the β-coefficient of the significant variables
The direction of the β-coefficients of every significant variable of each subject in the final models of logistic regression analyses are shown in the final models of the subjects in the logistic regression analyses. The dependent variables were accurate vs. unstable states, and accurate vs. deficient states of driving. The columns of accurate vs. deficient (D) driving are separated from rows of accurate vs. unstable (U) driving by shadowing. Some subjects do not have a column for accurate vs. deficient driving because they did not have any epoch classified as deficient driving, because they did not have any significant variable to enter into the first block of the logistic analyses, or because their model did not show any significant variable. The index in the name of variable denotes the epoch before the driving impairment. One epoch has length of 15.5 s.

Driving quality	U	D	U	U	U	D	U	U	U	D	U	D	U
Subject	1	1	2	3	4	4	5	6	7	7	8	8	9
delta$_{-1}$													
delta$_{-2}$		+					+						
delta$_{-3}$				–						+			
delta$_{-4}$													
theta$_{-1}$													
theta$_{-2}$					–		–						
theta$_{-3}$							–	–		–			
theta$_{-4}$	+					+			–				
sigma$_{-1}$				–					–				
sigma$_{-2}$													
sigma$_{-3}$													
sigma$_{-4}$	+	+						+					+
alpha$_{-1}$					+				+				
alpha$_{-2}$													
alpha$_{-3}$									+				
alpha$_{-4}$					+					+			

(continues)

TABLE 10. (continues)

Driving quality	U	D	U	U	U	D	U	U	U	D	U	D	U
Subject	1	1	2	3	4	4	5	6	7	7	8	8	9
beta$_{-1}$													
beta$_{-2}$													
beta$_{-3}$	+		–										
beta$_{-4}$								+		+			
BR$_{-1}$					+								
BR$_{-2}$													
BR$_{-3}$													
BR$_{-4}$				+	+							+	
BA$_{-1}$	–	–								–			+
BA$_{-2}$					–						+		
BA$_{-3}$						–							+
BA$_{-4}$													
HR$_{-1}$		–											–
HR$_{-2}$		–											–
HR$_{-3}$	–	–						+					
HR$_{-4}$	–												–

In general, it seems that some variables reflected driving quality better than the others. Theta, sigma and BA were the best predictors. The direction of the β-coefficient was not always in line with the hypothesis and it was different among subjects. Theta and beta were mostly against the hypotheses when predicting driving quality. The significant variables for predicting states were most often the variables at time of epoch$_{-4}$ for both dependent variables, but the significant variables were the ones in other epochs too. This means that the driving impairment is detectable through psychophysiological variables starting at least one minute before the incident, and that driving states further progress towards greater impairment. The predictability of driving errors from EEG variables is supported also by the result of Horne and Baulk (2004). According to this study, changes in EEG power are closely followed by driving incidents (Horne & Baulk, 2004). According to study of Numata et al (1998), a warning signal of driver sleepiness should be set to the level of sleepiness, which was reached in time minute before the crash.

Some methodological reasons that may have affected the significance of the logistic regression models are considered in the next chapter.

4.2. Discussion: methodology

4.2.1. The adequacy of the models

In this study, the simulated driving task for each subject was planned to have a duration of three hours. Eight out of nine subjects drove until this time was completed. Only one subject interrupted the driving because of sleepiness. There were also technical problems with this subject**,** which diminished the number of useful epochs to 145, while other subjects had over 600 epochs (table 4). Even though the number of epochs was sufficient for most of the subjects, the amount of epochs in the three driving quality states was not. In spite of these, every subject who had some epochs of unstable or deficient driving was included in the analyses.

The models of the dependent variables for each subject based on Nagelkerke R^2 were almost as good as based on the correct classification of driving quality states. Despite of high Nagelkerke R^2 values, the correct classifications of unstable and deficient states of driving were not very high. Nevertheless, there were some subjects with such high classification accuracies (> 40 %; subject 1; table 8 and table 9). The main reason for low classification accuracies of unstable and deficient state is a small number of epochs in those states. The connections between frequencies and goodness of the models are evident.

Two subgroups of drivers can be defined based on the frequency table (table 4) of the driving quality. One group had worse driving performance than the other. Those who had low frequency of epochs in unstable driving (< 30; subjects 2, 3, 5 and 8) were the same ones, who had low frequency of epochs in deficient driving (< 5). Participant 2 belonged to this group only because of the shorter experimental time. The other subjects (1, 6, 7 and 9) had more epochs in unstable state (< 100) and in deficient state (≥ 25). Participant 4 was the only one who did not fit into this pattern; high frequency of epochs in unstable driving state did not accompany the high frequency in deficient state of driving (table 4).

When the categories of accurate and unstable driving formed the dependent variable, the subjects with a small number of epochs rated 0 % for prediction of unstable state of driving and quite high Nagelkerke R^2 values (Nagelkerke $R^2 \geq 0.138$; table 4 and table 8). The subjects who had higher frequencies had mainly higher classification accuracies of unstable state of driving (with majority of subjects > 12 %) but lower R^2 values (Nagelkerke R^2 = 0.049-0.164). The increased amount of epochs in unstable state of driving increased the percent of classification accuracies of unstable state but not Nagelkerke R^2. One reason for the lower value of Nagelkerke R^2 could be that the states of accurate and unstable driving were not discriminative enough and the variability within these categories was too high. It is interesting that partly the same subjects who had small number of epochs in state of unstable driving also had the β-coefficient values contrary to the hypotheses in over half of the significant variables (subj. 3, 5, 6 and 8; table 4 and table 8).

When accurate and deficient states of driving formed the dependent variable there was not such pattern as with the other dependent variable between the number of epochs in driving quality states, Nagelkerke R^2 and classification accuracies. Instead higher Nagelkerke R^2 values and higher classification accuracies for deficient category tended to accompany each other (Nagelkerke $R^2 \geq 0.328$; prediction rate of deficient state ≥ 33.3 % vs. Nagelkerke $R^2 \leq 0.21$; prediction rate of deficient state ≤ 10 %; table 4 and table 9). The reason for higher values could be that the states of accurate and deficient driving differed enough unlike accurate and unstable states of driving. This can be also a reason why the values of R^2 and some classification accuracies of driving quality states were higher with this dependent variable than with the previous one, even though the frequencies in deficient driving quality state were a lot smaller than in unstable state of driving. Accurate and deficient driving quality states were also predicted more often according to the hypotheses than accurate and unstable states.

More epochs in this deficient state could result in models with higher R^2 values and classification accuracies. This is supported by the fact that for some subjects, the classification accuracies of deficient category were surprisingly high in some models even though there were only a few epochs classified as deficient driving (subj. 4: 25 %; subj. 8: 33.3 %; table 9). Thus, it seems possible that for these subjects more epochs in the deficient state of driving would increase the validity and classification accuracy of deficient driving. Basically, Nagelkerke R^2 should present directly the predicting part of the model with dependent variable (Metsämuuronen, 2003). On the other hand, too few data compared to the number of variables can cause R^2 values to be too high (Metsämuuronen, 2003). This may be one reason for high R^2 values while predicting the deficient category.

Unequal number of epochs in three driving quality states of subjects and across subjects increased the variability. Particularly, the small amount of epochs in deficient driving state caused validity problems. Four subjects did not have any model where accurate and deficient states of driving formed the dependent variable. Subjects 3 and 5 did not have any epochs of deficient driving (table 4), and subjects 6 and 9 did not have any significant variable entered into the first block of the model on the multiple variable logistic analysis (table 7). The small number of epochs in state of deficient driving increased the variability among subjects in the logistic regression analyses as well as the variability within and across subjects in the MANOVAs. Also inter-individual differences of independent variables increased the standard deviation between subjects in the MANOVA tests; the SD on the EEG variables was higher than the average.

MANOVA and logistic regression analyses can only use complete rows of data. Therefore the MANOVAs were performed on the averages of subjects, even though MANOVAs computed on the primary data of the subjects could have been better. Equal number of epochs in each state of driving quality should be desirable. With incomplete data, the use of statistical mixed models, would be a better approach to explore driving qualities. Another methodological flaw of this study was that the same subjects formed the categories of the dependent variables, which is not ideal in logistic regression analysis (Metsämuuronen, 2003).

4.2.2. Measuring driver fatigue

The basic assumption of this study was that the driving impairments reflect drowsiness or diminishing of alertness. This assumption is supported by the study of Campagne et al. (2004). They found that running-of-the-road-incidents (RORIs) or speed deviations can reflect changes of alertness (Campagne et al., 2004). Time on task effects are difficulties in guiding the vehicle (Rogé et al., 2002), more frequent and longer RORIs

(Campagne et al., 2004) or an increase in the number of accidents (Eoh et al., 2004). These effects were found also in this study either as evident increase in number of unstable and deficient states of driving or as a trend within subjects who had smaller number of epochs classified as unstable or deficient quality of driving.

In the study with monotonous driving at night-time by Verwey and Zaidel (2000) the error hierarchy was used for classification. As a result they considered more common and less serious incidents as possible predictors of the more serious incidents (Verwey & Zaidel, 2000). The results are similar to the observations made in this research. Subjects could have unstable driving quality (meaning short crossings of the lines on the track some time), but the deficient driving (meaning driving out of the road or crash) did not necessarily follow these smaller incidents. However, often the more severe incidents were preceded or accompanied by the smaller ones, even though over ratings were excluded. This observation and the result of Verwey and Zaidel (2000) support the idea of summing the less important and more relevant driving incidents assuming that they could reflect the same state (diminishing of alertness) but differ in its severity.

The problem with summing driving errors with different severity and type, is that the weighting of incidents is difficult. In this study two wheels out of the road (over the lane marking) and near crash, and four wheels out of the road (over the lane marking) and crash were evaluated similarly. The latter ones were estimated to be 2.5 times more severe than the preceding ones. These suppositions can naturally bear sources of error. The range of summed variable was divided into three ranges, which were decided to represent accurate, unstable and deficient categories of driving quality. These three categories covered each a wide range of summed variable and could partly overcome the issue of wrong weighting of incidents. The frequencies in the three categories, more specifically the small frequencies in the deficient state, could be a consequence of wrong classification or weighting of cases. The small frequencies of epochs in state of deficient driving could also mean that subjects were not sleepy enough. After one night of sleep-restriction, the more plausible explanation could be also that some subjects may have fought more strongly against sleepiness than others.

When considering the validity of simulated driving compared to real situations, it is assumed that the diminishing of attention or falling asleep follow the same pattern in simulated or real driving situation. In addition, the use of sleep deprivation or monotonous environments in simulator to induce sleepiness and falling asleep has this same point of view: the investigated phenomenon is the same independently of situation that induced it. However, the important difference between driving simulator task and field-task is that subject may not fight against the sleep as strongly in simulated environment as in the real environment. This can occur because the subjects know that there will not be disastrous consequences if they fall asleep. Apart from this, some subjects took the experiment more seriously. One subject bit his lip to prevent falling asleep. Differences in personality could explain some of the differences in falling asleep while driving, and perhaps fight against sleep. Sensation seeking extraverts seem to be more sensitive to fatigue-related driving errors (Thiffault & Bergeron, 2003a). According to other study, falling asleep and departure from the road were more typical for subjects who scored high on extraversion-boredom cluster based on principal component analysis, and crossing the lane markings was more typical for subject who scored high on disinhibition-honesty cluster (Verwey & Zaidel, 2000).

Åkerstedt et al. (1991) have stated the effect of fighting against sleep into psychophysical variables. According to them, it is possible that polysomnographic manifestations occur only when subject is sleepy enough, fights against sleep and is prevented from sleeping (Åkerstedt et al., 1991). In earlier study of this group with train drivers at night-time it was found that alpha bursts were part of dozing off and represented the failure to fight against sleep (Torsvall & Åkerstedt, 1987). Thus the explanation of this study to the contradictory results of EEG variables on the basis of the hypothesis and further for low classification accuracy percents while predicting the accurate and unstable or deficient states of driving could be that the subjects were not sleepy enough. This could also explain why the impaired driving occurred very rarely. Also performing an activating task could result that the sleep-deprivation is not visible in continuous EEG/EOG recording (Kecklund & Åkerstedt, 1993). In the simulator study with monotonous surroundings, and after one night of sleep deprivation, neither the lack of sleepiness is not quite likely and nor the finding the driving task as activating. Hence other reasons for the rare occurrence of impaired driving need to be considered.

The epoch length is essential when studying sleepiness. According to the study of Numata et al. (1998) the prediction of sleepiness should be done in blocks shorter than 75 s. In a study with train drivers failing to act on signals was accompanied by 20 s of alpha bursts and rolling eyes on the EOG (Torsvall & Åkerstedt, 1987). Even if the

EEG activity of sleepiness could be possible to detect as bursts, it might be that the epoch length of 15.5 is not able to capture power changes of different band widths even though threshold activity level of bursts would be 150 % of individual's normal activity level as used in the study by Kecklund and Åkerstedt (1993). They analyzed bursts as 7.5 s segments to avoid the diminishing of bursts in averaging (Kecklund & Åkerstedt, 1993) and found that amount of alpha and theta bursts increased within the last hours of driving at night-time. The analysis of bursts has also yielded other meaningful results in driving fatigue research. In the study of Eoh et al. (in press) the amount of alpha and theta bursts increased with driving time. According to their study, the length of a segment in a burst analysis should be less than 7.5 s. The bursts had durations of 1-3 s. According to them, theta activity can only be found in continuous sleep, and in burst analysis because of microsleeps (Eoh et al., in press). Too long epochs could explain some of the results contrary to hypothesis of theta power and other variables of this research.

The issue of microsleep in driver fatigue is supported also by Lal and Craig (2005). According to them, driver fatigue consists of episodes of microsleeps and the fatigue state can only occur during these episodes (Lal & Craig, 2005; microsleep: Harrison & Horne, 1996). On the basis of the blink duration in a field-study with bus-drivers the length of microsleeps was 0.69 s. (Häkkanen, Summala, Partinen, Tihonen & Silvo, 1999). The occurrence of microsleeps could also explain why the frequencies of impaired driving in this study were quite rare: subjects were able to correct the course of the car before the incident. Thus, it seems that a burst analysis and detection of microsleeps would yield better results in driving studies as predictor of sleepiness than using time segments of 15 s. Also the recording of the EEG-variables and predicting the driving quality on the basis of one channel is not an optimal solution. More channels are needed to obtain more reliable information from the EEG during driver sleepiness.

5. CONCLUSION

In this research it was found that the averages of the psychophysiological variables did not differ significantly between the different driving quality states. The psychophysiological variables predicted driving quality states more frequently according to the hypotheses. However, the prediction of driving quality was not very consistent for most of the subjects.

A sufficient amount of impaired driving events is essential for successful detection of driver fatigue using driving quality as a criterion. The definition of driving quality states should be as unambiguous as possible. With psychophysiological measures the burst analysis of EEG band power or some other measure for detection of microsleeps is necessary. The detection of long blink rate could reflect sleepiness better than the detection of blink rate in general. Also blink amplitude is, with proper measuring methods, a promising variable for the detection of sleepiness.

The occurrence of driving impairment with changes in some psychophysical variables or the prediction of driving impairment based on psychophysical variables has been significant in many studies (Morris & Miller 1996; Numata et al., 1998; Risser et al., 2000; Verwey et al., 2000; Horne & Baulk, 2004). Especially, research on the prediction of driver fatigue is needed for developing and providing effective countermeasures against driver fatigue. The use of EEG and heart rate has not been investigated enough from this point of view (MacLean et al., 2003). With the likely increases in the number of motor accidents in the world in the near future (Kopits & Cropper, 2005), the need to increase the safety of the drivers grows in parallel.

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