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# Analysis of Electroencephalogram Parameters to Determine Human Drowsiness

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**Abstract**. This study examines the assessment of human drowsiness using single-channel data from a forehead electrode processed with a spectral analysis algorithm. Spectral band analysis allows for the identification of key parameters related to drowsiness. Eye blink frequency was identified as a useful parameter based on the analysis of signal amplitude and time-frequency characteristics. Data were obtained under two conditions – after 20 hours of wakefulness and after a full night of sleep while participants read an e-book. Spectral analysis calculations and Random Forest and statistical algorithms were used for signal processing to identify the most informative features for the expert decision-making system. The analysis showed a close correlation between spectral indicators (especially alpha and beta bands) and subjective ratings of the Karolinska Sleepiness Scale. Eye blink frequency was also successfully determined using biopotential and video analysis. Expert judgment complements the logical relationships of the parameters for real-time fatigue monitoring, with applications in safety-critical situations and human-computer interaction.

Keywords: signal processing, drowsiness parameters, spectral analysis, brain biopotential

## Introduction

Risks associated with drowsiness are critical when assessing human fatigue and operational safety in the workplace. Reduced alertness can impair attention, slow reaction time, and increase the probability of errors, particularly in safety-critical environments. Physiological parameters serve as objective diagnostic indicators, contributing to fatigue monitoring and enabling real-time system feedback (Deepu et al., 2024). Reliable identification of drowsiness-related physiological markers therefore remains an important research problem.

Current methods to assess drowsiness fall into two broad categories: behavioural observation (e.g., video-based facial analysis) (Zhu et al., 2022) and physiological measurement (e.g., heart rate, EEG, or eye activity) (Xiong et al., 2022). Behavioural approaches analyse visible indicators such as eye closure duration, facial expressions, and head movements. While effective under controlled conditions, these methods may be influenced by lighting, camera positioning, and individual variability. In contrast, physiological approaches provide direct information about internal neurophysiological processes associated with vigilance and fatigue. Among physiological methods, electroencephalography (EEG) remains one of the most direct and objective techniques for assessing brain state changes related to fatigue and reduced alertness (Min et al., 2021). Spectral analysis of EEG signals has demonstrated that variations in theta, alpha, and beta band activity are associated with attention, cognitive workload, and drowsiness (Ismail and Karwowski, 2020; Benwell et al., 2020). Increases in theta activity and reductions in beta power are often linked to decreased vigilance, while modulation of alpha rhythms reflects transitions between focused and relaxed states (Klimesch, 1999). Composite indices derived from spectral band ratios, such as beta/(alpha+theta) or theta/alpha, have been proposed to quantify task engagement, attention, and stress (Prinzel et al., 2003; Lim et al., 2019; Picken et al., 2020).

Wearable single-channel EEG devices, such as the MindWave TGAM sensor, have gained attention due to their low cost and potential applicability in real-time monitoring scenarios outside laboratory settings (Teixeira et al., 2023). However, interpreting single-channel EEG data presents methodological challenges, including increased susceptibility to noise and artefacts, limited spatial resolution, and variability across individuals. As a result, identifying robust and physiologically meaningful parameters suitable for practical drowsiness assessment remains a challenge. To address these issues, expert systems and decision-support tools have been explored to assist in interpreting complex biosignal data. Expert systems emulate human reasoning by combining empirical evidence with structured logical rules, which can enhance transparency and interpretability compared to purely automated classification approaches (Goodall, 1985; Ismail and Karwowski, 2020). In the context of EEG-based drowsiness detection, integrating data-driven feature selection with expert evaluation may provide a balanced framework that supports both analytical robustness and clinical interpretability.

This study focuses on identifying objective parameters derived from EEG spectral features and eye muscle activity signals that contribute most significantly to the assessment of human drowsiness. Rather than constructing a fully automated classifier, machine learning methods such as Random Forest and Principal Component Analysis are used to prioritise informative signal features and support expert-based interpretation. The resulting framework aims to characterise transitions from alertness to drowsiness using single-channel EEG data in a manner suitable for real-time fatigue monitoring applications.

## Methods and materials

The aim of this study was to analyse brain and eye muscle activity signals recorded using a non-obtrusive sensor and to determine the objective parameters that contribute most significantly to the detection of a drowsiness state. To achieve this objective, two experiments were conducted. The first experiment measured EEG signals under two conditions—after 20 hours of wakefulness and after a full night of sleep—while participants performed an e-book reading task. The second experiment focused on eye blink rate measurements, during which volunteers performed controlled eye blink exercises. The study protocol was reviewed and approved by the Research Ethics Committee of Riga Technical University (Decision No. 04000-10.2.3-e/8, meeting date

26 January 2026). The research was conducted in accordance with the principles of the Declaration of Helsinki. All participants were adult volunteers and provided written informed consent prior to participation. Participants were informed of the study procedures, potential risks—including temporary sleep deprivation—and their right to withdraw at any time without adverse consequences..

The first experimental session consisted of two measurement conditions. During each session, a single-channel biopotential measurement was performed using the MindWave Mobile head-mounted sensor. In parallel, video recordings were obtained using a computer camera. Participants performed an e-book reading task during the recording (see Figure 1).

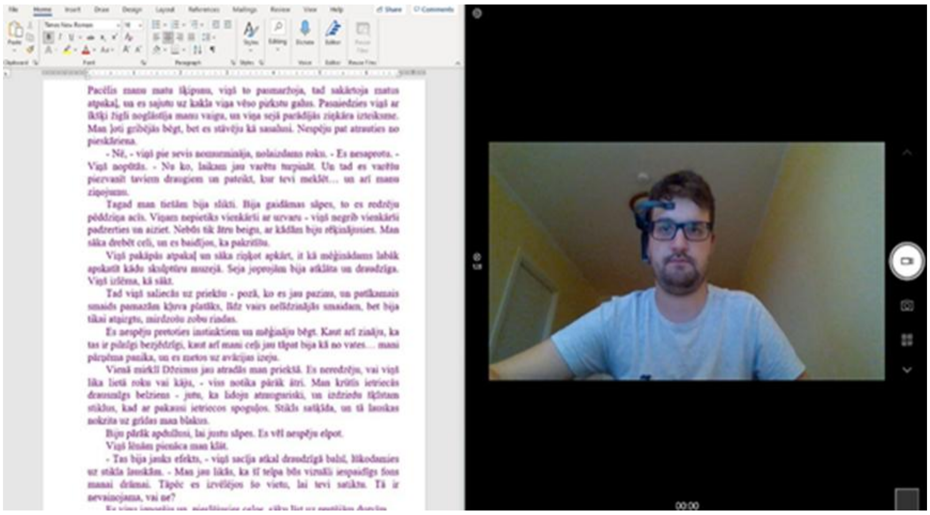

**Figure 1.** Example of participant during e-book reading task

Before the first measurement, participants underwent a 20-hour wakefulness period. For example, a volunteer would wake up at 3:00 a.m., complete a full day of regular activities without sleep, and then participate in the first measurement at approximately 11:00 p.m. This measurement was considered to represent a high sleepiness condition. Participants were instructed not to consume coffee, energy drinks, or other stimulating beverages during the wakefulness period. The exact wake-up and measurement times could vary by up to one hour, but the condition of 20 continuous hours without sleep was maintained. The second measurement was conducted the following morning after the participant had obtained a full night of sleep according to their individual needs. Sleep duration was not restricted; participants were instructed to wake naturally when feeling rested. The measurement was performed approximately one hour after awakening. Participants were again instructed to avoid consuming caffeine or other stimulating substances prior to the measurement. Each measurement lasted five minutes. During this time, participants performed a mental task by reading an e-book displayed on a computer screen. A summary of the experimental dataset is presented in Table 1.

**Table 1.** Input information for the electroencephalogram experiment

| **Input information for parameter comparison** |
|---|
| 30 measurements |
| 10 volunteers |
| 2-5 min measurement duration |
| 38 analysis parameters |
| Karolinska Sleepiness Self-Assessment (KSS) sleepiness classes (1-10) |

Video recording method, which uses a video camera data source is compared with an experimental method. A medical-grade device Mind Media Nexus 10 single-channel EEG sensor with an adhesive electrode is used as a reference or validation sensor (Autenrieth et al., 2023). To test the algorithm for determining eye activity from EEG signal readings, several measurement sessions were conducted, during which volunteers were required to perform 11 different specific eye activity-related exercises in a controlled manner (Alyan et al., 2023). The measurements use a Mindwave Mobile single-lead EEG sensor for data acquisition, which is commonly used in various brain-computer interface (BCI) applications (Teixera et al., 2023). Input physiological signals (Mindwave Mobile 2) single-lead EEG data frontal (FP1) electrode with ear reference. Data acquisition device – Android smartphone, acquires data (EEG and Mindwave spectral bands) using the smartphone (Sahu et al., 2021).

Python libraries for obtaining measured parameters were used for data processing according to the following algorithm, given in Figure 2, with sequential steps:

- Automatic selection and processing of data files.
- Spectral analysis (Welch periodogram, FFT spectrogram).
- Generation of the measured parameters result file from the data file.
- Parameter analysis (Python SciKit libraries).
- Selection and normalization of measured parameters.
- Principal component analysis (PCA).
- Random Forest classifier analysis.

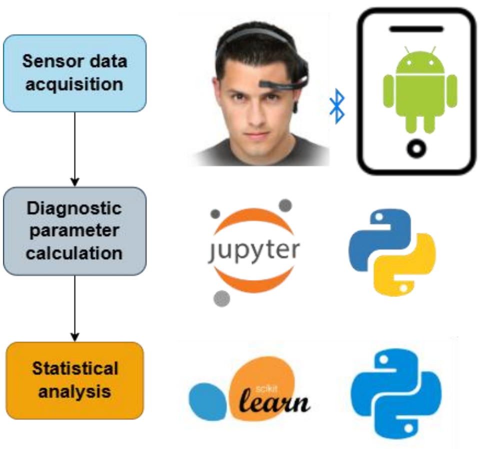


**Figure 2.** Experimental signal processing scheme

## Obtaining spectral parameters of the electroencephalogram

**Signal processing.** First, the absolute spectral power and amplitude of the EEG signal were determined. A Welch periodogram was implemented to analyse the frequency distribution within the selected frequency range. For the e-book reading measurements, the analysed signal duration was five minutes. However, in the discrete 8-band data stream provided by the MindWave sensor, spectral band values are calculated internally every second. Since the analysis was limited to the frequency range up to 50 Hz, additional high-frequency filtering was not required. The built-in 50 Hz AC noise filter of the MindWave sensor was used to suppress power line interference. The spectral power in the Welch periodogram can be characterised by the integrated area under the power spectral density (PSD) curve within the selected frequency bands. For each predefined spectral band, the absolute spectral power was calculated separately (Sałabun, 2014).

**Calculation of spectral power of band**s. In the next step, the absolute spectral power values were obtained for a five-band frequency distribution, based on the predefined frequency limits. These absolute values were subsequently converted into relative spectral power values by dividing the power of each band by the total power across the analysed frequency spectrum using the PSD (Pellegrino et al., 2016). This proportional representation can be extended to five-, seven-, or eight-band distributions. In the case of the MindWave sensor, an eight-band distribution is internally calculated every second and used to identify the dominant frequency band—defined as the band with the highest relative power within the considered time interval. In contrast, the proposed method applies a five-band relative distribution, which is sufficient for index formation without requiring finer subdivision of frequency bands (Benwell et al., 2020).

**Frequency dominance in time.** To determine which frequency band dominates during a specific time interval, the measurement data were segmented into one-second intervals. Spectral analysis and relative band power calculations were performed for each segment. The dominant frequency band for each second was defined as the band with the highest relative spectral power. The results were visualised using a time–frequency representation, illustrating changes in dominant frequency over time. In states of low sleepiness, higher-frequency bands such as gamma were typically dominant. Figure 3 presents an example from an experiment during which a volunteer gradually fell asleep. The moment of sleep onset was identified by the observer and marked on the diagram with a bold line. Approximately 250–500 seconds before sleep onset, increased dominance of alpha (green) and beta (yellow) frequency bands was observed. These intervals were later replaced by dominant delta (blue) and theta (violet) activity as the participant transitioned into sleep. The pre-sleep drowsiness phase is particularly important in human–computer interaction contexts. Detecting this transitional state enables the system to provide preventive feedback, such as alerts or recommendations, allowing the individual to react before complete sleep onset and thereby reducing the risk of accidents.

**Calculation of indices.** The following indices related to mental fatigue and drowsiness were selected for experimental verification based on the results of the literature analysis. These indices were calculated using the previously determined relative spectral band values. Table 2 summarises four commonly referenced indices in fatigue- and drowsiness-related research. Each index is expressed as a mathematical relationship between relative spectral band powers. In Table 2, “rel.” denotes the relative spectral power of the corresponding EEG frequency band, calculated as the ratio of the band power to the total spectral power. The selected indices represent different aspects of cognitive and vigilance-related states. Index1 (task engagement) reflects the relationship between beta activity and the combined alpha and theta bands, which is associated with sustained attention and cognitive involvement (Prinzel et al., 2003). Index2 (attention), defined as the theta-to-alpha ratio, has been linked to attentional processing and working memory performance (Klimesch, 1999). Index3 (stress), expressed as the theta-to-beta ratio, has been associated with stress levels and cognitive control (Lim et al., 2019; Picken et al., 2020). Index4 (vigilance), calculated as the alpha-to-beta ratio, has been proposed as an indicator of vigilance and alertness regulation (Ismail and Karwowski, 2020). These indices were computed for each measurement and subsequently analysed to determine their relevance to subjective sleepiness levels and expert-based evaluation criteria.

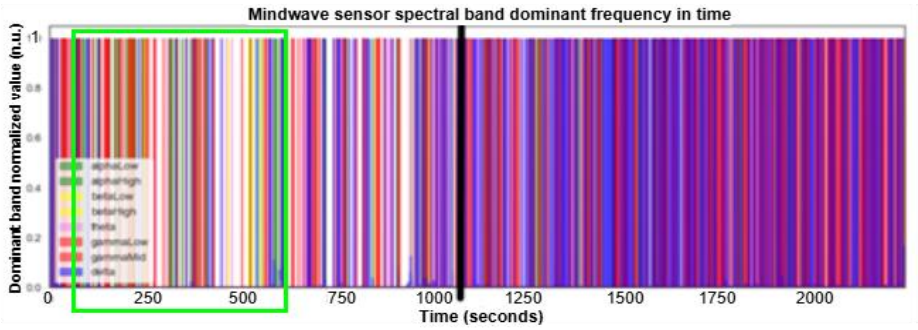


**Figure 3.** The moment a person falls asleep is marked in the spectrum of the electrode. Alpha dominant interval marked green

**Table 2.** Summary of electroencephalogram mental fatigue and drowsiness indexes

| Index name | Index formula | Physiological meaning |
|---|---|---|
| Index1 (task engagement) | rel. Beta / (rel. Alpha+ rel. Theta) | Interest (Prinzel et al., 2003) |
| Index2 (attention) | rel. Theta / rel. Alpha | Attention (Klimesch, 1999) |
| Index3 (stress) | rel. Theta / rel. Beta | Stress (Lim et al., 2019), Cognitive focus (Picken et al., 2020) |
| Index4 (vigilance) | rel. Alpha / rel. Beta | Vigilance (Ismail and Karwowski, 2020) |

# Eye blink detection algorithm

Eye blink detection is based on the amplitude and time-frequency characteristics of the signal, which reflect the human eye muscle activity as an artefact of the EEG signal (Abo-Zahhad et al., 2015). The given signal was obtained with a frequency of 512 Hz and reflects an 8.8-second recording, in which a person is instructed to blink his eyes in a controlled manner every 1 second. In total, 10 consecutive events are performed in a controlled manner. Thus, the sensor records the difference in electrical biopotentials between the forehead and ear electrodes, between which the eye muscles are also located. During the tension and relaxation of the eye muscles, visible biopotential peaks are formed in the positive and negative directions, which are clearly recorded in the reading of the electroencephalogram channel.

The signal is smoothed to remove noise. An exponential smoothing filter is used. The smoothing factor α=0.1 was chosen as it balances noise reduction with preservation of blink-related peaks, based on experimental validation and previous studies (Fried and George, 2011). The mean and base values of the signal are also fixed for the result.

The signal is divided into positive and negative biopotential parts to perform peak detection of the signal. The peak detection function requires sampling the signal with absolute values. Similar algorithms (Kleifges et al., 2017) propose to perform eye blink feature detection. In this case, the sensor data with frequent blinking does not correspond to the nature and peak shape formulated in the literature, because the signal has a high level of non-stationary noise, which makes it difficult to detect finer features, therefore only the highest and lowest potential peaks should be used.

Peak points are determined in the positive and negative parts of the signal. The local maximum peak detection (Schwartzman et al., 2011) function from the Python SciPy library is used. Peak points are filtered by the interval between points to remove points where multiple peak points are recorded for one blink. Such points are separated if the interval between points does not exceed a certain threshold. Figure 4 shows an example of peak point detection. The upper peaks are marked with a blue marker X and the negative peaks are visible with an orange marker O.

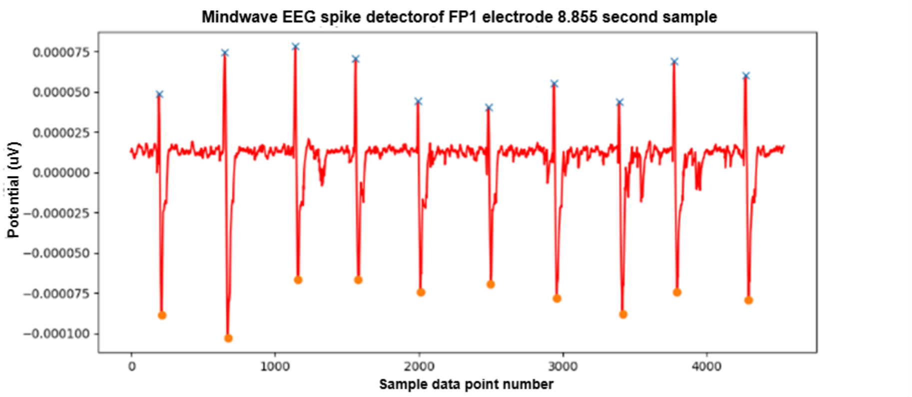


**Figure 4.** Peak finding in signal in 3 blink episodes per second

The peak points in the positive and negative parts of the signal are counted. If their number differs significantly, then only the positive part is used, since it was experimentally found that the number of positive peaks corresponds to the actual number of blinks, while the negative peaks at higher blink frequencies (>0.5 Hz) tend to overlap (Barr et al., 1978).

Executing the seven-step algorithm results in the detection of eye blink events and calculation of the eye blink rate. The eye blink rate (times/minute) is calculated by dividing the number of blinks by the duration of the EEG recording (in minutes).

## Statistical analysis

To support the expert evaluation of drowsiness-related EEG parameters, a Random Forest algorithm and Principal Component Analysis (PCA) were used for exploratory analysis, rather than as direct classification tools. The primary objective of these methods was to identify which features from the EEG signal exhibited the highest correlation with subjective drowsiness levels and to reduce the complexity of the parameter space for expert interpretation. To evaluate the importance of EEG features against the self-estimated values of drowsiness, a Random Forest classifier (Breiman, 2004) was implemented using the Python scikit-learn library. The task of the classifier is to create a pairwise comparison, or rather a sequence of binary decision trees. The input features for the model included 38 parameters derived from the EEG signals, such as relative spectral band powers (alpha, beta, theta, delta, gamma) and composite indices (e.g., task engagement, attention, stress, and vigilance). The target output variable was the drowsiness level, obtained from participants' self-assessment scores on the Karolinska Sleepiness Scale (KSS), which was discretized into three categories: Low (KSS 1–3), Medium (KSS 4–6), and High (KSS 7–10) sleepiness levels. The noise-based feature detection of Random Forests is calculated based on statistics obtained from the training data set: the importance can be high even for objects that do not predict the target variable, if the model is able to use them. A binarization algorithm is used, which is essentially a pairwise comparison of randomly selected pairs of parameters, where the end condition of the algorithm, or the number of variants considered, is determined to use all their different combinations.

The model was trained and evaluated using 5-fold cross-validation due to the limited size of the dataset (30 recordings). Hyperparameters were used with the number of decision trees was set to 250 without random state for reproducibility. Features for EEG were standardized by using Standard Scaler, the classifier was trained on the full feature set before the PCA transformation. Feature importance was calculated using the Mean Decrease in Impurity (MDI) method, which quantifies the contribution of each parameter in reducing classification error across all trees in the ensemble.

Such information can be obtained using principal component analysis (PCA), which is a statistical method for extracting features using orthogonal transformation to transform a set of possibly correlated input data attributes into a linearly uncorrelated data set, where n is the initial number of dimensions of the data set, and p is the number of principal components. The first step in the PCA algorithm is to normalize the data so that the mean value of each attribute is zero. Then, the principal components are calculated from the normalized data. The covariance matrix C of the sample set is calculated from the attributes, for which, by performing eigenvalue decomposition, a set of eigenvectors M is obtained (Susac et al., 2013). To identify the most informative EEG parameters and reduce dimensionality, Principal Component Analysis (PCA) was applied to the full set of extracted features. Prior to PCA, the dataset was standardized so that each feature had zero mean and unit variance. The covariance matrix of the standardized features was computed, and eigenvalue decomposition was used to obtain the principal components.

## Results

Statistical analysis was performed by using the Random Forest decision tree classifier, where observations from 10 individuals 3 times a day (30 measurements) are normalized into groups according to the Karolinska Sleepiness Rating Scale. The subjects are of different sex and age and have no reported illnesses during the experiment. This example shows the creation and use of decision trees to assess the importance of features in an artificial classification task.

The parameters are ranked in descending order of their significance according to the KSS self-assessment of sleepiness, as shown in Figure 5. Feature significance is assessed by their contribution to modelling drowsiness decisions. From the result of this experiment, the most significant are the average relative power according to the high beta frequency band parameter of the MindWave sensor. Similarly, index 2, which characterizes the person's involvement in the task, and the alpha or delta bands are significant.

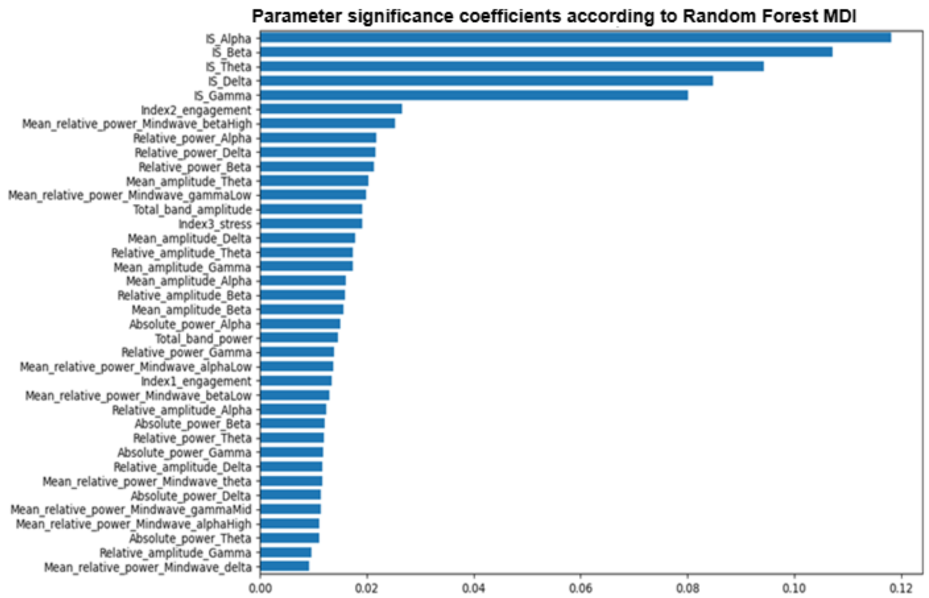


**Figure 5.** Parameter significance coefficients are sorted in descending order by Random Forest informativeness (MDI)

After the decision tree analysis, the most informative parameters are displayed, but it is necessary to determine which of these parameters are the most significant. The goal of PCA in this context was to determine how many components were sufficient to explain most of the variance in the dataset. It was found that the first six principal components accounted for 75.9% of the total variance. These components were primarily composed of relative spectral band powers and key indices such as task engagement and attention, indicating their central role in characterizing drowsiness states. The resulting PCA component variance curve plot is shown in Figure 6.

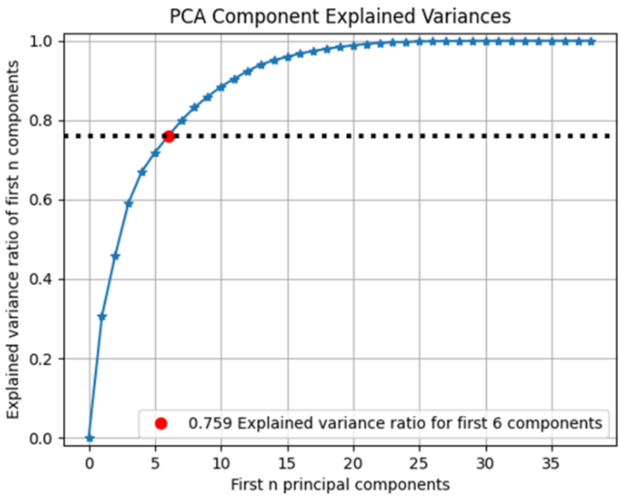


**Figure 6.** Of all the parameters, 6 principal components explain 75.9% of the data

Of all the parameters, 6 principal components explain 75.9% of the data. Since in the previous task an ordered list of the most informative parameters was obtained, in this case an estimate of the N most informative parameters is obtained from this list, where N=6. The most significant 6 PCA components from the selected parameter list are the corresponding relative values of the spectral bands and the mutual indices of the bands, of which the index of human involvement in the task dominates here.

The resulting eye blink rate values for 11 tests after measurements from 10 volunteers are shown in Figure 7. The comparison results show complete agreement of the assessment in tests 1-6 between the electroencephalogram, video and control assessments.

During intensive eye activity above 40 episodes per minute, problems are observed in correctly detecting eye blink episodes, because the EEG signal is unable to correctly return to the approximate average value area and the signal contains unnecessary positive and negative signal peaks that do not reflect real eye blink episodes. Moreover, in the case of the camera algorithm, an increased measurement error appears already at 30 episodes per minute. This also results from the specifics of the specific experiment, where there is a different eye blink distribution.

Blink episodes can be successfully detected in the EEG signal if the time interval between eye blinks is longer than 3-4 seconds, which is appropriate, because under monitoring conditions, a person blinks on average once every 5-6 seconds. As the sensor or eye fatigue increases, this number can exceed 20 episodes or as drowsiness increases, the number decreases to 0, when the eyes remain in a static (usually closed) state.

The results show that both methodologies work equally well in the task of detecting eye blink parameters up to 3-4 seconds of eye blink frequency tracking.

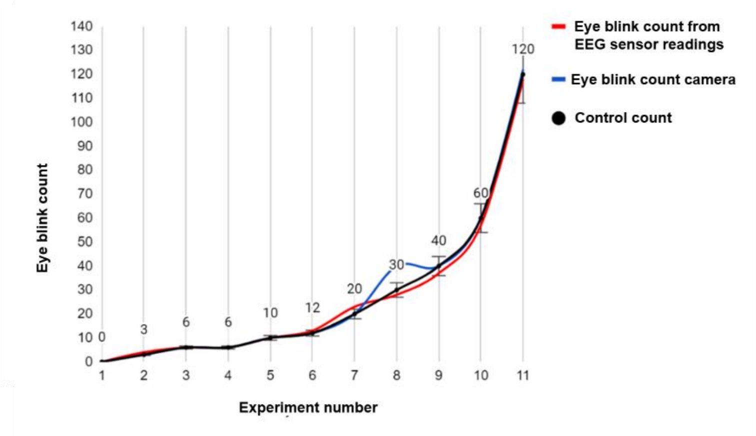


**Figure 7.** Summary of results for 10 volunteer measurements for the eye blink experiment, sorted by number of events

## Results of expert evaluation

The collected experimental data from 10 volunteer measurements were submitted to a team of experts from the Riga Stradiņš University Sleep Laboratory (Kendall's concordance coefficient for a team of physicians from one school is 0.8) with the aim of forming an expert decision on which parameters would be the most informative and their gradations for drowsiness assessment.

**Table 3.** The most informative EEG band index parameters for drowsiness assessment according to expert assessment

| **Measurable parameter group** | **Diagnostic parameter** | **Low** | **Medium** | **High** |
|---|---|---|---|---|
| Eye symptoms | Change in eye blink rate from baseline (%) | 0-10% | 10-30% | > 30% |
| Dominance of EEG spectral bands | Alpha rhythm duration (seconds) | 1, beta wave presence | 1-3 | > 3 |
| Change in EEG rhythm ratio indices from baseline (%) | Index1 (task engagement) | 0-10% | 10-30% | >30% |
| | Index2 (attention) | 0-10% | 10-30% | >30% |
| | Index3 (stress) | 0-10% | 10-30% | >30% |
| | Index4 (vigilance) | 0-10% | 10-30% | >30% |

The expert assessment of the material is given and a summary of the resulting informative indices and the logic of parameter decision for the expression of drowsiness indices and spectral band dominance is given in Table 3. The table presents expert-defined thresholds for drowsiness levels—Low, Medium, and High—based on deviations from each participant's baseline. For example, >30% change in blink rate or EEG index is considered High drowsiness.

## Conclusions

This study demonstrated that relative EEG spectral band parameters, particularly within the alpha and beta frequency ranges, show strong associations with subjective sleepiness levels as measured by the Karolinska Sleepiness Scale (KSS). These findings reinforce the value of EEG spectral analysis as an objective method for assessing drowsiness.

In well-rested individuals, alpha and beta bands were found to be the most informative, whereas delta and theta activity became more dominant during the transition toward sleep. The alpha/theta ratio emerged as a key indicator of the alertness–drowsiness transition, consistent with previous findings related to cognitive engagement and attentional processes.

The results indicate that single-channel EEG data acquired using the MindWave sensor, when analysed through spectral band distribution methods, provide a practical and non-intrusive approach to drowsiness assessment. The findings support the capability of wearable single-channel systems to deliver meaningful spectral indicators suitable for real-time monitoring in safety-critical and human–computer interaction contexts.

Additionally, eye blink activity—detected through EEG amplitude and time–frequency characteristics—proved to be a reliable complementary indicator of drowsiness. The applied peak detection algorithm enabled accurate estimation of blink frequency under typical conditions, supporting the feasibility of multimodal fatigue assessment using a single sensor.

Importantly, the identified EEG parameters and derived indices were evaluated and validated by a panel of clinical sleep experts. The expert assessment resulted in a structured framework for categorising drowsiness into low, medium, and high levels based on measurable spectral indices and blink rate deviations from baseline values. This validation enhances the interpretability and practical applicability of the proposed methodology.

Overall, the study confirms that combining single-channel EEG spectral analysis with eye blink detection, supported by expert-informed decision criteria, provides a feasible and interpretable framework for real-time human drowsiness monitoring. The proposed approach contributes to the development of wearable, low-cost fatigue detection systems applicable in occupational safety and human–computer interaction environments.

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