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PASSIVE OLFACTORY BRAIN-COMPUTER INTERFACE PARADIGM FOR AWARENESS LEVEL PREDICTION

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ABSTRACT: The sense of smell, also known as olfaction, can improve the usability of brain-computer interfaces (BCIs) and support passive modalities for monitoring cognitive states. In reactive BCI, users can assign specific scents to commands for natural interaction, while a passive application can monitor cognition. However, some challenges still need to be addressed, such as the need for accurate odor delivery systems and robust algorithms for detecting and interpreting brain activity patterns. We propose combining electroencephalogram (EEG) and electrobulbogram (EBG) in an olfactory modality oddball paradigm to predict a user's awareness level. Our pilot study indicates promising results for a new passive olfactory BCI modality combining CSP filtration and awareness level classification.

INTRODUCTION

Recent reports suggest a link between COVID-19 and loss of smell, also known as olfactory dysfunction [1]. Mounting evidence suggests that this condition may be an early symptom of Alzheimer's or Parkinson's syndromes [2, 3]. A new method of objectively measuring olfactory bulb (OB) activity named electrobulbogram (EBG) has been proposed [4], utilizing standard EEG amplifiers by placing electrodes above eyebrows to evaluate olfaction-related brain activity.

According to a recent study, olfactory sleep stimulation may improve cognitive and memory performance in the elderly, providing a potential intervention to protect against Alzheimer's syndrome [5]. As olfactory neuroscience and applied neurotechnology gain interest, their potential for use in BCI becomes more appealing [6]. The state-of-the-art visual [7], auditory [8], and tactile [9] modalities have been successfully implemented in BCI, and the olfactory modality could represent the next frontier.

Sensory awareness focuses on a specific sensory detail rather than simply responding to stimuli. In the context of olfactory awareness, it refers to the ability to distinguish a target odor in an oddball stimulus presentation. When evaluating the awareness level, we predict the subject's ability to differentiate between odors in a binary setting, i.e., whether they are above or below the chance level of half (three out of six) target stimulants.

Figure 1: An experimental setting with a subject wearing an EEG cap in front of an olfactometer delivering scent stimuli.

The authors recently conducted a pilot study to test a new form of olfactory stimulation. The study recruited ten healthy and BCI-naive participants and used wearable neurotechnology to capture their brainwave (EEG) and OB sensory activity (EBG). During the EEG and EBG preprocessing stages, we used the typical spatial pattern (CSP) filtering technique [10, 11] to extract features from the signals. Specifically, we focused on the gamma frequency band (which ranges from 35 to 100 Hz). This frequency band is known to carry the most meaningful olfactory responses, as reported in previous studies [4]. We then compared the classification accuracy of EEG-only, EBG-only, and combined EEG+EBG CSP features using various classifiers.

The paper is organized as follows: First, we will introduce the experimental conditions, signal preprocessing with CSP feature extractions, and classification techniques in the materials and methods section. Then, we will present preliminary results from pilot experiments

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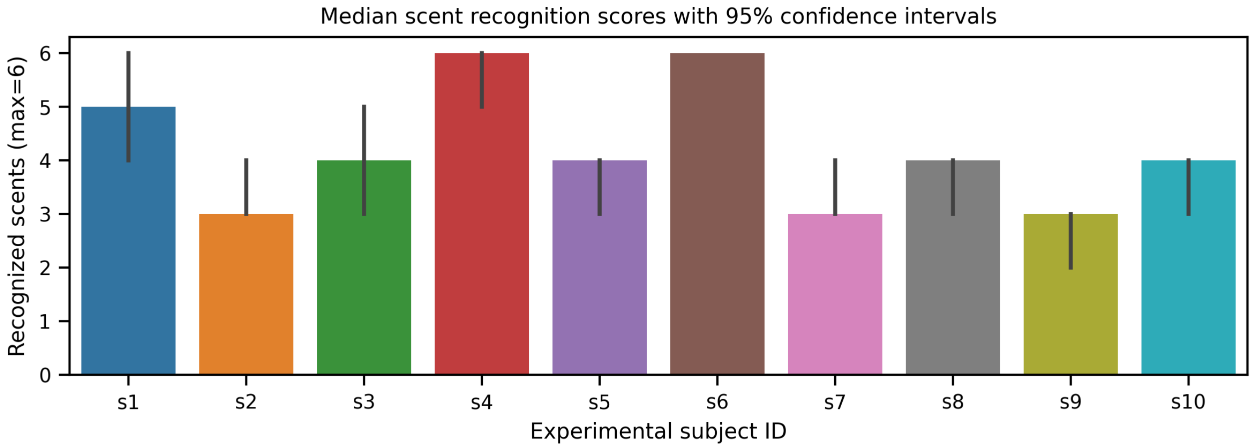

Figure 2: The study involved scent identification trials that included six targets each. The median results we represented as bar plots in the above figure, along with 95% confidence intervals. Out of all the subjects, only three of them were able to achieve the maximum score at once. The scores were then divided into two categories: lower awareness (scores ranging from 0 to 3) and high awareness (scores ranging from 4 to 6).

involving ten young, healthy olfactory BCI users. Finally, we will discuss these results and draw our conclusions.

MATERIALS AND METHODS

The olfactory BCI has the potential to revolutionize human-computer interaction. It can also passively monitor olfactory cognition and age-related changes, making it helpful in supporting the elderly. Our recent feasibility study involved ten technology novices to identify any potential usability and related unresolved issues. During the study, the users were asked to perform classical oddball-style olfactory BCI tasks while their brain activity was monitored using EEG and EBG electrodes. The users were also asked to report on the number of target scents they could identify in each trial. We utilized data from scents delivered through an oddball paradigm to train a machine-learning model. The model predicts levels of sensory awareness based on olfactory stimulation in a passive brain-computer interface (BCI) application. This application estimates the user's mental state instead of generating commands.

Olfactory oddball BCI paradigm:

In 2024, during winter, we conducted a pilot study on adult volunteers at Nicolaus Copernicus University in Toruń, Poland. The study aimed to record EEG and EBG using an olfactory passive BCI paradigm. The Institute of Psychology UNC Ethical Committee for Experiments with Human Subjects approved the investigation under the ethical principles of The Declaration of Helsinki. The study involved nine females and one male, with an average age of 20.4 ± 1.71 years. The report presents the study's findings.

This pilot project presents the findings of a study that employs the ETT Olfactometer2^S to deliver odors in an oddball BCI paradigm. Users are asked to identify and report the number of instructed target scenes in each session, comprising six odors. In each trial, one odor becomes a target accompanied by five randomly presented distractors. Our study uses classical reactive BCI settings to determine how well users can identify a specific target odor amidst other distracting odors. However, the actual application passively monitors the user's cognitive states. We used an olfactometer to ensure the odors were delivered uniformly in all trials. This system includes an airflow delivery unit, an odorant carrier, tubes, a nose applicator, and ETT Direct Control software. We have developed a Python script that communicates with the olfactometer's original software. This software connects to a laptop through a USB cable. The experiment setup can be seen in Figure 1. During the experiment, a participant wore a wireless Unicorn EEG wearable cap, manufactured by g.tec medical engineering, Austria, which was connected to a laptop running our in-house developed EEG with EBG recording and stimulus presentation software. This software controlled the delivery of olfactory stimuli from a pipe near the participant's nose. We used an ETT Olfactometer 2^S manufactured by Emerging Tech Trans, LLC., USA, to deliver the odor stimulus. The olfactometer can be identified as a blue box on the left side of the photograph in Figure 1, with a blue-orange pipe on the participant's right side. In our passive olfactory BCI paradigm experiments, we used an olfactometer with six scents to control odorant stimulation. Each scent stimulus lasts four seconds, followed by a four-second break without odor delivery. To ensure accurate results, we conducted a pilot study that included natural odors such as rose, cinnamon, lavender, orange, lemon, and vanilla. The subject is visually instructed on a computer screen to breathe at the beginning of each new odor presentation during the experiment. After each session of six oddball trials, the subject reported the number of correctly identified scents, with six being a perfect score and three a chance level. The behavioral results are summarized as

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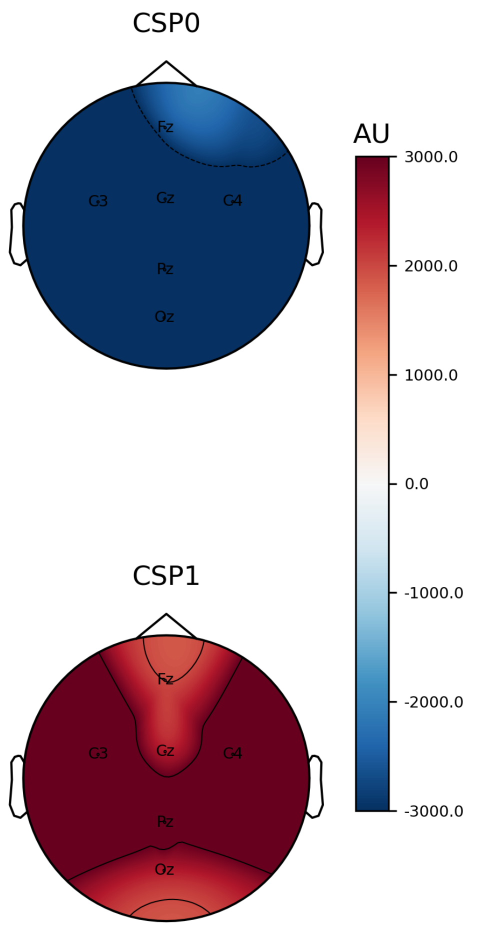

Figure 3: The averaged over all subjects and sessions head plot images show the CSP filter coefficients overlaid on a topographic map of the gamma (γ) frequency band. The EEG data was collected from six electrodes, namely $Fz, C3, Cz, C4, Pz$, and Oz. The $CSP0$ filter represents the low awareness, while $CSP1$ represents the high awareness signals in the passive olfactory BCI paradigm.

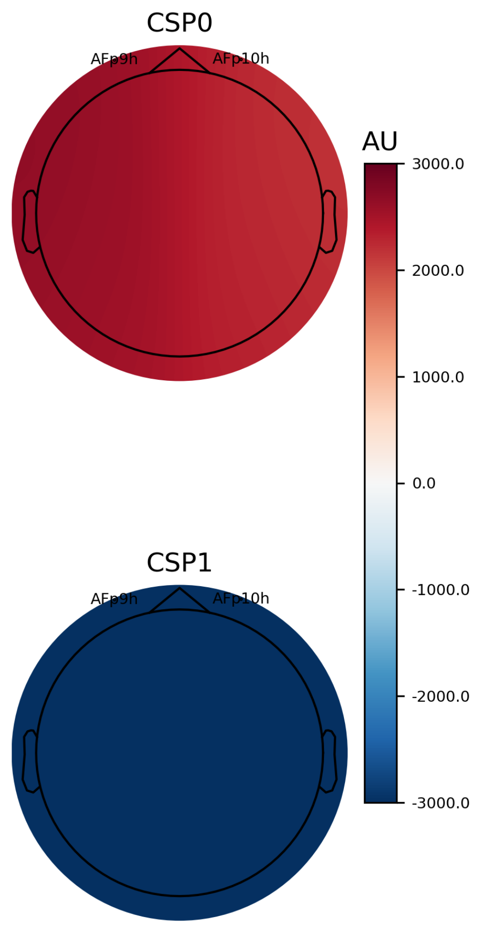

Figure 4: The averaged over all subjects and sessions head plot images show the CSP filter coefficients overlaid on a topographic map of the gamma (γ) frequency band. The EBG electrodes, $AFp9h$ and $AFp10h$, were employed. The gamma-band filter $CSP0$ represent low awareness, while $CSP1$ the high awareness in the passive olfactory BCI paradigm..

medians with 95% error bars in Figure 2. The results of this study provide valuable insights into odor-based BCI paradigms and their potential applications in medicine, psychology, and neuroscience.

EEG and EBG recording:

The reported pilot research study collected EEG and EBG data using the Unicorn EEG headset from g.tec medical engineering, based in Austria. Our previous studies have demonstrated the reliability of this device compared to other available wearables [12, 13]. We used six EEG channels in the pilot investigation: $Fz, C3, Cz, C4, Pz$, and Oz. We also placed two EBG sensors on a $10/5$ international standard EEG cap, approximately above each eyebrow at $AFp9h$ and $AFp10h$.

In the first preprocessing stage, we converted six EEG and two EBG streams into a digital format with a sampling frequency of 250 Hz. After that, we removed any baseline shifts and high-frequency noise outside the frequency range of 7 Hz and 100 Hz by applying a bandpass filter. To eliminate any power line interference at 50 Hz, we used a notch filter. We segmented the EEG and EBG signals into eight-second sections with four seconds of odor stimulation and four-second flush breaks, using experimental triggers recorded together in oddball, target, and non-target recognition tasks.

To ensure the accuracy of our data, we utilized the empirical mode decomposition (EMD) technique to remove distortions caused by eye blinks or muscle movements in the EEGs and EBGs. We applied this method separately to each channel, which allowed us to identify and eliminate artifacts effectively, thus improving the overall quality of the data, as previously proposed in [9, 13].

Using a CSP method, we transformed EEG and EBG signals to increase the variance in one class and decrease it in the other, as described in [10, 11]. We used the CSP method to create distinguishable patterns across space for the olfactory stimulus-induced potential in the gamma sub-bands. These patterns were generated for two different levels of awareness. The first level had behavioral median scores of three and below (three subjects in our study). The second level had median behavioral scores of four and above (seven subjects in our study). We have illustrated all possible user behavioral responses in Fig-

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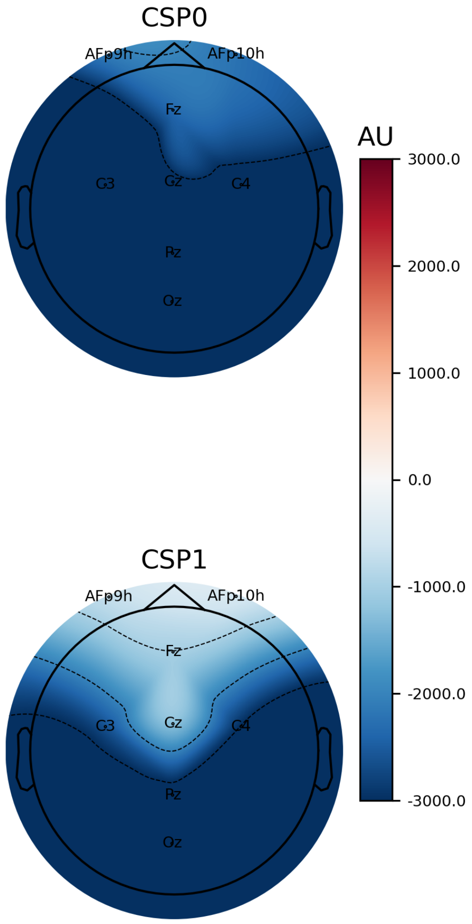

Figure 5: The averaged over all subjects and sessions head plot images display the CSP filter coefficients superimposed on a topographic map of the gamma (γ) frequency band. The EEG data was obtained from six electrodes, namely $Fz, C3, Cz, C4, Pz$, and Oz, and two EBG electrodes, $AFp9h$ and $AFp10h$, were employed. The gamma-band filters $CSP0$ represent low awareness, while $CSP1$ represents high awareness in the passive olfactory BCI paradigm.

ure 2. The patterns that could be distinguished were visualized in Figures 3, 4, and 5 for EEG-only, EBG-only, and combined EEG+EBG channels, respectively. We used the same scaling in arbitrary units (AU) [14]. The differences in CSP filter patterns that we observed were due to varying levels of EEG and EBG signals.

To assess the potential separability of a CSP feature, we used a supervised clustering technique called uniform manifold approximation and projection (UMAP) [15]. We merged CSP features derived from band-pass filtered EEG and EBG signals in the gamma band. This enabled us to obtain distinct clusters in a two-dimensional feature space. The CSP filters we used were four-dimensional.

As part of our research, we conducted a preliminary trial to test the accuracy of an offline passive olfactory BCI application. The trial involved three recording sessions, each comprising six single oddball trials. There were 36 EEG and EBG responses, each lasting eight seconds, with six targets and thirty non-target responses. We transformed these responses into two-dimensional CSP fea-

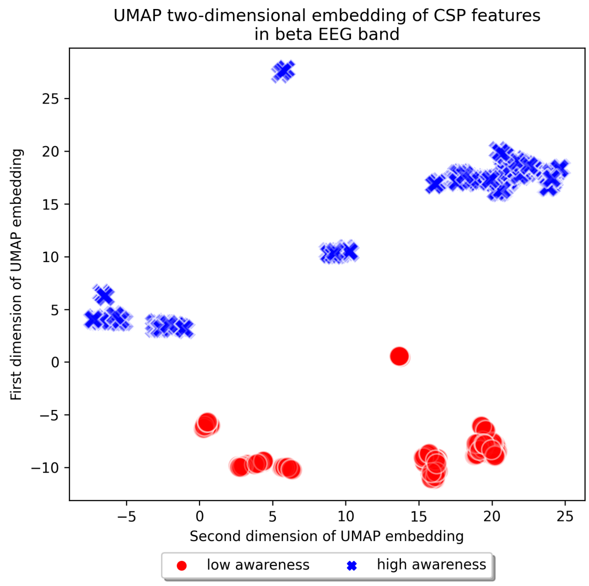

Figure 6: A scatter plot using two-dimensional UMAP results for EEG+EBG combined gamma bands.

tures in gamma EEG and EBG frequency bands, based on previous research that indicated higher frequency as the best carriers of olfactory information in the brainwaves [2, 3].

We used five different machine learning models for our experiment: linear SVM, random forest classifier (RCT), decision tree classifier (DTC), linear discriminant analysis (LDA), and deep fully connected neural network (DFNN). The DFNN had five hidden layers with $128, 64, 32, 4$, and 2 RELU units each. We performed ten-fold cross-validation using these models, available in scikit-learn v1.4.0 [16]. We did not observe overfitting of the machine learning models despite the unequal distribution of low and high awareness cases, as shown in Figure 2.

RESULTS

A pilot study was conducted using ten healthy subjects to fit spatial filters and analyze patterns in the EEG and EBG within the gamma frequency band. The study showed promising outcomes, summarized in Figures 3, 4, and 5, for EEG-only, EBG-only, and EEG+EBG combined, respectively. The outputs of CSP filtering also formed separable clusters of low versus high awareness mental states, as shown in Figure 6 using UMAP applied to EEG+EBG combined features. The results of the initial classification trials, which used ten-fold-cross-validation, are presented in Figure 7. The figure shows median balanced accuracies and percentile ranges. The evaluation used different classifiers, including linear SVM, LDA, RFC, DTC, and DFNN. All the results were significantly above the balanced accuracy chance level of 50%, are reported in Figure 7. The results also indicate that using combined EEG+EBG electrodes led to statistically significant balanced accuracy results (at $p < 0.05$) for RFC, DTC,

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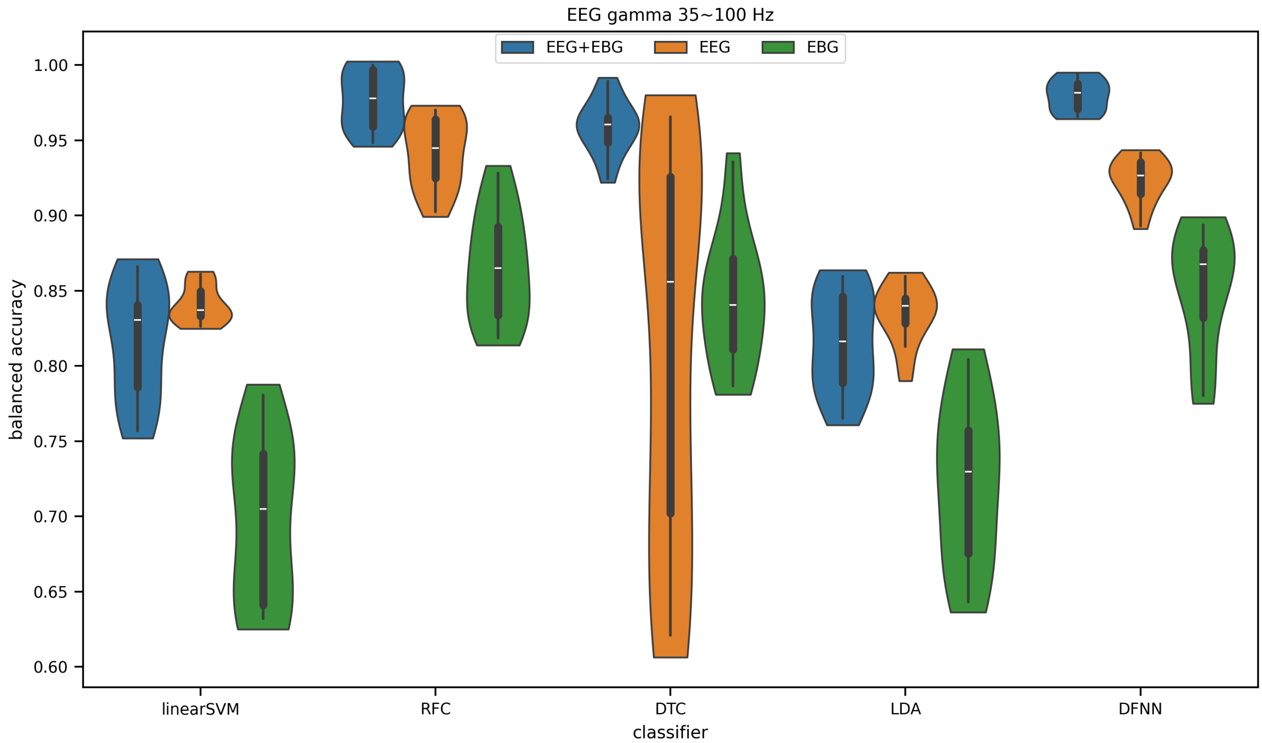

Figure 7: Distribution plots comparing EEG+EBG (blue), EEG-only (orange), and EBG-only (green) classification results for the evaluated classifiers in the reported study.

and DFNN classifiers, compared to EEG-only and EBG-only modality trials. The significance was tested using Wilcoxon tests. The RFC, DTC, and DFNN classifiers achieved median balanced accuracy scores above 95% for combined EEG+EBG electrode cases. Therefore, combining both electrode modalities creates a promising possibility in the olfactory modality for subject awareness estimation.

DISCUSSION

We conducted a trial study on a passive olfactory BCI, a non-invasive method that uses smell to track brain activity in order to estimate user awareness at a later stage. Our study has shown that olfactory stimuli can be processed quickly without causing attention overload. This makes it a promising area for BCI research and quantifying the mental state of users. The study discovered that using a combination of EEG and EBG electrodes with classifiers such as RFC, DTC, and DFNN resulted in almost perfect classification outcomes. This supports the hypothesis that recording brainwaves through multiple modes can lead to improved results. However, simpler linear classifiers such as SVM and LDA showed a different level of improvement and had lower median accuracies than the classifiers mentioned earlier.

CONCLUSIONS

The use of the olfactory modality in neurotechnology has recently become popular due to the positive results of the proposed passive olfactory Brain-Computer Interface (BCI). These results are based on a preliminary pilot study with young and healthy subjects. However, our team faces specific challenges that need to be addressed to improve our approach. These challenges include developing more reliable odor delivery systems and implementing more robust algorithms to detect brain activity patterns. To refine and validate our approach, we plan to conduct a more extensive study with elderly subjects who may have reduced awareness due to mind wandering or daydreaming.

The study aimed to explore the potential of a passive olfactory BCI that could be used to track dementia or COVID-19-related olfactory impairment, as well as interventions. A passive modality could be used in the future for this purpose. The study findings confirm the feasibility of using a passive olfactory BCI, which could be a tool in non-invasive monitoring of brain activity and associated disorders based on user awareness tracking in various cognitive tasks.

These findings have implications for developing non-invasive techniques for monitoring brain activity and associated disorders. The discovery of a practical passive olfactory BCI could help track olfactory impairment related to dementia or COVID-19, which would help develop early interventions. This could be particularly useful in the COVID-19 pandemic, where olfactory impairment has been identified as a common symptom.

The study concludes that a passive olfactory BCI option

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can be an effective way to track awareness, which may help in early interventions. The development of this technology can have significant implications for non-invasive monitoring of brain activity and related disorders.

AUTHOR CONTRIBUTIONS

TMR, HK, NN, and TK, and worked together to develop the concept of an olfactory brain-computer interface (BCI). TMR suggested using CSP to extract features from combined EEG and EBG time-series data and clustering/classification using supervised machine-learning techniques. HK and TK recruited subjects for the study. TMR designed and programmed the experimental stimulus presentation and the acquisition and analysis of EEG and EBG data. TMR and HK conducted the data analysis, while NN, TK, and MOM examined the results. TMR and HK wrote the manuscript.

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TK received support from Nicolaus Copernicus University's Emerging Field projects "Cognition and Language 2022" and "Culture, Development & Wellbeing" in Toruń, Poland.

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