The Legilimens! A scientific spell using neuroscience to read your mind: real-time emotion estimation application and its implications in the cosmetic industry

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Abstract

Background: Emotion plays an important role in the cosmetics industry. Consumers use and evaluate products with their senses, including smell (fragrance), touch (texture), sight (package), and even hearing (advertisement). The momentary emotions felt during these experiences have implications for product satisfaction and purchasing decision. The demand for emotional experiences has increased over time, especially among young consumers. A growing majority of cosmetic products are promoting their emotional benefits.

Methods: We used an 8-channel wearable EEG headset (MOOD8) and 100 healthy adults participated in the study. We used conventional EEG analysis methods and machine-learning algorithms to find applicable features for input into the emotion estimation application.

Results: We developed a windows application (MIND STREAM) to analyze data produced by the MOOD8. The application reads and records EEG data, runs the algorithm pipeline on these data, plots it in real-time, and outputs participants' emotions in real-time on the scales of arousal, valence, and preference.

Conclusion: This is the first attempt of applying neuroscience in real-time emotion estimation in the cosmetic industry. With this solution, we can find the scientific basis for the emotional efficacy of the products and it can be used at various stages such as research and marketing. Even though it was hard to create an algorithm that can also be generalized across unseen participants, as the demand and research for personalized cosmetics continue to grow, further research will play an important role in providing tailored solutions. We hope that this research brings up meaningful agenda in the cosmetic industry.

Keywords: Neuroscience; Consumer neuroscience; EEG; Emotion; Emotion estimation

Introduction.

We have witnessed loads of changes in our life after the COVID-19 pandemic, including in the beauty and cosmetic industry. Most people progressively started focusing on their innermost feelings and pursuing mental wellbeing. The increase in fragrance product sales confirms this trend. Many consumers were increasingly seeking and buying fragrance products, including perfumes, during the pandemic period than before. Such products, like lipstick, became a small luxury to young consumers.

We use fragrance for relaxing, refreshing, and sometimes when we are depressed. In the era of restricted traveling, fragrance can act as a mental getaway to escape from reality, unlike before. Fragrance can bring in specific moments of time or space as a sense of smell is strongly related to memory. Based on the importance of this aspect, research on consumer behavior towards fragrance has also developed.

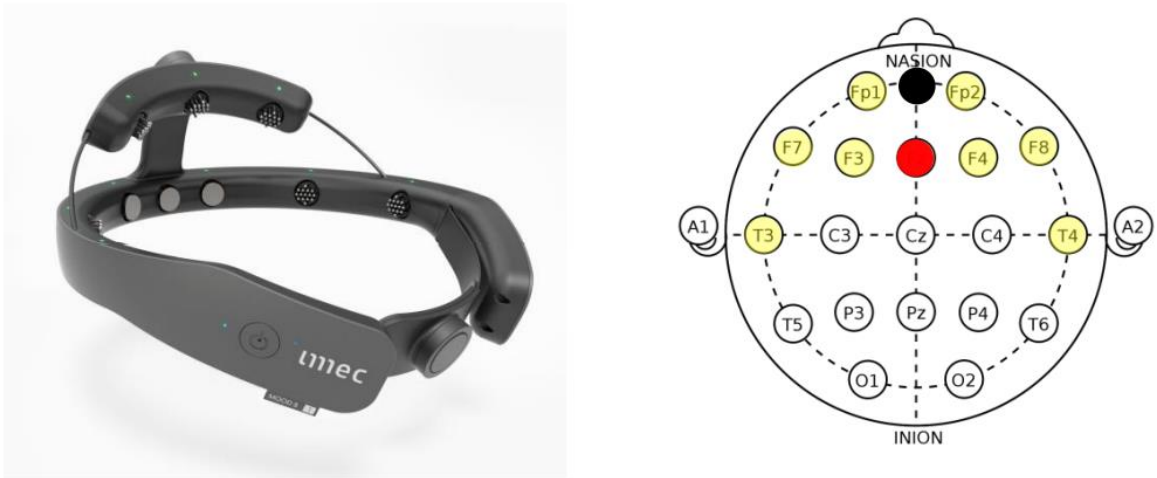
The sense of smell has a strong impact on our physiology and emotions. Understanding the exposure to fragrances via the olfactory system in the brain has been well documented in the literature [1-3]. Thanks to the development of neuroscientific techniques, we can nowadays estimate various emotions with better accuracy [4]. However, identifying specific emotions such as anger or joy can be difficult as they do not seem to have a universal neural fingerprint across people [5]. Therefore, we instead focused on the dimensional model of emotions, particularly on the idea of mapping the emotional state into a two-dimensional space of valence and arousal. Valence (positive or negative) and arousal (aroused or relaxed) are well-defined factors in describing emotional experience [6]. Previous studies have shown that it is feasible to detect the states of arousal and valence from EEG signals [7,8].

In this study, we introduced a real-time emotion estimation application and its use in cases using fragrance. In a way, we can call it a 'scientific spell,' which is pretty similar to the 'Legillimens' spell in Harry Potter, the practice of using magic to enter into another person's mind.

This is the first research case in the cosmetic industry that applies neuroscience to emotion estimation in real-time. With increasing interests and demands for emotional benefits and personalized solutions, our study can shed a light on the field of consumer neuroscience as well as sensory science and provide meaningful implications in the beauty and cosmetic industry.

Materials and Methods.

We used a wearable EEG headset (MOOD8, imec, Eindhoven, The Netherlands), which is a wireless and multimodal research-grade device in combination with soft dry polymer-coated Ag/AgCl electrodes (SoftPulse™, Datwyler, Altdorf, Switzerland) [9]. (measurement positions: F8, F4, F3, F7, T3, T4, C3/P3, and C4/P4) (Figure 1)



(a) (b)

Figure 1. MOOD8 EEG headset: a) Headset design; b) Electrode positions on the scalp based on the 10-20 electrode positioning system

One hundred healthy adults participated in this study (age range: 20-52; F = 82, M = 18, IRB approved: 2021-1CR-N21P). Subjective assessments of valence, arousal, and preference were captured via Likert scales, using the Psychopy GUI. Baseline measurements were performed to record reference data when no activity-specific tasks were performed. These measurements were eyes open (EO) and eyes closed (EC), 30 seconds each.

Six fragrances were administered via a dispenser and each fragrance was given three times. All the fragrances and their iterations were randomized. Each trial lasted 15 seconds and right after each fragrance, the participants were asked to fill in the 5-point Likert scales for valence, arousal, and preference in the Psychopy. A single trial from the fragrance onset until the rest period last approximately 1 minute. (Figure 2)

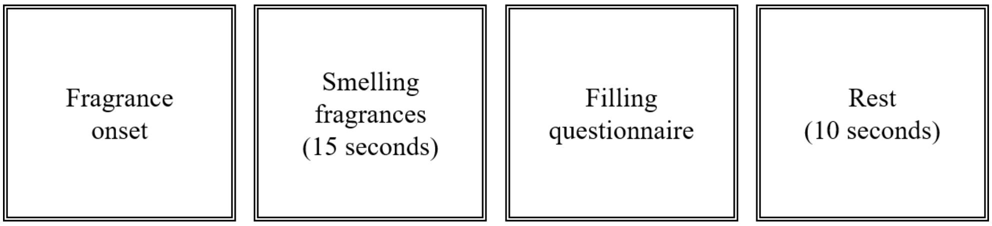


Figure 2. Fragrance sequence of events

EEG data were filtered between 0.5 and 40 Hz using an FIR filter. No notch filter was needed as the power line interference at 60 Hz was well suppressed. Filtering did not alter any in-band artifacts possibly present in the data such as blinks and motion. Every fragrance trial of 15-second length was segmented into 1-sec windows with 250ms overlap. Features were computed on each window both in time- (TD) and frequency-domain (FD). Basic statistical features included: mean, abs-mean, std, kurtosis, variance, rms, area, abs-area, range, and interquartile range. More complex time-domain features included entropy (approximate and sample) and Hjorth parameters (complexity and mobility). In the frequency domain, well-known features were computed for each brain wave, namely, delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-32 Hz), and gamma (32-40 Hz).

We implemented a blink artifact removal strategy based on the work by Raghavendra et al. [10] that combines in a novel way a blind source separation using canonical component analysis with wavelet-based artifact removal.

Our task was to predict a continuous value for arousal, valence, and preference which is a regression problem. Therefore, instead of accuracy, our metrics are mean absolute error and r2 (variance explained). To explore as many possible machine learning approaches as possible we used the Azure AutoML service that explores the fit of all suitable models, their combinations as well as hyperparameters.

We ran 30 different computing units in the cloud that systematically explored all sensible model configurations. This was done for valence, arousal, and preference. We attempted this by cross-validating over all data, as well as trying a leave-10-participants out cross-validation where the models were trained on 90 participants and tested on the remaining 10 to find the feasibility of applying our model to the unseen participants. The default Auto option in Azure AutoML was selected for validation. In cases where there are more than 20,000 rows in the dataset, the auto setting divided the data into 90% for training and 10% for validation. The metrics are then calculated on the performance of the 10% validation set.

Results.

The across participants analysis where we randomly sampled data from all participants into the test and training sets was able to achieve predictive power for all three labels. On average, the model could explain 29% - 34% of the variance in the data. (Table 1)

It is likely, due to a large number of blink artifacts, that the machine learning was learned at least partly patterns related to artifacts and not underlying brain activity. We also run multiple models such that we used leave-10-participants-out, but when we strictly split the training and validation by participant, our model performance decayed and did not reach meaningful results.

Table 1. Results across participants.

	Mean Absolute Error	R2 Score	Spearman correlation
Preference	0.668	0.336	0.578
Arousal	0.668	0.321	0.556
Valence	0.706	0.286	0.529

We developed a windows application (MIND STREAM; Figure 3) to work with imec's MOOD8 headset. It can read and record EEG data from the headset, plot it in real-time, run the algorithm pipeline on the data and finally show the participant emotions in real-time (arousal, valence, and preference). (Figure 4)

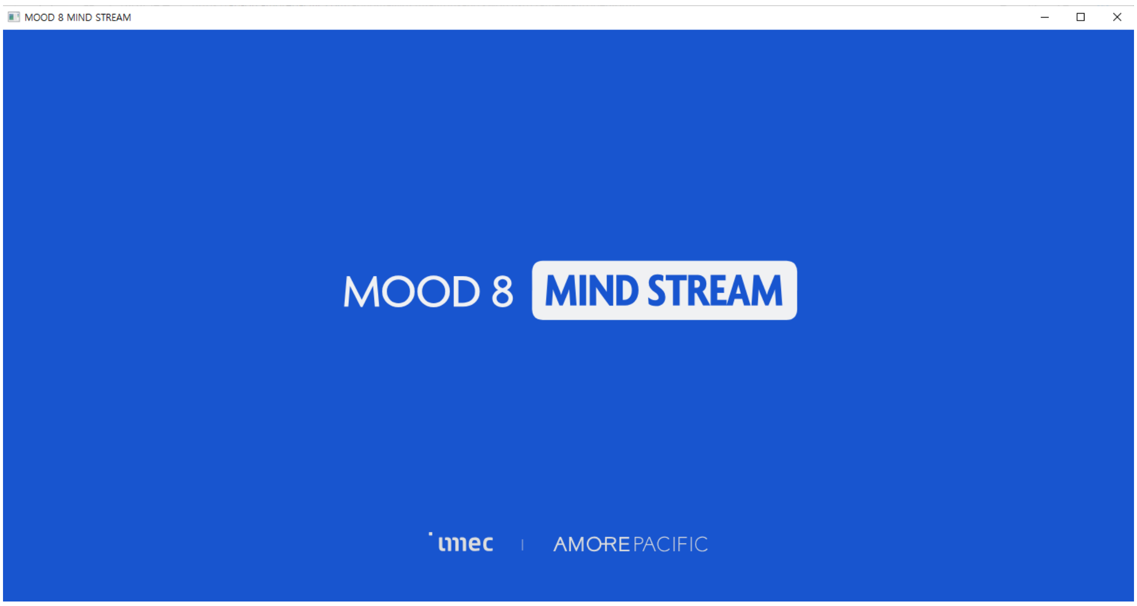


Figure 3. MIND STREAM

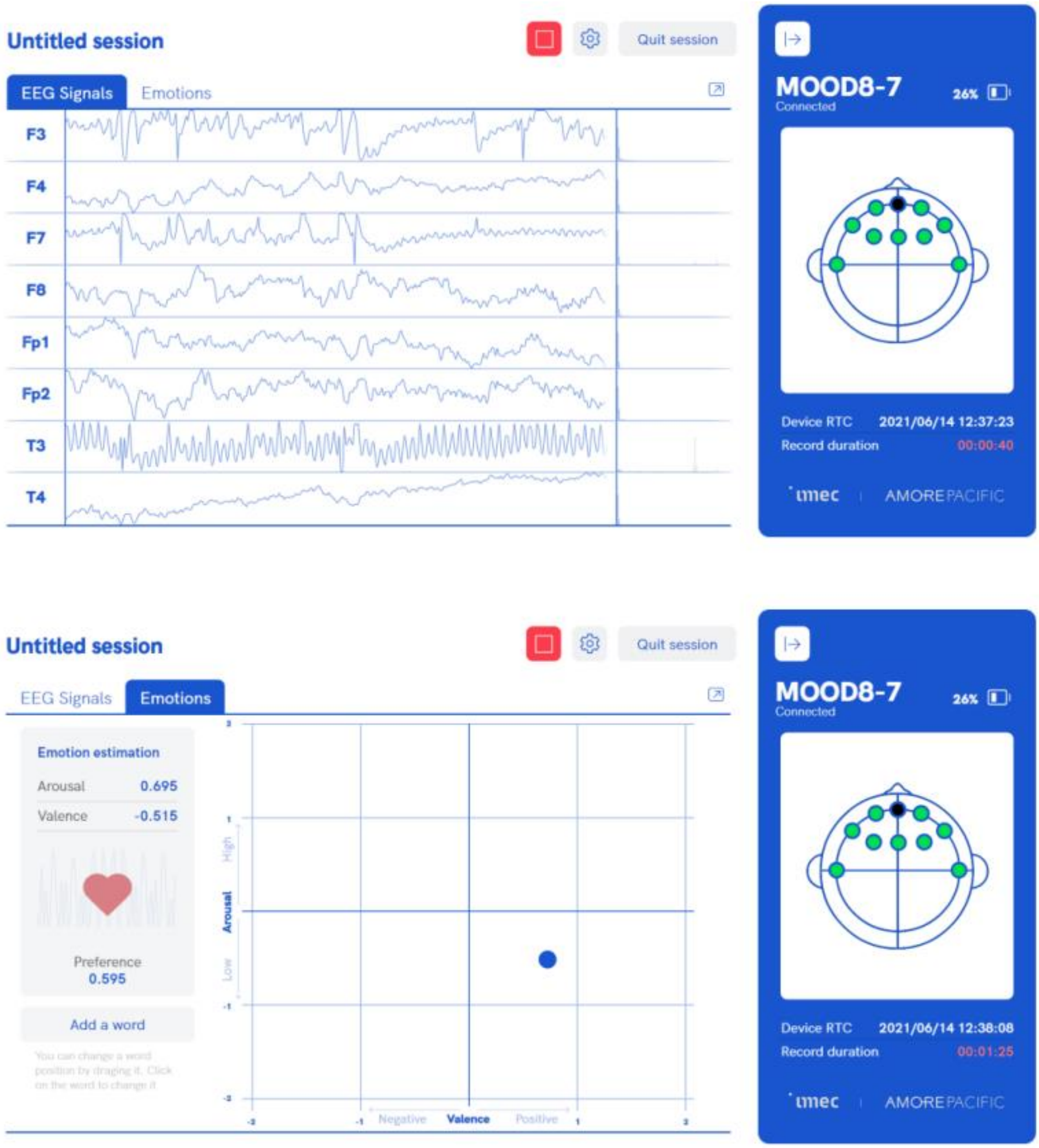


Figure 4. Captured images of a window application. Built-in functionality to visualize the filtered EEG signals both in time and frequency domain (upper) and visualization of the predicted emotions in the circumplex model of valence and arousal, with the predicted preference score. (below)

Discussion.

In this project, we presented a headset device (MOOD8) for acquiring EEG data and a portable application (MIND STREAM) for visualizing the data and insights created by the algorithms wrapped inside the app. An essential part of the algorithm is a machine learning model pre-trained using collected 100 subjects' data and self-reported emotional responses. Predicting human emotions from noisy EEG data and a limited number of self-reported stimuli-responses is not a trivial task. The majority of the studies in affect recognition are done across participants which is a considerably easier task than having a model that can generalize to completely unseen participants. Among technical challenges are the amount of noise, occasional motion artifacts and blinks present in the data. In the current data, these happen more often than it was expected. If these are not dealt with in some way, they cause major outliers in time- and frequency-domains features. A more fundamental challenge is the fact that all people are different. Even a relatively large dataset of 100 individuals cannot account for diversity in all potential users.

In the current use case, the algorithm has to be able to recognize changes in EEG when a participant reports inconsistent reaction to the same stimulus, but also adapt to variability in brain activity among different participants. To overcome this problem, the use case could be modified to allow a calibration procedure of some kind prior to general use. Then the model could adjust itself and make more personalized predictions.

Future work on improving the performance can include one or more of the following activities. For instance, data windows with full or partial blinks can be detected and discarded completely, which in our case of 15 seconds segments leads to losing most of the data and creating discontinuities. An alternative approach is to filter artifacts out, but any method will also change the signal itself in an uncontrolled manner. In addition, more complex methods require reference signals or templates such as EOG.

Finally, we can attempt to pursue a more knowledge-driven solutions, rather than a data-driven only. This requires more domain knowledge in physiology and neurology. For instance, clarifying differences in types of brain activity as measured by different channels. Or defining the best moment to capture emotions after the stimuli. This can also lead to creating a new set of features specific to the problem.

Conclusion.

Our work is a meaningful step toward a real business use case. We can use this application in various steps such as product development, consumer survey, and marketing. Further, this can solve the purpose of increased demands for a tailored beauty solution. This tool can help understand consumer behavior and mind in a novel way, thereby contributing to and providing multiple implications in the cosmetic industry, consumer neuroscience, and sensory science.

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Conflict of Interest Statement. NONE

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