Human body odour modulates neural processing of faces: effective connectivity analysis using EEG

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***Abstract*—Facial emotion processing by the brain plays a decisive role in human social interactions. This signal helps us interpret and predict people's behaviours. However, other social signals such as human voices or human body odours may facilitate or impair the identification of facial expressions. Here we studied the effects of emotional human body odours on face processing by measuring evoked neural responses and brain connectivity using the electroencephalogram (EEG). We used an emotion recognition task in which the participants attributed an emotion (i.e. happy vs fearful) to a presented face image while simultaneously exposed to emotional body odours. First, we measured face related potentials (FRP)s including P100 and N170 components. Statistical analyses revealed significant differences among FRPs recorded in different odour conditions. Second, we used a hierarchical Bayesian approach including a group dynamic causal model (DCM) followed by parametric empirical Bayes (PEB) to characterize the brain network explaining differences between FRPs. Our preliminary results suggested that different brain networks contribute to neutral face processing in presence of different emotional body odours.**

***Index Terms*—human body odour, social interaction, effective brain connectivity, dynamic causal model, parametric empirical Bayes.**

I. Introduction

The brain processes information with a high degree of efficiency in order to perform the most accurate inference from the data it receives. This complex process involves various neural mechanisms that analyze, filter, and combine incoming information to produce the best possible conclusion. One interesting example is the way the brain processes emotions conveyed by facial expressions in the presence of human body odors. Previous research suggested that the perception of facial expression is influenced by body odours collected in various emotional contexts [1]–[4]. In spite of this existing literature on the behavioural effects of body odours on face processing, its underlying neural mechanism is not understood.

In a recent study, Callara *et al.* [5] investigated the effects of happy and fearful body odours on neutral face processing. They used EEG to measure the modulation of neural responses in the context of emotional body odours. Estimated face related potentials indicated a significant increase in the amplitude of the late positive potential (LPP) in the central-left brain area. They also measured behavioural responses to investigate the level of valence and arousal induced by body odours. However, statistical analysis did not reveal significant changes in the behavioural responses collected. In other research, Rekow *et al.* [6], [7] performed an EEG study to explore the effects of body odours on visual categorisation. The measured EEG spectrum showed that body odour facilitated categorising ambiguous face-like objects as real faces. In addition, their findings revealed a significant effect of body odour on the amplitude of the EEG spectrum during visual processing and on the right hemisphere. Body odour assistance for face categorization has also been investigated by Leleu *et al.* [8]. The main focus of their research was to explore if maternal body odour can help infants for successful face categorization. In this study, maternal body odours were collected from the t-shirts of infants' mothers under controlled conditions. Leleu *et al.* [8] measured brain responses by averaging the power of EEG signals acquired during maternal and control odour conditions. Comparing the estimated powers indicated a significant increase in the amplitude of the EEG spectrum when using maternal body odours. The enhancement of neural responses was observed over the right occipito-temporal cortex. It is important to note that Rekow *et al.* [6], [7] and Leleu *et al.* [8] both relied on ambiguous visual signals being processed by the brain. This was examined by using face-like pictures and recruiting immature face processing systems in young infants in [6], [7] and [8] respectively. There is little EEG research in this area, and the existing literature suffers from a lack of brain connectivity analysis to identify the neural circuit modulated by body odours. Connectivity analysis could be particularly important when multiple sensory inputs must be combined. For example in the present study visual stimuli are blurred making both visual and olfactory cues important.

Here, we addressed this issue by performing connectivity analysis on an EEG data set to study how emotional body odours modulate neutral face processing in the brain. In light of previous findings, it was expected that the central-left brain area and the right occipito-temporal cortex play a central connectivity role. We proposed a data analysis pipeline based on dynamic causal modeling (DCM) and parametric empirical Bayes (PEB) for measuring effective connectivity in the level of hidden neural states [9], [10].

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Fig. 1: A schematic illustration of two sample trials. The experimental design consisted of one control and three experimental conditions each including 10 trials. RT in the figure denotes the response time.

II. Materials And Methods

A. Data acquisition

Data from 30 healthy subjects were recorded using 32 EEG electrodes at a sample rate of 500 Hz. All the participants had normal olfaction and normal or corrected-to-normal vision. In addition, they provided signed informed consent before undertaking the experiment. The EEG acquisition was performed by the Polytechnic University of Valencia (UPV). The study received approval from the scientific committee of the UPV ($P2\_18\_06\_19$).

B. Experimental protocol

In this study, an experimental protocol was designed using olfactory and visual stimuli to investigate the influence of body odours on facial emotion attribution. The olfactory stimuli consisted of clean air and body odours collected from donors when they experienced neutral, happy and fearful emotions [11]. For brevity, we call these four conditions *clean air*, *neutral*, *happy* and *fearful* body odours, respectively. The visual stimuli consisted of 40 face images (21 men, 19 women) expressing neutral emotion [12]. In order to enhance the effects of olfactory factors on decision-making, low-contrast face images were used in this study. The contrast was progressively increased (see Fig. 1) at a rate determined empirically when designing the experiment and kept fixed throughout the data collection. The experimental paradigm included four blocks of odours in which participants were exposed to clean air and body odours. The block with clean air was used as the baseline or control condition. In each block of odour presentation, 10 neutral face images were presented and the subjects were requested to decide whether the given face was happy or fearful by pressing two keys on the keyboard. The screen was cleared when the subject answered and then after one second the next face image was presented on the screen. Fig. 1 shows a schematic illustration of two sample trials used in our study. The order of images was randomised at each block and the order of olfactory blocks was also randomised for each individual subject.

C. Data Analyses

1) Preprocessing: All the preprocessing stages were performed using the scripts implemented by MATLAB and EEGLAB toolbox [13]. In the first stage of preprocessing, the acquired EEG signals were down-sampled to 128 Hz. Then a band-pass filter with cut-off frequencies at 0.1 Hz and 40 Hz was used for noise removal. In the third stage of preprocessing, non-EEG channels such as electrooculogram (EOG), flat-line channels, low-frequency drifts and short-time bursts were removed from the data. Then, the remaining channels were interpolated to retrieve the channels removed in the previous stage. After interpolation, common average referencing was used to re-reference the EEG signals. Then, the trial epochs were calculated by segmenting data from -1 s to 2 s around the face stimulus onsets. Then we performed a visual inspection to remove the epochs contaminated by abrupt artifacts. In the last stage, independent component analysis (ICA) was used to remove residual noise components such as eye blinks, eye movements and muscle movements.

2) Face Related Potentials: We estimated face related potentials associated with experimental and control conditions by averaging clean EEG epochs across all subjects. The computed FRPs represent the brain responses to face stimuli in different olfactory conditions. To measure the modulation of FRPs by odours, we focused on evaluating the FRPs differences in both scalp and neural spaces. The modulation of the scalp data was investigated by comparing FRPs measured in experimental (i.e. emotional body odour) and control (i.e. clean air) conditions using ANOVA. The threshold value was $p = 0.05$ and the results were corrected for multiple comparisons using false discovery rate (FDR). The modulation of brain responses in neural space was investigated by measuring brain connectivity underlying the observed FRPs. To this aim, the contrast between FRPs associated with emotional body odour and clean air was used to characterise the parameters of the brain network underlying each condition.

3) Brain Connectivity: We used the statistical parametric mapping (SPM) toolbox to conduct brain connectivity analyses [14]. In particular, we focused on measuring effective connectivity among brain regions. Effective connectivity infers directed causal influences among neural populations [15]. In this context, experiment factors may modulate one neural population's causal effect on another. Here, we used a hierarchical Bayesian approach based on DCM and PEB to characterise effective connectivity [10], [16]. The dynamic causal model is the most popular framework proposed to explore effective connectivity [9]. DCM employs a set of differential equations to explain the cognitive processes in the brain that produce the observed data. The parameters of the differential equations represent either the strength of connections among brain sources or the strength of connections' modulations resulting from experimental conditions. In DCM analysis, a forward model is needed to project the activities of the hidden neural populations to the scalp. Here, we used the ERP neural-mass model [17] that has been implemented in SPM12. The coordinate of the brain sources in MNI space and the prior value of the connectivity parameters should be specified for DCM first. Then DCM uses the Bayesian technique to estimate the posteriors. In this study, we specified five brain areas as the network's nodes that were detected through the group source inversion approach proposed by Litvak and Friston [18]. Group source inversion is a constrained source localisation technique

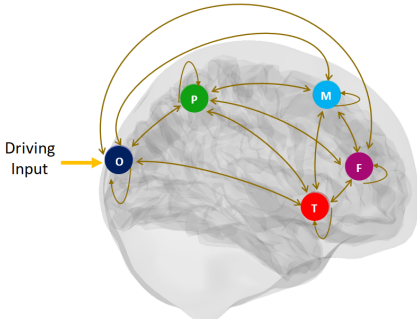


Fig. 2: The model specified as a prior to investigate effective connectivity among regions of interest during face and body odour processing. O, P, T, M, F refer to superior occipital, superior parietal, superior temporal, superior motor and inferior frontal respectively.

assuming all subjects rely on the same source priors. The brain regions identified by group source inversion and their corresponding MNI coordinates are:

- superior occipital (O): 14,-96,20
- superior parietal (P): 28,-50,64
- superior temporal (T): 54,0,-14
- superior motor (M): 14,18,56
- inferior frontal (F): 48,36,8

The above brain regions have been reported by the relevant research as the areas underlying visual/olfactory processing or decision-making tasks [19]–[21]. A fully connected DCM was generated using the above regions as the prior model of brain connectivity. We assumed all the connections could be modulated by the two factors (i.e. face and odour). Since we are interested in investigating the effects of olfactory stimuli on face processing, the face image stimulus was considered as the driving input in our analysis. Fig. 2 shows a schematic illustration of the model specified according to the above assumptions as a prior for brain connectivity investigation. We proposed a hierarchical Bayesian approach including two levels for measuring the posterior of the specified model. Fig. 3 shows the block diagram of the hierarchical brain

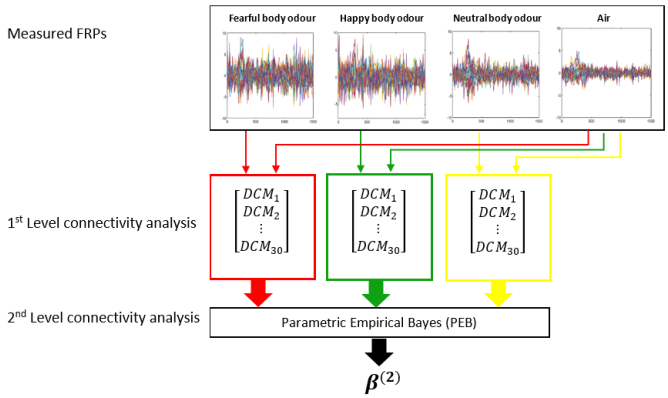


Fig. 3: Block diagram of brain connectivity analysis.

connectivity analysis used in this study. In the first level of the hierarchy, a group of DCMs was created for each experimental condition. Each member of the group DCM represents the brain connectivity of one subject. Then, the parameters of the models associated with a specific experimental condition were estimated using the contrast between observed FRPs in that condition and its corresponding control condition. Equation (1) shows the mathematical representation of the analysis performed in the first level [9]:

$$\begin{aligned} \dot{\mathbf{z}} &= f(\mathbf{z}, \mathbf{U}, \theta^{(1)}) \\ \mathbf{Y}_i &= \Gamma_i(\mathbf{z}, \theta_i^{(1)}) + \mathbf{W}_1 \lambda_i + \epsilon_i^{(1)}. \end{aligned} \tag{1}$$

The first line of (1) explains the variation of neural activity in the brain regions $\dot{\mathbf{z}}$ as a function of neural activity of brain sources involved in the network $\mathbf{z}$, inputs (i.e stimuli) $\mathbf{U}$ and network's parameters $\theta^{(1)}$. In the second line, $\mathbf{Y}_i$ represents the data observed from subject i, $\Gamma_i(\mathbf{z}, \theta_i^{(1)})$ indicates the first level DCM trying to interpret observed data using parameters $\theta_i^{(1)}$ and neural activity in the brain regions $\mathbf{z}$, $\mathbf{W}_1 \lambda_i$ models uninteresting components and $\epsilon_i^{(1)}$ denotes the residual noises obtained in the first level of the analysis. We generated three groups of DCMs (i.e. the colourful blocks in Fig.3) associated with three experimental conditions to study how emotional human body odours modulate face processing in the brain. After generating group DCMs, the posterior values of the parameters were estimated using the priors, observed data and mathematical approach explained by (1).

In the second level of the hierarchy, we performed Parametric Empirical Bayes (PEB) to estimate the average and the main effects of conditions [10]. Equation (2) explains the theory behind PEB enabling us to investigate our hypotheses about brain connectivity [16]:

$$\begin{bmatrix} \theta_{11} \\ \theta_{21} \\ \vdots \\ \theta_{n1} \\ \vdots \\ \theta_{1m} \\ \theta_{2m} \\ \vdots \\ \theta_{nm} \end{bmatrix}^{(1)} = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_k \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix}^{(2)} + \epsilon^{(2)} \tag{2}$$

In (2), $\theta^{(1)}$ is a matrix where each row represents the parameters estimated for each subject and each experimental condition in level one. For example, θ_{2m} is a row vector that refers to the parameters estimated for the subject 2 that participated in condition m. In PEB, these parameters can be modelled by General Linear Model (GLM) using a design matrix $\mathbf{X}$. Columns of the design matrix encode the hypotheses of interest such as the mean effect of one specific factor or group differences across conditions. In (2), $\beta^{(2)}$ is a matrix whose rows represents the second-level parameters. Each row of $\beta^{(2)}$ is associated with one column of $\mathbf{X}$. For example β_2

includes parameters explaining the hypothesis encoded by $\mathbf{x}_2$. Finally, $\epsilon^{(2)}$ represents the additive noise.

We investigated the average and the main effects of body odours on brain connectivity by generating a design matrix including four columns. The first column of the design matrix (i.e. $\mathbf{x}_1$) was a column of ones and encoded the mean effect of all conditions. The corresponding parameter can be interpreted as the overall effects of neutral face and body odours on brain connectivity. We used a combination of zeros and ones to encode the additive effects of emotional human body odours when the brain is involved in neutral face processing. Fig. 4 shows the schematic illustration of the design matrix utilised in our study. Since we were interested in the modulatory effects of the experimental conditions, $\theta^{(1)}$ in (2) included only the parameters representing modulation in the first level DCMs. Having the parameters estimated in the first level $\theta^{(1)}$ and the specified design matrix $\mathbf{X}$, the second level parameters $\theta^{(2)}$ can be calculated using (2). We inspected the quality of the model inversion (i.e. parameter estimation) by evaluating the free energy of the models in the first and second levels [22], [23]. Parameter estimation in the second level was then followed by the Bayesian model comparison (BMC) and the Bayesian model reduction (BMR). This stage led to identifying the parameters offering the most accurate and less complex interpretation of observed data [23], [24]. In the next section, the results obtained by our study are presented.

III. Results

A. Face related potentials

Fig. 5 represents the average power of brain potentials evoked by face stimuli over the scalp in each olfactory condition. The results revealed that the amplitude of brain responses was dominant in the frontal and occipital EEG electrodes. It is also observed that the fearful body odour increased the amplitude of brain responses. Fig. 6 shows the FRP waveforms measured by P3, P4 and FC6 in three experimental and their complementary control conditions. The measured FRPs included P100, N170 and P300. We conducted ANOVA to inspect the influence of emotional body odours on the FRP components. We used ($p_{value} = 0.05$) and FDR correction for multiple comparisons. The statistical analysis revealed some significant differences between the FRPs measured during experimental conditions (i.e. emotional human body dour) and control conditions (i.e. clean air). Time intervals with significant differences are shown by grey colour in Fig. 6. Inspecting the results indicated that significant differences among the measured FRPs happened in different time intervals across the scalp.

B. Brain connectivity

The results presented in this section explain the underlying brain process producing the observed FRPs. Fig. 7 shows the brain networks involved in each experimental condition. Fig. 7 represents only the connections that were modulated by the experimental factors. The numerical value of the networks' parameters, estimated by PEB, is written on each brain connection and indicates the strength of connectivity modulation due to applying specific experimental condition. Positive and negative values represent excitation and inhibition respectively. Fig. 7(a) provides a schematic illustration of the parameters corresponding to the first column of the design matrix. The main objective of this column was to encode the average modulation effects of all the factors on effective connectivity. The average effects of all factors can be interpreted as the baseline of connectivity. Fig. 7(b-d) explains the main effect of each emotional body odour on brain connectivity. The parameters of the networks shown by Fig. 7(b-d) are associated with columns $2-4$ of the design matrix. These columns encode the main effects of each body odour on brain connections. As seen in Fig. 7(a), common effects of all factors led to modulating 10 brain connections. Fig. 7(b-d), shows the connectivity pathway that was modulated by happy, fearful and neutral body odours. Comparing Figs. 7(a-d) indicated that applying happy and fearful body odours modulated more brain connections compared to neutral body odour. In addition,

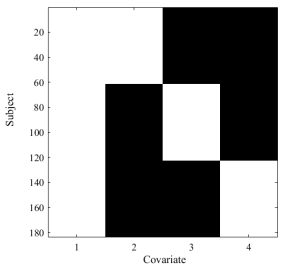


Fig. 4: Between subjects design matrix including 4 covariates encoding i) average effect of all conditions and the main effects of ii) happy iii) fearful, and iv)neutral body odours.

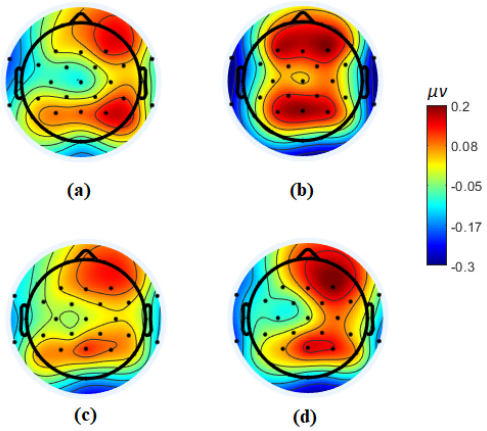
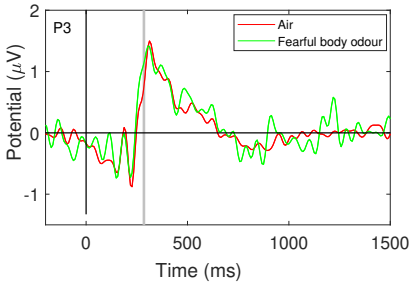
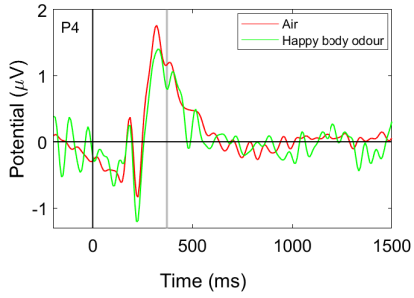


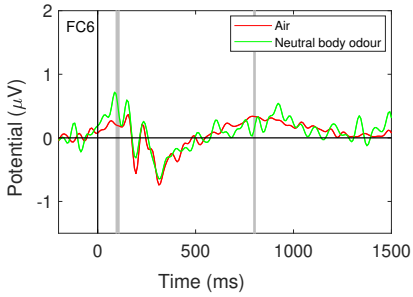
Fig. 5: average power of brain responses to face stimuli observed in (a) air, (b) fearful body odour, (c) happy body odour and (d) neutral body odour conditions. .



(a)



(b)



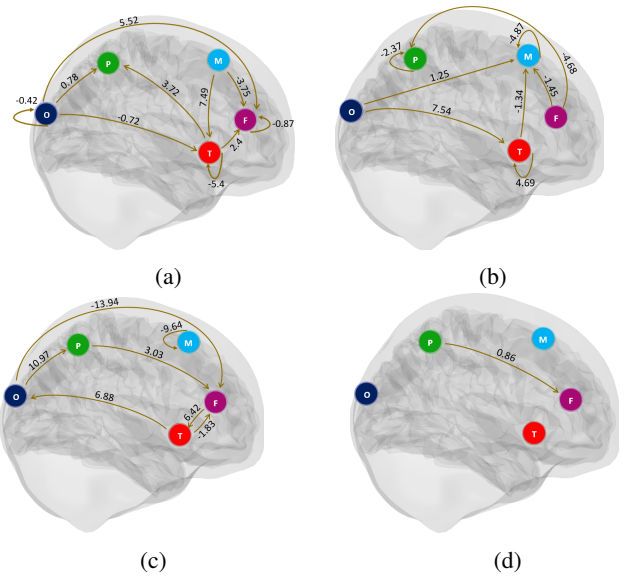
(c)

Fig. 6: Comparison of ERP waveforms measured in air condition and (a) fearful body odour, (b) happy body odour and (c) neutral body odour conditions. Time "0" in the figures indicates the face presenting onset.

the strength of modulation by happy and fearful body odour conditions was significantly higher than neutral body odour. According to the Figs. 7(b-c), fearful and happy body odours modulated the superior motor cortex significantly. This can be supposed as the influencing effect of the emotional body odours trying to tempt the subject to attribute the emotion to the presented face through pressing the button. In addition, the obtained results revealed that the connection between the superior parietal and inferior frontal was modulated by all three body odours. Comparing the parameter values measured for this connection show that the strength of modulation in fearful and happy body odour conditions was remarkably stronger than in neutral body odour condition.

IV. Discussion

In this preliminary study, we investigated the effects of emotional body odours on the neural processing of neutral face images. In our study, EEG was used to measure the



(a) (b) (c) (d)

Fig. 7: Pathway of effective connectivity underlying neutral face processing in (a) all olfactory, (b) fearful body odour, (c) happy body odour and (d) neutral body odour conditions. Reported values represent the effect of modulation resulted from the corresponding olfactory conditions. O, P, T, M, F refer to superior occipital, superior parietal, superior temporal, superior motor and inferior frontal respectively.

brain responses evoked by face processing when subjects were exposed to different odours. Measuring FRPs revealed face related components such as $P100$ and $N170$. The obtained evoked potentials have also been reported in a paper that explored a similar EEG experiment [19]. We also observed a strong LPP component in most of the channels. Analysis performed in [19] also led to obtaining strong late positive potential due to using emotional body odours and neutral face images simultaneously. The measured scalp maps indicated strong brain responses in the areas that were in line with the previous relevant studies [6]–[8]. We measured the modulation of brain responses by comparing i) FRPs and ii) effective connectivity acquired in different olfactory conditions. In all the comparisons, the air condition was considered as the baseline. Comparing the FRPs revealed that the emotional body odours induced some changes in the evoked responses. The results of group effective connectivity also led to revealing a more specific connectivity pattern underlying emotional body odour processing. The outcome of our connectivity analysis showed that fearful and happy body odours modulated brain connections remarkably. It is observed that fearful and happy body odours strongly modulated the connection among the superior occipital, superior temporal, superior parietal and inferior frontal. According to the relevant literature, all these brain areas play key roles in face, emotion and odour processing [20], [21]. Although our preliminary study revealed that emotional human body odours modulated face processing, further investigation will be needed to test the robustness of

these results. This can be obtained by increasing the number of subjects and using a more comprehensive design matrix for the PEB analysis.

REFERENCES

[1] R. G. Kamiloğlu, M. A. M. Smeets, J. H. B. de Groot, and G. R. Semin, "Fear Odor Facilitates the Detection of Fear Expressions Over Other Negative Expressions," *Chemical Senses*, vol. 43, no. 6, pp. 419–426, 05 2018.

[2] M. Rocha, V. Parma, J. N. Lundström, and S. C. Soares, "Anxiety body odors as context for dynamic faces: Categorization and psychophysiological biases," *Perception*, vol. 47, no. 10-11, pp. 1054–1069, 2018.

[3] O. A. Wudarczyk, N. Kohn, R. Bergs, K. S. Goerlich, R. E. Gur, B. Turetsky, F. Schneider, and U. Habel, "Chemosensory anxiety cues enhance the perception of fearful faces – an fmri study," *NeuroImage*, vol. 143, pp. 214–222, 2016.

[4] J. H. B. de Groot, M. A. M. Smeets, A. Kaldewaij, M. J. A. Duijndam, and G. R. Semin, "Chemosignals communicate human emotions," *Psychological Science*, vol. 23, no. 11, pp. 1417–1424, 2012.

[5] A. L. Callara, C. Cecchetto, E. Dal Bò, L. Citi, C. Gentili, N. Vanello, E. P. Scilingo, and A. Greco, "Human body odors of happiness and fear modulate the late positive potential component during neutral face processing: a preliminary erp study on healthy subjects," in *2022 44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2022, pp. 4093–4096.

[6] D. Rekow, J.-Y. Baudouin, K. Durand, and A. Leleu, "Smell what you hardly see: Odors assist visual categorization in the human brain," *NeuroImage*, vol. 255, p. 119181, 2022.

[7] D. Rekow, J.-Y. Baudouin, F. Poncet, F. Damon, K. Durand, B. Schaal, B. Rossion, and A. Leleu, "Odor-driven face-like categorization in the human infant brain," *Proceedings of the National Academy of Sciences*, vol. 118, no. 21, p. e2014979118, 2021.

[8] A. Leleu, D. Rekow, F. Poncet, B. Rossion, K. Durand, B. Schaal, and J. Y. Baudouin, "Maternal odor shapes rapid face categorization in the 4-month-old infant brain," in *Vision Sciences Society Annual Meeting*, vol. 18, no. 10. Assoc Research Vision Ophthalmology Inc., Rockville (United States), May 2018, p. 787, open access meeting abstract.

[9] K. Friston, L. Harrison, and W. Penny, "Dynamic causal modelling," *NeuroImage*, vol. 19, no. 4, pp. 1273–1302, 2003.

[10] P. Zeidman, A. Jafarian, M. L. Seghier, V. Litvak, H. Cagnan, C. J. Price, and K. J. Friston, "A guide to group effective connectivity analysis, part 2: Second level analysis with peb," *NeuroImage*, vol. 200, pp. 12–25, 2019.

[11] J. H. B. de Groot, M. A. M. Smeets, A. Kaldewaij, M. J. A. Duijndam, and G. R. Semin, "Chemosignals communicate human emotions," *Psychological Science*, vol. 23, no. 11, pp. 1417–1424, 2012.

[12] O. Langner, R. Dotsch, G. Bijlstra, D. H. Wigboldus, S. T. Hawk, and A. van Knippenberg, "Presentation and validation of the radboud faces database," *Cognition and Emotion*, vol. 24, no. 8, pp. 1377–1388, 2010.

[13] A. Delorme, T. Mullen, C. Kothe, Z. A. Acar, N. Bigdely-Shamlo, A. Vankov, and S. Makeig, "Eeglab, sift, nft, bcilab, and erica: New tools for advanced eeg processing," *Intell. Neuroscience*, vol. 2011, jan 2011.

[14] K. J. Friston, A. Holmes, K. J. Worsley, J. B. Poline, C. D. Frith, and R. S. J. Frackowiak, "Statistical parametric maps in functional imaging: A general linear approach," *Human Brain Mapping*, vol. 2, 1994.

[15] K. J. Friston, "Functional and effective connectivity: A review," *Brain Connectivity*, vol. 1, no. 1, pp. 13–36, 2011.

[16] P. Zeidman, A. Jafarian, N. Corbin, M. L. Seghier, A. Razi, C. J. Price, and K. J. Friston, "A guide to group effective connectivity analysis, part 1: First level analysis with dcm for fmri," *NeuroImage*, vol. 200, pp. 174–190, 2019.

[17] R. Moran, D. A. Pinotsis, and K. J. Friston, "Neural masses and fields in dynamic causal modeling," *Frontiers in Computational Neuroscience*, vol. 7, May 2013.

[18] V. Litvak and K. Friston, "Electromagnetic source reconstruction for group studies," *NeuroImage*, vol. 42, no. 4, pp. 1490–1498, 2008.

[19] A. Leleu, O. Godard, N. Dollion, K. Durand, B. Schaal, and J.-Y. Baudouin, "Contextual odors modulate the visual processing of emotional facial expressions: An ERP study," *Neuropsychologia*, vol. 77, pp. 366–379, 2015.

[20] C. Cinzia, L. Elisa, B. Domenica, R. I. Rumiati, and P. Valentina, "Body odors (even when masked) make you more emotional: behavioral and neural insights," *Scientific Reports (Nature Publisher Group)*, vol. 9, no. 1, 12 2019.

[21] C. Cecchetto, F. P. S. Fischmeister, S. Gorkiewicz, W. Schuehly, D. Bagga, V. Parma, and V. Schöpf, "Human body odor increases familiarity for faces during encoding-retrieval task," *Human Brain Mapping*, vol. 41, no. 7, pp. 1904–1919, 2020.

[22] K. Friston, J. Mattout, N. Trujillo-Barreto, J. Ashburner, and W. Penny, "Variational free energy and the laplace approximation," *NeuroImage*, vol. 34, no. 1, pp. 220–234, 2007.

[23] K. J. Friston, V. Litvak, A. Oswal, A. Razi, K. E. Stephan, B. C. van Wijk, G. Ziegler, and P. Zeidman, "Bayesian model reduction and empirical bayes for group (dcm) studies," *NeuroImage*, vol. 128, pp. 413–431, 2016.

[24] K. J. Friston and W. D. Penny, "Post hoc bayesian model selection," *Neuroimage*, vol. 56, pp. 2089 – 2099, 2011.