Paradigms for probing socio-affective Bayesian inference in individuals with blunted affect – preliminary insights

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Abstract

Despite their key impact on clinical outcomes, negative symptoms in schizophrenia remain poorly understood. We designed a functional Magnetic Resonance Imaging (fMRI) study to test a mechanistic hypothesis of negative symptoms, based on the Bayesian inference and predictive coding framework. We thus designed tasks and chose models that capture this inference process, i.e. a social-affective prediction task and a control task that can be fit with Bayesian generative models. Here we present preliminary data of a first pilot study testing whether we can extract prediction error (PE) learning quantities that are uniquely social-affective. This is a crucial component of the upcoming fMRI study. Our preliminary results indicate that the two tasks in conjunction with the models may capture learning quantities that are unique to the social-affective task as well as quantities that capture general specific PE-learning. Given the preliminary nature of the study, results may change.

Keywords: computational psychiatry; negative symptoms; constricted affect; blunted affect; prediction errors; Bayesian inference

Introduction

While neuroimaging and computational mechanistic investigations have improved our understanding of positive symptoms (e.g. Adams et al., 2013; Corlett et al., 2016; Murray et al., 2008; Powers, Kelley, et al., 2017; Powers, Mathys, et al., 2017), negative symptoms remain poorly understood. A recent proposed mechanistic hypothesis about how negative symptoms, and affective blunting specifically, may arise and persist suggests that altered learning about other people's affective reactions to their own affect may lead to blunted affect (Jeganathan & Breakspear, 2021). For instance, some individuals may perceive that their smiles are not met by others smiling back resulting in social affective PEs (saPEs) leading to a maladaptive (subconscious) strategy of avoiding saPEs by blunting their affect. We designed an fMRI study that tests these mechanistic hypotheses with patients with psychosis and individuals from the general population who score on different ends of the constricted affect score of the Schizotypal Personality Questionnaire (SPQ; (Raine, 1991)).

For this study we designed two trial-by-trial PE-learning tasks: (1) The SAP (Social Affective Prediction) task operationalizes saPE-learning and (2) the SAPC (Social Affective Prediction Control) task captures PE-learning in a different context.

In a first pilot study we test whether saPE learning in the SAP task is distinguishable from non-social and non-affective PE learning. This is crucial to show specific saPE signatures in the brain in our upcoming fMRI study.

Methods

In the main task of interest (SAP task), participants predict whether they will receive a smile from three different faces with different inherent probabilities of smiling (p=0.9, p=0.6, or p=0.2 respectively) on 120 trials. Participants are instructed that some of the faces are more likely to smile back than others. They indicate their prediction with a button press followed by them actively smiling at the face or staying neutral. The outcomes (whether a face smiles or not) are predetermined and the same for all participants. The control task (SAPC) uses the same predetermined outcome sequence, but instead of predicting smiles participants predict whether an egg will spoil or not.

The predetermined outcome sequence of both tasks was optimized regarding parameter recoverability based on simulations with a generative model that captures trial-by-trial PE learning, the extended binary Hierarchical Gaussian Filter (eHGF; C. Mathys, 2011; C. D. Mathys et al., 2014). The eHGF captures how uncertainty influences perception and hierarchical PE updating according to predictive coding principles.

In order to test for the effect of task on PE learning, we are running an ongoing small behavioural pilot study (N=5 to date). Pilots played both tasks in counterbalanced order and their responses were inverted with a binary 2-Level (eHGF2) and a binary 3-Level eHGF (eHGF3) model. We extracted Maximum A-Posteriori (MAP) estimates of the following parameters: $\omega_{2,eHGF2}$, $\omega_{2,eHGF3}$, $\omega_{3,eHGF3}$.

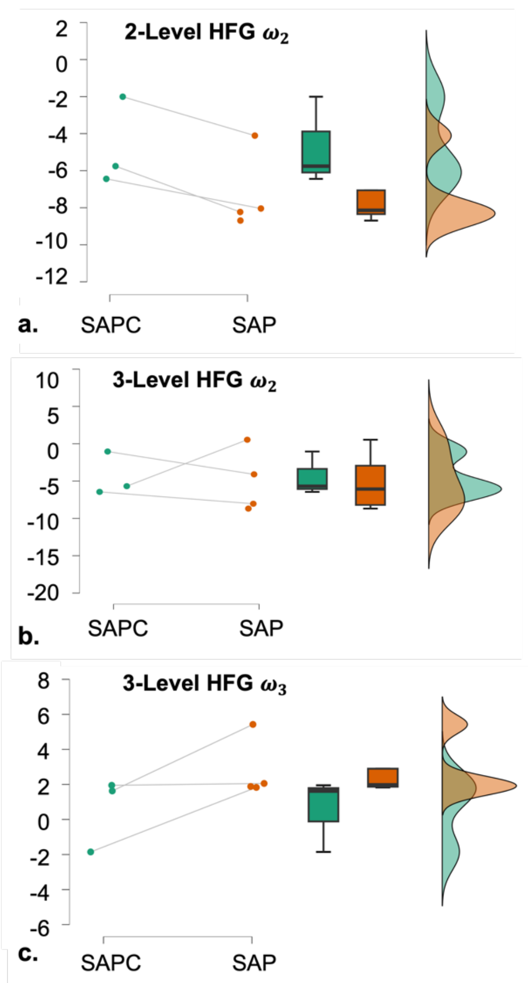

Figure 1, results.

a. Raincould plot $\omega_{2,eHGF2}$ for SAP vs. SAPC task: BF_{10}=1.967, $CI_{95\%}$: [-8.706, 0.340]
b. Raincould plot $\omega_{2,eHGF3}$ for SAP vs. SAPC task: BF_{10}=1.335, $CI_{95\%}$: [-4.164, 0.447]
c. Raincould plot $\omega_{3,eHGF3}$ for SAP vs. SAPC task: BF_{10}=0.749, $CI_{95\%}$: [-0.647, 1.919]

Results

We conducted Bayesian paired samples t-tests in JASP (JASP, 2023) for each one of the predefined parameter estimates. For both eHGF variations we found more evidence for there being a difference between learning captured by the 2nd-level *learning rate* (ω_2). For the other parameter ($\omega_{3,eHGF3}$) we found evidence for the absence of an effect of task (see Figure 1 for eHGF results).

Discussion

Given the small preliminary sample size, all of the reported Bayes Factors only provide anecdotal evidence for both hypotheses. Additional data (data collection is ongoing) is needed to identify the parameters that can differentiate learning in the different tasks and parameters that may capture similarities.

If, with more data, the evidence will accumulate in favour of the here identified effects, we could show that learning with the eHGF can distinguish between learning in the two tasks. More specifically, ω_2, the weight of the precision of the sensory input on the 2nd level is different on depending whether participants learn by weighing sensory input (or bottom-up information) differently in a social vs. as non-social context.

If the evidence for the absence of a task difference should also accumulate with more data points for parameter $\omega_{3,eHGF3}$, we would be able to show that the meta-volatility (the perception of participants about how fast the environment is changing) may be governed more by the stimulus-outcome sequence vs. to the content of the task. This may thus be a more general marker for PE-learning under uncertainty.

For our upcoming main fMRI study, these potential results suggest that we would be able to identify differences in learning that may be specific to social-emotional processes in individuals with highly constricted affect vs. individuals with no constricted affect. We will thus be able to directly test the hypotheses stated in a recent paper by (Jeganathan & Breakspear, 2021) and identify neural correlates of saPEs.

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