A joint model of risk-taking and learning related to risks based on behavioral and prefrontal oxygenation measures

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Abstract

This study examines the neural and cognitive mechanisms of risk-taking by integrating behavioral and fNIRS data through a joint modeling approach. Participants completed a modified Balloon Analogue Risk Task (BART) under conditions varying in uncertainty, while a functional near-infrared spectroscopy (fNIRS) device was used to monitor their prefrontal cortex (PFC) activity. A censored Bayesian model estimated individual risk-taking propensity, which was linked to HbO levels across PFC subregions with a joint model. Traditional analyses revealed condition-specific effects, whereas the joint model identified individual-level correlations between risk propensity and PFC activity. Notably, stronger correlations emerged in the left dorsolateral PFC under structured uncertainty and in the right dorsolateral PFC under random uncertainty—patterns not accounted by classical methods. These findings highlight the value of joint modeling in revealing latent brain–behavior relationships.

Keywords: decision making under risk and uncertainty; BART; joint modeling; fNIRS

Introduction

This study explores the neural correlates of risk-taking and probability learning under varying levels of uncertainty. The BART task, which assesses risk taking behavior in a computer environment (Aklin et al., 2005; Charness et al., 2013; Lejuez et al., 2002), is used in conjunction with fNIRS to examine decision-making across conditions. In BART, participants inflate a virtual balloon to increase potential earnings, with each pump raising both reward and the risk of explosion. They may cash out at any time; if the balloon bursts, no earnings are added for that trial.

We conducted two BART experiments (perfect gambling, probability learning) developed in OpenSesame (Lejuez et al., 2002; Zosky, 2019), using a repeated measures design while recording fNIRS data over the PFC. Fourty-nine participants with no reported neurological or psychiatric disorders completed both experiments. Each experiment included 75 trials: 30 with mixed-color balloons and 45 with constant-color balloons (15 red, blue, and yellow). The tasks were structurally identical, but only the probability learning condition assigned fixed explosion probabilities (blue = 1/8, red = 1/32, yellow = 1/128), allowing participants to learn risk levels. Additional monetary rewards were tied to performance.

fNIRS data were collected at 2 Hz from 16 optodes over the PFC. A finite impulse response filter was applied to attenuate physiological noise in the raw fNIRS data, which were then converted into oxygenated hemoglobin (HbO) concentration changes using the modified Beer–Lambert law. The HbO signals were averaged into five ROIs: left dlPFC (Optodes 1–4), left dmPFC (5&6), frontopolar (7–10), right dmPFC (11&12), and right dlPFC (13–16).

Behavioral and fNIRS data were analyzed using both traditional methods and a joint model to estimate participants' individual number of pumps (INOP) in the BART (Figure 1). The behavioral component, based on a censored log-normal model (Coon & Lee, 2022), produced participant-level estimates of risk-taking propensity (ρ) and behavioral consistency (β). The neural component, adapted from D'Alessandro et al. (2020), integrated ρ with HbO values from five PFC ROIs. The joint model estimated posterior correlations between ρ and HbO across blocks and conditions.

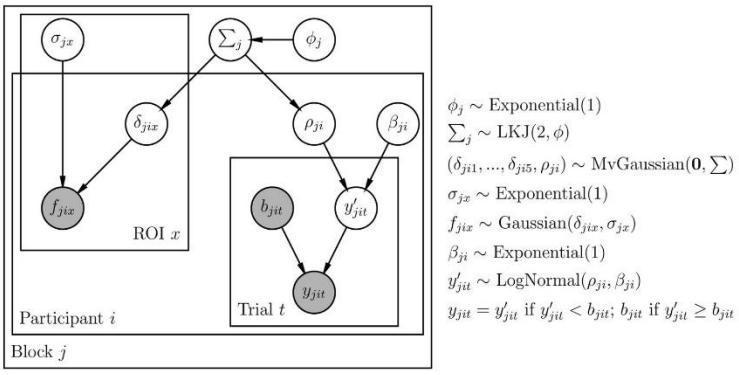

Figure 1. The joint model used in this study[1].

[1] f_{jix}: samples in each ROI, δ_{jix}: their mean value & σ_{jx}: variance, Σ_j: covariance matrix, ρ_{ji}: RTP, β_{ji}: behavioural consistency, y_{jit}: observed NOP, y'_{jit}: INOP, b_{jit}: trials balloon bursts.

Data Analysis & Results

A 3×2×2 repeated-measures ANOVA tested the effects of color, presentation order, and condition (probability learning vs. random) on total NOP, a common risk-taking measure. As shown in Figure 1, all main effects and interaction effects were significant, except for the order × condition interaction. When explosion probabilities were fixed, higher NOP values were observed for colors with lower explosion risk (e.g., yellow). In the mixed-order condition, NOP decreased for low-risk colors but remained stable for high-risk ones, indicating greater risk aversion.

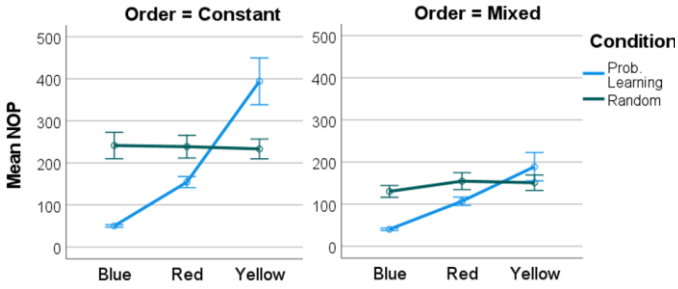

Figure 2. Mean NOP values for different balloon colors under different order and probability learning conditions.

fNIRS data were organized into four blocks (Mix, Blue, Red, Yellow) for each condition: probability learning (PMIX, PBLUE, PRED, PYELLOW) and perfect gambling (RMIX, RBLUE, RRED, RYELLOW). To assess PFC sensitivity to uncertainty, we first compared HbO levels between PMIX and RMIX using paired t-tests across 16 optodes, visualized with B-spline interpolation in fNIRSoft (Figure 3). Significantly higher HbO levels were found in the random condition at optode 13 (right dmPFC) and optode 16 (right dlPFC).

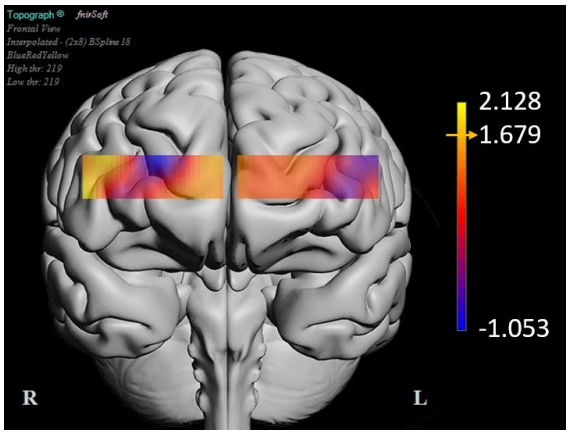

Figure 3. T-map contrasting PMIX and RMIX conditions.

While traditional analyses offered group-level insights, they did not account for individual variability or brain–behavior links. To address this, we used a joint model that integrates behavioral and neural data at the individual level, incorporating a censored model to include burst trials and better capture risk-taking in relation to PFC activity under uncertainty.

Figure 4 shows the posterior correlations between risk-taking propensity (RTP or ρ) and HbO activity across PFC regions estimated from the joint model. In the PMIX condition, ρ was most strongly associated with the left dlPFC (r = 0.54), with moderate correlations in other regions. In RMIX, correlations shifted toward the right PFC, notably the right dlPFC (r = 0.45) and right dmPFC (r = 0.48), while the left dlPFC showed a weaker link (r = 0.33). These findings suggest that subregions of the PFC are differentially engaged in relation to individual risk-taking tendencies, depending on the level of uncertainty in the task environment.

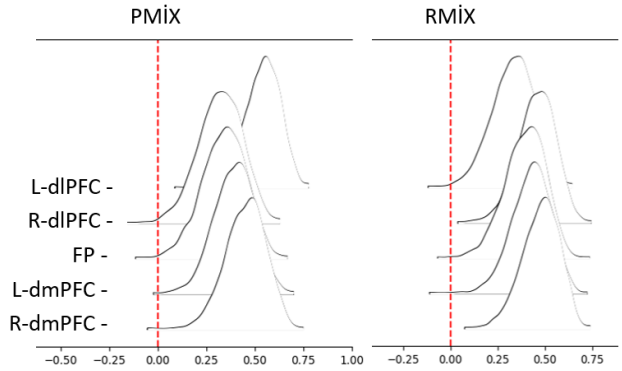

Figure 4. Posterior correlations between HbO levels and the censored RTP parameter from the joint model.

Conclusion

Overall, this study examined risk-taking behavior by integrating a censored behavioral model with fNIRS data in a joint modeling framework. While traditional contrast analyses highlighted increased right PFC activation under high uncertainty—likely reflecting heightened attentional demands and decision difficulty—they overlooked the role of left PFC in the probability learning condition. In contrast, the joint model uncovered condition-specific brain–behavior relationships, including the role of the left dlPFC in structured environments, by capturing the covariance structure between neural activity and individual differences in risk propensity. These findings underscore the potential of joint modeling for exploring latent brain–behavior relationships.

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