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NEUROPHYSIOLOGICAL CORRELATES OF RISKY DECISION-MAKING

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2. Yaple, Z., Shestakova, A., Klucharev, V. (2018). Feedback-related negativity reflects omission of monetary gains: evidence from ERP gambling study // Neuroscience Letters, 686, 145-49.
3. Yaple, Z., Martinez-Saito, M., Novikov, N., Altukhov, D., Shestakova, A., Klucharev, V. (2018). Power of feedback-induced beta oscillations reflect omission of rewards: evidence from an EEG gambling study. Frontiers in Neuroscience, 12, 776.
4. Yaple, Z., Martinez-Saito, M., Panidi, K., Shestakova, A., Klucharev, V. (accepted – expecting publication in 2019). Depletion of executive control during risky decision making reveals a correspondence between the reflection effect and trial-by-trial strategy formation // I.P. Pavlov Journal of Higher Nervous Activity.

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3. Frequency-specific modulation of responses to risk and certainty options across gains and losses. // 3rd Science Factory: TMS-EEG Summer School. Aalto University, Pajulahti, Finland. Sept. 2015.
4. Frequency-specific modulation of responses to risk and certainty options across gains and losses. // Society for Neuroeconomics: 13th Annual Meeting Program. Conrad Miami, Miami, Florida, USA. Sept. 2015.
5. The switch-risk task: evidence that volitional cognitive control load influences risky decision making // Video and Audio Signal Processing in the Context of Neurotechnologies. Pavlov Institute of Physiology, St. Petersburg, Russian Federation. June. 2016.
6. Hemispheric and frequency-dependent transcranial alternating current stimulation modulates risk-taking and volitional cognitive control // Cognitive control, communication and perception. Higher School of Economics, Moscow, Russian Federation. Dec. 2016.

INTRODUCTION

Economic risky decision-making involves choosing uncertain options when the probabilities are known. Inspired by Kahneman's dual process theory, that irrational decision-making increases when cognitive resources become depleted (Kahneman, 2011; Kahneman & Frederick, 2007; Kahneman, 2003), some have tested the influence of executive control on risky decision-making by administering the n-back task, a popular working memory task, in parallel with various risky decision-making tasks (e.g. Gathmann et al., 2014; Pabst et al., 2013; Starcke et al., 2011; Whitney et al., 2008).

Risky decision-making has been extensively investigated using electrophysiological measures alongside traditional task paradigms such as the monetary gambling task, probabilistic two-choice gambling task and the balloon analog risk task. Specifically, researchers have relied on event related potential (ERP) analysis, task-dependent neural oscillatory activity, and resting state oscillatory activity electroencephalography (EEG) to investigate and predict the neural correlates of economic risky decision-making. Neuromodulation techniques such as transcranial magnetic stimulation, transcranial direct current stimulation (tDCS) and transcranial alternating current stimulation (tACS), have also been applied to healthy participants for the purpose of modulating economic risky decision-making.

Risky decision making can be determined and predicted based on three stages of reward processing: an anticipation stage, a decision stage, and an outcome-appraisal stage which occurs after receiving feedback (Zheng et al., 2015; Cui et al., 2013). Our goal was to investigate behavioral and neurological underpinnings of the decision phase and feedback stage. We aim to test whether executive control measures can alter risky decision-making from the decision phase and whether feedback from the outcome-appraisal stage affected risky decision-making in the following

trials. We aimed to examine these stages both behaviorally and by using neurological technologies such as EEG and tACS. For the latter two techniques we aimed to explore the role of neural oscillations in association with risky decision making, and feedback processing.

Behavioural measures of risk and feedback processing

Executive control is an essential component of cognition that enables us to evaluate and plan decisions by retrieving relevant information, inhibit irrelevant information and flexibly adjust to goal-oriented demands (Miyake et al., 2000; Diamond, 2013). Dual process theory implies that decision-making biases occur when executive control resources become depleted (Kahneman, 2003; Kahneman & Frederick, 2007; Kahneman, 2011). The reflection effect is a bias in which individuals are more likely to gamble when the choices are prospective losses, as compared to when mathematically equivalent choices are prospective gains (Tversky and Kahneman, 1979; Tversky and Kahneman, 1981; also see Fagley, 1993). The reflection effect is one example of decision making bias that has been shown to be directly caused by depletion of executive resources, exemplified by increasing time pressure (Kirchler et al., 2017) or by increasing stress (Porcelli and Delgado et a., 2009).

To date, studies investigating the influence of executive control on risky decision making using dual tasks have only revealed relatively weak effects (Whitney et al., 2008; Pabst et al., 2013; Starcke et al., 2011; Deck and Jahedi, 2015). Perhaps employment of two tasks in succession (e.g. a decision-making task following a 2-back working memory task) may not take into account that executive control and decision-making often operate in parallel, subsequently yielding weak behavioural effects.

In this study, we designed a task that measures volitional cognitive control and risk-taking within a single response allow players to receive risky and certain monetary incentives depending on

the choice to switch or repeat task-sets. We aimed to investigate the influence of executive control depletion on risky decision making directly by using a task that examines risk–taking and executive control within a single event. We designed a task, which we refer to as the reward voluntary switch task (RVST) that combines the voluntary task-switching paradigm (Arrington and Logan, 2004) with binary lotteries. In this paradigm, participants selected between risky and safe options depending on the choice to switch or repeat task-sets. This task design allows one to examine the influence of cognitive control exertion on risk-taking within a single response. Importantly, the RVST was used in all empirical work reported in this report for the purpose of exploring executive control and risky decision making.

Using the RVST we were able to assess whether executive control measures can alter risky decision-making from the decision phase. As a secondary goal we aimed to test whether positive and negative feedback produced from risky decisions were likely to predict decision making. The RVST allowed us to test whether feedback from the outcome-appraisal stage affected risky decision-making in the following trials.

Biological marker for risk and cognitive control

Much research has been conducted on the neurobiological mechanisms of risky decision making demonstrating a large neural network comprised of the ventral striatum, amygdala, insula, cingulate, and prefrontal cortices (PFCs; Knutson et al., 2001a,b; O'Doherty et al., 2001; Kuhnen and Knutson, 2005; Rao et al., 2008; Fujiwara et al., 2009; Mohr et al., 2010; Kohls et al., 2013). In particular, the PFC plays an important role in voluntary risky decision making. For instance, Rao et al. (2008) demonstrated a link between the PFC and voluntary decisions to accept greater risk. They suggested that the PFC mediates the active volitional control or agency of the risk taker by means of an executive control component.

Theta related activity (4–8 Hz) has been inferred to reflect aspects of risky decision making and executive control. While numerous accounts have associated theta band oscillations with executive control functions (e.g., working memory, set-switching, conflict monitoring, error detection; Jensen and Tesche, 2002; Sauseng et al., 2006; Cunillera et al., 2012; Cavanagh and Frank, 2014), a recent EEG study reported fronto-central theta oscillations inferred to reflect an action monitoring system that compares potential outcomes of high- and low-risk options (Zhang et al., 2014).

Furthermore, theta band transcranial alternating current stimulation (tACS) applied on the left PFC was demonstrated to increase risky decision making (Sela et al., 2012). This stimulation technique allegedly entrains ongoing electrophysiological oscillatory activity (Veniero et al., 2015; Vosskuhl et al., 2015; Thut et al., 2011; Helfrich et al., 2014), suggesting that theta tACS entrains frontal-central theta oscillations. However, a disadvantage to this study is that frequency specificity could not be assessed since the authors did not control for other stimulation frequencies. In other words, the increase in risky decision making may have been driven by the stimulation alone and not necessarily by theta stimulation (for further details, see Feurra et al., 2012).

For our second study, we tested whether voluntary risky decision making under varied levels of executive control can be modulated by applying online tACS at various frequencies (sham, 5, 10, 20, and 40 Hz) to the left and right frontal hemispheres using the RVST which allows one to measure risky decision making and executive control.

Biological marker for feedback associated with decisions

Feedback processing is an important aspect of learning about prior decisions. In the human brain, feedback processing is often examined by measuring an event-related potential, the feedback-related negativity (FRN) component. The FRN is a mid-frontal negative deflection, which was

initially discovered when comparing negative with positive feedback (Miltner et al., 1997). The difference in amplitude appears between 200 - 400 ms and peaks around 250 ms. Typically, the FRN component is investigated by directly comparing gain with loss feedback randomized across trials; however, this method does not control for confounds associated with valence and unexpected feedback (Proudfit et al., 2015). More convincingly, the FRN does not have a suitable control feedback condition; gains and losses are typically compared directly, without considering the notion that gains and losses produce different neural networks (Mohr et al., 2010). For this study we used the RVST to investigate the sensitivity of FRN to positive and negative feedback separately for gains and losses. We aimed to understand whether the FRN component is specific to gains, losses or both when compared to gain and loss omission.

A secondary goal was to explore the role of feedback on decision making with respect to neural oscillations. Specifically, many have attempted to explore the functional role of high beta oscillations (20-35 Hz) between 200-400 ms which tend to increase in oscillatory power in response to monetary gains compared to monetary losses (Marco-Pallerés et al., 2008). A further attempt to explore this hypothesis revealed no association between probability of outcome, expected value nor reward prediction errors manifested by beta band rhythm (HajiHosseini and Holroyd, 2015b). Equivalent to the examination of the FRN component, we also examined the role of beta oscillations during the outcome-appraisal stage (i.e. during feedback). We specifically examined beta oscillations during which positive, neutral and negative feedback was received also gains and losses. We further explored whether feedback and the corresponding beta oscillations would influence (predict) decisions in the following trial.

Goals and objectives of the study

1. To investigate the behavior associated with executive control on risky decision making
2. To investigate the behavior associated with feedback on future risky decision making

3. To explore neural activity of executive control on risky decision making with tACS
4. To investigate feedback processing with the FRN component using event-related potential (ERP) analysis
5. To explore neural oscillations of feedback processing using event-related spectral perturbations (ERSP) and source analysis
6. To explore neural oscillations of feedback processing on future risky decision making

METHODOLOGY AND DESIGN RESEARCH

Participants

In total the three experiments comprised of ninety-two right-handed subjects (55 females; mean age 21.33 years; age range 18-35 years) with normal or corrected to normal vision and with no neurological disorders were recruited and provided a small amount of compensation (approx. 500 – 1000 RUB). Participants either taking drugs or prescribed with medications were excluded from the participant pool. All participants provided a written consent approved by the Higher School of Economics Committee on Interuniversity Surveys and Ethical Assessment of Empirical Research – in accordance with the Declaration of Helsinki.

Task design and procedure

In order to examine the role of executive control on risky decision making, participants performed the 'rewarded voluntary switch task' (RVST) – a modified version of the voluntary task-switching paradigm (Arrington and Logan, 2004), which allows subjects to select between risky or safe options by simultaneously switching or repeating task-sets between trials. Voluntarily switching and repeating task-sets has traditionally been used to measure the ability to flexibly adjust to goal-oriented demands (Arrington and Logan, 2004) and was used in the current experiment to measure exertion of high and low executive control, respectively. Importantly, in each trial of the task an act of executive control might be involved in the process of switching from one task to another.

Figure 1 illustrates the RVST. In each trial participants were presented with a randomly selected single digit number (1, 2, 3, 4, 6, 7, 8, or 9) and instructed to choose one of two games per trial: 1) an 'odd/even' game, to indicate parity; or 2) a 'high/lower than 5' game, in which subjects responded by pressing the corresponding 'high or 'low' response button. Participants responded

using the left and right index and middle fingers to indicate whether the digit was odd, even, higher or lower than 5.

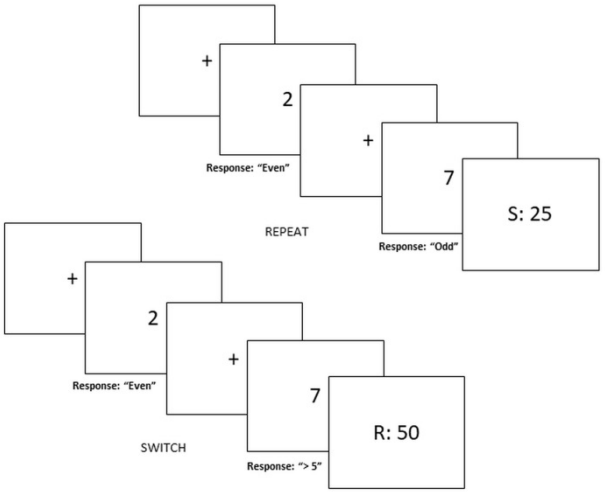


Figure 1. Switch-risk task. Risky decision making depends on voluntary switching and repeating task-sets. Safe decisions yield 25 MU with a probability of 100% whereas risky decisions yield 50 MU or 0 MU with a probability of 50%. Figure represents trial in the "Switch = Risk" reward block.

Subjects were instructed that repeating the same game in succession would yield a safe option (25 monetary units [MU] with a probability of 100%), while switching between games would result in a risky option (50 MU or 0 MU with a probability of 50%). Expected value was equal between gain and loss blocks to avoid confounds associated with probability calculation. The influence of executive control on risky decisions was counterbalanced across blocks. In half of the experiment, switching led to risky options ('Switch=Risk' blocks) and in the other half repeating led to risky options ('Repeat=Risk' blocks). In addition, subjects received positive or negative monetary incentives in separate blocks represented as gain and loss blocks, respectively. In total, all four block types were administered randomly throughout the experiment. Responses that were incorrect or exceeded 4000 ms generated negative feedback (i.e. 0 MU in the gain blocks and -50 MU in the loss blocks). Feedback for safe options consisted of 25 MU and -25 MU in gain and loss blocks, respectively. When subjects chose the risky option, feedback would either yield 50 MU or 0 MU randomly within the gain blocks, and 0 MU or -50 MU in the loss blocks; each with 50% probability, determined by a random generator. Trial feedback lasted for 1000 ms.

Due to complexity of the RVST and to reduce learning effects subjects received two rounds of training, which consisted of eight blocks of 10 trials resulting in 80 trials in total. After training, subjects received 12 blocks of 30 trials, totalling to 90 repetitions for each block type. Feedback was given per trial and at the end of the experiment total cumulative feedback was shown on the computer screen. Subjects received 500 MU for participation and an additional bonus, between -300 and + 300 MU (approx. 10 USD), based on the feedback outcomes of six randomly selected trials. Response buttons were counterbalanced across subjects. Block types were presented in pseudorandom order and counterbalanced too. Presentation of stimuli and data collection were controlled by E-Prime 2.0 software (Schneider et al., 2002). After the experiment, subjects were debriefed and asked about their strategies during the game.

General linear models analysis of behavioural strategies

Initially using two independent repeated measured ANOVA we tested the effect of Valence (gain blocks, loss blocks) and Switch condition ("Switch = Risk" blocks, "Repeat = Risk" blocks) on (a) mean probability of risky decisions and (b) mean probability of switching. We further explored the influence of executive control on decision making strategies based on prior feedback ("Win-stay", "Lose-shift", "Win-shift" and "Lose-stay") on a trial-by-trial basis.

Decision making strategies were classified based on the choice in the current trial (t) and outcomes of the following trial (t+1). For example, a "Win-stay" strategy occurred when participants selected the risky options after receiving positive feedback (i.e. a "Win"). The purpose of this trial by trial analysis was to examine whether feedback in the previous trial affected decisions in following trial. Four strategies: "Win-stay", "Lose-shift", "Win-shift" and "Lose-stay" coded as dummy variables and treated as response variables in four separate generalized linear models (GLM) with a logit function. Block types Valence and Switch condition were treated as predictors.

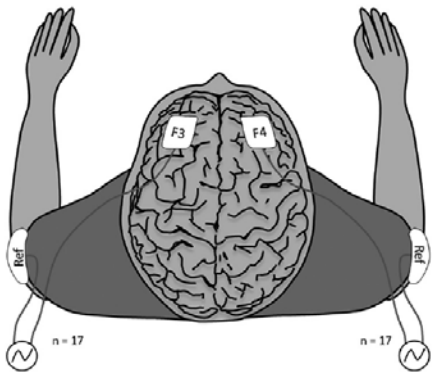
Irrespective of Valence, positive feedback was coded as 3 (+50 MU for gain, 0 MU for loss blocks), neutral as 2 (+25 MU for gain, -25 MU for loss blocks), and negative as 1 (0 MU for gain blocks, -50 MU for loss blocks).

tACS procedure

For the tACS experiment, tACS procedure By using the international electroencephalography 10-20 system, tACS was applied on the left or right frontal areas by placing a 7 – 5 cm saline-soaked electrode on F3 or F4 locations (see Figure 2). For both location sites, a reference electrode was placed on the ipsilateral deltoid to the target electrode (Im et al., 2012; Bai et al., 2014). tACS stimulation was randomized at fixed frequencies (5, 10, 20, 40 Hz) and sham (random noise stimulation between 0.1-100 Hz). This sham stimulation protocol was necessary in the current experiment due to the unconventional use of multiple stimulation protocols reflecting the harmonics of mean centre frequencies (i.e. theta, alpha, beta and gamma, respectively; Klimesch, 2012). Stimulation was delivered online during task performance, with exception to sham stimulation, which lasted for 30 seconds.

Stimulation current was set at 1 mA (500 mA peak-to-peak). The maximum current density at the stimulation electrode was ~14 µA/ cm2. The wave form of the stimulation was sinusoidal, and there was no direct current offset.

Figure 2. tACS montage. Active electrodes were placed on F3 and F4 electrode, representing left and right frontal area. Placement of the reference electrode was the ipsilateral deltoid for F3 and F4.



Statistical analysis of tACS study

Two separate logistic regression mixed models (Generalized Linear Mixed Model) on the raw data were performed on the following variables: (1) selection of risky decisions and (2) selection of switches between trials. Each model included the following categorical predictors: valence (gain, loss blocks), switch condition (switch _ risk blocks and repeat _ risk), frequency of stimulation (sham, 5, 10, 20, and 40 Hz) with sham as a reference variable, and hemisphere of stimulation (left, right). Before analysis error trials and trials exceeding response time of four seconds were omitted. Wald tests (Kuznetsova et al., 2016) were performed on all levels up to two interactions. To account for possible group differences, sham stimulation was used as a reference variable for each effect associated with frequency. In the logistic regression model participants, valence, switch condition, and frequency of stimulation were modeled with random effects, while hemisphere of stimulation (a between-subjects factor) was modeled with fixed effects.

EEG recording

The EEG data were recorded with BrainAmp amplifiers and BrainVision Recorder software (Brain Products GmbH, Munich, Germany) using silver ActiCap active scalp electrodes mounted in an elastic cap located at 60 standard positions according to the international 10–20 system. Impedances were kept<10 kΩ. EEG signals were referenced to the mean of the activity at the two mastoid processes. Electrooculogram were recorded with electrodes placed at both lateral canthi and below the left eye. The electrophysiological signals were filtered online using a sampling rate of 500 Hz in the frequency range 0.2–100 kHz.

Data preprocessing of the EEG data was performed using BrainVision Analyzer 2.0. First, signals in bad channels were replaced by signals averaged over surrounding channels. Second, a bandpass filter (1–40 Hz) was applied to the data, after which eye-blink- and eye movement-related

activity was removed in the data using independent component analysis. Finally, intervals containing non-systematic artifacts produced by electromyographic activity, skin potentials and other sources were manually rejected from the data. Across subjects, 10.1% (σ=0.090) of trials were excluded from the analysis. ERP's for each condition were segmented between -200 – 1000 ms and averaged across each condition. Baseline correction was performed using the time window of -200 – 0 ms. FRN difference waves were calculated by contrasting negative with positive feedback conditions, separately for gains and losses.

Time-frequency power analysis

EEG analysis for each feedback (positive, neutral, negative) x valence (gain, loss) condition was performed in Brainstorm (Tadel et al., 2011), which is documented and freely available for download online under the GNU general public license (http://neuroimage.usc.edu/brainstorm). Single trial time-frequency analysis was performed on a time window between -1000 ms to 2000 ms for each condition. For each trial, the segmented EEG data was convolved with a complex Morlet wavelet (from 1 to 40 Hz, linear increase). The frequency and time resolution of were set at the default settings (temporal resolution of 3 seconds at frequency 1 Hz) in Brainstorm, which uniquely define the temporal and spectral resolution of the wavelet for all other frequencies (Tadel et al., 2011). Changes in time varying energy (i.e. event-related spectral perturbations: $(x-\mu) / (\mu*100)$) with respect to pre-stimulus baseline (-200 ms to -1 ms) were computed per condition and averaged for each subject.

Mean beta power (12-20Hz) was calculated for FCz, FC1, FC2, Cz, C1, C2, CPz, CP1, and CP2 electrode positions for each feedback and valence condition within the 700-1000 ms post-response time window and entered into a repeated measures ANOVA test. Despite prior studies reports on a different frequency and time window, the specific frequency, latency and electrode

positions were selected based on statistical analysis of the ERSP data averaged over the experimental conditions and tested against zero (permutation test with FDR correction for multiple) using the TFCE (threshold-free cluster enhancement) algorithm (see Novikov et al., 2015, 2017 for prior examples; also see Smith and Nichols, 2009). Greenhouse-Geisser correction was applied. Using a custom-written Matlab script (The MathWorks, Inc.) time course of mean beta power for each condition was extracted from the time-frequency data.

Post-hoc testing

To assess whether the spectral power density of beta frequency influenced risky decisions in the following trial, we included several generalized linear models (GLMs) with a logit link function, performed separately for gains and losses. Spectral power density is characterized by the distribution of power for each frequency range within a specified time series (Duff et al., 2008). Predictors for these models included: positive feedback (with neutral feedback as reference), negative feedback (with neutral feedback as reference), beta (12-20 Hz), and theta (4-8 Hz) power spectral density. To compare these results, we also computed two GLMs with negative feedback as the reference variable corresponding with gains and losses. Theta power spectral density was included in the first two models to control for frequency specificity of beta (Tables 1 and 2), yet in further analysis we also computed GLMs excluding theta power as a predictor (see Tables 3 and 4), corresponding to neutral (Tables 1-4a) and negative feedback (Tables 1-4b) as the reference variable, respectively. Wald tests (Kuznetsova et al., 2016) were performed on all levels up to 2 interactions. Analysis of the GLMs were performed using R software (R Core Team, 2016) with the software package lme4 (Bates et al., 2014) and lmertest (Kuznetsova et al., 2016). Family-wise error rate was controlled using a Bonferonni correction procedure.

Source analysis

For the beta frequency component, source localization for each feedback condition across gains and losses were performed on single trials between 12-20 Hz between the 700-1000 ms time window. A default anatomy of the standard MNI brain was used to compute a head model using OpenMEEG software (Gramfort et al., 2010) with a symmetric boundary element model as an EEG forward model of volume currents. Prior to source-localization, a noise covariance matrix was calculated based on the pre-stimulus interval between 221 -500 to 0 ms to estimate the level of noise among the electrodes. Cortically unconstrained source-localization was performed on each trial using the standardized low resolution brain electromagnetic tomography (LORETA) technique. For each subject we calculated sources using a low spatial resolution of 2000 vertices and projected the grand averages to 15000 vertices to increase spatial resolution for the images. Resulting source maps per subject were averaged across trials for each condition. For visual purposes, the source activation maps were based on activation of at least 10 vertices with an amplitude threshold of 40%.

MAIN RESULTS OF RESEARCH

A repeated measures ANOVA revealed a main effect of Switch condition ($F_{1,32} = 7.065$, $p = 0.012$, partial $\eta^2 = 0.181$) on risk taking, indicating an overall decrease in risk taking during "Switch = Risk" blocks ($\mu = 49.8\%$) compared to "Repeat = Risk" blocks ($\mu = 57.7\%$). This finding supports the notion that depletion of high executive control decreases risk taking which corroborates the **first objective**.

We then tested whether feedback affected decisions in future trials. No significant effects were found for Win-stay, Lose-shift, and Win-shift strategies. However, the GLM revealed a significant interaction between Switch condition and Valence for the Lose-stay strategy: $\beta = -0.343$; z-score = 2.485 $p = 0.012$. This finding is similar to effect previously revealed by ANOVA. While

the ANOVA showed an influence of executive control on risk taking specifically in the gain domain, the post-hoc analysis revealed an influence of executive control on Lose-stay strategies in gain blocks. In other words, the aforementioned effect of executive control on risk taking within the gain domain may be linked to the influence of executive control on trial-by-trial strategies; specifically, on repeating risk taking after receiving negative outcomes. This finding supports the notion that behavior associated with feedback affects future risky decision making, corroborating the **second objective**.

To address the **third objective** we next determined whether the relationship between executive control and risky decision making can be influenced by transcranial electrical current stimulation. Since both executive control and risky decision making have shown to involve theta oscillations (Sauseng et al., 2012; Sela et al., 2012; Zhang et al., 2014), we predicted that both executive control and risky decision making can be modulated by 5 Hz tACS, reflecting modulation of endogenous theta band oscillations.

Surprisingly, a logistic regression mixed model for risky decision making revealed an increase in risky decision making during 20 Hz of stimulation particularly when stimulating the left PFC ($\beta = 0.989$; $p = 0.00194$; $p' = 0.043$). The effects of other tACS frequencies on risky decision making did not survive Holm-Bonferroni correction for multiple comparisons. The frequency- and hemisphere-specific effect of a 20-Hz stimulation was confirmed by a non-significant main effect of hemisphere of stimulation ($\beta = 0.072$, $p = 0.885$; $p' = 0.999$). Figure 3 displays means and standard error for each of the comparisons with regards to the frequency of stimulation hemisphere of stimulation interaction effect.

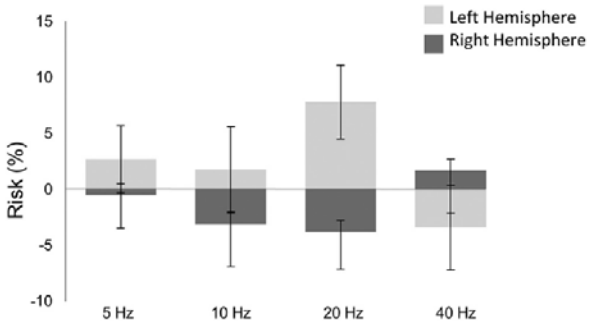


Figure 3. Mean percentage of risky decisions for each tACS condition with respect to sham; 20-Hz stimulation of the left frontal area increased selection of voluntary risky decisions. Error bars correspond to SEM.

Our **fourth objective** was to examine the biological component of feedback processing using the feedback-related negativity (FRN) component as a marker. Analysis of ERPs within the 200–400 ms time-window revealed a significant two-way interaction effect between factors feedback and valence ($F_{2,48}$=12.521, p=0.004, partial η^2=0.202). Post-hoc analysis demonstrated a reduced ERP's amplitude during negative feedback in gain blocks (2.190 μV) as compared to loss blocks (3.153 μV; p=0.003). Difference waves were calculated by subtracting ERPs of positive feedback from ERPs of negative feedback yielding a fronto-central FRN waveform. ERPs to negative feedback (+0 MU: 2.190 μV) were significantly lower than ERPs to positive feedback (+50 MU: 3.671 μV; p=0.001) within gain blocks. No statistically significant difference was found between ERPs to positive (-0 MU) and negative feedback (-50 MU) in loss blocks (all p > 0.05). Overall, our findings revealed that the FRN was most prominent in gain blocks as compared to loss blocks. Visual ERPs, scalp topographies, and mean amplitude for each feedback condition across gains and losses are displayed in Fig. 4a and 4b.

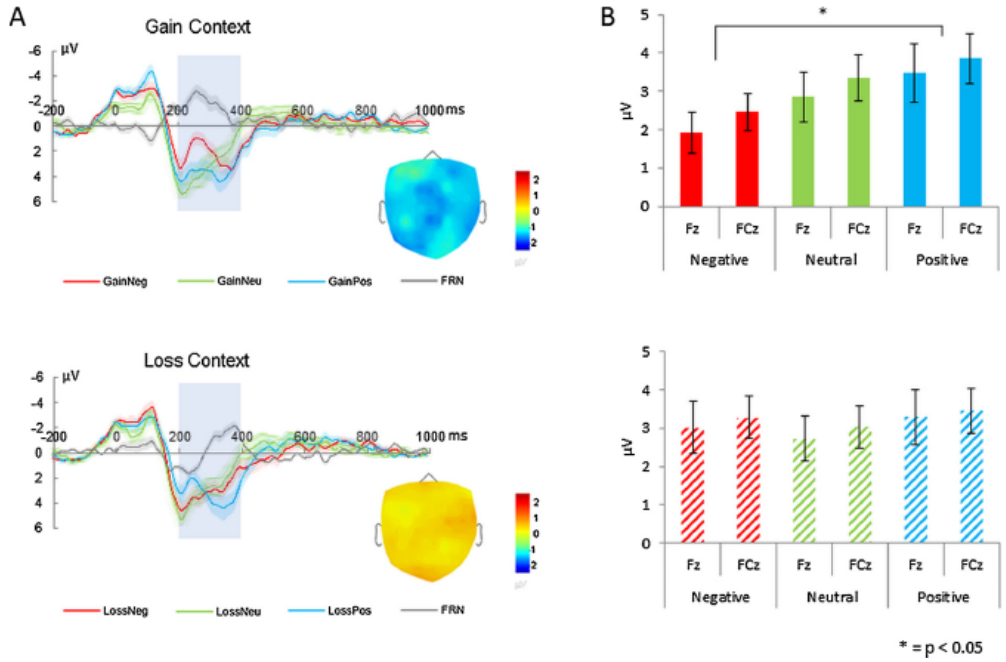


Figure 4. (a) ERPs and scalp topographies to positive, neutral and negative feedback during gain (up) and losses blocks (down) at electrode FCz. FRN is displayed as a difference wave between ERPs to negative and ERPs to positive feedback. Scalp topographies plotted for 200–400 ms time-windows. (b) Mean amplitude between 200–400 ms for each feedback condition at electrodes Fz and FCz for gains (up) and losses (down). Error bars represent standard error of the mean.

To explore the role of feedback we then re-analyzed this data using time-frequency analysis and source analysis. Unexpectedly, a late low beta (12-20 Hz) frequency component during the feedback display between 700-1000 ms was shown. Beta oscillations were significantly greater in power during the negative feedback condition in gain blocks. This was reflected in a three-way interaction effect between valence, feedback and electrode which had a moderate effect size ($F_{16,384}$ = 2.481, p = 0.001, partial η^2= 0.094). Post-hoc comparisons revealed a significant increase in beta power during processing of negative feedback as compared to positive and neutral feedback for gain blocks from all fronto-central electrode positions (all < 0.05) but not CPz, CP1 and CP2. No differences were observed between neutral and positive feedback in the gain domain and no differences were observed across feedback conditions within the loss domain (all p > 0.05).

Regarding source analysis, for all feedback conditions beta oscillations were localized to the right frontal cortex, left parietal cortex and medial frontal structures, possibly overlapping with the medial frontal cortex and the striatum. These source estimations seem to correspond with prior lesion studies (Pujara et al., 2015) and fMRI studies (Wrase et al., 2007; Pedroni et al., 2011) and when comparing the reception and omission of gains and losses.

Overall, these results suggest that changes in beta power oscillations have a specific role for gains, particularly during the omission of gains, which addresses our **fifth objective**. See Figures 5 and 6 for time-frequency maps, separated across gains and losses.

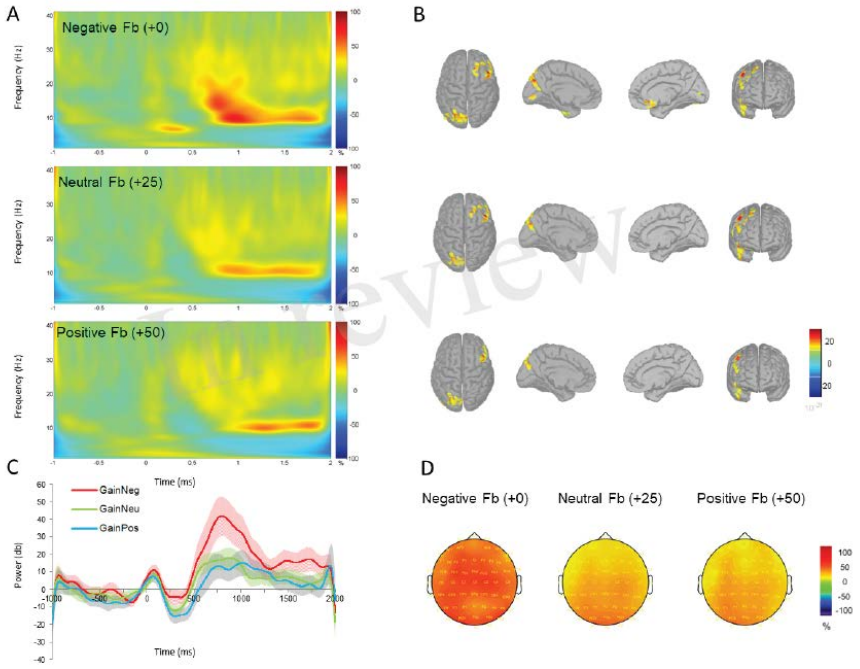


Figure 5. Time-frequency power (total) across negative (+0 MU), neutral (+25) and positive (+50) feedback for gain blocks. (a) Time-frequency plots at channel FCz displaying the changes in power from 700-1000 ms with respect to the pre-stimulus baseline (-200 to 0 ms). (b) Beta (12-20 Hz) source activity corresponding to each feedback type displayed for top, left medial, right medial and frontal views. Source activation maps are based on a minimum of 30 vertices with an amplitude threshold value is set to 30%. (c) Time-course of mean beta power with standard error bars in negative (red), neutral (green), and positive (blue) feedback conditions. (d) Scalp topographies plotted at 800 ms post-feedback for 15 Hz.

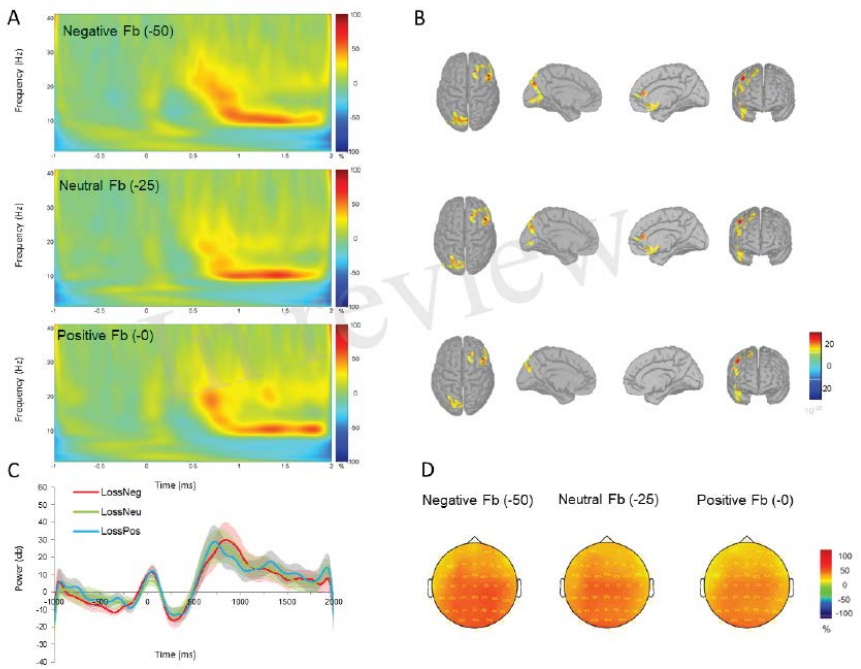


Figure 6. Time-frequency power (total) across negative (-50), neutral (-25) and positive (-0) feedback for loss blocks. (a) Time-frequency plots at channel FCz displaying the changes in power from 700-1000 ms with respect to the pre-stimulus baseline (-200 to 0 ms). (b) Beta (12-20 Hz) source activity corresponding to each feedback type displayed for top, left medial, right medial and frontal views. Source activation maps are based on a minimum of 30 vertices with an amplitude threshold value is set to 30%. (c) Time-course of mean beta power with standard error bars in negative (red), neutral (green), and positive (blue) feedback conditions. (d) Scalp topographies plotted at 800 ms post-feedback for 15 Hz.

Since beta oscillations were specific to gain blocks, corresponding to previous studies showing an increase in beta power during gains compared to losses (Cohen et al., 2007; Marco-Pallarés et al., 2008; 2015; Cunillera et al., 2012; HajiHosseini et al., 2012), we aimed to perform a series of GLMs to predict whether beta power in the current trial (t) can predict the selection of risky decisions in the following trial (t+1) within gain (Table 1a) and loss blocks (Table 1b). The rationale for this analysis is that if beta power density on the current trial can predict an increasing trend to select risky decisions in the following trial yet specifically for gain blocks, then perhaps changes in beta oscillations may shed light on the differences between decision making within gain and loss blocks. GLMs were performed with neutral feedback as a reference variable for positive and negative feedback.

First of all, our results reveal main effects of positive and negative feedback for both GLMs reflecting gain and loss blocks. Within the gain blocks, positive compared to neutral feedback ($\beta = 0.271$; $p' = 4.32x10^{-4}$), and negative compared to neutral feedback ($\beta = 0.246$; $p' = 0.002$) predicted risky decisions in the next trial (Table 1a). For the loss blocks, positive compared to neutral feedback ($\beta = 0.606$; $p' = 1.8x10^{-15}$), and negative compared to neutral feedback ($\beta = 0.494$; $p' = 9.18x10^{-13}$) predicted risky decisions in the next trial (Table 1b). These effects may suggest that risky decisions (positive and negative feedback) promote the tendency to select risky decisions in the next trial.

Furthermore, GLMs representing gain blocks (Table 1a and 2a) revealed significant interaction effects between beta power density x positive feedback ($\beta = -0.390$; $p' = 9.45x10^{-6}$; Table 1a). This interaction effect suggests that a decrease in beta power during positive feedback corresponds to an increase of number of risky decisions in the following trial.

Table 1a. GLM for rewards with neutral feedback as reference

	β	SE	z-value	p-value	p’
Theta PSD	-0.155	0.058	-2.672	0.007	0.063
Beta PSD	0.094	0.046	2.025	0.042	0.378
Fb (+50)	**0.246**	**0.066**	**3.693**	**$2.2x10^{-4}$**	**0.002**
Fb (+0)	**0.271**	**0.066**	**4.065**	**$4.8x10^{-5}$**	**$4.32x10^{-4}$**
Theta*Beta PSD	0.019	0.025	0.756	0.449	>0.999
Theta PSD*Fb (+50)	0.112	0.069	1.616	0.106	0.954
Theta PSD*Fb (+0)	0.008	0.069	0.124	0.901	>0.999
Beta PSD*Fb (+50)	**-0.390**	**0.080**	**-4.883**	**$1.05x10^{-6}$**	**$9.45x10^{-6}$**
Beta PSD*Fb (+0)	-0.130	0.074	-1.751	0.079	0.711

Table 1b. GLM for losses with neutral feedback as reference

	β	SE	z-value	p-value	p’
Theta PSD	-0.050	0.056	-0.891	0.372	>0.999
Beta PSD	0.061	0.052	1.184	0.236	>0.999
Fb (-0)	**0.606**	**0.658**	**9.197**	**$<2x10^{-16}$**	**$1.8x10^{-15}$**
Fb (-50)	**0.494**	**0.066**	**7.438**	**$1.02x10^{-13}$**	**$9.18x10^{-13}$**
Theta*Beta PSD	0.024	0.025	0.977	0.328	>0.999
Theta PSD*Fb (-0)	0.123	0.074	1.654	0.098	0.882
Theta PSD*Fb (-50)	-0.079	0.078	-1.020	0.307	>0.999
Beta PSD*Fb (-0)	-0.197	0.080	-2.453	0.014	0.126
Beta PSD*Fb (-50)	-0.116	0.072	-1.601	0.109	0.981

Note: β = Beta coefficient represent standardized effect sizes; SE = Standard error of the mean; z-value based on Wald test; PSD = Power Spectral Density; p’ = corrected p value; Fb = Feedback; Bold font indicates statistical significance after Holm-Bonferroni correction

Table 1. Generalized Logistic Model (GLM) predicting risk decision making in the following trial for rewards (a) and losses (b) with neutral feedback as the reference variable. Spectral power density was extracted from each trial between 4-8 Hz (Theta PSD) and 12-20 Hz (Beta PSD).

Table 2a. GLM for rewards with negative feedback as reference

	β	SE	z-value	p-value	p'
Theta PSD	-0.146	0.061	-2.365	0.018	0.162
Beta PSD	-0.035	0.067	-0.519	0.603	>0.999
Fb (+50)	-0.025	0.071	-0.357	0.721	>0.999
Fb (+25)	**-0.271**	**0.066**	**-4.065**	**$4.8x10^{-5}$**	**$4.32x10^{-4}$**
Theta*Beta PSD	0.019	0.025	0.756	0.449	>0.999
Theta PSD*Fb (+50)	0.103	0.072	1.426	0.154	>0.999
Theta PSD*Fb (+25)	-0.008	0.069	-0.124	0.901	>0.999
Beta PSD*Fb (+50)	**-0.260**	**0.092**	**-2.828**	**0.004**	**0.036**
Beta PSD*Fb (+25)	0.130	0.074	1.751	0.079	0.711

Table 2b. GLM for losses with negative feedback as reference

	β	SE	z-value	p-value	p'
Theta PSD	-0.130	0.065	-1.979	0.047	0.423
Beta PSD	-0.054	0.070	-0.776	0.437	>0.999
Fb (-0)	0.111	0.071	1.555	0.120	>0.999
Fb (-25)	**-0.494**	**0.066**	**-7.438**	**$1.02x10^{-13}$**	**$9.18x10^{-13}$**
Theta*Beta PSD	0.024	0.025	0.977	0.328	>0.999
Theta PSD*Fb (-0)	0.203	0.083	2.439	0.014	0.126
Theta PSD*Fb (-25)	0.079	0.078	1.020	0.307	>0.999
Beta PSD*Fb (-0)	-0.081	0.089	-0.915	0.360	>0.999
Beta PSD*Fb (-25)	0.116	0.072	1.601	0.109	0.981

Note: β = Beta coefficient represent standardized effect sizes; SE = Standard error of the mean; z-value based on Wald test; PSD = Power Spectral Density; p' = corrected p value; Fb = Feedback; Bold font indicates statistical significance after Holm-Bonferroni correction

Table 2. Generalized Logistic Model (GLM) predicting risk decision making in the following trial for rewards (a) and losses (b) with negative feedback as the reference variable. Spectral power density was extracted from each trial between 4-8 Hz (Theta PSD) and 12-20 Hz (Beta PSD).

CONCLUSION

For this report we examined behavioral and neurological effects of the decision and outcome-appraisal stages of risky decision making. We explored the possible influence of executive control on risky decision making during the decision stage as well as the influence of executive control and prior feedback on risky decision making. After which we examined these stages on a neurological basis by using tACS and EEG. We aimed to investigate multiple questions listed as our objectives.

To investigate the influence of depleted executive control on risky decision making we used the RVST in which decision to voluntary select risky or safe options was conditioned on choice to switch or repeat task-sets. We found a significant interaction effect between Switch condition and Valence which reflect an influence of executive control on risky decision making. We further explored this finding by re-coding risky decision making in light of the prior feedback. We aimed to test whether the influence of executive control on risky decision making can be explained by its differential influence on trial-by-trial strategies: Win-stay, Win-shift, Lose-stay, or Lose-shift. We found that executive control specifically decreased Lose-stay strategies within gain blocks. This particular strategy is described as events in which participants continue to select risky gambles even after receiving negative feedback. If we compare both findings; that executive control decreases the tendency for participants to select risky decisions in the gain domain, and that executive control decreases Lose-stay strategies with the gain domain; we may infer that these findings reflect the same behavioural measure. In other words, increasing executive control motivates participants to reduce risk taking specifically after receiving negative feedback. This finding may explain how high risky individuals succumb to decision making inertia, e.g. chronic gamblers whom gamble excessively despite receiving negative outcomes may have a lack of executive resources (Roca et al., 2008).

In the attempt to modulate oscillatory activity underling voluntary risky decision making and executive control we applied tACS (sham, 5, 10, 20, and 40 Hz) to the left and right PFC while participants performed the RVST that requires choosing between risky and certain decisions by switching or repeating task sets. The analyses of risky decision making revealed several significant effects, yet the influence of 20-Hz stimulation on risky decision making was the most robust, surviving Holm-Bonferroni correction.

The results of the current study contradict our expectations as well as a previous tACS study on risky decision making (Sela et al., 2012). However, the effect of theta-band tACS in the previous study (Sela et al., 2012) could be due to a modulation of feedback-related adjustments (Cavanagh et al., 2010; Cavanagh et al., 2012; Luft, 2014; Zhang et al., 2014) since the previous tACS paper used the Balloon Analog Risk Task, which measures risk-taking propensity across a cumulative number of responses, as opposed to measuring risky decision making within a single response, as in the current study. A possibility for the alternate results may be due to the differences in montage. For instance, a previous study that modulated executive functions, specifically working memory, stimulated both frontal and parietal areas using an F3–P3 montage (Polanía et al., 2012). We suggest that stimulation of the frontal lobe may modulate either a frontal-striatal network associated with voluntary risky decision making (Rao et al., 2008) or a frontal-parietal network in association with voluntary executive control (Orr and Banich, 2014) depending on the placement of the reference electrode (Bai et al., 2014).

Nevertheless we were able to show a robust frequency-specific increase in voluntary risky decision making from 20-Hz tACS, corresponding to beta oscillatory activity. Within recent years, EEG studies investigating oscillatory activity in gambling tasks have demonstrated a correspondence between frontal beta-oscillations (20–35 Hz) and anticipation of probable rewards (Bunzeck et al., 2011), as well as receiving unexpected rewarded feedback (Marco-Pallares et al.,

2008; HajiHosseini et al., 2012; HajiHosseini and Holroyd, 2015; Mas-Herrero et al., 2015). Marco-Pallarés et al. (2015) proposed that frontal beta-oscillatory activity during gambling paradigms might signify the functional coupling between cortical and subcortical regions such as the ventral striatum, known to be involved in reward processing (Mas-Herrero et al., 2015).

We next examined the neural correlates associated with the outcome-appraisal stage of risky decision making. We first examined feedback using ERP analysis, specifically examining the FRN component. Our results revealed a negative FRN-like deflection during the omission of gains compared to the reception of gains between 200 - 400 ms. Importantly, we found no statistically significant FRN response in loss blocks during the same time interval. Based on the notion that the FRN signifies negative feedback, after controlling for valence expectation, our results indicate that the FRN may be specific to the gain domain.

Finally we examined the outcome-appraisal stage of risky decision making using other EEG analyses such as time-frequency analysis and source analysis in association with beta oscillations. Rather than demonstrating a high beta component, the results demonstrated a significant moderate effect of late low beta band (12-20 Hz) for negative feedback in the gain context, but not for the loss context. Specifically, when participants selected risky gambles a significant increase in beta power during the omission of gains (negative feedback) compared to the reception of gains (positive feedback) was found. This increase in beta power during the omission of gains was also significant when compared to reception of gains after selecting the safe option (neutral feedback), similar to the ERP analysis.

An important distinction between the current results and prior studies relate to the spectral and temporal counterparts of beta oscillations. In the current study, beta oscillations were relatively low in frequency (12-20 Hz) 358 and late in time (700 to 1000 ms) compared to previous studies (Marco-Pallerés et al., 2008, 2015; HajiHosseini et al., 2012; Leicht et al., 2013; Mas-Herrero et al.,

2015; see Luft et al., 2014 for review). To date, only few studies investigating feedback processing have reported an increase in low beta power at around 800 ms (HajiHosseini et al., 2012; Leicht et al., 2013; Luft et al., 2014; Novikov et al., 2017). For example, when comparing low to high probable rewards HajiHosseini and colleagues (2012) revealed an increase in low beta power between 700-1000 ms, resembling a similar pattern of activity in the current experiment. Others have offered the possibility that multiple beta frequency components may co-occur during feedback processing (Luft et al., 2014). Luft and colleagues (2014) suggest that an additional beta component between 17-24 Hz may reflect a learning mechanism that orchestrates sensorimotor processing in response to errors by strengthening responses associated with wins and weaken responses associated with losses. However, it is unlikely that low beta oscillations in the current study are strictly attributed to sensorimotor processing since they were localized to the right frontal and left parietal regions, which corresponds to the topographic distribution of a late beta frequency component at around 15 Hz after losses (Leicht et al., 2013). Secondly, the source localization of the current study showing activity within the right lateralized frontal area corresponds with high beta oscillations in an earlier study (HajiHosseini and Holroyd, 2015a), which may indicate that high and low frequency oscillations reflect intersecting oscillating processes.

Modelling studies suggested that low beta might be the result of cross-frequency interactions between high beta and gamma oscillations (Kramer et al., 2008; also see Roopun et al., 2008). Finally, while in previous studies the monetary gambling task was used to induce positive (reward) and negative (loss) feedback, our experiment used a novel task design 381 that induces positive and negative feedback separately across gain and loss blocks by means of a risk-taking component. Due to the differences in study designs it is unclear whether our results reveal similar or different mechanism as prior studies reveal. Hence, further testing is necessary to explore the late beta component.

To explore the functional role of beta oscillations on risky decision making, we also investigated whether beta power density on each trial would predict the tendency to select risky decisions on the following trial. The GLM predicting risky decision making in the following trial demonstrated an interaction effect between beta oscillatory power and positive feedback, yet specifically for gain blocks. The relationship between the interaction (beta PSD x positive feedback) and risky decision making was negative (i.e. $\beta = -0.390$), suggesting that during positive feedback a decrease in beta oscillatory power reflects an increase in risky decision making in the following trial.

This suggests that the reduction in beta power during the negative feedback display motivates one to select risky decisions in following trials. To interpret this result, we propose a reward learning mechanism marked by changes in beta oscillations between trials. When receiving positive feedback, an increase in beta power reinforces the decision maker to continue to select risky gambles. However, during the absence of gains, a violation of rewards occurs in which the gain omission relative to alternative prospective outcomes results to an increase in beta oscillatory power as the result of perceiving gain omission as a 'loss' (see Palminteri et al., 2015 for more details). In turn, this reward violation decreases the tendency to select future risky gambles.

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