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Modulating preferences during intertemporal choices through exogenous midfrontal transcranial alternating current stimulation: A registered report

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ABSTRACT

Decision conflicts may arise when the costs and benefits of choices are evaluated as a function of outcomes predicted along a temporal dimension. Electrophysiology studies suggest that during performance monitoring a typical oscillatory activity in the theta rhythm, named midfrontal theta, may index conflict processing and resolution. In the present within-subject, sham controlled, cross-over preregistered study, we delivered online midfrontal transcranial Alternating Current Stimulation (tACS) to modulate electrocortical activity during intertemporal decisions. Participants were invited to select choice preference between economic offers at three different intermixed levels of conflict (i.e., low, medium, high) while receiving either theta -, gamma-, or sham tACS in separate blocks and sessions. At the end of each stimulation block, a Letter-Flanker task was also administered to measure behavioural aftereffects. We hypothesized that theta-tACS would have acted on the performance monitoring system inducing behavioural changes (i.e., faster decisions and more impulsive choices) in high conflicting trials, rather than gamma- and sham-tACS. Results very partially confirmed our predictions. Unexpectedly, both theta- and gamma-driven neuromodulation speeded-up decisions compared to sham. However, exploratory analyses revealed that such an effect was stronger in the high-conflict decisions during theta-tACS. These findings were independent from the influence of the sensations induced by the electrical stimulation. Moreover, further analyses highlighted a significant association during theta-tACS between the selection of immediate offers in high-conflict trials and attentional impulsiveness, suggesting that individual factors may account for the tACS effects during intertemporal decisions. Finally, we did not capture long-lasting behavioural changes following tACS in the Flanker task. Our findings

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may inform scholars to improve experimental designs and boost the knowledge toward a more effective application of tACS.

1. Introduction

Intertemporal choices are daily-life decisions requiring planning and selecting actions that generate consequences over time. Nevertheless, choosing between different appealing gratifications may induce decision conflicts that affect preferences and choices. Indeed, each decision reflects a detailed evaluative process of multiple elements that lead organisms to prefer the best solution among several alternatives (Rangel et al., 2008). To reach optimal decisions, the brain requires efficient and specialized systems capable of integrating different levels of analysis and thus producing appropriate behaviours and minimizing errors. Important elements of such computations are the conflict and error monitoring functions that play fundamental roles in modulating behavioural performance (Ullsperger et al., 2001; Yeung et al., 2004).

Theoretical and computational models partly developed from neuroimaging studies identify the anterior cingulate cortex (ACC) and the medial frontal cortex (MFC) as two hub-like, neural regions that detect the occurrence of conflicts and errors, trigger the recruitment of top-down control, and thus optimize ongoing behavioural adjustments during challenging circumstances (Botvinick et al., 2001; Carter et al., 1998; MacDonald et al., 2000). Electrophysiological investigations indicate that conflict and error processing are associated with the presence of enhanced midfrontal theta oscillations (MFθ) that may act as a communication signal underlying the need for control and synchronize the activity of frontal structures (Cavanagh et al., 2014; Luu et al., 2004). Critically, mounting evidence suggests that MFθ is a plausible electrocortical biomarker of response conflict (Cavanagh, Zambrano-Vazquez, & Allen, 2012; Cohen, 2014; Cohen et al., 2008), which is elicited by cognitive control tasks such as the Stroop (Hanslmayr et al., 2008), the Flanker (Nigbur et al., 2011) and the Simon (Töllner et al., 2017).

In the last two decades, non-invasive transcranial electric stimulation (tES) techniques have been applied to investigate the causal relationship between neurophysiological, cognitive, and behavioural processes (Paulus, 2011). Neuroscience and clinical neurophysiology studies indicate that the application of weak electric fields over the scalp may produce a polarization of the neuronal membrane that modifies cortical excitability and thus induce behavioural changes (Fertonani and Miniussi, 2016). One type of electric stimulation technique that has become increasingly popular is transcranial Alternating Current Stimulation (tACS), which has the property of entraining endogenous oscillatory activity affecting neuronal membrane potentials at determined frequencies (Antal et al., 2013). Notably, tACS has been used to investigate the causal link between frontal theta activity and top-down processing (Fusco et al., 2018; Lehr et al., 2019; Wischnewski

et al., 2016), corroborating the hypothesis that MFθ does not reflect spurious or epiphenomenal processes, but reflects one of the mechanisms by which the cognitive control system regulates behaviour. However, further investigations are needed to test whether MFθ merely indexes neuro-computational conflict and error monitoring codes or is instead causally associated with other aspects of information processing. Interestingly, studies suggest that value-based choices (Polanìa et al., 2015) and risk-taking behaviour (Sela et al., 2012) in decision-making processes are modulated by tACS, with specific effects induced by gamma (Polanìa et al., 2015) and theta (Sela et al., 2012) frequencies. What remains unclear is the extent to which MFθ causally mediates conflict monitoring and influences preferences and behaviour during economic choices. Importantly, tACS is particularly suitable for investigating how MFθ entrainment modulates and interacts with different levels of decision conflict to drive behaviour during value-guided choice.

1.1. Decision conflicts in temporal discounting

When monetary rewards are offered at different delays, people may have the tendency to discount the value of the delayed proposal with a large payoff and instead prefer a smaller payoff offered in the immediate present (Ainslie, 1975; Critchfield, 2001). This discounting effect occurs because the temporal delay until receipt of the larger payoff reduces the perceived subjective value assigned to the larger but delayed offer (Peters & Büchel, 2011). Value-based decisions in economic intertemporal paradigms depend on two factors: (i) the magnitude of the offer and the delay interval, and (ii) where an individual lies on the impulsiveness-patience spectrum (Odum et al., 2011). A common way to describe the behavioural preferences of decision makers in temporal discounting relies on the hyperbolic function, which describes how the subjective values of offers decrease hyperbolically as a function of delay (Green & Myerson, 2004; Mazur, 1987). In particular, this model accounts for the effect of different temporal delays on the value of the offers perceived subjectively (Kirby and Maraković, 1995). Within experimental settings, participants usually express their preferences between binary choices reflecting a little amount of money offered immediately (small sooner reward) or a higher amount available in the future (larger later reward; McClure et al., 2004; Berns et al., 2007). If the delay is far from the present (e.g. Do you prefer 5€ today or 10€ in 180 days?), participants may tend to choose more the small sooner rather larger later reward, exhibiting impulsive attitudes in intertemporal decision-making. Such a behavioural strategy is exacerbated in clinical populations affected by pathological impulsiveness like gamblers (Dixon et al., 2003; Madden et al., 2011) and substance abusers (Bickel et al., 2007; Kirby et al., 1999) who

typically show steeper rates of delay discounting. Conversely, if the amount of the immediate offer is perceived as less desirable or the temporal delay is not too far from the present (e.g., Do you prefer 2€ now or 20€ in 7 days?), the likelihood of choosing delayed options increases, likely reflecting implementation of top-down cognitive control to increase regulatory behaviour (Berns et al., 2007).

Moreover, for each person there is a so-called indifference point, where the decision is most difficult because the immediate and delayed options have similar subjective values, a circumstance that induces high conflict in decision-making (e.g. very low immediate offer vs high but delayed offer: Do you prefer 3€ today or 50€ in 180 days?). On these indifferent decisions, people tend to choose the immediate and delayed options 50 % of the time and respond relatively slowly because of increased decision conflict (e.g., Basile et al., 2015). Interestingly, an EEG study showed that during these high conflict trials involving indifferent decisions, theta power increases over the midfrontal electrodes, especially under the FCz electrode corresponding to the MFC (Lin et al., 2018). Moreover, emerging evidence from neuromodulation studies indicates that the administration of transcranial direct current stimulation (tDCS) over the frontal cortex may change neuronal computations affecting economic intertemporal decisions (Manuel et al., 2019; Nejati et al., 2021; Shen et al., 2016). What remains unclear is how MFθ is recruited by the cognitive control system during intertemporal decisions and how it causally influences choices. Electrocorticography evidence from two epileptic patients showed the presence of increased theta activity over the left lateral prefrontal cortex, a brain region that is associated with impulsive decisions during intertemporal choice (Gui et al., 2018). However, frontal theta enhancement has also been found to correlate with other decision processes during risk-taking behaviour (Pinner & Cavanagh, 2017), attentional orientation (Rajan et al., 2019), and reward processing (Pornpattananangkul & Nusslock, 2016), highlighting the possibility that this electrocortical activity, rather than being selective, may reflect a general neurophysiological code used by the cognitive control to causally influence decision making.

Here, by parametrically varying the amount of conflict inherent to a given decision, we attempted to modulate the time taken to process the subjective value of the immediate and delayed rewards and ultimately the preferences under uncertainty. Studies demonstrate that applying tACS while people make value-guided decisions it is possible to engage neural oscillations associated with cognitive control and cognitive processing (Polanìa et al., 2015). In view of this, we expect to entrain theta task-related oscillations (i.e., MFθ) and modulate the communication between frontal structures during information processing. The present study aimed to explore how individual choices between economic offers changed during band-specific tACS. In particular, we expected that tACS modulated reaction times (RTs) at indifference points (high conflict trials) and that such modulations were different for theta and sham stimulation (see the Hypotheses and Proposed Analyses section for more details).

1.2. Purposes of the study

In accordance with the 'manifesto' promoted by Munafò et al. (2017), we proposed a Registered Report format that is ideal for obtaining robust data and results in social and cognitive neuroscience. The present single-blind, within-subject and controlled cross-over study aimed at investigating the effects of midfrontal theta-tACS on cognitive control, conflict processing, and behavioural preferences during a Temporal Discounting task. Further, to explore behavioural carry-over effects induced by frequency-specific tACS, we administered the Flanker task to study motor-perceptual conflicts after electrical modulation offset. We report how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

2. Material and methods

2.1. Participants

Our sample size was determined by means of a-priori simulations. 1000 data sets of an initial dimension of 10 participants were simulated, for the choices of the Temporal Discounting task. To simulate the data, we used the effect sizes coming from the pilot in the regressor that has a key role in the main hypothesis of the experiment (see the Hypothesis paragraph). A Bayesian Multilevel Analysis was applied for each data set. If the key regressor did not reach $BF_{10} > 6$ or $BF_{10} < 1/6$, the sample size was increased of 5 simulated participants, with a maximum of 500 participants. The prior of each regressor was a Cauchy distribution, with mean 0 and scale derived from the pilot data (see the section Hypotheses and proposed analyses).

Bayesian Multilevel Models were computed using the JAGS software (http://mcmc-jags.sourceforge.net/) and the jagsUI package (Kellner, 2017). Bayes Factors were estimated by means of the Savage-Dickey Density Ratio (Dickey, 1971). See the appendix for the whole code.

The sample size for the Temporal Discounting task was estimated in 40 participants (See Fig. 1). However, given possible drop-outs and technical failures, we kept recruiting until 40 useable subjects were obtained (age: 20−35). Participants reported to be not taking chronic medications or have any neurological or psychiatric conditions, history of epilepsy, implanted metal devices. Exclusion criteria was evaluated through the Screening Questionnaire for Transcranial Electrical Stimulation (TES; Antal et al., 2017). All experimental protocols have been approved by the ethics committee of the Fondazione Santa Lucia in accordance with the standards of the 2013 Declaration of Helsinki. Volunteers received a total compensation of 30€ for their participation.

The homemade functions for the sample size computation are showed in the Appendix section.
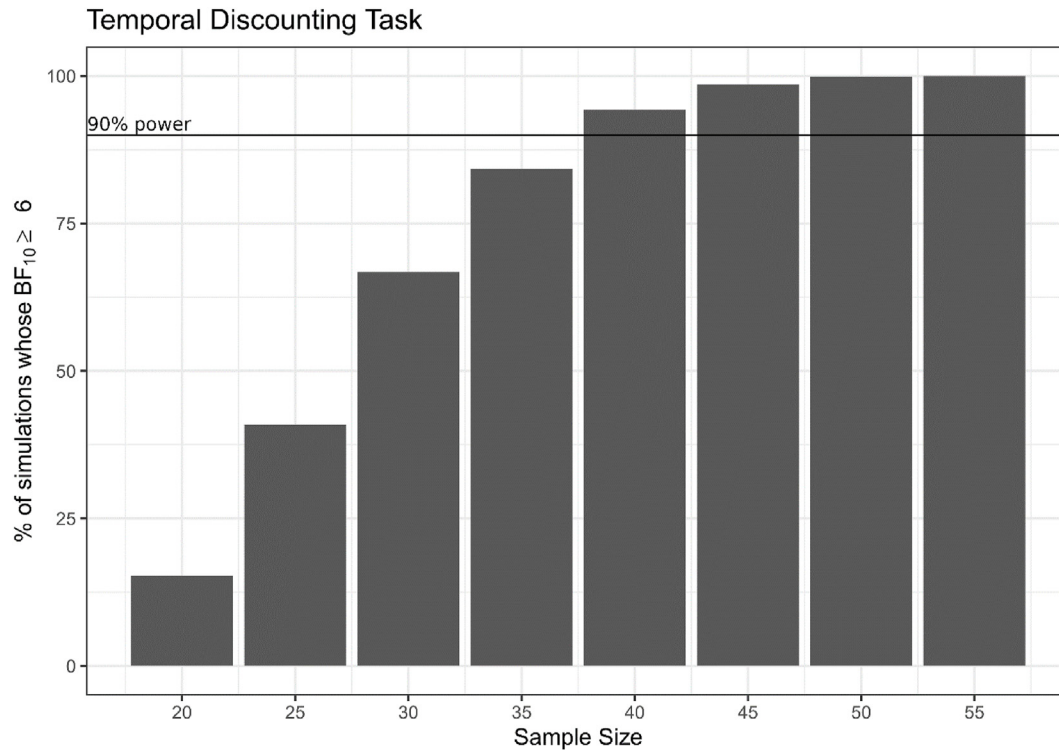
Temporal Discounting Task

Fig. 1 — Sample Size estimation.

2.2. Experimental design and tasks

The study was divided in two phases: preliminary and experimental. For the preliminary phase, we contacted volunteer candidates from our laboratory database (https://agliotilab.org) with the request to take part in a study investigating the behavioural determinants of decision-making.

2.2.1. Preliminary phase
Participants were asked to complete an online reduced version of the Temporal Discounting task in which they had to choose between 36 pairs of hypothetical economic offers representing small amounts offered immediately (soon small reward) and higher but delayed rewards in the future (later large reward). The delayed reward was fixed at 110€ and presented randomly at delays of 2, 10, 21, 50, 90, 180 days (six trials for each delay), while the immediate rewards changed trial by trial according to a staircase procedure. Specifically, the immediate offer value was increased or decreased if the participant chose respectively the delayed or immediate rewards, such that after 6 trials, the program would have found the indifference value at a particular delay. For each participant, we then fitted the hyperbolic discounting model and a simple reciprocal model to the six indifference values (one at each delay):

$$\text{Simple reciprocal} : V = A \,/\, kD$$

$$\text{Hyperbolic model} : V = A \,/\, (1 + kD)$$

where A is the objective amount of the reward, D is the delay and k is a parameter estimated by the model that reflects the degree to which the subjective value V of future rewards is discounted (Green & Myerson, 2004; Mazur, 1987). The two models were compared by means of the Akaike information criterion (AIC), and the k parameter for both models was computed. Only the participants who discount rewards in a hyperbolic manner (AIC for the Hyperbolic model < AIC for the Simple reciprocal; k > .0033), and whose goodness-of-fit is adequate (checked by means of a Kolmogorov-Smirnoff test, accepted p-values >.1), were enrolled in the brain stimulation sessions. The pre-screening task was designed to measure the individual discounting rate (k) and thus develop customized trials for the experimental task. The threshold of .0033 was arbitrarily defined on the basis of the customized trials computation that was sensitive to the k value and took into account the value difference between the immediate and delayed rewards. In particular, k values lesser than .0033 could generate (especially in the low conflict trials), delayed objective amounts that resulted lower in nominal value than the immediate offers.

2.3. Experimental phase

Following Lin et al. (2018), for each suitable participant, we used the individual's hyperbolic function to create participant-specific delayed rewards with the goal of parametrically manipulating decision conflict in each choice pair that was presented during the experimental task. The effects of tACS on conflict processing was investigated in two separate sessions (minimum 5 days between them) each consisting of a preliminary and an experimental phase. During the experimental phase, the two tasks namely the Temporal Discounting and the letter Flanker (Eriksen & Eriksen, 1974), were administered in three consecutive blocks.

2.3.1. Temporal Discounting Task

In the Temporal Discounting task, 180 stimuli with different combinations of delays and reward amounts were randomly shown on the left (option 1) or right side (option 2) of a PC monitor (51 cm × 40 cm), after the presentation of a 500-ms central fixation cross (Fig. 2). The participant-specific choice pairs had 5 pre-determined levels of decision conflict, which we varied parametrically by manipulating how similar in subjective values the immediate and delayed rewards were (value differences: 0 [high conflict], ±3 [medium conflict], ±6 [low conflict]). That is, the high conflict trials (value difference = 0) referred to those combinations in which the immediate and delayed rewards were perceived subjectively as more similar in value as compared to the low conflict trials (±6). The immediate offer was fixed at 80€ and was maintained constant for all the blocks whereas the future rewards changed according to the participants' k-values and presented at 4 different delays (25, 40, 60, 90 days). Thus, the choice pairs (20 unique pairs in total) were repeated 9 times in each block. Moreover, a random jitter of some value between −.30€ to +.30€ was added to the model-derived delayed reward, so that the participants, never saw the same objective amount twice. Participants did respond by pressing one of two keys of a keyboard corresponding on immediate and delayed choices that were counterbalanced across the subjects. Participants had to respond as quickly as they can in a temporal window of maximum 2.5 s in which each choice pair (e.g. "Do you prefer 80€ today or 93€ in 40 days?") remained visible until a response was made. If no response was given, a visual feedback (i.e. "No response") was presented at the centre of the screen. The task was administered using PsychoPy (Peirce, 2007). Following each block of the intertemporal choice task, participants performed a block of the Flanker task.

2.3.2. Flanker Task

The task required participants to respond as accurately and fast as possible to target letters (H or S) by pressing the two-corresponding coloured key buttons (yellow and blue) on the keyboard. The order of keys was counterbalanced across participants. Targets were flanked by distractors, two on each side, which could be same (congruent condition) or different (incongruent condition) with respect to the target. Each stimulus appeared at the centre of the screen (visual angle of 7.15° horizontally and 1.42° vertically) for 80 ms followed by a temporal window of 920 ms in which the response had to be given. In the case of responses provided after 500 msec, a beeping sound (1000Hz) was delivered through a pair of headphones with the purpose to remind the participants to answer more quickly in the subsequent trials. If no response was made, the visual feedback "Non hai risposto" ("You did not answer") was screened. A total of 108 trials (54 congruent and 54 incongruent) were randomly presented in each Flanker block. The task was presented using E-prime 2.0 Professional software (Psychology Software Tools Inc., Sharping, PA, USA).
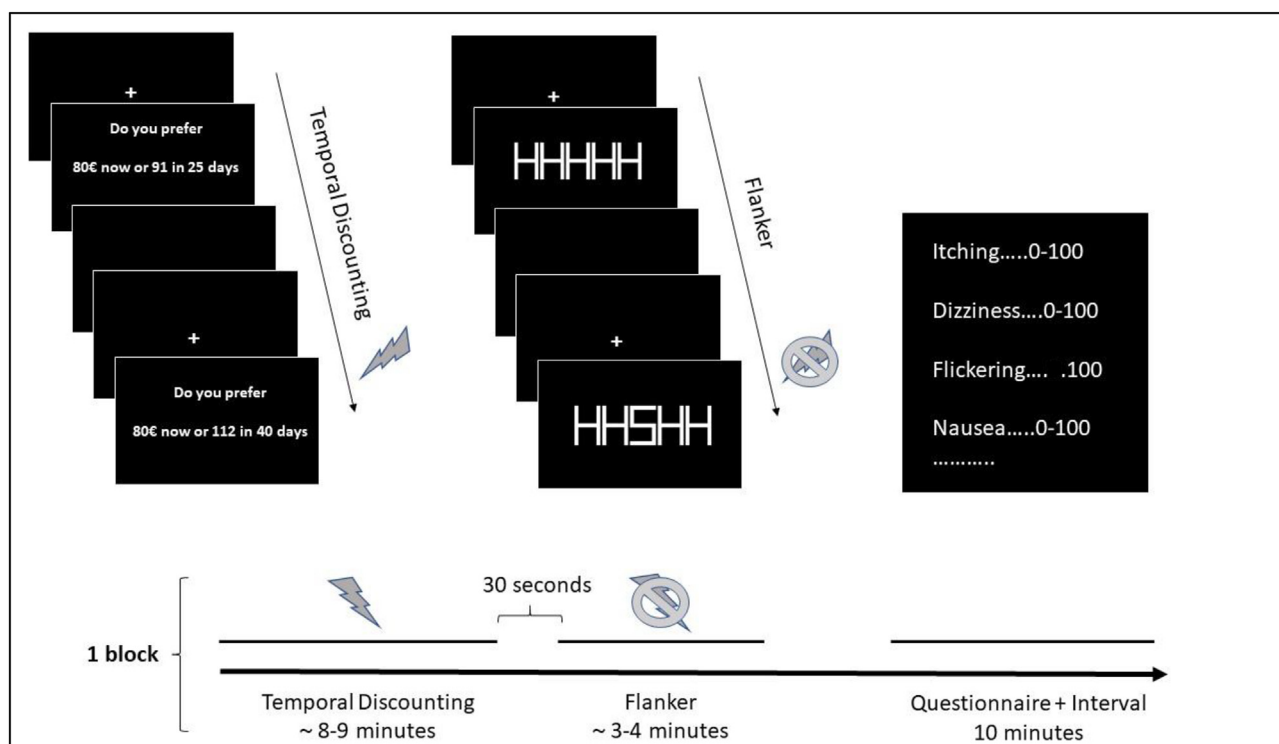

Fig. 2 − **Event timeline in the experimental tasks. In the first part of the experimental block, participants received tACS during the Temporal Discounting task. Immediately after the first task ends (break of 30s), participants performed the Flanker without neurostimulation. Finally, the questionnaire on the physical sensations was administered during an interval break lasting 10 min. For each session/day, three consecutive experimental blocks were presented. Each block consisted of temporal discounting and Flanker tasks.**

2.4. Procedure

Participants were invited to come to our laboratory in two different sessions, separated by at least 5 days. They sat about 80 cm from the PC monitor in a dimly lit room. Following a familiarization procedure with the device in which participants received a brief stimulation (i.e., 5s of ramp-up, 5s of alternating current at 750uA intensity and 13Hz frequency, 5s of ramp-down), the experimenter introduced the behavioural tasks and explained how to complete two practice blocks. If at this stage participants showed any discomfort associated with the neuromodulation, they were not asked to complete the actual tasks in the experimental phase. During the temporal discounting practice block, participants were asked to choose between 20 pairs of immediate (i.e., 80€ today) and delayed rewards (i.e. the delayed model-derived offers). Thus, for each response, a visual feedback of the selected preference was shown (e.g. "You chose 80€ today") at the centre of the monitor. Importantly, such a feedback was not be presented during the experimental task. For the practice block of the Flanker task, participants had to respond to 32 randomized stimuli (16 congruent and 16 incongruent) with the possibility of repeating the block once in the case the task demands were not properly understood. Following the familiarization, the experimental session began. To avoid carry-over effects, theta-tACS and gamma-tACS were administered during the temporal discounting task in two separate sessions/days. Therefore, the two sessions were structured in three experimental blocks, one block for the sham-tACS, one for the frequency1-tACS and one for the frequency2-tACS of the same oscillatory band (see Electrical modulation section for more details). Each block

consisted of the temporal discounting task followed 30s later by the Flanker with an inter-block interval of 10 min (Fig. 3). Throughout the IBI, participants were required to verbally report the sensorial and physical perceptions of the tACS-induced effects using a 0–100 scale (0 = no sensation at all − 100 = max sensation perceived). Since electrical current may affect skin and peripheral nervous structures (e.g. nerves or retina) that in turn may generate secondary effects such as skin discomfort or visual phosphenes (Fertonani and Miniussi, 2015; Fusco et al., 2018), participants were asked to evaluate the following perceptive categories: *Somatosensory* (i.e. itching, heating, tingling, burning, and prickling felt in the skin under the electrode areas); *Visual* (i.e. flickering, flashes and bright dots observed in the central or peripheral visual field); *Taste* (i.e. iron) and *Other sensations* (i.e. fatigue, dizziness, head heaviness, nausea, headache, and sleepiness). Finally, at the end of the second session, individual variability in impulsiveness, trait-anxiety and negative emotions, were measured asking participants to complete the following scales: the *Barratt Impulsivity Scale* (BIS, Patton et al., 1995), the *State- Trait Anxiety Inventory Form Y* (STAI-Y1 and STAI-Y2, respectively for the State and Trait scale, Spielberger, 2010), the *Behavioural Inhibition and Activation Scales* (BIS/BAS, Carver & White, 1994), and the 16-item reduced form of the *Need for Closure Scale* (NCC, Roets & Van Hiel, 2011).

2.5. Electrical modulation

tACS was delivered through a rechargeable battery-operated stimulator system (Starstim/Enobio, Neuroelectrics, Barcelona, Spain) controlled by Bluetooth connection and via two
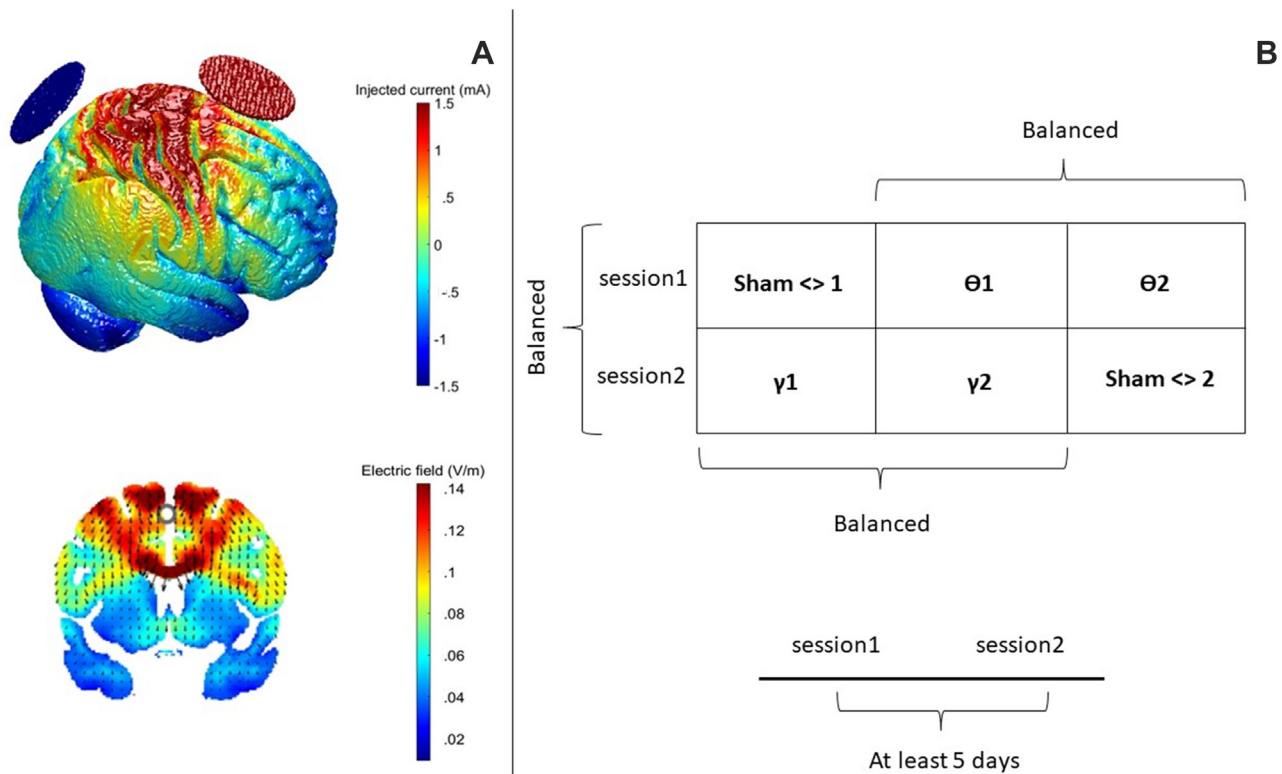

Fig. 3 — A. 3D cortical maps representing the electric field intensity distribution over the medial frontal cortex simulated through the open-source software: ROAST (https://www.parralab.org/roast/; Huang et al., 2019) B. Structural design of the proposed study.

circular sponge-conductive- electrodes (Sponstim, 25 cm^2, Neuroelectrics, Barcelona, Spain) attached to a stimulator that was soaked in physiologic solution (NaCl) and coated with electroconductive gel (only the side facing the scalp). At the beginning of each session, we identified the FCz and Pz locations on the participant's scalp using the 10—20 International System and their locations relative to medial frontal (10 % in front of the Cz position) and parietal (20 % behind the Cz position) areas. To reduce skin impedance, the two sites were cleaned with a cotton swab soaked in ethyl alcohol and then marked with a hypoallergenic broad tip pen. Afterwards, the electrodes were fixed to a tear-off cap and applied over the two spots of interest (electrode 1 over FCz and electrode 2 over Pz of the 10—20 International System). This electrode configuration has been previously adopted to entrain midfrontal theta during cognitive control (Fusco et al., 2018; Vosskuhl et al., 2015). A-*posteriori* simulation confirmed the current electric-field distribution over the fronto-medial cortical sites (see Fig. 3A). The sinusoidal current stimulation, with no DC offset and 0° relative phase, was set at 1500uA (peak-to-peak) intensity and administered during the Temporal Discounting task following 30s of ramp-up. Impedance was kept below 5 kΩ. At the end of the Temporal Discounting task, the experimenter manually interrupted the device thus triggering 30s of current ramp-down. Two frequencies-tACS for theta (Ө1: 5Hz; Ө2: 7Hz) and gamma (γ1: 30Hz; γ2: 70Hz) bands were administered separately during the two sessions (Fig. 3B). Thus, for each block and for the total duration of the intertemporal choice task, tACS was applied at one frequency of the specific band. Importantly, no modulation was applied during the Flanker task. As a baseline measure, a sham controlled condition (one block for each session) was arranged always before or after the two tACS blocks (balanced across the participants). Sham-tACS (<>) was characterized by the administration of 30s of ramp-up, alternating current for 30 s of the block at the theta or gamma frequency (depending on the session balancing) and then it was interrupted leading to 30s of ramp-down (Palm et al., 2013).

2.6. Bayesian Analyses

All statistical analyses were conducted using a Bayesian approach (Kruschke, 2014, pp. 1—759), which is an alternative approach to Null Hypothesis Significance Testing (NHST) that has been recently at the centre of controversies (Cohen, 1990; Hubbard & Lindsay, 2008; Ioannidis, 2014; Open Science Collaboration, 2015). We fitted Bayesian multilevel models using the *brms* R package (Bürkner, 2017). Bayesian multilevel models offer greater flexibility for researchers across sciences (Gelman & Hill, 2006) by allowing the modelling of data measured on different levels at the same time, taking into account random effects (effects that are not under the control of the experimenter) and fixed effects (effects under the control of the experimenter) within the same model. The use of Bayesian multilevel models allowed us to use the whole data set, and not only the averaged dependent variables. Furthermore, it was possible to take into account as random effects all the *within-subjects* effects, their interactions and the time since the start of the experimental session, in order to take into account possible fatigue effects.

Bayesian multilevel models were compared using Bayes Factors (BF$_{10}$). The BF$_{10}$ is the standard method to quantify the evidence in favour of the alternative, or the null hypothesis (Kruschke, 2014, pp. 1—759). In particular, we used zero-centred Cauchy distributions as priors, with scale parameters computed on the data of our pilot experiments (see Hypothesis and Proposed Analyses), following the seminal suggestions stated in Zoltan (2019). For each model, we ran 4 Markov chains, with 2500 burn-in and 2500 sampling iterations, resulting in a total of 10000 iterations for each model. The resulting Bayesian multilevel models were checked using diagnostic indexes. In particular, we used the Gelman & Rubin's diagnostic index $\hat{R}$ (Brooks & Gelman, 1998; Gelman & Rubin, 1992) to test the convergence among the four Markov chains ($\hat{R} \leq 1.1$), the Posterior Predictive *p*-value (Gelman, 2013) to test whether the Bayesian model actually represents the data ($p \approx .5$), by using the mode statistics (see Code snippet 1, Appendix), and the Effective Sample Size (ESS, Kass et al., 1998), a measure of the number of independent iterations in the Markov chains, excluding the autocorrelation effects. If the models pass all diagnostics, we compared their BF$_{10}$ values.

Otherwise, multiple specific strategies were applied to improve diagnostic indexes:

We fitted the model with a larger number of iterations, doubling the number of warm-up and sampling iterations. If the diagnostic indexes were still not satisfactory, we increased the number of warm-up and sampling iterations by step of 2500, with a maximum of 25000 warm-up and sampling iterations each chain (for a total of 100,000 warm-up and 100,000 sampling iterations).

If the increment of the iterations did not give satisfactory diagnostic indexes, we simplified the part of the random effects. Thus, we removed the random effect with the most unsatisfactory diagnostic indexes (i.e., the greatest $\hat{R}$ or, if all $\hat{R}$ are less than 1.1, the lower Effective Sample Size).

If some diagnostic indexes were still denoting problems, we fitted a series of models characterized by the complete fixed-effects part (all fixed-effects and their interactions), and all the possible simplifications of the random-effects part. All the models that converge were compared among them by means of the Widely Applicable Information Criteria (WAIC, Vehtari et al., 2017; 2018), and the random-effects part of the model with the lowest WAIC was used.

If all the random effects had satisfactory diagnostic indexes, but some diagnostic indexes were still denoting problems, we modified the prior distributions of regressor coefficients. We changed them into more liberal distributions, multiplying the scale parameter of the Cauchy distributions, by 2, by 3, 4 and 5, and if good diagnostic indexes were not reached, we used stricter prior distributions, dividing the scale parameter of the Cauchy distributions, by 2, by 3, 4 and 5. Random effects or prior modifications were applied to all the Bayesian models concerning that specific dependent variable. Model comparisons were computed by using the bridge sampling algorithm (the bayes_factor and post_prob functions, Gronau et al., 2020). If the use of bridge sampling was not possible, caused by memory limits or other aspects not related

to model convergence, statistical inference was executed by means of Savage-Dickey Bayes Factors.

Bayes Factors based on bridge sampling or Savage-Dickey Density ratios can be subject to variations, dependent on the posterior samples. For this reason, Bayes Factors were computed 5 times with new posterior samples for each analysis. If the differences among the Bayes Factors of the analysis was less than a tenth of the average of the Bayes Factors observed for that analysis, these was considered consistent. Otherwise, we applied the same strategies used to improve the diagnostic indexes, until consistency was not met.

Bayes Factors stability was verified by means of a sensitivity analysis (Liu & Aitkin, 2008). The convergence with Bayes Factors computed with weakly informative priors ($\beta \sim Normal(0, 5)$; $\sigma^2 \sim HalfNormal(0, 1)$) was tested. However, because Bayes Factors tend to be biased towards the null hypothesis with weakly informative priors, a $BF_{10} > 1$ with weakly informative priors was considered as a valid confirmation of a $BF_{10} > 6$ obtained with informative priors.

3. Hypotheses and Proposed Analyses

The two tasks within the experimental phase were implemented with different purposes.

In the Temporal Discounting Task, the critical hypothesis involves the modulatory effect of θ-tACS on behaviour during high conflict trials (value difference = 0). In particular, we expected that in the combinations where participants experienced high decisional conflicts, the exogenous alternating current applied over the medial frontal cortex in the theta band might lead to specific changes of neuronal excitability through modulation of the firing rate effectiveness and of the temporal and computational dynamics of task-related electrocortical activity.

At the behavioural level, we expected to observe faster RTs and more immediate choices during θ-tACS than sham-tACS and γ-tACS in high conflict trials. This effect might reflect the capability of the exogenous MFθ in modulating the communication among specific frontal structures (ACC-MFC-DLPFC) during the emergence of decision conflicts. However, faster RTs could decrease the probability of selecting delayed rewards, which might indicate a weaker role of the cognitive-control system in driving the behavioural choices of the participants toward future preferences. Therefore, immediate rewards should be preferred and selected more frequently since they could represent a rapid behavioural strategy to cope with high levels of conflict under uncertainty.

It is noteworthy that, our a-priori hypothesis predicted that θ-tACS compared to sham and γ-tACS, could modulate the exchange of neuronal signals during high conflict trials and speed-up intertemporal decisions. The direction of the preference toward immediate rewards was inferred as the more likely scenario (suggested also from our pilot data) that could occur under time pressure where cognitive control had not much time to exert top-down effects (e.g. the choice of future rewards).

H0_RTs: θ-tACS = sham-tACS in high conflict trials, γ-tACS in high conflict trials

H1_RTs: θ-tACS < sham-tACS in high conflict trials, γ-tACS in high conflict trials

H0_immediate choices: θ-tACS = sham-tACS in high conflict trials, γ-tACS in high conflict trials

H1_immediate choices: θ-tACS > sham-tACS in high conflict trials, γ-tACS in high conflict trials

In order to test our hypothesis, the contrast matrices of the Band factor and the Conflict factor had a treatment contrast design, with θ band as the baseline level for the former, and high conflict for the latter. This way, we had the possibility to directly observe the BF_{10} concerning the difference between θ-tACS and sham-tACS in high versus low conflict trials.

The main purpose of the Flanker Task is to assess possible carry-over effects caused by tACS. In Fusco et al. (2018) we observed that online θ-tACS reduced Post-Error Slowing (PES) during congruent trials and after error execution. PES is a classic example of behavioural adaptation that drives one to implement a prudent, conservative response strategy (Rabbitt & Rodgers, 1977). Such self-regulative processes minimize the likelihood that an error is repeated later in a sequence (Danielmeier & Ullsperger, 2011).

Thus, we hypothesized that if carry-over effects of tACS do exist, the PES in congruent trials measured after θ-tACS should be significantly lower than following sham-tACS. However, taking into consideration that the effect of θ-tACS stimulation was assessed during an offline Flanker session (i.e., no tACS during task performance), we were not able to predict whether the effect size could be similar or different compared to Fusco et al. (2018).

H0_PES for congruent trials: θ-tACS = sham-tACS

H1_PES for congruent trials: θ-tACS < sham-tACS

For RTs and Accuracy, accordingly to the finding of our previous study (Fusco et al., 2018), we hypothesized that:

H0_θ-tACS = sham-tACS, γ-tACS

However, since the tACS protocol that we intended to adopt here was different from our previous study, we could not exclude that offline effects of theta-tACS might led to a change in the behavioural performance. Although we predicted the occurrence of H0 (null model) we could expect alternatively as H1 model:

RTs: θ-tACS < sham-tACS, γ-tACS

Accuracy: θ-tACS < sham-tACS, γ-tACS

In order to test the hypothesis, the contrast matrices of the Band factor and the Congruency factor had a treatment contrast design, with θ band as the baseline level for the former, and congruent for the latter. This way, we had the possibility to directly observe the BF_{10} concerning to the difference between θ-tACS and sham-tACS in congruent versus incongruent conflict trials.

Question	Hypothesis	Sampling plan (e.g. power analysis)	Analysis Plan	Interpretation given different outcomes
Does θ-tACS modulate preferences during high conflicting intertemporal economic choices?	We expect that in the combinations where participants experience high decisional conflicts, the exogenous alternating current applied over the medial frontal cortex in the theta band may lead to specific changes of neuronal excitability through modulation of the firing rate effectiveness and of the temporal and computational dynamics of task-related electrocortical activity. We expect to observe faster RTs and more immediate choices during θ-tACS than sham-tACS and γ-tACS in high conflict trials. H0_RTs: θ-tACS = sham-tACS in high conflict trials, γ-tACS in high conflict trials H1_RTs: θ-tACS < sham-tACS in high conflict trials, γ-tACS in high conflict trials Faster RTs may decrease the probability of selecting delayed rewards, which might indicate a weaker role of the cognitive-control system in driving the behavioural choices of the participants toward future preferences. Therefore, immediate rewards should be preferred and selected more frequently since they may represent a rapid behavioural strategy to cope with high levels of conflict under uncertainty. H0_immediate choices: θ-tACS = sham-tACS in high conflict trials, γ-tACS in high conflict trials H1_immediate choices: θ-tACS > sham-tACS in high conflict trials, γ-tACS in high conflict trials	Our sample size was determined by means of a-priori simulations. 1000 data sets of an initial dimension of 10 participants were simulated, for the choices of the Temporal Discounting task. To simulate the data, we used the effect sizes coming from the pilot in the regressor that has a key role in the main hypothesis of the experiment (see the Hypothesis paragraph). A Bayesian Multilevel Analysis was applied for each data set. If the key regressor did not reach $BF_{10} > 6$ or $BF_{10} < 1/6$, the sample size was increased of 5 simulated participants, with a maximum of 500 participants. The prior of each regressor was a Cauchy distribution, with mean 0 and scale derived from the pilot data (see the section Hypotheses and proposed analyses). Bayesian Multilevel Models were computed using the JAGS software (http://mcmc-jags.sourceforge.net/) and the jagsUI package (Kellner, 2019). Bayes Factors were estimated by means of the Savage-Dickey Density Ratio (Dickey, 1971). See the appendix for the whole code. The sample size for the Temporal Discounting task was estimated in 40 participants. However, given possible drop-outs and technical failures, we kept recruiting until 40 useable subjects were obtained (age: 20–35). Participants must not be taking chronic medications or have any neurological or psychiatric conditions, history of epilepsy, implanted metal devices. For each participant, we fitted the hyperbolic discounting model and a simple reciprocal model to the six indifference values (one at each delay): Simple reciprocal: $V = A/kD$ Hyperbolic model: $V = A/(1 + kD)$ where A is the objective amount of the reward, D is the delay and k is a parameter estimated by the model that reflects the degree to which the subjective value V of future rewards is discounted (Green & Myerson, 2004; Mazur, 1987). The two models were compared by means of the Akaike information criterion (AIC), and the k parameter for both models will be computed. Only the participants who discount rewards in a hyperbolic manner (AIC for the Hyperbolic model < AIC for the Simple reciprocal; k > .0033), and whose goodness-of-fit is adequate (checked by means of a Kolmogorov-Smirnoff test, accepted p-values >.1), were enrolled in the brain stimulation sessions.	In order to test our hypothesis, the contrast matrices of the Band factor and the Conflict factor had a treatment contrast design, with θ band as the baseline level for the former, and high conflict for the latter. This way, we had the possibility to directly observe the BF_{10} concerning the difference between θ-tACS and sham-tACS in high versus low conflict trials. The analyses considered as Fixed Effects Conflict (high, medium, low, with a treatment contrast design with high as baseline), Band (theta, gamma, sham, with a treatment contrast design with theta as baseline) and their interaction. The Random Effects, grouped by participant, were Conflict, Band and their interaction (within-subjects effects), and as Random Covariate the block sequence of the experiment to account for learning effects (in brms syntax: y ~ Conflict * Band + (Block + Conflict * Band | participant)). Log RTs and choices were analysed by fitting Bayesian multilevel models using Gaussian distributions or binomial distributions with logit link function For the dependent variables, the model with the interaction with Conflict and Band should be the best fitting model. Then, we expect a $BF_{10} > 6$ in the coefficient representing the interaction between the θ-tACS vs. sham-tACS coefficient, and the high conflict vs. low conflict coefficient. The comparison between γ-tACS vs. θ-tACS in high conflict vs. low conflict trials is not planned by Design, but was computed as secondary analyses, by setting the baseline level of the Band factor to γ-tACS. We expected a $BF_{10} < 1/6$ in this case. No other effects should be noticeable. Furthermore, alongside the main analyses, we computed BF_{10} with a zero-centred half-cauchy prior, with the scale parameters mentioned above, to directly test the hypothesis θ-tACS < sham-tACS in high-conflict trials for each dependent variable.	First scenario: Slower RTs and more immediate choices in high conflict level trials for a possible increment of conflict processing due to the massive presence of MFθ (alarm activity) and interpreted by the cognitive control as a signal that requires a "more caution" response mode. Slower RTs and more immediate choices in high conflict level trials may maximize the likelihood to select more delayed compared to immediate choices (more time for the self-control to intervene) Second scenario: null results. There is evidence of no difference between conditions

Question	Hypothesis	Sampling plan (e.g. power analysis)	Analysis Plan	Interpretation given different outcomes
Does θ-tACS generate offline carry-over effects during the resolution of conflicting representations in a Flanker task?	For RTs and Accuracy, accordingly to the null results for these variables that we found in our previous study (Fusco et al., 2018), we hypothesize that: H0_θ-tACS = sham-tACS, y-tACS However, since the tACS protocol that we intend to adopt here is different from our previous study, we cannot exclude that offline effects of theta-tACS might led to a change in the behavioural performance. Although we predict theccurrednce of H0 (null model) we may expect alternatively as H1 model a fasting of reaction times that reduce the likelihood to reach correct performance (e.g. more errors) RTs: θ-tACS < sham-tACS, y-tACS Accuracy: θ-tACS < sham-tACS, y-tACS	Because our main hypotheses are on the Temporal Discount task, our sample size is based on that task.	The fixed effects was the Congruency (congruent, incongruent, with a treatment contrast design with congruent as baseline), Band (theta, gamma, sham, with a treatment contrast design with theta as baseline) and their interaction. Since this is a repeated-measure design, the fixed effects were also be used as random effects, altogether with the block sequence, grouped by participant (in brms syntax: y ~ Congruency * Band + (Block + Congruency * Band | participant)). Reaction Times after logarithmic transformation (correct trials) and Post-Error Slowing (PES) were be modelled as Gaussian-distributed data and Accuracy as binomial-distributed data (with logit link function). Alongside the main analyses, we computed BF_{10} with a zero-centred half-cauchy prior, with the scale parameters derived from the pilot study (and reported above), to test the hypothesis θ-tACS < sham-tACS during the flanker task for each dependent variable.	First scenario: Slower RTs and PES for a possible increment of conflict processing due to the massive presence of MFθ (alarm activity) and interpreted by the cognitive control as a signal that requires a "more caution" response mode. Such a temporal slowing may induce trade-off speed-accuracy leading to a more accurate performance (e.g. less errors Second scenario: null results. There is evidence of no difference between conditions and carry-over effects

4.   Temporal Discounting Task

For this task, the analyses considered as Fixed Effects Conflict (high, medium, low, with a treatment contrast design with high as baseline), Band (theta, gamma, sham, with a treatment contrast design with theta as baseline) and their interaction. The Random Effects, grouped by participant, were Conflict, Band and their interaction (within-subjects effects), and as Random Covariate the block sequence of the experiment to account for learning effects (in brms syntax: y ~ Conflict * Band + (Block + Conflict * Band | participant)).

Log RTs and choices were analysed by fitting Bayesian multilevel models using Gaussian distributions or binomial distributions with logit link function, respectively. Trials with RTs less than 200 ms were excluded from the analysis because considered as automatic responses. If choices were biased toward immediate or delayed preferences (>90 %), the participant was excluded from the analysis. The scale parameter for the Cauchy prior for the RTs is .147, for choices is 1.062 for the beta and Intercept parameters, while for the standard deviations a Half Normal distribution with mean 0 and sigma 1 was used. We took these scale factors by dividing the individual means of RTs collected in the pilot study between theta stimulation and sham in high conflict trials (i.e., mean RTs theta/means RTs sham in high conflict trials = 1.03 s). For choices we subtracted the percentage of immediate choices selected by the participants during theta-tACS from the percentage of immediate choices collected in the sham (i.e., % immediate choices theta - % immediate choices sham = 7.44). To obtain the scale factors for Cauchy priors, both the values of RTs and percentage of immediate choices were divided by 7 as suggested in Dienes (2019).

The candidate models were:

y ~ Conflict * Band + (Block + Conflict * Band | participant)

y ~ Conflict + Band + (Block + Conflict * Band | participant)

y ~ Conflict + (Block + Conflict * Band | participant)

y ~ Band + (Block + Conflict * Band | participant)

y ~ 1 + (Block + Conflict * Band | participant)

The random-effects part can be different from the one here reported, in order to have a model that correctly converges, as reported in the "Bayesian Analyses" section.

For the dependent variables, the model with the interaction with Conflict and Band should be the best fitting model.

Then, we expected a $BF_{10} > 6$ in the coefficient representing the interaction between the θ-tACS vs. sham-tACS coefficient, and the high conflict vs. low conflict coefficient. The comparison between γ -tACS vs. θ -tACS in high conflict vs. low conflict trials was not planned by design, but was computed as secondary analyses, by setting the baseline level of the Band factor to γ -tACS. We expected a $BF_{10} < 1/6$ in this case. No other effects should be noticeable.

Furthermore, alongside the main analyses, we computed BF_{10} with a zero-centred half-cauchy prior, with the scale parameters mentioned above, to directly test the hypothesis θ-tACS < sham-tACS in high-conflict trials for each dependent variable.

5.   Flanker Task

The fixed effects were the Congruency (congruent, incongruent, with a treatment contrast design with congruent as baseline), Band (theta, gamma, sham, with a treatment contrast design
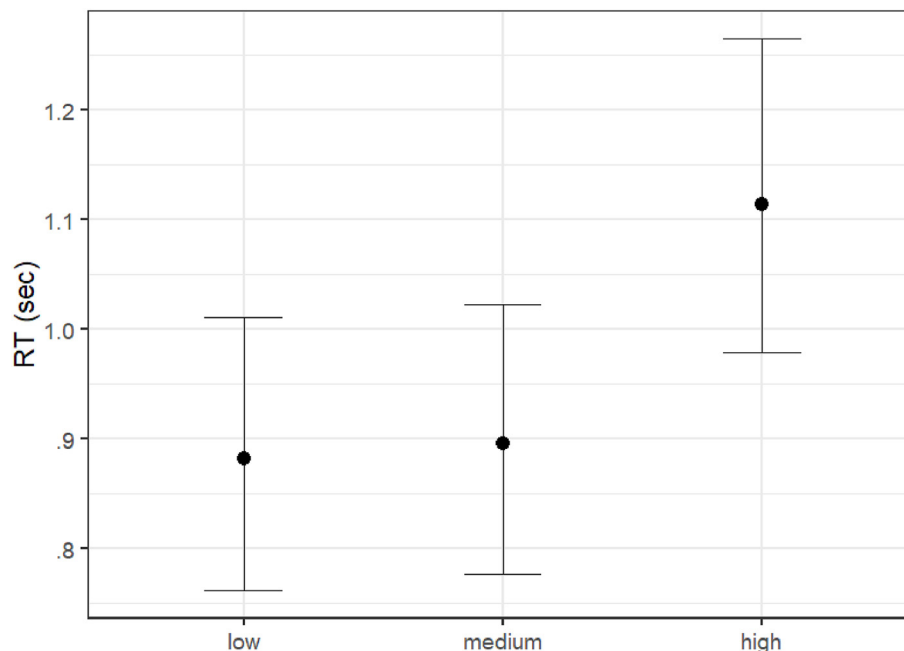

Fig. 4 − Marginal effects from the posterior distribution of the data analysis of the RTs from the Temporal Discounting task. Average RTs and the 95 % credible intervals are shown for each conflict level.

with theta as baseline) and their interaction. Since this was a repeated-measure design, the fixed effects were also used as random effects, altogether with the block sequence, grouped by participant (in brms syntax: y ~ Congruency * Band + (Block + Congruency * Band | participant)).

Reaction Times after logarithmic transformation (correct trials) and Post-Error Slowing (PES) were modelled as Gaussian-distributed data and Accuracy as binomial-distributed data (with logit link function). Trials with RTs less than 200 ms were excluded from the analysis. The scale parameter for the Cauchy priors for the beta and intercept parameters, for the RTs is .144 (i.e. mean RTs correct in theta-tACS condition/mean RTs correct in sham = 1.01), for the Accuracy is .146 (i.e. % correct in theta-tACS condition - % correct in sham = 1.02), and for the PES is .16 (i.e. mean PES in theta-tACS condition/mean PES in sham = .97). The priors for the standard deviations are a Half Normal distribution with mean 0 and sigma 1 were used. To obtain the scale factors for Cauchy priors, the obtained values for RTs, Accuracy and PES were divided by 7 as suggested in Dienes (2019).

PES was computed with the robust method that was able to take into account motivational and attentional fluctuations during the performance compared to the traditional method (Damaso et al., 2020; Dutilh et al., 2012; Williams et al., 2016). In turn the index was calculated as the average of:

RTs (E + 1) − RTs (E − 1) for all errors E

y ~ Congruency + (Block + Congruency * Band | participant)

y ~ Band + (Block + Congruency * Band | participant)

y ~ 1 + (Block + Congruency * Band | participant)

The random-effects part can be different from the one here reported, in order to have a model that correctly converges, as reported in the "Bayesian Analyses" section.

We expected $BF_{10} > 6$ for the Band effect and in particular PES should be greater after sham than theta-tACS.

In particular, our two analyses focused on the coefficients concerning the θ-tACS v. sham contrasts, expecting a $BF_{10} > 6$.

Alongside the main analyses, we computed BF_{10} with a zero-centred half-cauchy prior, with the scale parameters derived from the pilot study (and reported above), to test the hypothesis θ-tACS < sham-tACS during the flanker task for each dependent variable.

5.1. Pilot data

We analyzed pilot data from 17 participants (male = 9; LH = 2; age = 25.05 ± 2.07; k = .0233 ± .0377). Two participants were excluded (drop-out between the two sessions).

Subject 13 was excluded because she showed a strong bias toward the future choices (i.e. the participant chose the delayed offers in more than 92 % of the trials in all the conditions).

	subj.1	subj.2	subj.3	subj.4	subj.5	subj.6	subj.7	subj.8	subj.9	subj.10	subj.11	subj.12	subj.13	subj.14	subj.15
K values	.1516	.0149	.0066	.0128	.0032	.0084	.0033	.0211	.0327	.0055	.0033	.0454	.0316	.0038	.0063

where RTs (E + 1) is the correct trial post-error and RTs (E − 1) the correct trial pre-error (Dutilh et al., 2012).

The candidate models were:

y ~ Congruency * Band + (Block + Congruency * Band | participant)

y ~ Congruency + Band + (Block + Congruency * Band | participant)

All analyses on pilot data were executed with weakly informative priors:

$\beta \sim \mathrm{Normal}(0, 5); \sigma^2 \sim \mathrm{HalfNormal}(0, 1)$

All participants completed the Temporal Discounting task and the Flanker task.

We modelled RTs as a function of Band (theta, gamma or sham) and Conflict (High, Medium or Low). Random effects were grouped by participant, and were the intercept, the

Code Snippet 1: analysis of Reaction Times from the Pilot experiments for the Temporal Discounting Task

```
library(brms)
load(rt.data)


mdl1 = brm(RT~band*conflict+(band*conflict|ID),data=datum)
mdl2 = brm(RT~band+conflict+(band*conflict|ID),data=datum)
mdl3a= brm(RT~conflict+(band*conflict|ID),data=datum)
mdl3b= brm(RT~band+(band*conflict|ID),data=datum)
mdl4 = brm(RT~1+(band*conflict|ID),data=datum)


post_prob(mdl1,mdl2,mdl3,mdl3a,mdl4,maxiter=5000)
# mdl1          mdl2          mdl3          mdl3a         mdl4
# 7.833858e-16 4.118548e-06 9.999959e-01 1.210714e-20 1.967274e-14
```

slopes of Band, Level of Conflict and their interaction. The R code below shows how we fitted 5 Bayesian hierarchical multilevel models using the *brms* package and compared them using BF_{10}.

Model 3 (mdl3), characterized by only the independent variable of Level of Conflict, is the best model (posterior probability >.99). This is explained by the fact that high levels of conflict cause larger RTs (see Fig. 4).

We modelled choices using hierarchical Bayesian multi-level models for binomial data. Our dependent variable was the frequency of choices, converted in 1 = delayed choice and 0 = immediate choice. The independent variables were Level of Conflict and Band, as seen in the previous analysis. The random part took into consideration the intercept grouped by each participant.

Model 2 (mdl2), compared to all the other models, showed a posterior model probability >.99. Therefore, both the Level of Conflict and the Band affected the performance of the pilot sample, but not their interaction (see Figs. 5 and 6).

Finally, we analysed Post-Error Effects (PES) from the Flanker task. The dependent variable was the PES and the independent variables were Band and Congruency (Congruent/Incongruent). We used as random effects the intercept and the slopes of Band, Congruency and their interaction grouped by participant.

The analyses were computed with the following code.

Code Snippet 2: analysis of the Choices from the Pilot experiments for the Temporal Discounting Task

```
library(brms)
load(choices.data)


mdl1 = brm(y|trials(N)~band*conflict+(1|ID),data=datum,family""binomia"")
mdl2 = brm(y|trials(N)~band+conflict+(1|ID),data=datum,family""binomia"")
mdl3a= brm(y|trials(N)~conflict+(1|ID),data=datum,family""binomia"")
mdl3b= brm(y|trials(N)~band+(1|ID),data=datum,family""binomia"")
mdl4 = brm(y|trials(N)~1+(1|ID),data=datum,family""binomia"")


mdl1          mdl2         mdl3a         mdl3b          mdl4
6.388029e-07 9.999994e-01 4.149852e-09 7.719057e-27 1.854995e-34
```

Code Snippet 3: analysis of PES from the Pilot experiments for the Flanker Task

```
library(brms)
load(pes.data)


mdl1 = brm(pes~band*congruency+(band*congruency|ID),data=datum)
mdl2 = brm(pes~band+congruency+(band*congruency|ID),data=datum)
mdl3a = brm(pes~congruency+(band*congruency|ID),data=datum)
mdl3b= brm(pes~band+(band*congruency|ID),data=datum)
mdl4 = brm(pes~1+(band*congruency|ID),data=datum)


post_prob(mdl1,mdl2,mdl3a,mdl3b,mdl4,maxiter=5000)
# mdl1      mdl2      mdl3a     mdl3b     mdl4
# 0.1660826 0.1977298 0.1916152 0.2202014 0.2243710
```

Bayesian analysis clearly shows that there is no best fitting model.

6. Results

6.1. Pre-registered analysis

For all comparisons based on Bayes Factors, the decision thresholds are BF $\geq$ 6 for the alternative hypothesis and BF $\leq$ 1/6 for the null hypothesis. Posterior predictive checking, Gelman and Rubin's diagnostic (R̂, Gelman & Rubin, 1992) and sensitivity analysis (Liu & Aitkin, 2008) are reported in the Supplementary Materials. It was not necessary to modify neither the number of iterations of the chains, the priors, or the random effects of the Bayesian Models, because the diagnostic indexes were satisfactory in all cases.

6.2. Temporal discounting - reaction times (RTs)

Model comparisons by means of bridge sampling (Gronau et al., 2020) show that the most plausible model is the one with the two main effects (Conflict and Band), but without their interaction (see Table 1, row 2).

By computing the directional Bayes Factors reported in the pre-registered analysis, we found a significant reduction of the RTs in high-conflict trials during θ-tACS compared to
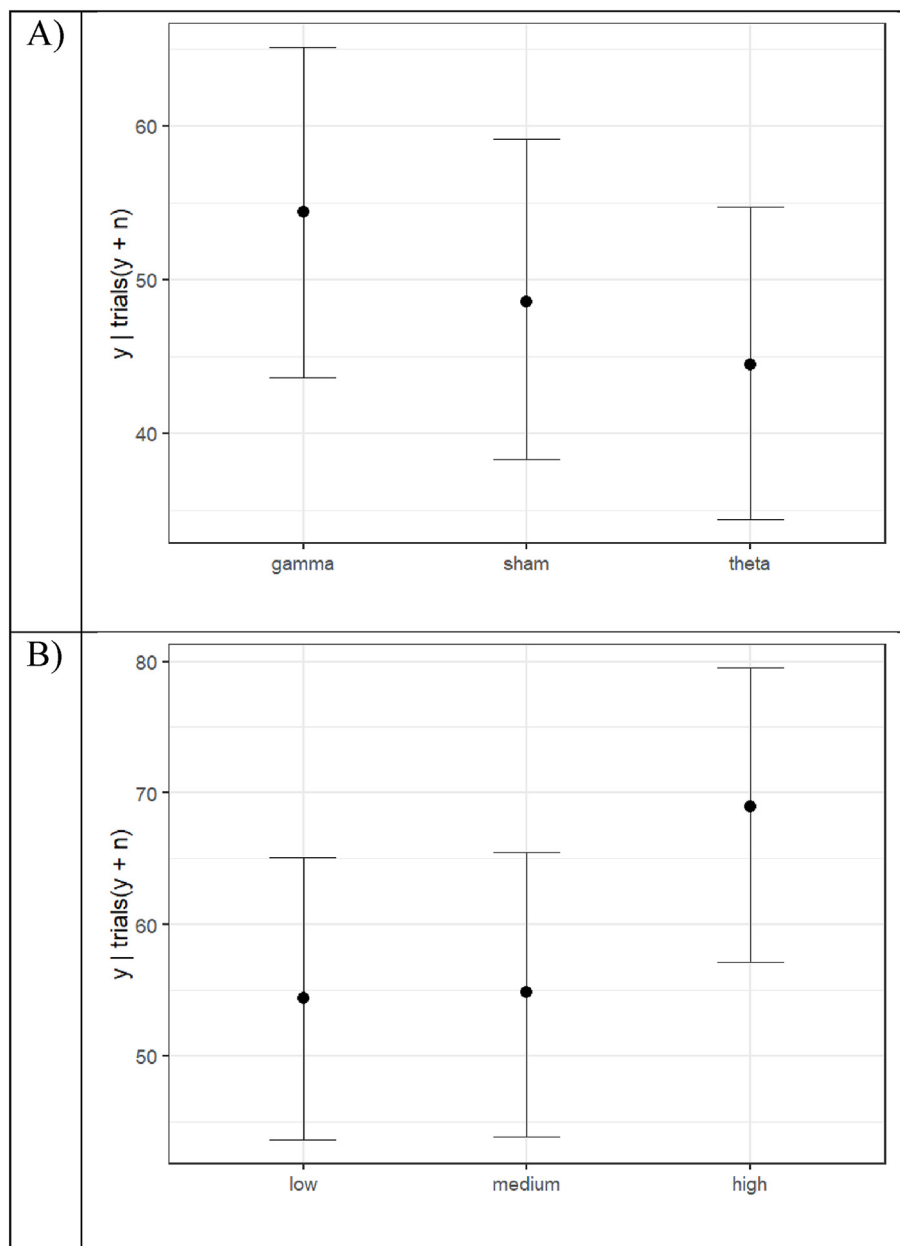

Fig. 5 — Marginal effects from the posterior distribution of the data analysis of the Choices from the Temporal Discounting task. Average choice (probability of choosing the delayed reward) and the 95 % credible intervals are shown. A. Posterior distributions are divided by band. B. Posterior distributions are divided by Level of Conflict.
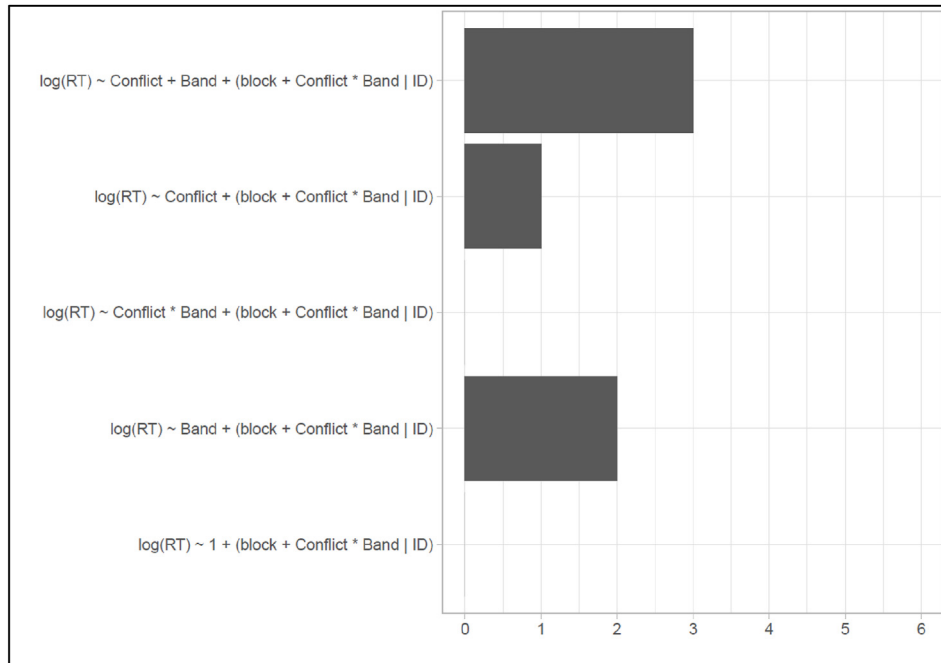
Fig. 6 − Graphical representation of Table 1. The horizontal bars represent the frequency, out of six comparisons, where the one is the most credible model according to the post_prob function.

sham-tACS ($BF_{\theta\text{-tACS}<\text{sham-tACS}} = 10.95$), while this effect did not emerge for the θ-tACS < γ-tACS hypothesis ($BF_{\theta\text{-tACS}<\gamma\text{-tACS}} = .70$). These effects were also observed in medium- ($BF_{\theta\text{-tACS}<\text{sham-tACS}} = 12.93$; $BF_{\theta\text{-tACS}<\gamma\text{-tACS}} = .79$) and low-conflict trials ($BF_{\theta\text{-tACS}<\text{sham-tACS}} = 14.46$, $BF_{\theta\text{-tACS}<\gamma\text{-tACS}} = .77$).

6.3. Temporal discounting − choices

Choices were classified as 1 = Delayed and 0 = Immediate. Model comparison showed that the null model is the most plausible one (see Table 2 row 5 and Fig. 7).

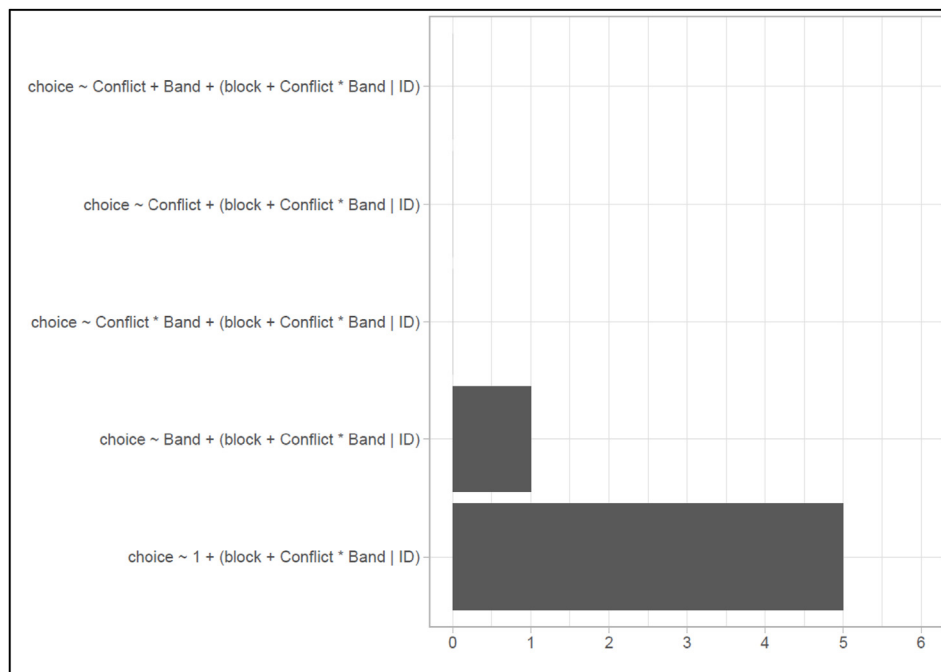**Fig. 7 − Graphical representation of Table 2. The horizontal bars represent the frequency, out of six comparisons, where the one is the most credible model according to the post_prob function.**
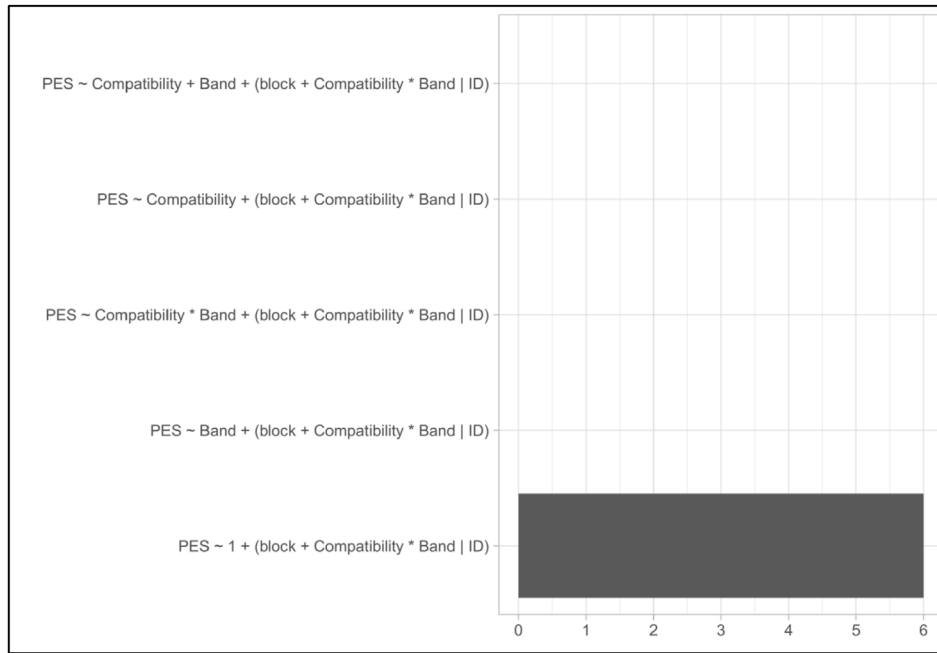
Fig. 8 − Graphical representation of Table 3. The horizontal bars represent the frequency, out of six comparisons, where the one is the most credible model according to the post_prob function.
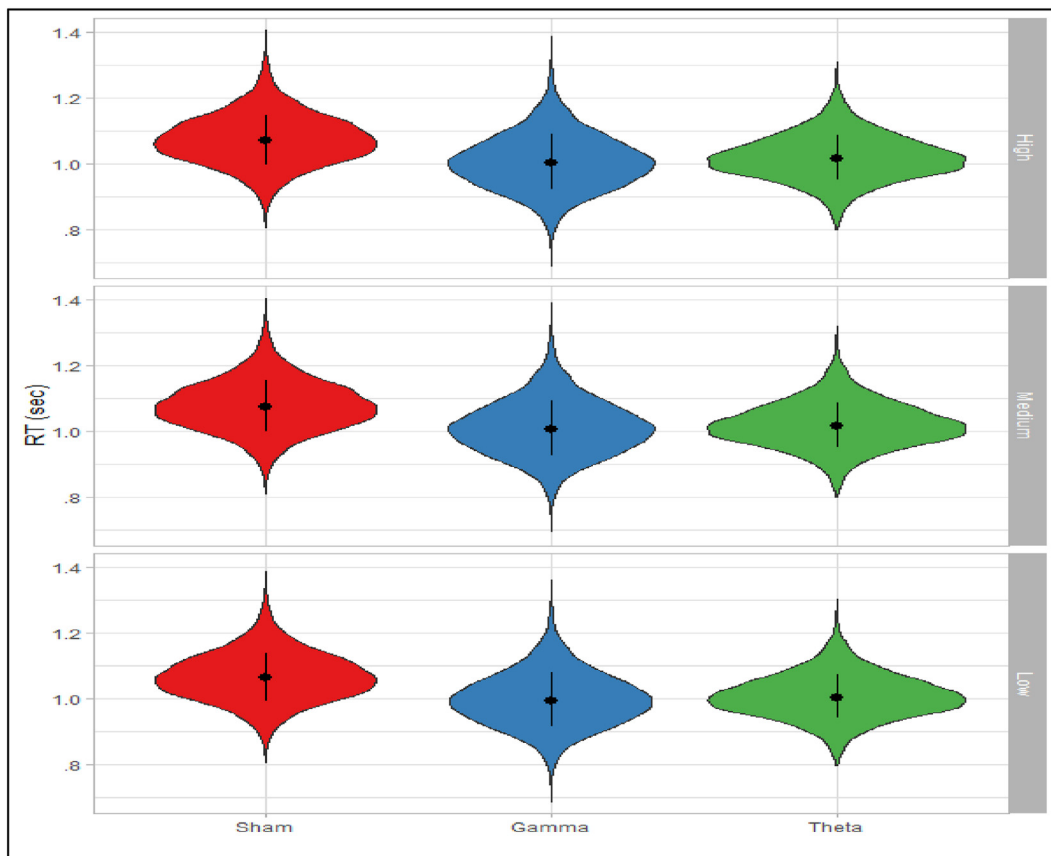
Fig. 9 − Graphical representation of the marginal posterior distributions resulting from the Reaction Time analyses for each band (Theta = θ-tACS, Gamma = γ-tACS) and level of Conflict (high, medium, low). The violin plot represents the whole posterior distribution, while the point with the error bar represents the mean and standard deviation.

Fig. 10 — Graphical representation of the marginal posterior distributions resulting from the analyses of the Conflict:BIS11-AI interaction on choices during θ-tACS. The blue line represents the mean of the marginal posterior distribution, the grey shadow the 95 % Credible Interval. In the y-axes is reported the proportions of delayed choices.
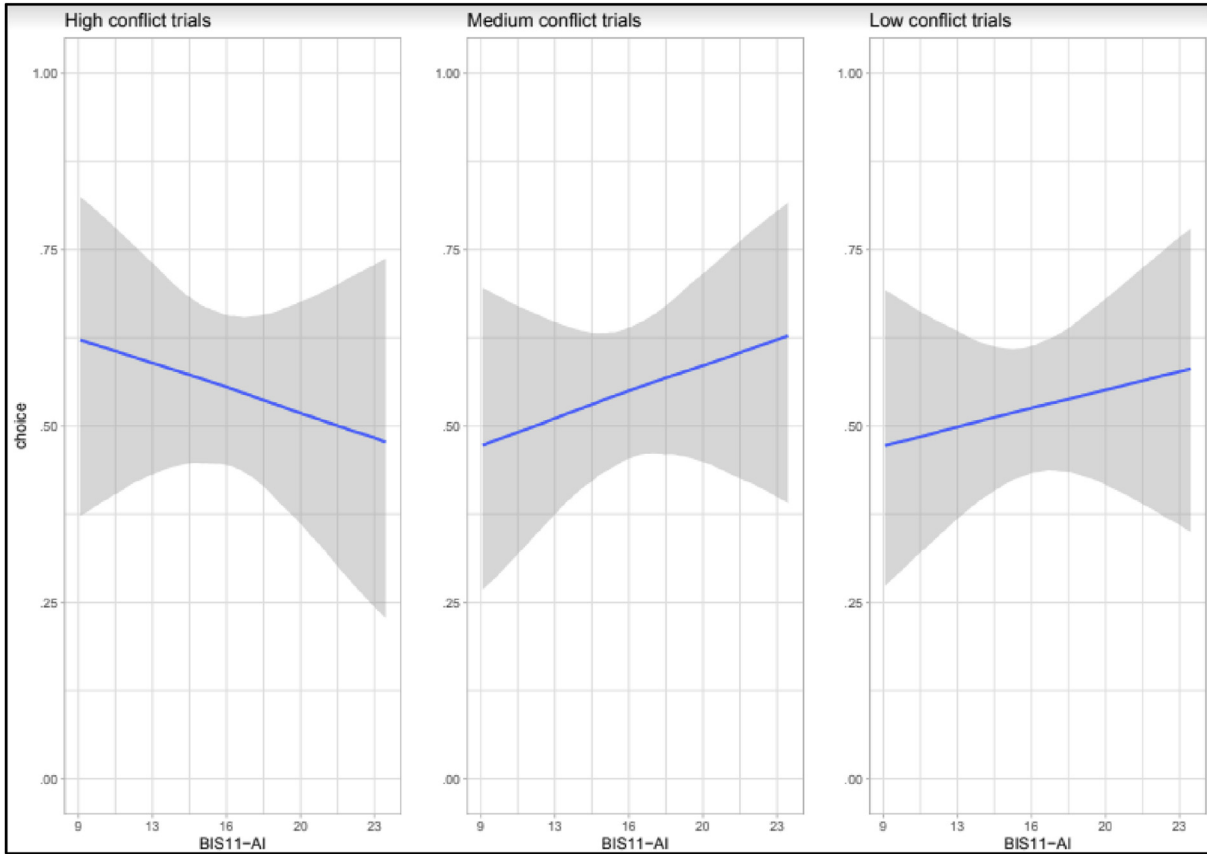
Table 1 — Proportions obtained on six runs of model comparisons conducted by means of the post_prob function. The proportions closer to 1 indicate the most plausible model. In three out of six comparisons the model is characterised by the two main effects (row 2), in two out of six by the Band main effect (row 4), and in one out of six by the model with the Conflict main effect (row 3).

	1	2	3	4	5	6
log(RT) ~ Conflict * Band + (Block + Conflict * Band | ID)	0	.00	0	0	0	0
log(RT) ~ Conflict + Band + (Block + Conflict * Band | ID)	1	.98	0	0	1	0
log(RT) ~ Conflict + (Block + Conflict * Band | ID)	0	.02	0	0	0	1
log(RT) ~ Band + (Block + Conflict * Band | ID)	0	.00	1	1	0	0
log(RT) ~ 1 + (Block + Conflict * Band | ID)	0	.00	0	0	0	0

No directional Bayes Factor from the registered report reached the decision threshold (all BFs >.50 and < 1.24). In turn, by applying the Principle of Parsimony (Vandekerref et al., 2015) we can conclude an absence of effects on choices caused by the level of Conflict, the Band, or their interaction.

6.3.1. Flanker — Post-Error Slowing
Comparing models for Post-Error Slowing indicate that no model is more plausible than the others (see Table 3A and Fig. 8). For this reason, we tested Savage-Dickey density ratios (Dickey, 1971; Wagenmakers et al., 2010) on the full model (see

Table 2 — Proportions obtained on six runs of model comparisons conducted by means of the post_prob function. The proportions closer to 1 indicate the most plausible model that in five out of six comparisons is the null one (only characterised by the intercept) and in one out of six is the one with the Band main effect.

	1	2	3	4	5	6
choice ~ Conflict * Band + (Block + Conflict * Band | ID)	.00	.00	.00	.00	.00	.00
choice ~ Conflict + Band + (Block + Conflict * Band | ID)	.00	.00	.00	.00	.00	.00
choice ~ Conflict + (Block + Conflict * Band | ID)	.00	.08	.15	.00	.24	.13
choice ~ Band + (Block + Conflict * Band | ID)	.27	.02	.00	.90	.00	.00
choice ~ 1 + (Block + Conflict * Band | ID)	.73	.90	.85	.10	.76	.87

Table 3 – A) Proportions obtained on six runs of model comparisons carried out by means of the post_prob function. The proportions closer to 1 indicate the most plausible model. The probabilities are too close to determine a more plausible model. B) Summary of the marginal posterior distributions of the full model. Mean, SE and 95 % CI are respectively the mean, standard error and 95 % credible interval of the posterior distribution of the fixed effects. $\hat{R}$ is the Gelman and Rubin's diagnostic, Bulk and Tail ESS are the effective sample size, an estimation of independent iterations of the posterior distributions towards the centre of the distribution, and towards the extremes respectively. BF_{10} is the inverse of the Savage-Dickey density ratio and can be estimated as a Bayes Factor.

A)	1	2	3	4	5	6
PES ~ Compatibility * Band + (Block + Compatibility * Band | ID)	.25	.29	.30	.21	.21	.33
PES ~ Compatibility + Band + (Block + Compatibility * Band | ID)	.11	.18	.10	.18	.16	.17
PES ~ Compatibility + (Block + Compatibility * Band | ID)	.20	.17	.15	.17	.13	.12
PES ~ Band + (Block + Compatibility * Band | ID)	.22	.18	.23	.24	.28	.24
PES ~ 1 + (Block + Compatibility * Band | ID)	.21	.18	.22	.20	.21	.14

B)	Mean	SE	95 % CI		$\hat{R}$	Bulk ESS	Tail ESS	BF_{10}
Intercept	24.32	2.11	20.19	28.47	1.00	15638	7197	>150
Compatibility	.10	.64	−.95	1.81	1.00	6492	1886	3.72
band1 (gamma v. theta)	−.03	.56	−1.25	1.01	1.00	8491	2164	3.72
band2 (sham v. theta)	.57	1.45	−.62	5.30	1.00	3860	2435	4.22
Compatibility:band1 (gamma v. theta)	−.19	.78	−2.52	.68	1.00	5703	1748	3.58
Compatibility:band2 (sham v. theta)	−.21	.82	−2.69	.68	1.00	5171	1969	3.63

Table 3B), without finding any BF_{10} reaching the decision thresholds (all $BF_{10} > 3.7$ and <4.3, except for the Intercept). In turn, we conclude that the most plausible model for post-error slowing data is the null model.

6.3.2. Exploratory analysis

To draw a clearer picture of the effects observed in the pre-registered analysis on the reaction times, we further compared the tACS control conditions and analysed the difference between γ-tACS and sham-tACS. The analysis showed a similar pattern of results, namely the presence of RT reduction during γ-tACS compared to sham-tACS in all levels of conflict (high conflict: $BF_{10} = 8.46$, medium conflict: $BF_{10} = 8.17$, low conflict: $BF_{10} = 8.56$ – see Fig. 9 for a graphical representation).

Moreover, to better understand the potential differences between θ- and γ-tACS modulations, we added a further exploratory analysis, comparing the sham-corrected effects on θ and γ modulations, by computing the directional Bayes Factor (θ-tACS − Sham) > (γ-tACS − Sham) for each conflict level. The effect was only present in the high-conflict trials ($BF_{(θ\text{-}tACS − Sham)>(γ\text{-}tACS − Sham)} = 19.92$), while the medium- and low-conflict trials did not reach the decision boundaries ($BF_{(θ\text{-}tACS − Sham)>(γ\text{-}tACS − Sham)} = 1.26$ and 1.30, respectively). In other words, theta-tACS induced a stronger effect compared to gamma-tACS during the processing of high-conflict trials.

Considering that the most plausible model is the model without the interaction between Conflict and Band, we also investigated the main effect of Conflict. From this exploratory analysis, high-conflict trials have slower response times than low conflict trials $BF_{High\ Conflict>Low\ Conflict} = 6.82$, while the high-conflict trials > medium-conflict trials comparison leads to a non-conclusive result ($BF_{High\ Conflict>Medium\ Conflict} = .37$). However, medium-conflict trials showed longer reaction times than low-conflict trials ($BF_{Medium\ Conflict>Low\ Conflict} = 14.65$). See Table 4 for the means and standard deviations of the logarithm of reaction times.

6.3.3. Flanker - reaction times (RTs)

Beyond testing our hypothesis on post-error slowing, we explored and analysed the presence of possible carry-over effects associated with the other main variables related to the Flanker task. For the RTs, model comparisons show that the most plausible model is the one characterised by the Compatibility main effect (see Table 5 row 3).

No other directional Bayes Factor reached the decision thresholds (all BFs >.50 and < 4.2).

Exploratory analysis on the compatibility main effect showed that Incongruent trials are slower than Congruent trials ($BF_{Incongruent\ >\ Congruent} > 150$). See Table 6 in which means and standard deviations of the logarithm of reaction times are reported.

Table 4 – Raw data means and standard deviations (in brackets) of the logarithms of reaction times for the Temporal Discounting task divided by Conflict (high/medium/low) and band (θ-tACS, γ-tACS, sham). (All) refers to the marginal means (standard deviations).

Conflict	γ-tACS	SHAM	θ-tACS	(all)
high conflict	−.03 (.377)	.015 (.409)	−.029 (.371)	−.015 (.386)
low conflict	−.031 (.371)	.017 (.406)	−.035 (.359)	−.017 (.379)
medium conflict	−.024 (.38)	.022 (.417)	−.029 (.374)	−.011 (.391)
(all)	**−.028 (.376)**	**.018 (.411)**	**−.031 (.367)**	**−.014 (.386)**

Table 5 — Proportions obtained on six runs of model comparisons conducted by means of the post_prob function. The proportions closer to 1 indicate the most plausible model. In six out of six comparisons the model is characterised by the main effect Compatibility.

	1	2	3	4	5	6
log(RT) ~ Compatibility * Band + (Block + Compatibility * Band | ID)	.00	0	0	0	0	0
log(RT) ~ Compatibility + Band + (Block + Compatibility * Band | ID)	.11	0	0	0	0	0
log(RT) ~ Compatibility + (Block + Compatibility * Band | ID)	.89	1	1	1	1	1
log(RT) ~ Band + (Block + Compatibility * Band | ID)	.00	0	0	0	0	0
log(RT) ~ 1 + (Block + Compatibility * Band | ID)	.00	0	0	0	0	0

Table 6 — Raw data means and standard deviations (in brackets) of the logarithms of reaction times for the Flanker task divided by Compatibility (Congruent/Incongruent) and band (θ-tACS, γ-tACS, sham). (all) refers to the marginal means (standard deviations).

Compatibility	γ-tACS	SHAM	θ-tACS	(all)
Congruent	5.951 (.163)	5.963 (.165)	5.963 (.172)	**5.959 (.167)**
Incongruent	6.053 (.172)	6.058 (.169)	6.075 (.17)	**6.062 (.171)**
(all)	**5.998 (.175)**	**6.007 (.173)**	**6.014 (.18)**	**6.006 (.176)**

Table 7 — Proportions obtained on six runs of model comparisons conducted by means of the post_prob function. The proportions closer to 1 indicate the most plausible model. In six out of six comparisons it is the model with the Compatibility main effect as fixed effect.

	1	2	3	4	5	6
Accuracy ~ Compatibility * Band + (Block + Compatibility * Band | ID)	0	.13	.01	.01	.02	.00
Accuracy ~ Compatibility + Band + (Block + Compatibility * Band | ID)	0	.11	.01	.42	.07	.01
Accuracy ~ Compatibility + (Block + Compatibility * Band | ID)	1	.76	.98	.58	.91	.99
Accuracy ~ Band + (Block + Compatibility * Band | ID)	0	0	.00	.00	.00	.00
Accuracy ~ 1 + (Block + Compatibility * Band | ID)	0	0	.00	.00	.00	.00

Table 8 — Proportions and standard deviations of the accuracies for the Flanker task divided by Compatibility (Congruent/Incongruent) and band (θ-tACS, γ-tACS, sham). (all) refers to the marginal means (standard deviations).

Compatibility	γ-tACS	SHAM	θ-tACS	(all)
Congruent	.94 (.237)	.941 (.235)	.944 (.229)	**.942 (.234)**
Incongruent	.804 (.397)	.808 (.394)	.8 (.4)	**.804 (.397)**
(all)	**.872 (.334)**	**.875 (.331)**	**.872 (.334)**	**.873 (.333)**

6.3.4. Flanker — Accuracy

Comparing the models using as dependent variable the accuracies of the Flanker task (i.e., the rate of correct responses), the most plausible model is the one characterised by the main effect of Compatibility (see Table 7 row 3 and Table 8).

The registered report directional Bayes Factor did not show any conclusive result (all BFs >.6 and < .9), suggesting no overall effect of Band on the accuracies of the Flanker task.

Exploratory analysis on the Compatibility effect showed that Incongruent trials lead to minor Accuracy than Congruent trials ($BF_{Incongruent > Congruent} > 150$).

6.4. Covariation analyses

The analyses are all exploratory and have the main purpose to investigate the effects of individual characteristics of participants in the task and how these might be associated with tACS modulation. The individual characteristics taken into consideration are: a) psychophysical and sensorial responses to tACS (self-reported cutaneous, visual, physical or gustatory reactions); b) impulsivity, as assessed by the Barratt Impulsiveness Scale (BIS11), and its subscales Attentional Impulsiveness (BIS11-AI), motor impulsiveness (BIS11-MI), and Non Planning Impulsiveness (BIS11-NPI); c) the behavioural inhibition system and the behavioural activation system via the BIS/BAS scale, and its subscales Behavioural Inhibition System (BIS/BAS-BIS), Reward (BIS/BAS-R), Drive (BIS/BAS-D), Fun (BIS/BAS-F); and lastly d) the State-Trait Anxiety Inventory, all converted in z-scores to avoid biases.

In both tasks, we separately analysed the type of tACS stimulation (θ-tACS, γ-tACS and sham) and the dependent variables in interaction with the scales.

In contrast to the previous exploratory analysis, that were necessary to better understand the pre-registered comparisons, the following analyses investigate effects that are not related to the pre-registered hypotheses. For this reason, the presence of effects is estimated using a more conservative approach and then by means of Bayes Factors computed with Savage-Dickey density ratios (Dickey, 1971; Wagenmakers et al., 2010), avoiding the use of Directional Bayes Factors.

In this way, we estimated four different models for each tACS stimulation, dependent variable, and task, for a total of 60 models. For sake of conciseness, here we report only the model with Bayes Factors that reached the decision thresholds, with the exception of the main effect of Conflict or Compatibility, whose effect was already reported in the registered analyses. The full results are reported in the Supplementary Materials (see the folder 'explorative questionnaires' on https://osf.io/5t6vz/).

6.5. Temporal discounting − choices and BIS11 during Ɵ-tACS

The estimated model is choice ~ Conflict * (BIS11-AI + BIS11-MI + BIS11-NPI) + (Block + Conflict | id). The resulting model showed an interaction between Conflict and BIS11-AI, suggesting that their relationship has a plausible impact on choices ($BF_{10} = 15.15$) during high-conflict trials. In contrast, this link was not present in medium- and low-conflict trials ($BF_{10} = .18$ and $.28$, respectively − for a graphical representation, see Fig. 10).

7. Discussion

Electrocortical recordings have systematically emphasized the correlational link between midfrontal theta (MFƟ), performance monitoring and top-down processing during challenging laboratory-based tasks (Cohen, 2014; Gratton et al., 2018). According to a neurocomputational perspective, MFƟ acts as an electrophysiological signal that synchronizes the electrocortical dynamics between distal and proximal brain structures to implement control and optimize the ongoing goal-directed performance (Botvinick et al., 2001; Cavanagh et al., 2014). Nevertheless, how exactly MFƟ guides conflict resolution and affects decisions, has yet to be determined.

In the present registered report, we hypothesized that theta-tACS could promote faster response times while participants performed a temporal discounting paradigm and made rapid, highly conflicting decisions, i.e., choosing between immediate and delayed rewards with overlapping subjective value. Such a gain in information processing would have hindered cognitive control and forced decisions toward the selection of more impulsive but certain economic offers. Results partially met our predictions. While we hypothesized a specific effect during high-conflict trials, theta-driven

neuromodulation speeded-up decisions for all the conflict levels, likely suggesting that MFƟ-tACS may have induced a general activation of the performance monitoring network thus likely facilitating information processing. Moreover, it is plausible that rapid and random decisions made at different intermixed levels of intertemporal conflicts might have forced the need to maintain a continuous monitoring over task-related representations (e.g., temporal delays, subjective values) to evaluate preferences and select optimal choices. On this regard, Lin et al. (2018), observed theta power enhancements during high-conflict trials, but also found that theta activity increased during intertemporal decisions in condition of minimal conflict (Lin et al., 2018). Thus, we may speculate that MFƟ-tACS acting on neural coding that underpins the monitoring of conflicting representations may have optimized the subsequent stage of choice processing and improved reaction times (RTs). Crucially, the temporal change did not affect choice selection at all, confuting our pre-registered prediction and corroborating the null hypothesis, namely the absence of effects on preferences caused by theta-tACS.

Studies delivering non-invasive alternating current over the frontal networks showed a causal involvement of theta oscillations in modulating conflict and error monitoring during task performance (Boukarras et al., 2022; Fusco, Cristiano, et al., 2022). It has been shown for example, that 6Hz-tACS may influence behavior by affecting conflict adaptation (van Driel et al., 2015), post-error adjustment (Fusco et al., 2018) and cognitive interference (Lehr et al., 2019). Of note, all these investigations reported changes on response times thus revealing a possible neurocomputational advantage induced by theta rhythms that may underlie improvements in the interneural communication and information coding. In this respect, we have recently reported modulations of the long-range communication between neuronal populations underlying conflict monitoring and visuo-perceptual encoding of hand stimuli while participants received theta-tACS over the MFC and the right extrastriate body area (Fusco, Fusaro, & Aglioti, 2022). Crucially, the neuromodulation reduced response times without causing speed-accuracy tradeoff and only for the conflict selectively evoked by the corporeal stimuli. An effect that was not observed during gamma-tACS and sham stimulation (Fusco, Fusaro, & Aglioti, 2022). Consistently here, although RTs were maximal in high-compared to medium- and low-conflict trials for all the tACS conditions, the intertemporal cost/benefit computation between competing subjective values may turn out to be optimized under theta oscillations.

However, theta- and gamma-tACS did not significantly differ from each other, as we predicted in the pre-registration, leaving open the possibility that gamma oscillations might have induced similar changes on decision time processing. To further test this hypothesis, we computed post-hoc exploratory analyses and found that midfrontal gamma-tACS actually mirrored the effects induced by theta-tACS, showing the same RTs pattern (i.e., faster RTs during intertemporal decisions

and regardless the conflict level compared to sham). In turn, one may question that tACS was effective in modulating behavior as mere consequence of potential attentional biases caused either by the sensorial or psychophysical sensations induced by the electrical current.

We further probed such a possibility by analyzing the link between the subjective scores provided in the questionnaires investigating visual, cutaneous, taste and physical sensations with the RTs recorded during the temporal discounting task. Results did not show any relation and we may orient our interpretation toward other possibilities. To deepen and better understand θ- and γ-related dependent modulations, we looked at their difference normalizing the effects on the sham condition for each conflict level. From this exploratory analysis it emerged that theta-tACS resulted in stronger modulation of RTs than gamma-tACS only in the high-conflict decisions, while no differences emerged in the medium- and low-conflicts. This may indicate that different cognitive processes could intrinsically explain the behavioral modulation of decision times. Nevertheless, if exogenous midfrontal theta oscillations might have affected conflict monitoring, what was the functional mechanism that could explain gamma-driven changes?

Endogenous gamma rhythmic cycles are involved in neuronal communication and their synchronization partially depends on the inhibitory/excitatory balancing between interneurons and pyramid cells dynamics (Fries et al., 2008). This cortical activity seems to be associated with the neuro-computation of top-down control and with the involvement of inhibitory networks that operate through the γ -aminobutyric acid (GABA) neurotransmitter (Barr et al., 2009). Although the functional significance is not completely clear to date, studies suggest that frontal and parietal gamma oscillations might be associated with cognitive processes like attentional control, abstract reasoning and working memory (Howard et al., 2003; Jensen et al., 2007; Taylor et al., 2022) highlighting the possible functional specialization in feature binding and integration that may support internal representations (Tallon-Baudry et al., 1999). Mounting evidence from tACS investigations further confirms that gamma can modulate behavior acting on fluid intelligence (Santarnecchi et al., 2013), self-awareness (Voss et al., 2014), spatial working memory (Alekseichuk et al., 2017), visual perception (Palmisano et al., 2023) and implicit learning (Giustiniani et al., 2019), even if no studies reported direct gamma-driven effects on decision-making. However, critics have been leveled on linking gamma rhythms to high-order and cognitive processing proposing to assign them to an exclusive basic operational role at infrastructural neuronal level (e.g., neuronal homeostasis, metabolic support) that is shared by several neural systems (Merker, 2013). While no clear picture on the role of changes induced by gamma-tACS can be drawn, one can speculate that frontoparietal neuro-modulation may have optimized (regardless of whether affecting systems at functional or structural levels) the stage

of integration between the different representations activated during task performance (e.g., perceptual, temporal, value encoding, cost/benefit, response selection). This supposed facilitation may have consequently improved information coding and then, response times. However, such an interpretation requires further evidence and additional *in-vitro* and *in-vivo* studies are needed to understand whether and how exogenous injected gamma oscillations may affect neuronal computation and behavior. An alternative interpretation of the involvement of gamma oscillations in the regulation of motor control and learning can be offered. Evidence from both human and non-human primates indicate an increase in gamma activity over the motor and pre-motor cortices during the updating of action representations and the execution of motor programs (Hosaka et al., 2016; Nowak et al., 2018). These findings have been further supported by tACS studies that delivered gamma frequency stimulation over the primary motor cortex, resulting in reduced response times during the performance of sequential finger movements (Bologna et al., 2019; Spooner et al., 2023). It is possible, therefore, that the alternating electric field at gamma rhythms may have modulated the functional activity of neural populations within the medial pre- and motor areas (e.g., pre-SMA, SMA, M1), enhancing the computation of motor actions and response selection during decision-making. This could partially explain why the improvement in reaction times was more pronounced for theta-tACS compared to gamma-tACS during high-conflict trials, where cognitive (rather than motor) resources are likely required to handle demanding intertemporal choices.

In addition to effects on RTs, it is currently under debate whether theta-dependent changes are effective in modulating choice preferences during decision-making. Looking at our data neither θ- (as we predicted in the pre-registration) nor γ-tACS (as we explored after data collection) were capable to affect choice preference, thus suppling evidence for the null hypothesis. On the one hand, Sela et al. (2012) reported an increase of impulsive decisions in the Balloon Analog Risk Task when the left dorsolateral prefrontal cortex (DLPFC) was neuromodulated at 6Hz-tACS compared to sham (Sela et al., 2012). Unfortunately, no control frequencies were used in the experimental design and no strong conclusions about the causal role of theta oscillations in driving choices can be drawn (Feurra et al., 2012). Soutschek and collaborators (2022) instead, found that the administration of MFθ-tACS induced a preference bias (i.e., measured as a shift of the decision starting point during information accumulation) toward high rewards that required great effort, thus suggesting that a modulatory effect of motivation might have implemented the information processing underpinning goal-directed choices (Soutschek et al., 2022). On the other hand, when people are exposed to advice-guided decisions predicting rewards and punishments, the offline neuromodulation in theta frequency seems to leave

unaltered the choice selection (Wischnewski et al., 2021). Indeed, despite neurophysiological after-effects (e.g., the amplitude reduction of the P3b component) were reported, the frontopolar theta-tACS did not affect decision-making while participants evaluated the most expensive object between two items and decide whether following the advice cued by experts, amateurs, or novices (Wischnewski et al., 2021). Yet, no theta- but beta-dependent effects were reported during risky rewarded decisions when the online tACS was delivered over the DLPFC in a block-wise fashion (Yaple et al., 2017). Building on these findings, we attempted to modulate MFθ and causally affect two interactive stages of information processing that are both essential for cognitive control, namely conflict monitoring and decision-making. Even if our hypotheses were mainly oriented toward the modulation of response times during high-conflicting decisions, we also expected changes on choice selection as a possible consequence of having caused a neurocomputational constraint for cognitive control (i.e., less time to exert top-down control). Again, our results do not provide evidence on the tACS effectiveness in modulating choice preference. Contrary to our pilot study conducted in a small sample size (n = 14), where we observed a response time slowing during theta-tACS followed by an increase of immediate choice preference, in the experimental sample (n = 40), we did not find any decision modulations. A possible explanation could be related with the electrode arrangement that was not optimized to target cortical structures that are commonly involved in value coding and control processing, like the DLPFC and Ventromedial Prefrontal Cortex (Hutcherson et al., 2012). Moreover, we may have used a low AC intensity that did not induce strong electric fields on cortical tissues and thus failed to trigger considerable neuromodulatory effects on decision-making (Alekseichuk et al., 2022; Vöröslakos et al., 2018). However, exploratory analyses revealed that theta-tACS during high-conflict trials may cause the immediate reward selection in condition of attentional impulsiveness, supporting the hypothesis that frontal theta rhythms may represent a functional electrophysiological biomarker that prevents uncertainty and urges the preference of the most certain option to solve the conflict (Cavanagh, Zambrano-Vazquez, & Allen, 2012). In this regard, EEG studies found variations of frontal theta activity correlating with impulsiveness. In healthy adults for example, a greater theta power over the antero-central site of the frontal cortex was associated with low measures of impulsivity in a gain/loss monetary gambling task (Kamarajan et al., 2008). Similarly, in Vipassana meditators, it has been reported a significant inverse relation between decrements of MFθ power and higher proficiency in inhibiting preponderant responses during the Go/NoGo performance (Andreu et al., 2019). The link between midfrontal theta activity and impulsivity may also extend to sub-clinical and clinical conditions. For example, in alcohol-dependent abusers it has been shown a significant reduction of frontal theta activity associated with more impulsive and risk-taking choices during the performance of a gambling task (Kamarajan et al., 2012). Additionally, in patients with a diagnosis of attention-deficit/hyperactivity disorder (ADHD) quantitative EEG recordings have consistently reported the presence of higher theta power in comparison to healthy control groups during the resting state activity (Bresnahan et al., 1999; Koehler et al., 2009; Snyder et al., 2006). This may suggest that atypical frontal theta oscillations could be considered as an electrocortical biomarker of the altered functioning of the frontal network that causes attentional and inhibitory impairments. Thus, we may speculate that midfrontal theta-tACS could have activated the performance monitoring system and modulated the attentional impulsiveness inducing faster responses toward the selection of the intertemporal options, regardless the reward value. Notably, our result appears in line with recent evidence reporting a functional dissociation between electrocortical activities involved in intertemporal decision-making (Gui et al., 2018). Indeed, while theta activity was mostly related to impulsive decisions, beta oscillations were associated to conservative choice strategies and with the selection of delayed rewards (Gui et al., 2018). Although these investigations show mixed results, frontal theta oscillations and impulsive intertemporal choices would seem related in some way, but further studies are required to unveil whether they might be also causally linked.

Finally, by administering two tasks requiring cognitive control, we aimed at testing whether the matching between task-related and exogenous theta oscillations inducing effects on intertemporal conflicts might facilitate the ability to perform conflicting stimuli and solve cognitive interference in absence of neuromodulation. Because of methodological similitudes, we oriented the prediction in the same direction of our previous study where we found a significant reduction of PES during theta-tACS compared to sham (Fusco et al., 2018). Evidence from co-registration investigations reported both electrocortical (Kasten et al., 2016; Wischnewski et al., 2019; Zaehle et al., 2010) and behavioral post-stimulation effects (Kasten et al., 2017; Klírová et al., 2021; Moliadze et al., 2019) as a likely consequence of neural plastic changes characterizing the application of transcranial electrical stimulation techniques (Medeiros et al., 2012; Wischnewski et al., 2023). However, following the tACS offset we did not capture long-lasting changes neither on the variable of our interest (i.e., the post-error slowing, PES) nor in the other measures collected in the Flanker (e.g., RTs and Accuracy) questioning the tACS effectiveness for offline applications. At least two reasons might explain the absence of post-modulatory behavioral effects. First, the theta frequencies that we used in Fusco et al. (2018) and here were different. Indeed, while in the former study participants were stimulated online at 6Hz, in the present study participants were

tested offline following either 5Hz- or 7Hz-tACS. Second, contextual variables related to the experimental procedure (e.g., the interaction between tasks involving different neural mechanisms and cognitive functions) and individual dispositions or responsiveness to tACS might have also played a role in determining such null aftereffects (Krause and Cohen Kadosh, 2014; Fertonani and Miniussi, 2016).

8. Conclusion

Conflict and error monitoring play a strategic role in mapping stimulus-response representations and eventually, strengthen cognitive control for driving decision-making (Miller, 2001). Non-invasive brain stimulation (NIBS) studies provide a unique methodological opportunity to investigate the dysfunctional processing of performance monitoring in clinical populations (Fusco et al., 2023; Pezzetta et al., 2023; Pyasik et al., 2022). However, due to the heterogeneity of adopted NIBS protocols and variability that intrinsically characterize individuals, experimental results may often be mixed and controversial. Here we have showed that both theta- and gamma-tACS may induce modulation on performance monitoring. However, this result needs replication also using different AC rhythms. Further studies using protocols with multiple tACS frequencies may be needed to shed lights on this issue. Overall, to what extent tACS can be considered as an effective technique is currently under debate. Although investigations seem to indicate that tACS can induce changes non-invasively on electrophysiology, cognition, and behavior (Fusco, Cristiano, et al., 2022; Herrmann et al., 2013; Klink et al., 2020), other studies may contradict such evidence showing in some cases unsuccessful applications (Brauer et al., 2018; Coldea et al., 2021; Veniero et al., 2017). However, we believe that studies reporting null results are deeply informative for scholars and provide solid fundaments for the (neuro) scientific understanding.

Although effortful, the registered report format may represent a good compromise to develop reliable, open and transparent science, providing theoretical and methodological insights which benefit the entire scientific community, especially when rigorous approaches led to null results. In our knowledge this is the first registered report in which predictions on theta-tACS effects have been made aprioristically. We hope our findings may inform scholars to improve experimental designs and boost the knowledge toward a more effective application of tACS.

Open practices

The study in this article earned Open Data, Open Material and Preregistered badges for transparent practices.

The data, materials are available at: https://osf.io/5t6vz and preregistered studies at https://osf.io/7v6ed.

CRediT author statement

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Declaration of competing interest

The authors declare that they have no conflict of interest.

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Appendix

Below the home-made functions used in the simulations for the sample size estimation.

Code Snippet 4: JAGS code and R functions for the sample size estimation

```r
library(jagsUI)
library(logspline)
library(ggplot2)

writeLines("
model{
    #Likelihood
    for(j in 1:Ntotal){
        y[j] ~ dbern(mu[j])
        logit(mu[j]) <- inprod(X[j,],beta) + u[grouping[j]]
    }

    #Priors
    for(i in 1:Nparameters){
        beta[i] ~ dt(0,1/pow(ES,1/2),1)
    }

    #Hyperpriors

    # Define priors for the random effects
    for ( s in 1:Ngrouping ) {
        u[s] ~ dnorm(0,1)
    }

}",con="blmm2.jags")


fitJAGS = function(data,fixed,grouping,y,ES,type="gauss"){
  X = model.matrix(fixed,data=data)
  y = as.numeric(y)
  groupp = as.numeric(grouping)

  #Put dependent and independent variables into a list
  data.list = list(y = y, X = X,
                   #number of fixed effects
                   Nparameters = ncol(X),
                   #declare our grouping factor
                   grouping = groupp,
                   #number of levels of the grouping factor
                   Ngrouping= length(unique(groupp)),
                   #and the total number of observations (y)
                   Ntotal = length(y),
                   ES = ES)

  #### JAGS

  fit.jags= jags(data=data.list,parallel=TRUE,n.cores=4,
                 parameters.to.save = "beta",
                 n.chains=4,n.adapt=1000,n.burnin = 2000,n.iter = 4000,
                 model.file = "blmm2.jags"
                 )

  return(fit.jags)
}
```

Below the iterative code for the Temporal Discounting Task.

```r
ES = 1.062

invlogit = function(x) 1/(1+exp(-x))

SavageDickey = function(fit.jags, ES ){
  ##savage-dickey density ratio
  betas  = as.matrix(fit.jags$samples[,c("beta[1]",
                                         "beta[2]","beta[3]","beta[4]",
                                         "beta[5]","beta[6]",# )])
                                         "beta[7]","beta[8]","beta[9]")])
  betas_logspl = apply(betas,2,logspline)
  BF10j = lapply(betas_logspl,function(x){dcauchy(0,0,ES)/dlogspline(0,x)})
  return(BF10j)
}

iterations = 1000#number of iterations

#dataset for a single subject
datum = data.frame(
  conflict = factor(rep(c("low","medium","high"),each=36)),
  band     = factor(rep(c("theta","gamma","sham"),each=12)),
  ntrial   = 1:108
)
#set the contrasts
contrasts(datum$conflict) = contr.treatment(n=3)
contrasts(datum$band) = contr.treatment(n=3)
#set the regressors
intercept   = 0
b.conflict1 = 0
b.conflict2 = 0
b.band1     = 0
b.band2     = 0
b.conf1band1= 0
b.conf2band1= 0
b.conf1band2= ES # effect size KEY REGRESSOR IN POSITION 8
b.conf2band2= 0

betas00 = c(intercept,b.conflict1,b.conflict2,
            b.band1,b.band2,b.conf1band1,b.conf2band1,
            b.conf1band2,b.conf2band2)

out = list()
i_out = 1
n_subj = seq( from = 20, to = 500, by = 5 ) # sample size vector

# iterative loop
for(i in 1:iterations){
  BF = 0
  i_subj = 1##index for the sample size vector

  #for each iteration, starts with 10 participants and add 5 of them
  #since you reach BF>6 or sample size = 500
  repeat{
    #simulating the data set
    dat = list()
    for(j in 1:n_subj[i_subj]){
      dat[[j]] = datum
      dat[[j]]$subj = j
      probs = invlogit(model.matrix(~conflict*band,data=datum)%*%betas00 +
rnorm(n=108))
      dat[[j]]$y =  sapply(probs, rbinom, n=1, size=1)
    }
    datz = do.call("rbind",dat)
    datz$subj = factor(datz$subj)

    ggplot(datz,aes(y=y,x=band,colour=conflict)) +
      stat_summary(geom="pointrange",fun.data ="mean_se")

    starting.time = Sys.time()
    mdl = fitJAGS(datz,~conflict*band,
                  interaction(datz$subj,datz$conflict,datz$band),
                  datz$y,
                  ES=ES,
                  type = "binomial")
    print(Sys.time()-starting.time)

    BF = SavageDickey(mdl, ES = ES)

    ##recording data
    out[[i_out]] = data.frame(n = n_subj[i_subj], bf = BF, iter = i)
    write.csv2(file="TEMPORALDISCOUNTING-binomial.csv",do.call("rbind",out))

    i_out = i_out + 1

    print(paste0("N = ",n_subj[i_subj],"; iter = ",i,"; BF10 = ",BF[8]))

    ##if we reach the 500 boundary, or BF>=6, exit
    if(BF[8]<=1/6 || BF[8]>=6 || i_subj==length(n_subj))  break

    i_subj = i_subj + 1##increasing the index of the sample size vector
  }
}

out = do.call("rbind",out)
```

Below the R code for the graph.

Code Snippet 6: R code for the graphical representation of the sample size

```r
out = read.csv2("TEMPORALDISCOUNTING-binomial.csv")

out$y = ifelse(out$bf.beta.8.>=6,1,
               ifelse(out$bf.beta.8.<=1/6,-1,0))

graph = aggregate(y~n,data=out,FUN=sum)
graph$y = cumsum(graph$y)/10

ggplot(graph,aes(y=y,x=n))+
  geom_bar(stat="identity")+
  geom_abline(intercept = 90,slope=0)+
  theme_bw(base_size = 18)+
  xlab("Sample Size")+
  ylab(bquote("% of simulations whose"~ BF[10] >= ~" 6"))+
  scale_x_continuous(breaks=seq(from=10,to=60,by=5))+
  ggtitle("Temporal Discounting Task")
```

Code Snippet 7: computation and graphical representation of the Posterior Predictive P-Value.

```r
## mode function
my_mode <- function(x, na.rm = FALSE) {
  if(na.rm) x <- x[!is.na(x)]
  if(length(x)>1){
    return(density(x)$x[which.max(density(x)$y)])
  }else return(x)
}

## y_rep extraction
ppp <- posterior_predict(mdl1 , nsamples = 1000)

## posterior predictive p-value computation
mean( apply(ppp, 2, my_mode) > my_mode(datum$value) )

## graphical representation
bayesplot::ppc_stat(y = datum$value,
                    yrep = ppp,
                    stat = "my_mode")
```

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