Modulating preferences during intertemporal choices through exogenous midfrontal theta transcranial alternating current

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1 **Abstract**

2 Decision conflicts may arise when the costs and benefits of choices are evaluated as a function
3 of outcomes predicted along a temporal dimension. When economic binary alternatives are offered
4 in the present or in the future (e.g. Do you prefer 5€ now or 15€ in 120 days) people may show
5 different decision strategies depending on how sensitive they are to the discounting effect of time.
6 Electrophysiology studies suggest that during decision conflicts it is possible to record over the
7 medial frontal cortex (MFC) a typical oscillatory activity in theta rhythm named midfrontal theta
8 (MF θ). Such activity may be an index of the processes underpinning top-down cognitive control.
9 Tellingly, MF θ appears associated with the temporal dynamics of different brain areas, thus operating
10 as a synchronizer during the request of control. Although the correlational link between activity in
11 MFC and MF θ has been demonstrated, their causal relation with conflict processing has yet to be
12 deeply explored. A methodological approach that may fill this lack of knowledge is represented by
13 the application of alternating current over the brain areas under investigation. The transcranial
14 Alternating Current Stimulation (tACS) is an emerging, innovative technique that changes
15 endogenous patterns of oscillatory activity by entraining neural networks acting on the behavioural
16 performance in a frequency-dependent manner. In accordance with the Registered Report format, we
17 propose a within-subject, sham controlled, cross-over study, in which we will explore the tendency
18 to choose between economic offers during theta, gamma, and sham tACS, with the goal of modulating
19 reaction times (RTs) and choice preferences when different levels of conflict, induced by combining
20 specific delays and payoffs, occur. Hypothesis testing, sample size estimate and analysis of pilot
21 results have been conducted using Bayesian statistics. We expect that our approach will advance the
22 study of cognitive control and conflict processing during decision making.

1 **Introduction**

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

11 Theoretical and computational models partly developed from neuroimaging studies identify
12 the anterior cingulate cortex (ACC) and the medial frontal cortex (MFC) as two hub-like, neural
13 regions that detect the occurrence of conflicts and errors, trigger the recruitment of top-down control,
14 and thus optimize ongoing behavioural adjustments during challenging circumstances (Carter et al.,
15 1998; MacDonald et al., 2000; Botvinick et al., 2001). Electrophysiological investigations indicate
16 that conflict and error processing are associated with the presence of enhanced midfrontal theta
17 oscillations (MF θ) that may act as a communication signal underlying the need for control and
18 synchronize the activity of frontal structures (Luu et al., 2004; Cavanagh et al., 2014). Critically,
19 mounting evidence suggests that MF θ is a plausible electrocortical biomarker of response conflict
20 (Cavanagh et al., 2012; Cohen et al., 2008; Cohen, 2014), which is elicited by cognitive control tasks
21 such as the Stroop (Hanslmayr et al., 2008), the Flanker (Nigbur et al., 2011) and the Simon (Töllner
22 et al., 2017).

23 In the last two decades, non-invasive transcranial electric stimulation (tES) techniques have
24 been applied to investigate the causal relationship between neurophysiological, cognitive, and
25 behavioural processes (Paulus, 2011). Neuroscience and clinical neurophysiology studies indicate
26 that the application of weak electric fields over the scalp may produce a polarization of the neuronal
27 membrane that modifies cortical excitability and thus induce behavioural changes (Fertonani et al.,
28 2015). One type of electric stimulation technique that has become increasingly popular is transcranial
29 Alternating Current Stimulation (tACS), which has the property of entraining endogenous oscillatory
30 activity affecting neuronal membrane potentials at determined frequencies (Antal et al., 2013).
31 Notably, tACS has been used to investigate the causal link between frontal theta activity and top-
32 down processing (Wischniewski et al., 2016; Fusco et al., 2018; Lehr et al., 2019), corroborating the

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

12 ***Decision conflicts in temporal discounting***

13 When monetary rewards are offered at different delays, people may have the tendency to
14 discount the value of the delayed proposal with a large payoff and instead prefer a smaller payoff
15 offered in the immediate present (Ainslie, 1975; Critchfield, 2001). This discounting effect occurs
16 because the temporal delay until receipt of the larger payoff reduces the perceived subjective value
17 assigned to the larger but delayed offer (Peters and Büchel, 2011). Value-based decisions in economic
18 intertemporal paradigms depend on two factors: (i) the magnitude of the offer and the delay interval,
19 and (ii) where an individual lies on the impulsiveness-patience spectrum (Odum et al., 2011). A
20 common way to describe the behavioural preferences of decision makers in temporal discounting
21 relies on the hyperbolic function, which describes how the subjective values of offers decrease
22 hyperbolically as a function of delay (Mazur, 1987; Green & Myerson, 2004). In particular, this model
23 accounts for the effect of different temporal delays on the value of the offers perceived subjectively
24 (Kirby & Marakovic, 1995). Within experimental settings, participants usually express their
25 preferences between binary choices reflecting a little amount of money offered immediately (small
26 sooner reward) or a higher amount available in the future (larger later reward; McClure et al., 2004;
27 Berns et al., 2007). If the delay is far from the present (e.g. Do you prefer 5€ today or 10€ in 180
28 days?), participants may tend to choose more the small sooner rather larger later reward, exhibiting
29 impulsive attitudes in intertemporal decision-making. Such a behavioural strategy is exacerbated in
30 clinical populations affected by pathological impulsiveness like gamblers (Dixon et al., 2008;
31 Madden et al., 2011) and substance abusers (Kirby et al., 1999; Bickel et al., 2007) who typically
32 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 (Shen et al., 2016; Manuel et al., 2019; Nejati et al, 2020). What remains unclear is how MFO 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., 2018), 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.

We propose that by parametrically varying the amount of conflict inherent to a given decision, we can 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 (Polania et al., 2015). In view of this, we expect to entrain theta task-related oscillations (i.e. MFO) and modulate the communication between frontal structures during information processing. The present study aims to explore how individual choices between economic offers might change during band-specific tACS. In particular, we expect that tACS modulates reaction times (RTs) at indifference points (high conflict trials) and that such modulations

1 are different for theta and sham stimulation (see the Hypotheses and Proposed Analyses section for
2 more details).

3 Our results may inform theories of how neural oscillations causally influence impulsive and
4 controlled behavior and decision processes in everyday life.

5 ***Purposes of the study***

6 In accordance with the ‘manifesto’ promoted by Munafò and colleagues (2017), we propose
7 a Registered Report format that is ideal for obtaining robust data and results in social and cognitive
8 neuroscience. The present single-blind, within-subject and controlled cross-over study aims at
9 investigating the effects of midfrontal theta-tACS on cognitive control, conflict processing, and
10 behavioural preferences during a Temporal Discounting task. Further, to explore behavioural carry-
11 over effects induced by frequency-specific tACS, we will administer the Flanker task to study motor-
12 perceptual conflicts after electrical modulation offset. Sample-size analysis, Methodology, Bayesian
13 statistics, Hypotheses and Pilot Data are presented in the following sections.

14

15 **Material and Methods**

16 ***Participants***

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

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

28 The sample size for the Temporal Discounting task was estimated in 40 participants. However, given
29 possible drop-outs and technical failures, we will keep recruiting until 40 usable subjects will be

1 obtained (age: 20-35). Participants must not be taking chronic medications or have any neurological
 2 or psychiatric conditions, history of epilepsy, implanted metal devices. Exclusion criteria will be
 3 evaluated through the Screening Questionnaire for Transcranial Electrical Stimulation (TES; Antal
 4 et al., 2017). All experimental protocols have been approved by the ethics committee of the
 5 Fondazione Santa Lucia in accordance with the standards of the 2013 Declaration of Helsinki.
 6 Volunteers will receive a total compensation of 30€ for their participation.

Figure 1: Sample Size estimation.

10 The homemade functions for the sample size computation are showed in the Appendix section.

11

12 *Experimental design and tasks*

The study will be divided in two phases: preliminary and experimental. For the preliminary phase, we will contact 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.

Preliminary phase

Participants will be asked to complete an online reduced version of the Temporal Discounting task in which they will have 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 will be 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 will change trial by trial according to a staircase procedure. Specifically, the immediate offer value will be 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 will then fit 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 (Mazur, 1987, Green and Myerson, 2004). The two models will be 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; $k > 0.0033$), and whose goodness-of-fit is adequate (checked by means of a Kolmogorov-Smirnoff test, accepted p-values > 0.1), will be 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 0.0033 was arbitrarily defined on the basis of the customized trials computation that is sensitive to the k value and takes into account the value difference between the immediate and delayed rewards. In particular, k values lesser than 0.0033 may generate (especially in the low conflict trials), delayed objective amounts that result lower in nominal value than the immediate offers.

Experimental phase

Following Lin et al., (2018), for each suitable participant, we will use the individual's hyperbolic function to create participant-specific delayed rewards with the goal of parametrically manipulating decision conflict in each choice pair that will be presented during the experimental task. The effects of tACS on conflict processing will be 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 one (Eriksen and Eriksen, 1974), will be administered in three consecutive blocks.

Temporal Discounting Task

In the Temporal Discounting task, 180 stimuli with different combinations of delays and reward amounts will be randomly shown on the left (option 1) or right side (option 2) of a PC monitor (51 cm x 40 cm), after the presentation of a 500-ms central fixation cross (Fig. 2). The participant-specific choice pairs will have 5 pre-determined levels of decision conflict, which we will vary parametrically by manipulating how similar in subjective values the immediate and delayed rewards are (value differences: 0 [high conflict], ± 3 [medium conflict], ± 6 [low conflict]). That is, the high conflict trials (value difference = 0) refer to those combinations in which the immediate and delayed rewards will be perceived subjectively as more similar in value as compared to the low conflict trials (± 6). The immediate offer will be fixed at 80€ and will be maintained constant for all the blocks whereas the future rewards will change 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) will be repeated 9 times in each block. Moreover, a random jitter of some value between -0.30€ to +0.30€ will be added to the model-derived delayed reward, so that the participants, will never see the same objective amount twice. Participants will respond by pressing one of two keys of a keyboard corresponding on immediate and delayed choices that will be counterbalanced across the subjects. Participants will have to respond as quickly as they can in a temporal window of maximum 2.5 seconds in which each choice pair (e.g. "Do you prefer 80€ today or 93€ in 40 days?") will remain visible until a response is made. If no response is given, a visual feedback (i.e. "No response") will be presented at the centre of the screen. The task will be administered using PsychoPy (Peirce, 2007). Following each block of the intertemporal choice task, participants will perform a block of the Flanker task.

Flanker Task

The task will require 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.

1 The order of keys will be counterbalanced across participants. Targets will be flanked by distractors,
2 two on each side, which could be same (congruent condition) or different (incongruent condition)
3 with respect to the target. Each stimulus will appear at the centre of the screen (visual angle of 7.15°
4 horizontally and 1.42° vertically) for 80 ms followed by a temporal window of 920 ms in which the
5 response will have to be given. In the case of responses provided after 500 msec, a beeping sound
6 (1000Hz) will be delivered through a pair of headphones with the purpose to remind the participants
7 to answer more quickly in the subsequent trials. If no response was made, the visual feedback “Non
8 hai risposto” (“You did not answer”) will be screened. A total of 108 trials (54 congruent and 54
9 incongruent) will be randomly presented in each Flanker block. The task will be presented using E-
10 prime 2.0 Professional software (Psychology Software Tools Inc., Sharpsburg, PA, USA).

11 ***Procedure***

12 Participants will be invited to come to our laboratory in two different sessions, separated by
13 at least 5 days. They will sit about 80 cm from the PC monitor in a dimly lit room. Following a
14 familiarization procedure with the device in which participants receive a brief stimulation (i.e. 5s of
15 ramp-up, 5s of alternating current at 750uA intensity and 13Hz frequency, 5s of ramp-down), the
16 experimenter will introduce the behavioural tasks and explain how to complete two practice blocks.
17 If at this stage participants show any discomfort associated with the neuromodulation, they will not
18 be asked to complete the actual tasks in the experimental phase. During the temporal discounting
19 practice block, participants will be asked to choose between 20 pairs of immediate (i.e. 80€ today)
20 and delayed rewards (i.e. the delayed model-derived offers). Thus, for each response, a visual
21 feedback of the selected preference will be shown (e.g. “You chose 80€ today”) at the centre of the
22 monitor. Importantly, such a feedback will not be presented during the experimental task. For the
23 practice block of the Flanker task, participants will have to respond to 32 randomized stimuli (16
24 congruent and 16 incongruent) with the possibility of repeating the block once in the case the task
25 demands were not properly understood. Following the familiarization, the experimental session will
26 begin. To avoid carry-over effects, theta-tACS and gamma-tACS will be administered during the
27 temporal discounting task in two separate sessions/days. Therefore, the two sessions will be structured
28 in three experimental blocks, one block for the sham-tACS, one for the frequency1-tACS and one for
29 the frequency2-tACS of the same oscillatory band (see Electrical modulation section for more
30 details). Each block consists of the temporal discounting task followed 30s later by the Flanker with
31 an inter-block interval of 10 minutes (Fig.3). Throughout the IBI, participants will be required to
32 verbally report the sensorial and physical perceptions of the tACS-induced effects using a 0-100 scale
33 (0 = no sensation at all – 100 = max sensation perceived). Since electrical current may affect skin and

1 peripheral nervous structures (e.g. nerves or retina) that in turn may generate secondary effects such
 2 as skin discomfort or visual phosphenes (Fertonani et al., 2015; Fusco et al., 2018), participants will
 3 be asked to evaluate the following perceptive categories: *Somatosensory* (i.e. itching, heating,
 4 tingling, burning, and prickling felt in the skin under the electrode areas); *Visual* (i.e. flickering,
 5 flashes and bright dots observed in the central or peripheral visual field); *Taste* (i.e. iron) and *Other*
 6 *sensations* (i.e. fatigue, dizziness, head heaviness, nausea, headache, and sleepiness). Finally, at the
 7 end of the second session, individual variability in impulsiveness, trait-anxiety and negative emotions,
 8 will be measured asking participants to complete the following scales: the *Barratt Impulsivity Scale*
 9 (BIS, Patton et al., 1995), the *State- Trait Anxiety Inventory Form Y* (STAI-Y1 and STAI-Y2,
 10 respectively for the State and Trait scale, Spielberger, 2010), the *Behavioural Inhibition and*
 11 *Activation Scales* (BIS/BAS, Carver & White, 1994), and the 16-item reduced form of the *Need for*
 12 *Closure Scale* (NCC, Roets & Van Hiel, 2011).

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17 **Fig.2** Event timeline in the experimental tasks. In the first part of the experimental block, participants will
 18 receive tACS during the Temporal Discounting task. Immediately after the first task ends (break of 30s),
 19 participants will perform the Flanker without neurostimulation. Finally, the questionnaire on the physical
 20 sensations will be administered during an interval break lasting 10 minutes. For each session/day, three

consecutive experimental blocks will be presented. Each block will consist of temporal discounting and Flanker tasks.

Electrical modulation

tACS will be delivered through a rechargeable battery- operated stimulator system (Starstim/Enobio, Neuroelectronics, Barcelona, Spain) controlled by Bluetooth connection and via two circular sponge-conductive- electrodes (Sponstim, 25 cm², Neuroelectronics, Barcelona, Spain) attached to a stimulator that will be soaked in physiologic solution (NaCl) and coated with electroconductive gel (only the side facing the scalp). At the beginning of each session, we will identify 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 will be cleaned with a cotton swab soaked in ethyl alcohol and then marked with a hypoallergenic broad tip pen. Afterwards, the electrodes will be 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; Fig.3A). This electrode configuration has been previously adopted to entrain midfrontal theta during cognitive control (Vosskuhl et al., 2015; Fusco et al., 2018). The sinusoidal current stimulation, with no DC offset and 0° relative phase, will be set at 1500uA (peak-to-peak) intensity and administered during the Temporal Discounting task following 30s of ramp-up. Impedance will be kept below 5 kΩ. At the end of the Temporal Discounting task, the experimenter will manually interrupt the device thus triggering 30s of current ramp-down. Two frequencies-tACS for theta (Θ1: 5Hz; Θ2: 7Hz;) and gamma (γ1: 30Hz; γ2: 70Hz) bands will be administered separately during the two sessions (Fig.3B). Thus, for each block and for the total duration of the intertemporal choice task, tACS will be applied at one frequency of the specific band. Importantly, no modulation will be applied during the Flanker task. As a baseline measure, a sham controlled condition (one block for each session) will be arranged always before or after the two tACS blocks (balanced across the participants). Sham-tACS (<>) will be characterized by the administration of 30s of ramp-up, alternating current for 30 seconds of the block at the theta or gamma frequency (depending on the session balancing) and then it will be interrupted leading to 30s of ramp-down (Palm et al., 2013).

Fig.3 A. Electrode configuration and parameters adopted for tACS. Electrode 1 will be placed over the FCz channel (10-20 International System) corresponding to the medial frontal cortex, electrode 2 over the Pz channel corresponding to the medial parietal cortex. **B.** Structural design of the proposed study.

Bayesian Analyses

All statistical analyses will be conducted using a Bayesian approach (Kruschke, 2014), 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 will fit Bayesian multilevel models using the *brms* R package (Bürkner, 2017). Bayesian multilevel models offer greater flexibility for researchers across sciences (Gelman and 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 will allow us to use the whole data set, and not only the averaged dependent variables. Furthermore, it will be 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 will be 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). In particular, we will use 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

1 suggestions stated in Zoltan (2019). For each model, we will run 4 Markov chains, with 2500 burn-
 2 in and 2500 sampling iterations, resulting in a total of 10000 iterations for each model. The resulting
 3 Bayesian multilevel models will be checked using diagnostic indexes. In particular, we will use the
 4 Gelman & Rubin's diagnostic index $\hat{R}$ (Gelman & Rubin, 1992; Brooks & Gelman, 1998) to test the
 5 convergence among the four Markov chains ($\hat{R} \leq 1.1$), the Posterior Predictive p-value (Gelman,
 6 2013) to test whether the Bayesian model actually represents the data ($p \approx 0.5$), by using the mode
 7 statistics (see Code snippet 1, Appendix), and the Effective Sample Size (ESS, Kass et al., 1998), a
 8 measure of the number of independent iterations in the Markov chains, excluding the autocorrelation
 9 effects. If the models pass all diagnostics, we will compare their BF_{10} values.

10 Otherwise, multiple specific strategies will be applied to improve diagnostic indexes:

11 We will fit the model with a larger number of iterations, doubling the number of warm-up and
 12 sampling iterations. If the diagnostic indexes are still not satisfactory, we will increase the number of
 13 warm-up and sampling iterations by step of 2500, with a maximum of 25000 warm-up and sampling
 14 iterations each chain (for a total of 100,000 warm-up and 100,000 sampling iterations).

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

18 If some diagnostic indexes are still denoting problems, we will fit a series of models characterized by
 19 the complete fixed-effects part (all fixed-effects and their interactions), and all the possible
 20 simplifications of the random-effects part. All the models that converge will be compared among
 21 them by means of the Widely Applicable Information Criteria (WAIC, Vehtari et al., 2017; 2019),
 22 and the random-effects part of the model with the lowest WAIC will be used.

23 If all the random effects have satisfactory diagnostic indexes, but some diagnostic indexes are still
 24 denoting problems, we will modify the prior distributions of regressor coefficients. We will change
 25 them into more liberal distributions, multiplying the scale parameter of the Cauchy distributions, by
 26 2, by 3, 4 and 5, and if good diagnostic indexes are not reached, we will use stricter prior distributions,
 27 dividing the scale parameter of the Cauchy distributions, by 2, by 3, 4 and 5. Random effects or prior
 28 modifications will be applied to all the Bayesian models concerning that specific dependent variable.
 29 Model comparisons will be computed by using the bridge sampling algorithm (the `bayes_factor` and
 30 `post_prob` functions, Gronau et al., 2020). If the use of bridge sampling will not be possible, caused

1 by memory limits or other aspects not related to model convergence, statistical inference will be
2 executed by means of Savage-Dickey Bayes Factors.

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

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

15 **Hypotheses and Proposed Analyses**

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

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

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

1 It is noteworthy that, our a-priori hypothesis predicts that Θ -tACS compared to sham and γ -tACS,
2 modulates the exchange of neuronal signals during high conflict trials and speeds-up intertemporal
3 decisions. The direction of the preference toward immediate rewards is inferred as the more likely
4 scenario (suggested also from our pilot data) that may occur under time pressure where cognitive
5 control has not much time to exert top-down effects (e.g. the choice of future rewards).

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

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

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

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

10 In order to test our hypothesis, the contrast matrices of the Band factor and the Conflict factor will
11 have a treatment contrast design, with Θ band as the baseline level for the former, and high conflict
12 for the latter. This way, we will have the possibility to directly observe the BF10 concerning the
13 difference between Θ -tACS and sham-tACS in high versus low conflict trials.

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

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

25 H0_PES for congruent trials: Θ -tACS = sham-tACS

26 H1_PES for congruent trials: Θ -tACS < sham-tACS

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

1 H0_Θ-tACS = sham-tACS, y-tACS

2 However, since the tACS protocol that we intend to adopt here is different from our previous study,
3 we cannot exclude that offline effects of theta-tACS might led to a change in the behavioural
4 performance. Although we predict the occurrence of H0 (null model) we may expect alternatively as
5 H1 model:

6 RTs: Θ-tACS < sham-tACS, y-tACS

7 Acc: Θ-tACS < sham-tACS, y-tACS.

8 In order to test the hypothesis, the contrast matrices of the Band factor and the Congruency factor
9 will have a treatment contrast design, with Θ band as the baseline level for the former, and congruent
10 for the latter. This way, we will have the possibility to directly observe the BF10 concerning to the
11 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 y-tACS in high conflict trials. H0_RT: Θ-tACS = sham-tACS in high	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	In order to test our hypothesis, the contrast matrices of the Band factor and the Conflict factor will have a treatment contrast design, with Θ band as the baseline level for the former, and high conflict for the latter. This way, we will have the possibility to directly observe the BF10 concerning the difference between Θ-tACS and sham-tACS in high versus low conflict trials. The analyses will consider as Fixed Effects Conflict (high, medium, low, with a treatment contrast	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)

	<p>conflict trials, y-tACS in high conflict trials</p> <p>H1_RTs: Θ-tACS < sham-tACS in high conflict trials, y-tACS in high conflict trials</p> <p>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.</p> <p>H0_immediate choices: Θ-tACS = sham-tACS in high conflict trials, y-tACS in high conflict trials</p> <p>H1_immediate choices: Θ-tACS > sham-tACS in high conflict trials, y-tACS in high conflict trials</p>	<p>section Hypotheses and proposed analyses).</p> <p>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.</p> <p>The sample size for the Temporal Discounting task was estimated in 40 participants. However, given possible drop-outs and technical failures, we will keep recruiting until 40 usable subjects will be obtained (age: 20-35). Participants must not be taking chronic medications or have any neurological or psychiatric conditions, history of epilepsy, implanted metal devices.</p> <p>For each participant, we will fit the hyperbolic discounting model and a simple reciprocal model to the six indifference values (one at each delay):</p> <p>Simple reciprocal: $V = A / kD$</p> <p>Hyperbolic model: $V = A / (1 + kD)$</p> <p>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 (Mazur, 1987, Green and Myerson, 2004). The two models will be compared by means of the</p>	<p>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, will be 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: $y \sim \text{Conflict} * \text{Band} + (\text{Block} + \text{Conflict} * \text{Band} \text{participant})$)).</p> <p>Log RTs and choices will be analysed by fitting Bayesian multilevel models using Gaussian distributions or binomial distributions with logit link function</p> <p>For the dependent variables, the model with the interaction with Conflict and Band should be the best fitting model.</p> <p>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</p>	<p>Second scenario: null results. There is evidence of no difference between conditions</p>
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		<p>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; $k > 0.0033$), and whose goodness-of-fit is adequate (checked by means of a Kolmogorov-Smirnoff test, accepted p-values > 0.1), will be enrolled in the brain stimulation sessions.</p>	<p>between γ-tACS vs. Θ-tACS in high conflict vs. low conflict trials is not planned by design, but will be computed as secondary analyses, by setting the baseline level of the Band factor to γ-tACS. We will expect a $BF_{10} < 1/6$ in this case. No other effects should be noticeable.</p> <p>Furthermore, alongside the main analyses, we will compute 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.</p>	
Does Θ -tACS generate offline carry-over effects during the resolution of conflicting representations in a Flanker task?	<p>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:</p> <p>H_0 Θ-tACS = sham-tACS, γ-tACS</p> <p>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.</p>	Because our main hypotheses are on the Temporal Discount task, our sample size is based on that task.	<p>The fixed effects will be 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 will also be used as random effects, altogether with the block sequence, grouped by participant (in</p>	<p>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.</p> <p>Such a temporal slowing may induce trade-off speed-accuracy leading to a more accurate performance (e.g. less errors</p> <p>Second scenario: null results. There is</p>

	<p>Although we predict the occurrence of H0 (null model) we may expect alternatively as H1 model a fastening of response times that reduce the likelihood to reach correct performance (e.g. more errors)</p> <p>RTs: Θ-tACS < sham-tACS, y-tACS</p> <p>Acc: Θ-tACS < sham-tACS, y-tACS</p>		<p>brms syntax: $y \sim \text{Congruency} * \text{Band} + (\text{Block} + \text{Congruency} * \text{Band} \text{participant})$.</p> <p>Reaction Times after logarithmic transformation (correct trials) and Post-Error Slowing (PES) will be modelled as Gaussian-distributed data and Accuracy (ACC) as binomial-distributed data (with logit link function).</p> <p>Alongside the main analyses, we will compute BF10 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.</p>	evidence of no difference between conditions and carry-over effects

1

2 Temporal Discounting Task

3 For this task, the analyses will consider as Fixed Effects Conflict (high, medium, low, with a
4 treatment contrast design with high as baseline), Band (theta, gamma, sham, with a treatment contrast
5 design with theta as baseline) and their interaction. The Random Effects, grouped by participant, will
6 be Conflict, Band and their interaction (within-subjects effects), and as Random Covariate the block

1 sequence of the experiment to account for learning effects (in brms syntax: $y \sim \text{Conflict} * \text{Band} +$
2 $(\text{Block} + \text{Conflict} * \text{Band} \mid \text{participant})$)).

3 Log RTs and choices will be analysed by fitting Bayesian multilevel models using Gaussian
4 distributions or binomial distributions with logit link function, respectively. Trials with RTs less than
5 200 ms will be excluded from the analysis because considered as automatic responses. If choices will
6 be biased toward immediate or delayed preferences ($> 90\%$), the participant will be excluded from
7 the analysis. The scale parameter for the Cauchy prior for the RTs is 0.147, for choices is 1.062 for
8 the beta and intercept parameters, while for the standard deviations a Half Normal distribution with
9 mean 0 and sigma 1 will be used. We took these scale factors by dividing the individual means of
10 RTs collected in the pilot study between theta stimulation and sham in high conflict trials (i.e. mean
11 RTs theta / means RTs sham in high conflict trials = 1.03 seconds). For choices we subtracted the
12 percentage of immediate choices selected by the participants during theta-tACS from the percentage
13 of immediate choices collected in the sham (i.e. % immediate choices theta - % immediate choices
14 sham = 7.44). To obtain the scale factors for Cauchy priors, both the values of RTs and percentage of
15 immediate choices were divided by 7 as suggested in Dienes (2019).

16 The candidate models are:

17 $y \sim \text{Conflict} * \text{Band} + (\text{Block} + \text{Conflict} * \text{Band} \mid \text{participant})$

18 $y \sim \text{Conflict} + \text{Band} + (\text{Block} + \text{Conflict} * \text{Band} \mid \text{participant})$

19 $y \sim \text{Conflict} + (\text{Block} + \text{Conflict} * \text{Band} \mid \text{participant})$

20 $y \sim \text{Band} + (\text{Block} + \text{Conflict} * \text{Band} \mid \text{participant})$

21 $y \sim 1 + (\text{Block} + \text{Conflict} * \text{Band} \mid \text{participant})$

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

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

26 Then, we expect a $\text{BF}_{10} > 6$ in the coefficient representing the interaction between the Θ -tACS vs.
27 sham-tACS coefficient, and the high conflict vs. low conflict coefficient. The comparison between γ -
28 -tACS vs. Θ -tACS in high conflict vs. low conflict trials is not planned by design, but will be

1 computed as secondary analyses, by setting the baseline level of the Band factor to γ -tACS. We will
2 expect a $BF_{10} < 1/6$ in this case. No other effects should be noticeable.

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

6 **Flanker Task**

7 The fixed effects will be the Congruency (congruent, incongruent, with a treatment contrast
8 design with congruent as baseline), Band (theta, gamma, sham, with a treatment contrast design with
9 theta as baseline) and their interaction. Since this is a repeated-measure design, the fixed effects will
10 also be used as random effects, altogether with the block sequence, grouped by participant (in brms
11 syntax: $y \sim \text{Congruency} * \text{Band} + (\text{Block} + \text{Congruency} * \text{Band} \mid \text{participant})$)).

12 Reaction Times after logarithmic transformation (correct trials) and Post-Error Slowing (PES) will
13 be modelled as Gaussian-distributed data and Accuracy (ACC) as binomial-distributed data (with
14 logit link function). Trials with RTs less than 200 ms will be excluded from the analysis. The scale
15 parameter for the Cauchy priors for the beta and intercept parameters, for the RTs is 0.144 (i.e. mean
16 RTs correct in theta-tACS condition / mean RTs correct in sham = 1.01), for the ACC is 0.146 (i.e.
17 % correct in theta-tACS condition - % correct in sham = 1.02), and for the PES is 0.16 (i.e. mean PES
18 in theta-tACS condition / mean PES in sham = 0.97). The priors for the standard deviations are a Half
19 Normal distribution with mean 0 and sigma 1 will be used. To obtain the scale factors for Cauchy
20 priors, the obtained values for RTs, ACC and PES were divided by 7 as suggested in Dienes (2019).

21 PES will be computed with the robust method that is able to take into account motivational and
22 attentional fluctuations during the performance compared to the traditional method (Dutilh et al.,
23 2012; Williams et al., 2016; Damaso et al., 2020). In turn the index will be calculated as the average
24 of:

$$25 \quad \text{RTs (E + 1)} - \text{RTs (E-1)} \text{ for all errors E}$$

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

28 The candidate models are:

$$29 \quad y \sim \text{Congruency} * \text{Band} + (\text{Block} + \text{Congruency} * \text{Band} \mid \text{participant})$$

1 $y \sim \text{Congruency} + \text{Band} + (\text{Block} + \text{Congruency} * \text{Band} \mid \text{participant})$

2 $y \sim \text{Congruency} + (\text{Block} + \text{Congruency} * \text{Band} \mid \text{participant})$

3 $y \sim \text{Band} + (\text{Block} + \text{Congruency} * \text{Band} \mid \text{participant})$

4 $y \sim 1 + (\text{Block} + \text{Congruency} * \text{Band} \mid \text{participant})$

5 The random-effects part can be different from the one here reported, in order to have a model that

6 correctly converges, as reported in the “Bayesian Analyses” section.

7 We expect $\text{BF}_{10} > 6$ for the Band effect and in particular PES should be greater after sham than theta-

8 tACS.

9 In particular, our two analyses will focus on the coefficients concerning the Θ -tACS v. sham

10 contrasts, expecting a $\text{BF}_{10} > 6$.

11 Alongside the main analyses, we will compute BF_{10} with a zero-centred half-cauchy prior, with the

12 scale parameters derived from the pilot study (and reported above), to test the hypothesis Θ -tACS <

13 sham-tACS during the flanker task for each dependent variable.

14

15 *Pilot Data*

16 We analyzed pilot data from 17 participants (male= 9; LH=2; age = 25.05 ± 2.07 ; $k = 0.0233$

17 ± 0.0377). Two participants were excluded (drop-out between the two sessions).

18 Subject 13 was excluded because she showed a strong bias toward the future choices (i.e. the

19 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	0.1516	0.0149	0.0066	0.0128	0.0032	0.0084	0.0033	0.0211	0.0327	0.0055	0.0033	0.0454	0.0316	0.0038	0.0063

20

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

22
$$\beta \sim \text{Normal}(0, 5); \sigma^2 \sim \text{HalfNormal}(0, 1)$$

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

24 We modelled RTs as a function of Band (theta, gamma or sham) and Conflict (High, Medium or

25 Low). Random effects were grouped by participant, and were the intercept, the slopes of Band, Level

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

3 **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
```

4

5 Model 3 (mdl3), characterized by only the independent variable of Level of Conflict, is the best model
6 (posterior probability > 0.99). This is explained by the fact that high levels of conflict cause larger
7 RTs (see Fig.4).

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.

We modelled choices using hierarchical Bayesian multilevel 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.

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

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

Model 2 (mdl2), compared to all the other models, showed a posterior model probability > 0.99. Therefore, both the Level of Conflict and the Band affected the performance of the pilot sample, but not their interaction (see Fig.5).

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.

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

1 as random effects the intercept and the slopes of Band, Congruency and their interaction grouped by
2 participant.

3 The analyses were computed with the following code:

4 **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
```

5
6 Bayesian analysis clearly shows that there is no best fitting model.

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1 Appendix

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

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

```
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)
```

```
}
```

1

2

3 Below the iterative code for the Temporal Discounting Task:

4 **Code Snippet 5:** Simulation of data and iterative code for sample size estimation

```
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)

```

1

2

3

4 Below the R code for the graphs:

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

```

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")

```

1

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

```

3 ## mode function
4 my_mode <- function(x, na.rm = FALSE) {
5   if(na.rm) x <- x[!is.na(x)]
6   if(length(x)>1) {
7     return(density(x)$x[which.max(density(x)$y)])
8   } else return(x)
9 }
10
11 ## y_rep extraction
12 ppp <- posterior_predict(mdl1 , nsamples = 1000)
13
14 ## posterior predictive p-value computation
15 mean( apply(ppp, 2, my_mode) > my_mode(datum$value) )
16
17 ## graphical representation
18 bayesplot::ppc_stat(y = datum$value,
19                    yrep = ppp,
20                    stat = "my_mode")

```

21