

1    **Title:**

2    Preparation for mental effort recruits Dorsolateral Prefrontal Cortex: an fNIRS  
3    investigation

4    **Abbreviated title:** DLPFC activity during preparation for mental effort

5

6    **Authors:** Eliana Vassena<sub>1,2</sub>, Robin Gerrits<sub>2</sub>, Jelle Demanet, Tom Verguts<sub>2</sub>, Roma

7                    Siugzdaite<sub>2</sub>

8                    1. Donders Institute for Brain, Cognition and Behavior, Radboud University

9                    2. Department of experimental psychology, Ghent University

10

11    **Corresponding author:** Eliana Vassena, Donders Institute for Brain, Cognition and

12    Behavior, Radboud University Nijmegen, Kapittelweg 29, 6525 EN, Nijmegen, The

13    Netherlands, +31 (0)24 3610618

14    Email: e.vassena@donders.ru.nl

15

16    **Keywords:** Mental effort, task-preparation, DLPFC, fNIRS, difficulty, mental

17    arithmetic

18

19    **Acknowledgements:** EV was supported by the Marie Skłodowska-Curie action with a

20    standard IF-EF fellowship, within the H2020 framework (H2020-MSCA-IF2015,

21    Grant number 705630).

22

23

24

25

26

27

## 28     **Abstract**

29             Preparing for a mentally demanding task calls upon cognitive and motivational  
30     resources. The underlying neural implementation of these mechanisms is receiving  
31     growing attention, given the implications for professional, social, and medical  
32     contexts. While several fMRI studies converge in assigning a crucial role to a cortico-  
33     subcortical network including Anterior Cingulate Cortex (ACC) and striatum, the  
34     involvement of Dorsolateral Prefrontal Cortex (DLPFC) during mental effort  
35     anticipation has yet to be replicated. This study was designed to target DLPFC  
36     contribution using functional Near Infrared Spectroscopy (fNIRS), as a more cost-  
37     effective tool measuring cortical hemodynamics. We adapted a validated mental effort  
38     task, where participants performed easy and difficult mental calculation, while  
39     measuring DLPFC activity during the anticipation phase. As hypothesized, DLPFC  
40     activity increased during preparation for a hard task as compared to an easy task.  
41     Besides replicating a previous fMRI study, these results establish fNIRS as an  
42     effective tool to investigate cortical contributions to preparation for effortful behavior.  
43     This is especially useful if one requires testing large samples (e.g., to target individual  
44     differences), populations with contraindication for functional MRI (e.g., infants or  
45     patients with metal implants), or subjects in more naturalistic environments (e.g.,  
46     work or sport).

47

48

49

50

51

52

## 53 **Introduction**

54       Humans face cognitively challenging situations on a daily basis.

55       Accomplishing such tasks requires a great deal of cognitive resources, and typically

56       successful completion is facilitated by the possibility of gaining a reward. Preparing

57       for demanding tasks and anticipating possible rewards are core components of

58       motivation. Several studies investigating cost-benefit trade-offs in decision-making

59       showed that these motivational processes rely on a cortical-subcortical brain network,

60       involving the medial Prefrontal Cortex (MPFC, including dorsal Anterior Cingulate

61       Cortex, dACC) and striatum (Chong et al., 2017; Prévost, Pessiglione, Météreau,

62       Cléry-Melin, & Dreher, 2010; Westbrook & Braver, 2013, 2015). Interestingly, some

63       studies demonstrated that these regions are also implicated in preparing for effortful

64       performance (unconfounded by motor or decision-making factors), showing increased

65       neural activity when preparing for a harder task. For example, this is the case when

66       participants prepare for upcoming mentally demanding arithmetic problems (Vassena

67       et al., 2014) or perceptual discrimination (Krebs, Boehler, Roberts, Song, & Woldorff,

68       2012). This evidence is often interpreted as indexing proactive control, i.e. top-down

69       deployment of attentional control to ensure successful performance (Braver, 2012).

70       Recently, computational frameworks have been proposed where MPFC activity would

71       reflect the value of engaging in an effortful task to the extent that it can lead to a

72       reward (Holroyd & McClure, 2015; Holroyd & Yeung, 2012; Shenhav, Botvinick, &

73       Cohen, 2013; Verguts, Vassena, & Silvetti, 2015) or the monitoring processes

74       detecting the frequency of occurrence of motivationally relevant variables (Vassena,

75       Deraeve, & Alexander, 2017). Notwithstanding the different computational

76       implementation, all accounts agree in assigning to MPFC a crucial role in mechanisms

77       underlying effortful behavior.

78           The role of the Dorsolateral Prefrontal Cortex (DLPFC) in preparing for  
79   cognitively demanding tasks is however less clear. DLPFC activity is generally  
80   implicated in higher level cognitive processing (Miller & Cohen, 2001), such as  
81   working memory updating, goal maintenance and task set representation. According  
82   to recent theories, DLPFC indeed maintains abstract information about task-related  
83   rules, instructions or context (Alexander & Brown, 2015; Badre, 2008; Koechlin &  
84   Summerfield, 2007; Nee & Brown, 2012). One recent study showed that MPFC  
85   coding of reward expectation seems to drive strategy selection in DLPFC, which in  
86   turn regulates MPFC activity (Domenech, Redouté, Koechlin, & Dreher, 2017). This  
87   dynamic provides theoretical support for DLPFC role in learning how to deploy  
88   control when reward is available. Therefore, as DLPFC and MPFC interact in guiding  
89   strategy-selection according to reward prospect, comparable dynamics may be  
90   hypothesized in the context of preparing for a more effortful task.

91           In an earlier study using functional MRI (fMRI) we provided preliminary  
92   evidence that preparing for an effortful task relies on a network also implicated in  
93   reward expectation (Vassena et al., 2014). In this study we also showed that DLPFC  
94   was more active when expecting to perform a mentally effortful task (as compared to  
95   an easy task). The goal of the current study was to independently replicate  
96   anticipation of effort in DLPFC with a novel and promising measurement technique.  
97   The use of functional Near-Infrared spectroscopy (fNIRS) is rapidly growing in  
98   cognitive and social neuroscience (Balconi & Vanutelli, 2017), as it allows measuring  
99   cortical variations in regional blood oxygenation levels in a comparable way to fMRI,  
100   but without a number of downsides that MRI has. In particular, fNIRS technology  
101   does not involve a strong magnetic field nor gradients. As a consequence,  
102   contraindications for participation due to the magnetic field do not apply.

103 Furthermore, the fNIRS machinery (and its use) has a much lower cost than an MRI  
 104 machine. Because of these two reasons, one can test a larger sample of participants,  
 105 with lower cost, including patients and other subjects with (non MR-compatible)  
 106 metal implants, children, and babies (who normally do not undergo fMRI strictly for  
 107 research purposes), and in more ecological context (as the equipment is portable,  
 108 Ayaz et al., 2013; Balardin et al., 2017). Finally, motion artifacts are less problematic  
 109 with fNIRS, which makes it an interesting tool to test hypotheses in domains where  
 110 movement is required (Metzger et al., 2017; Pinti et al., 2015); a relevant example in  
 111 the current context would be physical effort (where participants are normally required  
 112 to move to exert force). One final noteworthy advantage is that subjects can be tested  
 113 simultaneously and while interacting, making it an ideal tool for social neuroscience  
 114 experiments (Balconi & Vanutelli, 2017).

115 Exploiting these advantages to investigate cortical contributions to preparation  
 116 for mental effort requires establishing fNIRS as a reliable measurement method of  
 117 cortical (prefrontal) activity, by replicating cortical hemodynamic effects observed  
 118 with fMRI. We therefore adopted fNIRS to investigate the contribution of bilateral  
 119 DLPFC in preparation for effortful tasks. We adapted a mental effort task from  
 120 previous studies (Vassena et al., 2014; Vassena, Cobbaert, Andres, Fias, & Verguts,  
 121 2015). Participants were presented with cues indicating if the upcoming task was  
 122 going to be easy or hard. We measured oxygenated hemoglobin dynamics in 26  
 123 measurement channels covering frontal cortex. Moreover, we tested whether DLPFC  
 124 sensitivity to task demand during preparation was bilateral or lateralized to one  
 125 hemisphere. For this purpose, we controlled participants' handedness, as previous  
 126 studies show that left handers are more likely to present opposite or reduced

functional lateralization as compared to right-handers (e.g. in language, Mazoyer et al., 2014; and in face processing, Frässle, Krach, Paulus, & Jansen, 2016).

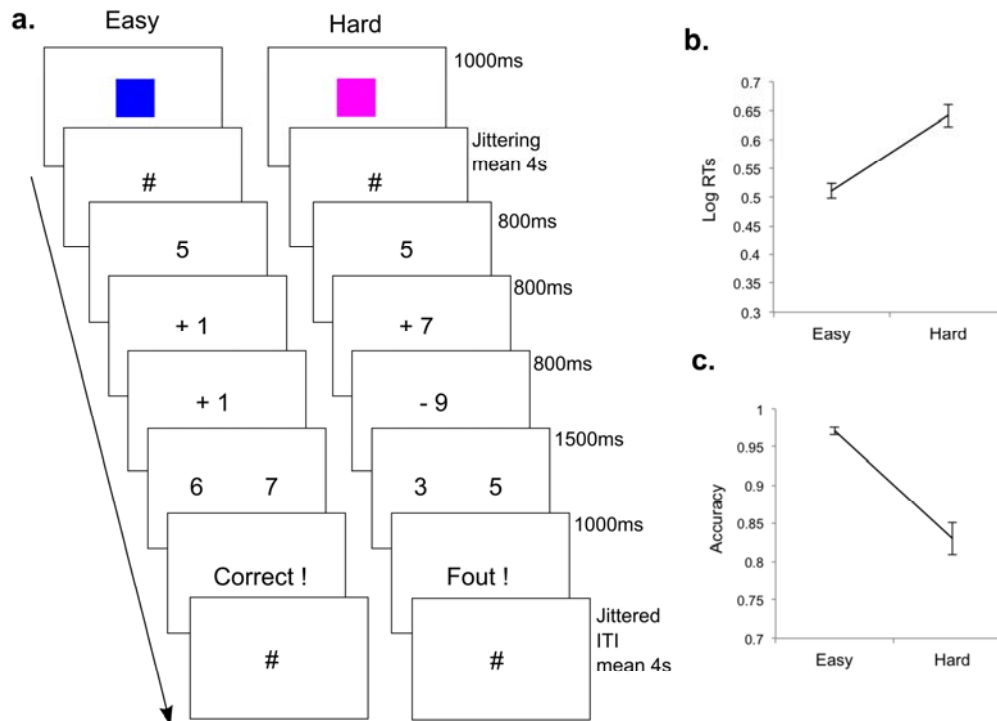
## **Materials and methods**

### *Participants*

Twenty undergraduate students from Ghent University participated in this study (mean age  $20.1 \pm 2.74$  years, 13 females, 9 left handed), receiving one study credit as compensation to participate in the study. Written informed consent was obtained from all participants prior to participation. The study protocol was approved by the Local Ethics Committee of Ghent University. After data collection, one participant was excluded from further analysis due to technical failure. Sample size was determined based on previous studies using fNIRS to investigate cognitive function (Causse, Chua, Peysakhovich, Del Campo, & Matton, 2017; Ferreri et al., 2014; Nakahachi et al., 2008).

### *Experimental procedure*

We examined difficulty-related hemodynamic cortical activation while participants performed a task consisting of easy and difficult arithmetic calculations (Figure 1).



146

147 **Figure 1.** Task and behavioral performance. a.Task structure. Each trial started with a cue  
148 indicating if the upcoming task was going to be easy (blue square) or difficult (magenta  
149 square). After a jittered interval, two subsequent operations (additions or subtractions) were  
150 presented on the screen, followed by two possible results. Participants had to indicate the  
151 response they thought to be correct by pressing right or left response button, and received  
152 performance feedback. Subsequent inter-trial interval was also jittered. b. Log-transformed  
153 reaction times for responses in easy as compared to hard trials. c. Accuracy of the responses  
154 for easy as compared to hard trials. Error bars represent  $\pm$  one standard error of the mean.  
155 Responses to easy trials were significantly more accurate and faster as compared to hard trials.  
156

157 The procedure consisted of one block with 130 trials, of which 65 were easy  
158 trials and 65 were difficult trials. Easy and difficult trials were randomly intermixed.  
159 At the beginning of every trial, a cue was presented for 1000 ms, indicating if the  
160 upcoming trial was going to be easy (a blue square) or difficult (a magenta square),  
161 followed by a screen showing the symbol # at fixation with a pseudo-exponentially  
162 jittered duration (range 2.2 – 8 seconds, mean 4 seconds). Subsequently, the task was  
163 presented. In an easy trial, the task consisted of a sequence of two arithmetic  
164 operations, with three small numbers shown on subsequent screens (e.g., example 3 +  
165 1 + 1). Each number remained on the screen for 800 ms, and first and second number

166 were followed by a blank screen (600 ms). In a difficult trial, the task consisted of a  
167 sequence of more difficult arithmetic operations with three larger numbers shown on  
168 subsequent screens (e.g.  $8 + 15 - 6$ , same timing as easy trials) and requiring carrying  
169 and borrowing at each operation. We adapted this procedure from previous  
170 experiments, as it elicits a reliable difficulty effect (Vassena et al., 2014, 2015). After  
171 the arithmetic problem, two possible results were presented on the screen, and  
172 participants had to select the result they thought to be correct, by pressing either a left  
173 or a right button (F or J on the keyboard, response time limit 1500 ms). The response  
174 was followed by a feedback screen, which could be correct (showing the Dutch word  
175 “correct”), incorrect (showing the Dutch word “fout”) or too late (showing the Dutch  
176 words “te laat”). The feedback was followed by a 500 ms blank screen, and a pseudo-  
177 exponentially jittered inter-trial interval, with a screen showing the # symbol at  
178 fixation (range 2.2 – 8 seconds, mean 4 seconds). Participants were instructed to be as  
179 fast and accurate as possible. Before starting the experimental block, 8 training trials  
180 were administered. During the training only, at the end of every trial participants were  
181 asked to rate the trial on perceived difficulty and pleasantness. The questions were  
182 presented on the screen one by one (randomized across participants) and participants  
183 were asked to respond by pressing the number corresponding to their response on the  
184 keyboard. The difficulty question asked how difficult that trial was for them (on a  
185 visual 7-point scale, with 1 meaning very easy and 7 meaning very difficult). The  
186 pleasantness question asked how much they liked to perform that trial (on a visual 7-  
187 point scale, with 1 meaning not at all and 7 meaning very much). This procedure has  
188 been used in previous studies to confirm subjective perception of difficult trials as  
189 more difficult (Vassena et al., 2014, 2015).

190



# 191    *Questionnaires*

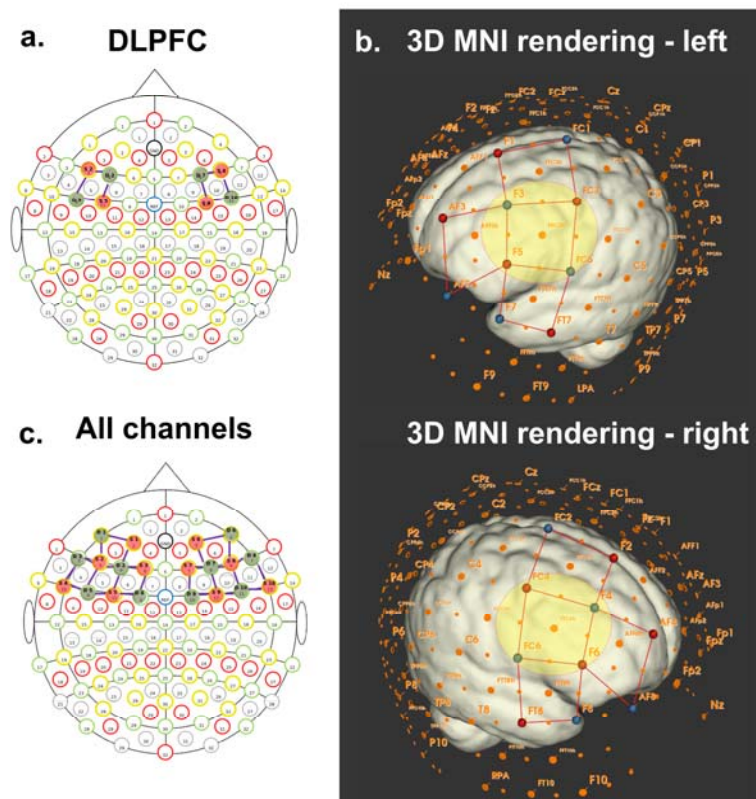
192            Participants filled in the Positive And Negative Affect Scales (PANAS,  
193    (Watson, Clark, & Tellegen, 1988) twice, before and after the experimental session.  
194    The goal of this procedure was to measure changes in affective state, and test whether  
195    such changes may be related to task difficulty (by testing the correlation with  
196    accuracy and reaction times at the task). At the end of the session, participants also  
197    filled in the Need for Cognition scale (short version, (Cacioppo, Petty, & Kao, 1984),  
198    assessing how much participants enjoy engaging in mentally demanding endeavors,  
199    and the BisBas scale (Carver & White, 1994), assessing participants' behavioral  
200    inhibition and activation tendencies.

201

# 202    *fNIRS methods*

203            We used the continuous-wave NIRS system (NIRScout; NIRx Medical  
204    Technologies, Brooklyn, NY) utilizing two wavelengths of near-infrared light (760  
205    and 850 nm). Data were acquired from the prefrontal cortex with 5 sources and 5  
206    detectors per hemisphere, covering the lateral and medial PFC. The distance between  
207    each source-detector pair was 3 cm, which provides an adequate compromise between  
208    depth sensitivity and signal to noise ratio (G. E. Strangman, Li, & Zhang, 2013). An  
209    a-priori DLPFC region-of-interest (ROI) was anatomically determined, by visual  
210    inspection of optode locations projected on a 3D MNI atlas (Figure 2, Okamoto et al.,  
211    2004), and by convergence of such locations with previously reported DLPFC activity  
212    in a comparable task (Vassena et al., 2014). The DLPFC-ROI included the channels  
213    F5-F3, F5-FC5, FC3-F3 and FC3-FC5 (for each hemisphere, note that in each pair the  
214    first label is the sender, and the second label is the receiver). This approach had one  
215    main limitation: our procedure did not include neuronavigation with the subject-

specific MRI scan, thus preventing from projecting specific MNI coordinates to the subject's adapted cortical coordinates. However, given the spatial resolution of the current fNIRS setup, and the large extent of DLPFC activity reported in above-mentioned studies, it seems plausible that a finer anatomical characterization would be difficult to achieve (and not necessary for the current purpose). Figure 2 shows the channel configuration.



**Figure 2.** fNIRS setup a. fNIRS montage visualized on the 10-20 EEG template. Selected optodes and channels covering DLPFC. b. Whole montage visualized on a 3D rendering of MNI space, with optode coordinates projected on the cortex. The yellow circles highlight the channels included in the DLPFC-ROI. c. Whole montage visualized on the 10-20 EEG template.

## 233 **Data analysis**

### 234 *Behavioral data analysis*

235 A paired-sample t-test was performed on log-transformed reaction times  
236 (RTs), comparing easy vs. difficult trials. A second paired-sample t-test was  
237 performed, comparing accuracy in the easy vs. difficult trials. Reported significance  
238 values are two-tailed.

239 We calculated the difference between positive and negative PANAS scores by  
240 subtracting scores at the beginning of the session to the scores at the end of session.  
241 Subsequently, these differences for positive and negative PANAS separately were  
242 correlated with accuracy and RTs at the task, to test potential influences of difficulty  
243 (as measured by indexes of task performance) on affective state. Performance was  
244 also correlated with difficulty and liking ratings. Furthermore, we calculated Need for  
245 Cognition and Bis and Bas scores, to test the relationship between task performance  
246 and attitude towards mental effort and behavioral inhibition and activation. One  
247 should note that these correlational analyses were exploratory in nature.

248

### 249 *fNIRS data preprocessing*

250 We analyzed the optical data using Homer2 NIRS processing package  
251 functions (Huppert, Diamond, Franceschini, & Boas, 2009) based on MATLAB  
252 (Mathworks, MA USA). For every participant, the raw optical intensity data series  
253 were converted into changes in optical density (OD). Then PCA was performed,  
254 which automatically adjusts the amount of variance to be removed from the data on a  
255 subject-by-subject basis. A PCA parameter of 80% was chosen as it is more  
256 conservative and removes only the variance supposed to account for the motion  
257 artifacts (Brigadoi et al., 2014). Then a motion detection algorithm was applied to the

258 OD time series to identify residual motion artifacts (AMPthresh=0.5, SDThresh=50,  
259 tMotion=0.5 s, tMask=1s). This means that if, over a temporal window of length 0.5 s,  
260 the standard deviation increases by a factor exceeding 50, or the peak-to-peak  
261 amplitude exceeds 0.5, then the segment of data of length 1 s starting at the beginning  
262 of that window is defined as motion. Stimuli with artifacts from the HRF calculation  
263 were excluded if any artifact appeared 5 seconds before the stimulus appearance, and  
264 10 seconds after. Low-pass filtering with a cut-off frequency of 0.5 Hz was applied to  
265 the data in order to remove variability due to the cardiac cycle. The OD data were  
266 then converted into concentration changes using the modified Beer-Lambert law  
267 (Cope & Delpy, 1988; Delpy et al., 1988) with the differential path length factors set  
268 to 0.6. This method enabled us to calculate signals reflecting the oxygenated  
269 hemoglobin (OxyHb), deoxygenated hemoglobin (DeoxyHb), and total hemoglobin  
270 (Total Hb) signal changes. Afterwards, to recover the mean hemodynamic response  
271 we solved the GLM based on ordinary least squares (Ye, Tak, Jang, Jung, & Jang,  
272 2009), modeling the HRF with a modified gamma function convolved with its  
273 derivative and 3<sup>rd</sup> order polynomial for drift correction. Statistics were done outside  
274 Homer with in-house written scripts in Matlab. Note that we performed all further  
275 analysis on the OxyHb signal. Most fNIRS studies focus on OxyHb, as previous  
276 research showed that this signal correlates more robustly with the fMRI-BOLD signal  
277 in several tasks, possibly due to a higher signal-to-noise ratio as compared to  
278 DeoxyHb (Hoge et al., 2005; Huppert, Hoge, Diamond, Franceschini, & Boas, 2006;  
279 Mehagnoul-Schipper et al., 2002; Okamoto, Dan, Shimizu, et al., 2004; G.  
280 Strangman, Culver, Thompson, & Boas, 2002).

281  
282  
283  
284

# *fNIRS Statistical analysis*

We used a mixed linear modeling (MLM) approach (Baayen, Davidson, & Bates, 2008, also ) to analyze the relation between the peak OxyHb and task difficulty. All analyses were performed using the package lme4 (version 1.1-13) in R version 3.3.1.

Two sets of analyses were performed one on the data averaged within the DLPFC-ROI, and one on all channels. In all analyses, we followed a model building procedure. In a first step, we estimated a benchmark model (including only a random intercept for channels nested into participants, see Jasinska & Petitto, 2013 for a similar approach) to account for between-subjects variability in OxyHb concentration changes across channels. Next, three more complex models were created by expanding the baseline model with one of the fixed effects for Difficulty (Easy vs Difficult), Handedness (Left- vs Right-handed) or Hemisphere (Left vs Right). Each expanded model was compared to the benchmark model using a likelihood ratio test (significance level of 0.05). We introduced the factor Hemisphere to test whether preparation-related activity in PFC would be bilateral or lateralized; Handedness was introduced as a control factor.

In the second step, a new benchmark model was constructed by including the random effects of the original benchmark model, plus each statistically significant fixed effect from the first step. This benchmark model was then compared to the same model plus each two-way interaction effect.

In a third step, a third benchmark model was estimated, consisting of the previous benchmark model plus all significant two-way interaction effects from the second step. This benchmark model was then compared to the same model plus the three-way interaction effect.

311 As a control, all analyses were also conducted with the first benchmark model  
312 including only a random intercept for participant (thus without nesting channels  
313 within participants). This control analysis returned very similar results and therefore  
314 will not be reported.

315 Finally, in order to explore brain-behavioral relationships, a difference score  
316 was calculated for behavioral performance indexes (RTs and accuracy) and for  
317 OxyHb peak within the DLPFC ROI (difficult – easy condition). Next we computed  
318 Pearson’s correlations between these measures.

319

320

## 321 **Results**

### 322 *Behavioural results*

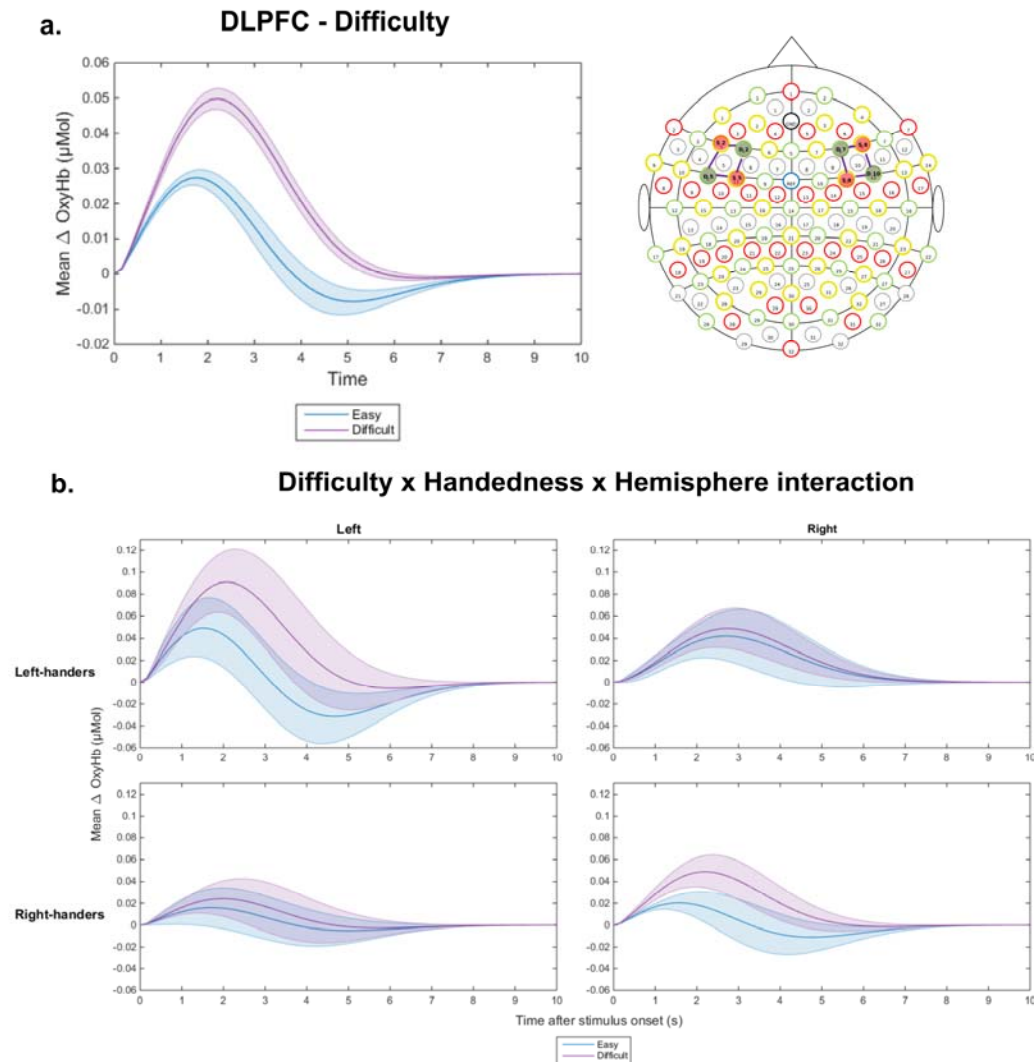
323 Prior to analysis, RTs were log-transformed. In line with previous reports,  
324 participants responded faster to easy trials as compared to hard trials ( $t_{(18)}=-6.56$ ,  
325  $p<.0001$ , mean difference  $-.13$ ). Responses to easy trials were also more accurate as  
326 compared to hard trials ( $t_{(18)}=6.73$ ,  $p<.0001$ , mean difference  $.14$ ), confirming  
327 successful manipulation of task difficulty. Next we analyzed the ratings about task  
328 difficulty and liking, given during the training.

329 Participants judged hard trials as more difficult ( $t_{(18)}=2.31$ ,  $p=.03$ ). Participants  
330 who found hard trials more difficult also liked the easy trials more ( $r=.51$ ,  $p=.03$ ), and  
331 showed larger RT differences between hard and easy trials performance ( $r=.54$ ,  
332  $p=.02$ ).

333 No significance difference was found in the liking ratings (how much  
334 participants reported to like the easy as compared to the hard trials).

335           Next, we computed the results of the PANAS questionnaire, which was  
336   administered before and after the task to check participants' affective state. Both  
337   positive ( $t_{(18)}=6.43$ ,  $p<.001$ ) and negative affect scores ( $t_{(18)}=3.29$ ,  $p=.004$ ) were  
338   significantly lower after the task (possibly due to the long duration of the experiment,  
339   which lasted about a hour including set up time and task performance time).  
340   Subsequently, we performed an exploratory correlation analysis, correlating the  
341   difference between hard and easy condition in RTs and Accuracy with the difference  
342   in affective state pre- and post-task (both for negative and positive PANAS).  
343   However, no significant correlation surviving correction for multiple comparisons  
344   was observed. Performance also did not correlate with other questionnaires measures.

345  
346  
347  
348   *fNIRS results*  
349  
350  
351   Statistical significance of the results was assessed by likelihood ratio testing.  $\chi^2$  and p-  
352   values refer to comparisons between the benchmark model and the same model plus  
353   the fixed effect or interaction of interest. As the model residuals were right-skewed, a  
354   square root transformation was applied to the OxyHb.



355

356 **Figure 3.** DLPFC fNIRS results. a. Cortical hemodynamic response of OxyHb within  
 357 the DLPFC ROI time-locked with cue-onset (during task preparation) for easy (blue  
 358 line) and difficult (pink line) trials. Shades around the lines represent  $\pm$  standard error  
 359 of the mean. b. Same as a, split by handedness (upper panels left-handers, lower  
 360 panels right-handers) and hemisphere (left panels left hemisphere, right panels right  
 361 hemisphere). In all plots shades around the lines represent  $\pm$  one standard error of the  
 362 mean.

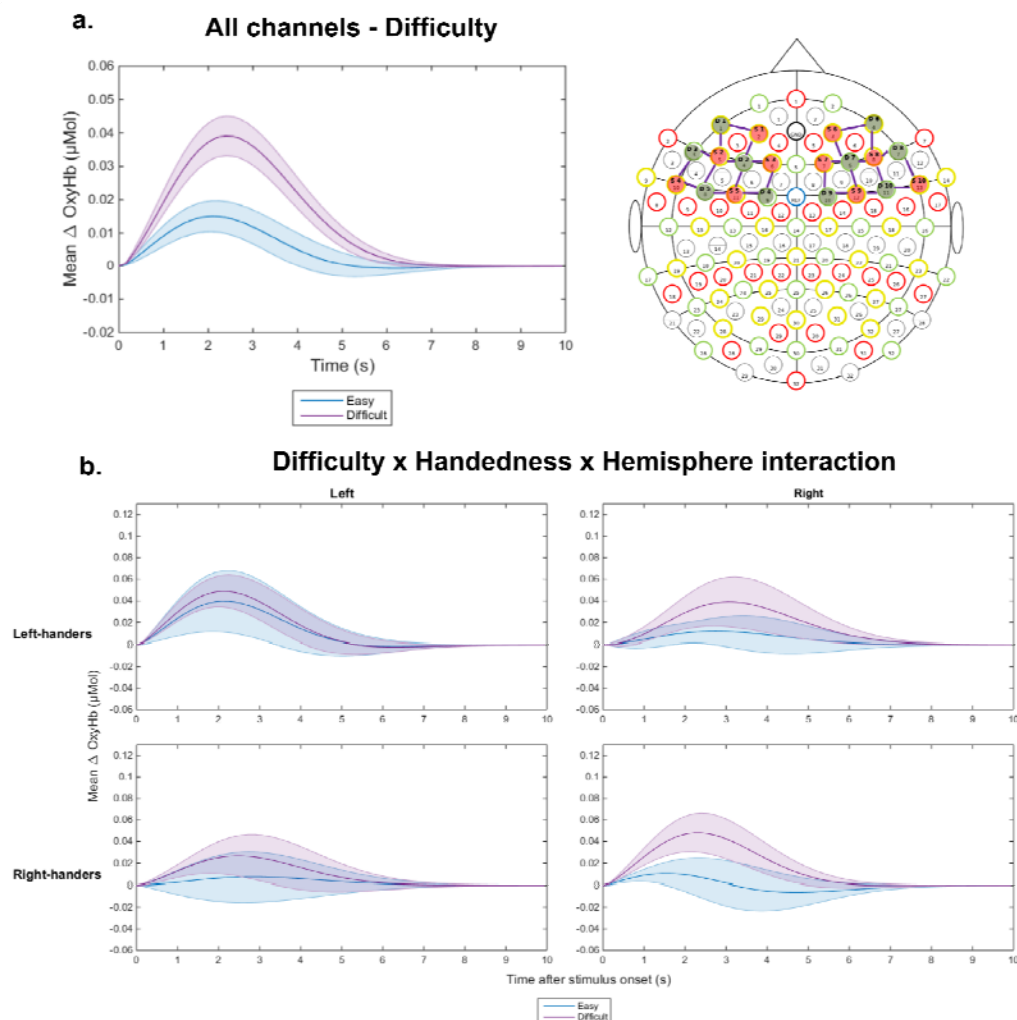
363

364 The analysis on the DLPFC-ROI revealed a main effect of difficulty ( $\chi^2(1)=6.63$ ,  
 365  $p=.010$ ). Specifically, the average OxyHb peak was higher in the hard condition than  
 366 in the easy condition (Figure 3). None of the other main effects demonstrated  
 367 significance (Handedness:  $\chi^2(1)=.07$ ,  $p=.790$  ; Hemisphere:  $\chi^2(1)=3.16$ ,  $p=.075$ ). A



368 significant Handedness  $\times$  Hemisphere interaction was also observed ( $\chi^2(3)=8.85$ ,  
369  $p=.031$ ), reflecting increased activity in the left DLPFC of left-handers. Again, no  
370 other interaction effects were found to be significant (Difficulty  $\times$  Handedness:  
371  $\chi^2(2)=3.67$ ,  $p=.159$  ; Difficulty  $\times$  Hemisphere:  $\chi^2(2)=.15$ ,  $p=.923$ ). The three-way  
372 interaction (Difficulty  $\times$  Handedness  $\times$  Hemisphere) showed a trend towards  
373 significance ( $\chi^2(3)=7.06$ ,  $p=.070$ ). This reflects the fact that the difficulty effect was  
374 more pronounced in right DLPFC for right-handers and in left DLPFC for left-  
375 handers. This exploratory result is consistent with previous findings on lateralization  
376 and handedness, demonstrating that left-handers tend to show effects in the opposite  
377 hemisphere as opposed to right-handers. However, the sample size in each group was  
378 small, so this finding should be further addressed and corroborated in future studies.  
379 For the model including all the channels, a significant main effect for difficulty was  
380 observed ( $\chi^2(1)=20.59$ ,  $p<.001$ ). The OxyHb activity was higher for difficult trials  
381 compared to easy trials. (Figure 4). None of the other main effects reached  
382 significance (Handedness:  $\chi^2(1)=.88$ ,  $p=.349$  ; Hemisphere:  $\chi^2(1)=2.89$ ,  $p=.089$ ). A  
383 significant Handedness  $\times$  Hemisphere interaction was also observed ( $\chi^2(1)=14.90$ ,  
384  $p=.002$ ), but no three-way interaction ( $\chi^2(3)=2.41$ ,  $p=.491$ ). No other two-way  
385 interactions reached significance (Difficulty  $\times$  Handedness:  $\chi^2(2)=3.33$ ,  $p=.189$  ;  
386 Difficulty  $\times$  Hemisphere:  $\chi^2(2)=2.77$ ,  $p=.251$ ).

387 Finally, for completeness in Figure 5 we plot cortical hemodynamic responses  
388 for all channels across the whole montage, showing OxyHb, DeoxyHb and total Hb in  
389 the hard (Figure 5a) and easy condition (Figure 5b).

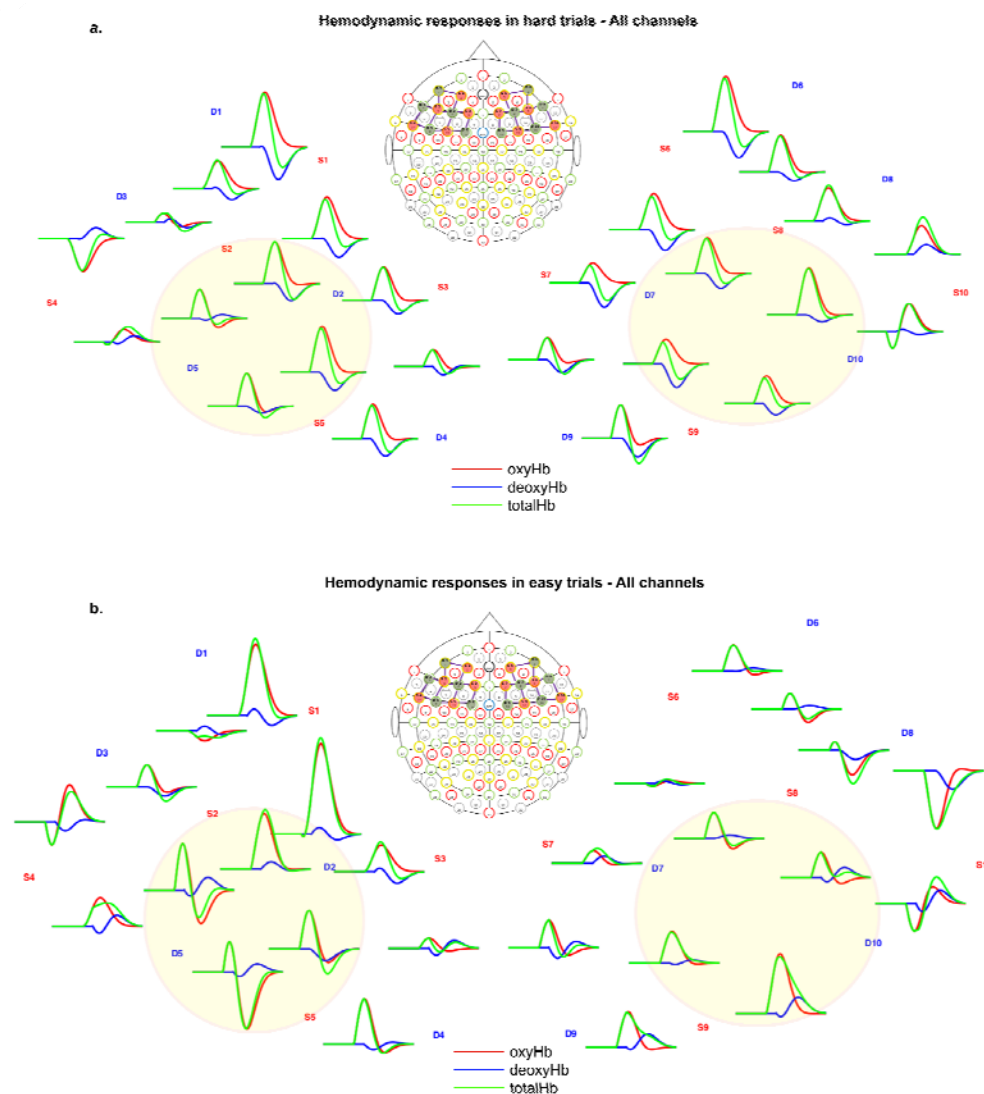


390

391 **Figure 3.** fNIRS results averaged over the whole montage (shown at top right). a.  
392 Cortical hemodynamic response of OxyHb averaged over all channels, time-locked  
393 with cue-onset (during task preparation) for easy (blue) and difficult (pink) trials. b.  
394 Same as a, split by handedness (upper panels left-handers, lower panels right-handers)  
395 and hemisphere (left panels left hemisphere, right panels right hemisphere). In all  
396 plots shades around the lines represent  $\pm$  one standard error of the mean.  
397

398 Next, we correlated the difficulty effect on the OxyHb peak within the left and  
399 right DLPFC ROI (hard > easy) with difference scores of accuracy and RTs. Although  
400 no significant correlations were observed, there was a trend for a negative relationship  
401 between peak magnitude difference in Left DLPFC and RT difference ( $r=-.400$ ,  
402  $p=.09$ ), and accuracy difference ( $r=-.404$ ,  $p=.086$ ). While this may indicate that

403 increased preparation-related activity in left DLPFC might reduce difficulty effects on  
 404 performance, this relationship cannot be confirmed on the basis of this data and  
 405 should be investigated in further research. No correlation was found for Right DLPFC  
 406 ( $r=.33$ ,  $p=.16$ ).  
 407



408  
 409 **Figure 5.** Hemodynamic responses for all channels separately. a. OxyHb  
 410 (red), DeoxyHb (blue) and total Hb (green) time-locked with cue onset in the hard  
 411 trials. b. OxyHb (red), DeoxyHb (blue) and total Hb (green) time-locked with cue  
 412 onset in the easy trials. In both panels the whole montage is shown. The yellow circles  
 413 highlight the DLPFC-ROI channels.  
 414

## 415     **Discussion**

416             This study investigated the role of DLPFC during preparation for a mentally  
417     effortful task. Our results revealed an increase over DLPFC during expectation of a  
418     mentally effortful task (difficult arithmetic problem). These results confirm a  
419     contribution of DLPFC to anticipation of mental effort, as suggested by a previous  
420     fMRI study (Vassena et al., 2014), and establishes optical imaging with fNIRS as a  
421     non-invasive and cost-effective tool to investigate the role of DLPFC in motivation  
422     for effortful behavior.

423             Growing neuroimaging evidence shows that preparing to exert mental effort is  
424     associated with activity in medial PFC, especially dorsal ACC (e.g., Vassena et al.  
425     2014, Parvizi, Rangarajan, Shirer, Desai, & Greicius, 2013). Few studies suggest a  
426     crucial contribution of DLPFC to this process as well. For example, Vassena et al  
427     (2014) and Sohn et al. (Sohn, Albert, Jung, Carter, & Anderson, 2007) found an effect  
428     of task preparation prior to performing hard trials in DLPFC. McGuire & Botvinick  
429     (2010) observed that MFC correlated with errors and RTs, but only DLPFC correlated  
430     with avoidance ratings when performance (errors and RT) were factored out,  
431     suggesting a more general role in strategic preparation.

432             Previous fNIRS studies have investigated DLPFC contribution to several  
433     processes cognitive, such as word-encoding in a memory task (Ferreri et al., 2014),  
434     inhibitory control in drug users (Roberts & Montgomery, 2015), dual motor and  
435     cognitive task-performance (Mandrick et al., 2013). Relevant to the current results,  
436     two studies targeted hemodynamic responses in DLPFC in effortful tasks, specifically  
437     testing the effect of varying mental load in a working memory task (Molteni et al.,  
438     2012), and comparing laboratory measures of load (executive function task) with real-  
439     life effort (operating a flight-simulator Causse et al., 2017). Both studies confirm a

440 PFC contribution to the process. However, in both cases hemodynamic changes were  
 441 measured *during* task performance, and not during task preparation as in our case.  
 442 Interestingly, Causse and colleagues found no effects of performance on DLPFC  
 443 activity, and conclude that this region may play a motivational role in sustaining effort  
 444 exertion, rather than affecting task performance. Finally, a few studies also  
 445 investigated the potential of fNIRS signal decoding in PFC as a Brain-Computer  
 446 Interface, showing reliable decoding of brain activity during mental arithmetic as  
 447 compared to rest (Bauernfeind, Steyrl, Brunner, & Muller-Putz, 2014; Bauernfeind et  
 448 al., 2014; Herff et al., 2013).

449         The results of the current study thus relate to previous fNIRS evidence on  
 450 DLPFC involvement during effortful tasks, showing for the first time with fNIRS a  
 451 clear contribution of DLPFC to preparation for mental effort. It is however important  
 452 to highlight a few limitations. First, the fNIRS montage used to measured cortical  
 453 hemodynamics included only frontal channels. Although a similar approach has been  
 454 adopted in several others studies (Bembich et al., 2014; Ernst et al., 2013; Laguë-  
 455 Beauvais, Brunet, Gagnon, Lesage, & Bherer, 2013), other areas must be targeted in  
 456 future work. In particular parietal cortex has often been found to be co-activated with  
 457 DLPFC, including during preparation for mental effort (e.g., Boehler et al., 2011).  
 458 Several studies suggest that DLPFC and parietal cortex form the fronto-parietal  
 459 network (Dosenbach, Fair, Cohen, Schlaggar, & Petersen, 2008), implicated in  
 460 attentional and top-down control, goal-directed behavior and translation of instruction  
 461 to action (Buschman & Miller, 2007; Farooqui, Mitchell, Thompson, & Duncan,  
 462 2012; Hartstra, Waszak, & Brass, 2012; Muhle-Karbe, Duncan, De Baene, Mitchell,  
 463 & Brass, 2017). A second limitation is that the fNIRS technology only allows  
 464 recording cortical activity; deeper regions such as dACC or subcortical structures

cannot be targeted. However, these regions have already been investigated in the context of preparation for mental effort (Kurniawan, Guitart-Masip, Dayan, & Dolan, 2013; Vassena et al., 2014), and therefore this caveat does not affect the relevance of the current findings. One last potential drawback concerns the interpretation of our results. We propose that DLPFC activity reflects the subject's preparation for the upcoming effortful task (i.e., as in Vassena et al., 2014). However, two alternative interpretations may be possible. This activity may reflect simply predicting the nature of the upcoming task (i.e., is it difficult or not, Vassena, Deraeve, et al., 2017), as opposed to playing a causal role in effort preparation (Brown & Alexander, 2017; Verguts et al., 2015). Alternatively, it may predict other variables related to task difficulty, such as increased error likelihood (Brown & Braver, 2005) or time-on-task (Grinband et al., 2011), although these models predict these effects in the dACC rather than DLPFC. Future designs should disentangle these possibilities, referring to available computational models of PFC function, which attempt to described the contribution of this region to task performance in a mechanistic fashion (Alexander, Vassena, Deraeve, & Langford, 2017; Koechlin, 2016). Future theorizing efforts should also consider the relative contribution of DLPFC, as opposed to dACC (Vassena, Holroyd, & Alexander, 2017) to develop novel frameworks able to describe the interaction between the two regions (Domenech et al., 2017; Kerns et al., 2004).

The conclusion that DLPFC activation is measurable via fNIRS opens up several avenues for research, given the portability and low price of fNIRS setups. In particular, it allows measurement while engaged in (or preparing for) active tasks, which is not possible with standard (e.g., EEG, fMRI) measurement protocols. This is especially of potential relevance in physical effort tasks, in which movement seems

almost by definition required, and for example in the emergent field of sport psychology.

Another group of studies in which fMRI protocols are problematic, and hence fNIRS is an interesting alternative, are those where measurement time is necessarily long, either because a single session is long (e.g., studies on fatigue; Wang, Trongnetrpunya, Samuel, Ding, & Kluger, 2016) or because several sessions must be administered (e.g., studies on learning or memory). For example, concerning fatigue, (Wang et al., 2016) conducted a Stroop task for 160 minutes using EEG. They observed an anterior-frontal ERP that increased during the first 80 minutes of test-taking; during that period, accuracy remained approximately constant. However, as soon as the ERP dropped (after 80 minutes on the task), also accuracy dropped. They thus interpreted the frontal ERP as a “compensation” signal, reflecting the investment of cognitive effort to maintain task performance at an acceptable level (around 10% errors). fNIRS could be fruitfully used to investigate the spatial localization of this component more precisely. fNIRS also opens up interesting possibilities for studies that require large groups. Examples include between-subject designs, studies on individual differences, or studies where effect sizes are expected to be small. Due to the cost of a single MRI scan, such large-group studies are typically not possible in fMRI. Thus, fNIRS might provide an opportunity to better control Type-I and Type-II errors in neuroimaging (Button et al., 2013). Finally, fNIRS also allows testing in subjects with contra-indications for fMRI (e.g., pregnancy, non-removable ferromagnetic implants, or pacemakers, children). Based on our findings, one could investigate the development of the difficulty effect in children across the life-span. Finally, one could investigate preparation for effortful behavior in populations that show clinically impaired motivation and effort exertion.

514

515

516

517

## 518 **References**

519

520 Alexander, W. H., & Brown, J. W. (2015). Hierarchical Error Representation: A

521 Computational Model of Anterior Cingulate and Dorsolateral Prefrontal

522 Cortex. *Neural Computation*, 27(11), 2354–2410.

523 [https://doi.org/10.1162/NECO\\_a\\_00779](https://doi.org/10.1162/NECO_a_00779)

524 Alexander, W. H., Vassena, E., Deraeve, J., & Langford, Z. D. (2017). Integrative

525 Modeling of pFC. *Journal of Cognitive Neuroscience*, 1–10.

526 [https://doi.org/10.1162/jocn\\_a\\_01138](https://doi.org/10.1162/jocn_a_01138)

527 Ayaz, H., Onaral, B., Izzetoglu, K., Shewokis, P. A., McKendrick, R., &

528 Parasuraman, R. (2013). Continuous monitoring of brain dynamics with

529 functional near infrared spectroscopy as a tool for neuroergonomic research:

530 empirical examples and a technological development. *Frontiers in Human*

531 *Neuroscience*, 7, 871. <https://doi.org/10.3389/fnhum.2013.00871>

532 Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with

533 crossed random effects for subjects and items. *Journal of Memory and*

534 *Language*, 59(4), 390–412. <https://doi.org/10.1016/j.jml.2007.12.005>

535 Badre, D. (2008). Cognitive control, hierarchy, and the rostro–caudal organization of

536 the frontal lobes. *Trends in Cognitive Sciences*, 12(5), 193–200.

537 Balardin, J. B., Zimeo Morais, G. A., Furuchio, R. A., Trambaiolli, L., Vanzella, P.,

538 Biazoli, C., & Sato, J. R. (2017). Imaging Brain Function with Functional



- 539 Near-Infrared Spectroscopy in Unconstrained Environments. *Frontiers in*
- 540 *Human Neuroscience*, 11, 258. <https://doi.org/10.3389/fnhum.2017.00258>
- 541 Balconi, M., & Vanutelli, M. E. (2017). Cooperation and Competition with
- 542 Hyperscanning Methods: Review and Future Application to Emotion Domain.
- 543 *Frontiers in Computational Neuroscience*, 11, 86.
- 544 <https://doi.org/10.3389/fncom.2017.00086>
- 545 Bauernfeind, G., Steyrl, D., Brunner, C., & Muller-Putz, G. R. (2014). Single trial
- 546 classification of fNIRS-based brain-computer interface mental arithmetic data:
- 547 a comparison between different classifiers. *Conference Proceedings: ...*
- 548 *Annual International Conference of the IEEE Engineering in Medicine and*
- 549 *Biology Society. IEEE Engineering in Medicine and Biology Society. Annual*
- 550 *Conference, 2014*, 2004–2007. <https://doi.org/10.1109/EMBC.2014.6944008>
- 551 Bembich, S., Clarici, A., Vecchiet, C., Baldassi, G., Cont, G., & Demarini, S. (2014).
- 552 Differences in time course activation of dorsolateral prefrontal cortex
- 553 associated with low or high risk choices in a gambling task. *Frontiers in*
- 554 *Human Neuroscience*, 8, 464. <https://doi.org/10.3389/fnhum.2014.00464>
- 555 Boehler, C. N., Hopf, J.-M., Krebs, R. M., Stoppel, C. M., Schoenfeld, M. a, Heinze,
- 556 H.-J., & Noesselt, T. (2011). Task-load-dependent activation of dopaminergic
- 557 midbrain areas in the absence of reward. *Journal of Neuroscience*, 31(13),
- 558 4955–61. <https://doi.org/10.1523/JNEUROSCI.4845-10.2011>
- 559 Braver, T. S. (2012). The variable nature of cognitive control: a dual mechanisms
- 560 framework. *Trends in Cognitive Sciences*, 16(2), 106–13.
- 561 <https://doi.org/10.1016/j.tics.2011.12.010>
- 562 Brigadoi, S., Ceccherini, L., Cutini, S., Scarpa, F., Scatturin, P., Selb, J., ... Cooper,
- 563 R. J. (2014). Motion artifacts in functional near-infrared spectroscopy: a

- 564 comparison of motion correction techniques applied to real cognitive data.
- 565 *NeuroImage*, 85 Pt 1, 181–191.
- 566 <https://doi.org/10.1016/j.neuroimage.2013.04.082>
- 567 Brown, J. W., & Alexander, W. H. (2017). Foraging Value, Risk Avoidance, and
- 568 Multiple Control Signals: How the ACC Controls Value-based Decision-
- 569 making. *Journal of Cognitive Neuroscience*, 1–18.
- 570 [https://doi.org/10.1162/jocn\\_a\\_01140](https://doi.org/10.1162/jocn_a_01140)
- 571 Brown, J. W., & Braver, T. S. (2005). Learned predictions of error likelihood in the
- 572 anterior cingulate cortex. *Science (New York, N.Y.)*, 307(5712), 1118–21.
- 573 <https://doi.org/10.1126/science.1105783>
- 574 Buschman, T. J., & Miller, E. K. (2007). Top-down versus bottom-up control of
- 575 attention in the prefrontal and posterior parietal cortices. *Science*, 315(5820),
- 576 1860–1862.
- 577 Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S.
- 578 J., & Munafò, M. R. (2013). Power failure: why small sample size undermines
- 579 the reliability of neuroscience. *Nature Reviews Neuroscience*, 14(5), 365–376.
- 580 <https://doi.org/10.1038/nrn3475>
- 581 Cacioppo, J. T., Petty, R. E., & Kao, C. F. (1984). The efficient assessment of need
- 582 for cognition. *Journal of Personality Assessment*, 48(3), 306–307.
- 583 [https://doi.org/10.1207/s15327752jpa4803\\_13](https://doi.org/10.1207/s15327752jpa4803_13)
- 584 Carver, C. S., & White, T. L. (1994). Behavioral inhibition, behavioral activation, and
- 585 affective responses to impending reward and punishment: The BIS/BAS
- 586 Scales. *Journal of Personality and Social Psychology*, 67(2), 319.
- 587 Causse, M., Chua, Z., Peysakhovich, V., Del Campo, N., & Matton, N. (2017).
- 588 Mental workload and neural efficiency quantified in the prefrontal cortex

589 using fNIRS. *Scientific Reports*, 7(1), 5222. [https://doi.org/10.1038/s41598-](https://doi.org/10.1038/s41598-017-05378-x)  
590 017-05378-x

591 Chong, T. T.-J., Apps, M., Giehl, K., Sillence, A., Grima, L. L., & Husain, M. (2017).  
592 Neurocomputational mechanisms underlying subjective valuation of effort  
593 costs. *PLoS Biology*, 15(2), e1002598.  
594 <https://doi.org/10.1371/journal.pbio.1002598>

595 Cope, M., & Delpy, D. T. (1988). System for long-term measurement of cerebral  
596 blood and tissue oxygenation on newborn infants by near infra-red  
597 transillumination. *Medical & Biological Engineering & Computing*, 26(3),  
598 289–294.

599 Delpy, D. T., Cope, M., van der Zee, P., Arridge, S., Wray, S., & Wyatt, J. (1988).  
600 Estimation of optical pathlength through tissue from direct time of flight  
601 measurement. *Physics in Medicine and Biology*, 33(12), 1433–1442.

602 Domenech, P., Redouté, J., Koechlin, E., & Dreher, J.-C. (2017). The Neuro-  
603 Computational Architecture of Value-Based Selection in the Human Brain.  
604 *Cerebral Cortex*. <https://doi.org/10.1093/cercor/bhw396>

605 Dosenbach, N. U. F., Fair, D. a, Cohen, A. L., Schlaggar, B. L., & Petersen, S. E.  
606 (2008). A dual-networks architecture of top-down control. *Trends in Cognitive*  
607 *Sciences*, 12(3), 99–105. <https://doi.org/10.1016/j.tics.2008.01.001>

608 Ernst, L. H., Plichta, M. M., Lutz, E., Zesewitz, A. K., Tupak, S. V., Dresler, T., ...  
609 Fallgatter, A. J. (2013). Prefrontal activation patterns of automatic and  
610 regulated approach-avoidance reactions - a functional near-infrared  
611 spectroscopy (fNIRS) study. *Cortex*, 49(1), 131–142.  
612 <https://doi.org/10.1016/j.cortex.2011.09.013>

- 613 Farooqui, A. A., Mitchell, D., Thompson, R., & Duncan, J. (2012). Hierarchical  
614 organization of cognition reflected in distributed frontoparietal activity.  
615 *Journal of Neuroscience*, 32(48), 17373–17381.  
616 <https://doi.org/10.1523/JNEUROSCI.0598-12.2012>
- 617 Ferreri, L., Bigand, E., Perrey, S., Muthalib, M., Bard, P., & Bugaiska, A. (2014).  
618 Less Effort, Better Results: How Does Music Act on Prefrontal Cortex in  
619 Older Adults during Verbal Encoding? An fNIRS Study. *Frontiers in Human*  
620 *Neuroscience*, 8, 301. <https://doi.org/10.3389/fnhum.2014.00301>
- 621 Frässle, S., Krach, S., Paulus, F. M., & Jansen, A. (2016). Handedness is related to  
622 neural mechanisms underlying hemispheric lateralization of face processing.  
623 *Scientific Reports*, 6, 27153–27153. <https://doi.org/10.1038/srep27153>
- 624 Grinband, J., Savitskaya, J., Wager, T. D., Teichert, T., Ferrera, V. P., & Hirsch, J.  
625 (2011). The dorsal medial frontal cortex is sensitive to time on task, not  
626 response conflict or error likelihood. *NeuroImage*, 57(2), 303–11.  
627 <https://doi.org/10.1016/j.neuroimage.2010.12.027>
- 628 Hartstra, E., Waszak, F., & Brass, M. (2012). The implementation of verbal  
629 instructions: dissociating motor preparation from the formation of stimulus-  
630 response associations. *NeuroImage*, 63(3), 1143–1153.  
631 <https://doi.org/10.1016/j.neuroimage.2012.08.003>
- 632 Herff, C., Heger, D., Putze, F., Hennrich, J., Fortmann, O., & Schultz, T. (2013).  
633 Classification of mental tasks in the prefrontal cortex using fNIRS. *Conference*  
634 *Proceedings: ... Annual International Conference of the IEEE Engineering in*  
635 *Medicine and Biology Society. IEEE Engineering in Medicine and Biology*  
636 *Society. Annual Conference, 2013*, 2160–2163.  
637 <https://doi.org/10.1109/EMBC.2013.6609962>

- 638 Hoge, R. D., Franceschini, M. A., Covolan, R. J. M., Huppert, T., Mandeville, J. B.,  
639 & Boas, D. A. (2005). Simultaneous recording of task-induced changes in  
640 blood oxygenation, volume, and flow using diffuse optical imaging and  
641 arterial spin-labeling MRI. *NeuroImage*, 25(3), 701–707.  
642 <https://doi.org/10.1016/j.neuroimage.2004.12.032>
- 643 Holroyd, C. B., & McClure, S. M. (2015). Hierarchical Control Over Effortful  
644 Behavior by Rodent Medial Frontal Cortex: A Computational Model.  
645 *Psychological Review*, 122(1), 54–83.
- 646 Holroyd, C. B., & Yeung, N. (2012). Motivation of extended behaviors by anterior  
647 cingulate cortex. *Trends in Cognitive Sciences*, 16(2), 122–8.  
648 <https://doi.org/10.1016/j.tics.2011.12.008>
- 649 Huppert, T. J., Diamond, S. G., Franceschini, M. A., & Boas, D. A. (2009). HomER:  
650 a review of time-series analysis methods for near-infrared spectroscopy of the  
651 brain. *Applied Optics*, 48(10), D280-298.
- 652 Huppert, T. J., Hoge, R. D., Diamond, S. G., Franceschini, M. A., & Boas, D. A.  
653 (2006). A temporal comparison of BOLD, ASL, and NIRS hemodynamic  
654 responses to motor stimuli in adult humans. *NeuroImage*, 29(2), 368–382.  
655 <https://doi.org/10.1016/j.neuroimage.2005.08.065>
- 656 Jasinska, K. K., & Petitto, L. A. (2013). How age of bilingual exposure can change  
657 the neural systems for language in the developing brain: a functional near  
658 infrared spectroscopy investigation of syntactic processing in monolingual and  
659 bilingual children. *Developmental Cognitive Neuroscience*, 6, 87–101.  
660 <https://doi.org/10.1016/j.dcn.2013.06.005>
- 661 Kerns, J. G., Cohen, J. D., MacDonald, A. W., Cho, R. Y., Stenger, V. A., & Carter,  
662 C. S. (2004). Anterior cingulate conflict monitoring and adjustments in

- 663 control. *Science (New York, N.Y.)*, 303(5660), 1023–1026.
- 664 <https://doi.org/10.1126/science.1089910>
- 665 Koechlin, E. (2016). Prefrontal executive function and adaptive behavior in complex
- 666 environments. *Current Opinion in Neurobiology*, 37, 1–6.
- 667 <https://doi.org/10.1016/j.conb.2015.11.004>
- 668 Koechlin, E., & Summerfield, C. (2007). An information theoretical approach to
- 669 prefrontal executive function. *Trends in Cognitive Sciences*, 11(6), 229–235.
- 670 <https://doi.org/10.1016/j.tics.2007.04.005>
- 671 Krebs, R. M., Boehler, C. N., Roberts, K. C., Song, A. W., & Woldorff, M. G. (2012).
- 672 The involvement of the dopaminergic midbrain and cortico-striatal-thalamic
- 673 circuits in the integration of reward prospect and attentional task demands.
- 674 *Cerebral Cortex*, 22(3), 607–15. <https://doi.org/10.1093/cercor/bhr134>
- 675 Kurniawan, I. T., Guitart-Masip, M., Dayan, P., & Dolan, R. J. (2013). Effort and
- 676 valuation in the brain: the effects of anticipation and execution. *Journal of*
- 677 *Neuroscience*, 33(14), 6160–6169. [https://doi.org/10.1523/JNEUROSCI.4777-](https://doi.org/10.1523/JNEUROSCI.4777-12.2013)
- 678 12.2013
- 679 Laguë-Beauvais, M., Brunet, J., Gagnon, L., Lesage, F., & Bherer, L. (2013). A
- 680 fNIRS investigation of switching and inhibition during the modified Stroop
- 681 task in younger and older adults. *NeuroImage*, 64, 485–495.
- 682 <https://doi.org/10.1016/j.neuroimage.2012.09.042>
- 683 Mandrick, K., Derosiere, G., Dray, G., Coulon, D., Micallef, J.-P., & Perrey, S.
- 684 (2013). Prefrontal cortex activity during motor tasks with additional mental
- 685 load requiring attentional demand: a near-infrared spectroscopy study.
- 686 *Neuroscience Research*, 76(3), 156–162.
- 687 <https://doi.org/10.1016/j.neures.2013.04.006>

688 Mazoyer, B., Zago, L., Jobard, G., Crivello, F., Joliot, M., Perchey, G., ... Tzourio-  
689 Mazoyer, N. (2014). Gaussian Mixture Modeling of Hemispheric  
690 Lateralization for Language in a Large Sample of Healthy Individuals  
691 Balanced for Handedness. *PLOS ONE*, 9(6), e101165.  
692 <https://doi.org/10.1371/journal.pone.0101165>

693 McGuire, J. T., & Botvinick, M. M. (2010). Prefrontal cortex, cognitive control, and  
694 the registration of decision costs. *Proceedings of the National Academy of*  
695 *Sciences*, 107(17), 7922–7926. <https://doi.org/10.1073/pnas.0910662107>

696 Mehagnoul-Schipper, D. J., van der Kallen, B. F. W., Colier, W. N. J. M., van der  
697 Sluijs, M. C., van Erning, L. J. T. O., Thijssen, H. O. M., ... Jansen, R. W. M.  
698 M. (2002). Simultaneous measurements of cerebral oxygenation changes  
699 during brain activation by near-infrared spectroscopy and functional magnetic  
700 resonance imaging in healthy young and elderly subjects. *Human Brain*  
701 *Mapping*, 16(1), 14–23.

702 Metzger, F. G., Ehlis, A.-C., Haeussinger, F. B., Schneeweiss, P., Hudak, J.,  
703 Fallgatter, A. J., & Schneider, S. (2017). Functional brain imaging of walking  
704 while talking - An fNIRS study. *Neuroscience*, 343, 85–93.  
705 <https://doi.org/10.1016/j.neuroscience.2016.11.032>

706 Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex  
707 function. *Annual Review of Neuroscience*, 24, 167–202.  
708 <https://doi.org/10.1146/annurev.neuro.24.1.167>

709 Molteni, E., Contini, D., Caffini, M., Baselli, G., Spinelli, L., Cubeddu, R., ...  
710 Torricelli, A. (2012). Load-dependent brain activation assessed by time-  
711 domain functional near-infrared spectroscopy during a working memory task

712 with graded levels of difficulty. *Journal of Biomedical Optics*, 17(5), 56005.  
713 <https://doi.org/10.1117/1.JBO.17.5.056005>

714 Muhle-Karbe, P. S., Duncan, J., De Baene, W., Mitchell, D. J., & Brass, M. (2017).  
715 Neural Coding for Instruction-Based Task Sets in Human Frontoparietal and  
716 Visual Cortex. *Cerebral Cortex (New York, N.Y.: 1991)*, 27(3), 1891–1905.  
717 <https://doi.org/10.1093/cercor/bhw032>

718 Nakahachi, T., Ishii, R., Iwase, M., Canuet, L., Takahashi, H., Kurimoto, R., ...  
719 Takeda, M. (2008). Frontal activity during the digit symbol substitution test  
720 determined by multichannel near-infrared spectroscopy. *Neuropsychobiology*,  
721 57(4), 151–158. <https://doi.org/10.1159/000147467>

722 Nee, D. E., & Brown, J. W. (2012). Rostral–caudal gradients of abstraction revealed  
723 by multi-variate pattern analysis of working memory. *NeuroImage*, 63(3),  
724 1285–1294. <https://doi.org/10.1016/j.neuroimage.2012.08.034>

725 Okamoto, M., Dan, H., Sakamoto, K., Takeo, K., Shimizu, K., Kohno, S., ... Dan, I.  
726 (2004). Three-dimensional probabilistic anatomical cranio-cerebral correlation  
727 via the international 10-20 system oriented for transcranial functional brain  
728 mapping. *NeuroImage*, 21(1), 99–111.

729 Okamoto, M., Dan, H., Shimizu, K., Takeo, K., Amita, T., Oda, I., ... Dan, I. (2004).  
730 Multimodal assessment of cortical activation during apple peeling by NIRS  
731 and fMRI. *NeuroImage*, 21(4), 1275–1288.  
732 <https://doi.org/10.1016/j.neuroimage.2003.12.003>

733 Parvizi, J., Rangarajan, V., Shirer, W. R., Desai, N., & Greicius, M. D. (2013). The  
734 Will to Persevere Induced by Electrical Stimulation of the Human Cingulate  
735 Gyrus. *Neuron*, 80(6), 1359–1367.  
736 <https://doi.org/10.1016/j.neuron.2013.10.057>



737 Pinti, P., Aichelburg, C., Lind, F., Power, S., Swingler, E., Merla, A., ... Tachtsidis, I.  
738 (2015). Using Fiberless, Wearable fNIRS to Monitor Brain Activity in Real-  
739 world Cognitive Tasks. *Journal of Visualized Experiments: JoVE*, (106).  
740 <https://doi.org/10.3791/53336>

741 Prévost, C., Pessiglione, M., Météreau, E., Cléry-Melin, M.-L., & Dreher, J.-C.  
742 (2010). Separate valuation subsystems for delay and effort decision costs.  
743 *Journal of Neuroscience*, 30(42), 14080–14090.  
744 <https://doi.org/10.1523/JNEUROSCI.2752-10.2010>

745 Roberts, C. A., & Montgomery, C. (2015). fNIRS suggests increased effort during  
746 executive access in ecstasy polydrug users. *Psychopharmacology*, 232(9),  
747 1571–1582. <https://doi.org/10.1007/s00213-014-3795-8>

748 Shenhav, A., Botvinick, M. M., & Cohen, J. D. (2013). The expected value of control:  
749 An integrative theory of Anterior Cingulate Cortex function. *Neuron*, 79(2),  
750 217–240. <https://doi.org/10.1016/j.neuron.2013.07.007>

751 Sohn, M.-H., Albert, M. V, Jung, K., Carter, C. S., & Anderson, J. R. (2007).  
752 Anticipation of conflict monitoring in the anterior cingulate cortex and the  
753 prefrontal cortex. *Proceedings of the National Academy of Sciences of the*  
754 *United States of America*, 104(25), 10330–4.  
755 <https://doi.org/10.1073/pnas.0703225104>

756 Strangman, G., Culver, J. P., Thompson, J. H., & Boas, D. A. (2002). A quantitative  
757 comparison of simultaneous BOLD fMRI and NIRS recordings during  
758 functional brain activation. *NeuroImage*, 17(2), 719–731.

759 Strangman, G. E., Li, Z., & Zhang, Q. (2013). Depth Sensitivity and Source-Detector  
760 Separations for Near Infrared Spectroscopy Based on the Colin27 Brain

761           Template. *PLOS ONE*, 8(8), e66319.

762           <https://doi.org/10.1371/journal.pone.0066319>

763   Vassena, E., Cobbaert, S., Andres, M., Fias, W., & Verguts, T. (2015). Unsigned

764           value prediction-error modulates the motor system in absence of choice.

765           *NeuroImage*, 32(122), 73–79.

766   Vassena, E., Deraeve, J., & Alexander, W. H. (2017). Predicting motivation:

767           computational models of PFC can explain neural coding of motivation and

768           effort-based decision-making in health and disease. *Journal of Cognitive*

769           *Neuroscience*.

770   Vassena, E., Holroyd, C. B., & Alexander, W. H. (2017). Computational models of

771           anterior cingulate cortex: At the crossroads between prediction and effort.

772           *Frontiers in Neuroscience*, 11. <https://doi.org/10.3389/fnins.2017.00316>

773   Vassena, E., Silvetti, M., Boehler, C. N., Achten, E., Fias, W., & Verguts, T. (2014).

774           Overlapping neural systems represent cognitive effort and reward anticipation.

775           *PloS One*, 9, 1–9.

776   Verguts, T., Vassena, E., & Silvetti, M. (2015). Adaptive effort investment in

777           cognitive and physical tasks: a neurocomputational model. *Frontiers in*

778           *Behavioral Neuroscience*, 9. <https://doi.org/10.3389/fnbeh.2015.00057>

779   Wang, C., Trongnetrpunya, A., Samuel, I. B. H., Ding, M., & Kluger, B. M. (2016).

780           Compensatory Neural Activity in Response to Cognitive Fatigue. *The Journal*

781           *of Neuroscience* □: *The Official Journal of the Society for Neuroscience*,

782           36(14), 3919–24. <https://doi.org/10.1523/JNEUROSCI.3652-15.2016>

783   Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief

784           measures of positive and negative affect: the PANAS scales. *Journal of*

785           *Personality and Social Psychology*, 54(6), 1063.

786 Westbrook, A., & Braver, T. S. (2013). The economics of cognitive effort. *Behavioral*  
787 *and Brain Sciences*, 36(6), 704–705.

788 <https://doi.org/10.1017/S0140525X13001179>

789 Westbrook, A., & Braver, T. S. (2015). Cognitive effort: A neuroeconomic approach.  
790 *Cognitive, Affective, & Behavioral Neuroscience*, 15(2), 395–415.

791 <https://doi.org/10.3758/s13415-015-0334-y>

792 Ye, J. C., Tak, S., Jang, K. E., Jung, J., & Jang, J. (2009). NIRS-SPM: statistical  
793 parametric mapping for near-infrared spectroscopy. *NeuroImage*, 44(2), 428–  
794 447. <https://doi.org/10.1016/j.neuroimage.2008.08.036>

795

796

797

798 **Conflict of interests statement:**

799 The authors have no competing interests to declare.

800