1	Hemispheric asymmetry of globus pallidus relates to alpha modulation in reward-
2	related attentional tasks
3	Subcortical modulation of visual alpha oscillations
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#### 20 Abstract

21

22 While subcortical structures such as the basal ganglia (BG) have been widely explored in 23 relation to motor control, recent evidence suggests that their mechanisms extend to the 24 domain of attentional switching. We here investigated the subcortical involvement in reward 25 related top-down control of visual alpha-band oscillations (8 - 13 Hz), which have been 26 consistently linked to the mechanisms supporting the allocation of visual spatial attention. 27 Given that items associated with contextual saliency (e.g. monetary reward or loss) attract 28 attention, it is not surprising that alpha oscillations are further modulated by the saliency 29 properties of the visual items. The executive network controlling such reward-dependent 30 modulations of oscillatory brain activity has yet to be fully elucidated. Although such network has been explored in terms of cortico-cortical interaction, it likely relies also on the 31 32 contribution of subcortical regions. To uncover this, we investigated whether derived measures of subcortical structural asymmetries could predict interhemispheric modulation of 33 34 alpha power during a spatial attention task. We show that volumetric hemispheric 35 lateralization of globus pallidus (GP) and thalamus (Th) explains individual hemispheric 36 biases in the ability to modulate posterior alpha power. Importantly, for the GP, this effect became stronger when the value-saliency parings in the task increased. Our findings suggest 37 38 that the Th and GP in humans are part of a subcortical executive control network, differently 39 involved in modulating posterior alpha activity. Further investigation aimed at uncovering the 40 interaction between subcortical and neocortical attentional networks would provide useful 41 insight in future studies.

## 42 Introduction

43 Within the domain of spatial attentional allocation, the involvement of neocortical networks 44 has been extensively studied. However, there is also growing evidence pointing to the role of 45 subcortical areas extending into higher level cognitive functions. 46 In order to efficiently operate in natural environments, our brains must rely on neuronal 47 mechanisms which selectively gate stimuli by prioritizing relevant information while 48 reducing the interference of distractors [1]. It is well established that deployment of 49 attentional resources is biased towards stimuli associated with salience (e.g. monetary reward 50 or loss), even when unrelated to the current task goals [2]. Converging evidence has shown 51 that modulations of posterior neuronal oscillations in the alpha band (8 - 13 Hz) reflect the allocation of covert attention [3–5]. In particular, a selective suppression of alpha-band 52 oscillations is observed over visual areas contralateral to the attended hemifield, while a 53 relative increase occurs ipsilaterally [5]. It is now clear that the dorsal attention network 54 55 (DAN) plays a crucial role in the modulation of alpha band activity in spatial attention tasks [6–10]; however, the involvement of subcortical regions in such modulation is yet to be fully 56 57 uncovered. Previous literature has indeed linked subcortical activity to cognitive control[11– 58 13], but remains to be elucidated whether subcortical areas - in coordination with the DAN exert top-down control over posterior alpha band oscillations. 59 60 Activity from such subcortical regions are not likely to be detectable with magnetoencephalography (MEG) due to the lower sensitivity of the technique to deeper 61 62 structures in the brain. As an alternative, recent studies have succeeded in relating structural 63 brain properties derived from magnetic resonance imaging (MRI) to the ability to modulate oscillatory brain activity, measured by MEG [14,15]. For instance, it has been demonstrated 64 that individual hemispheric asymmetries in the volume of the superior longitudinal fasciculus 65 (SLF) [8], a white matter tract connecting fronto-parietal regions, was related to the 66

individual ability to modulate alpha oscillations in visual cortical regions. Importantly, the 67 68 study demonstrated that subjects with greater right than left SLF volume were also the ones 69 displaying higher modulation of posterior alpha activity in the left hemisphere, compared to 70 the right (and vice versa). Through an analogous approach, we postulated that volumetric 71 asymmetries of subcortical areas would be reflected by individual interhemispheric biases in 72 the modulation of alpha oscillations during selective attention in a reward context. Basal 73 ganglia (BG), in addition to motor control, have a well-established role in reward processing 74 and salience attribution [13,16–18], although recent evidence has already pointed to their 75 functions extending into higher level cognitive processing. This notion has been initially 76 explored in animal recordings [19–24], while in humans, it has recently been suggested that 77 the BG play also a specific role in spatial attention and selection [25–27]. Consistent with these lines of evidence, volumetric abnormalities related to the BG have been associated with 78 symptoms of inattention in attention deficit and hyperactivity disorder (ADHD) [28-30] and 79 80 with aberrant salience attribution abilities in patient with schizophrenia [31–35]. On the other hand, other subcortical structures such as the thalamus, have been involved in 81 82 the regulation of synchronized activity in the visual cortex in relation to visual attentional 83 processes [36,37]. Similarly to the premises in [8], we here assumed that a larger subcortical volume would reflect higher control over alpha oscillations in a hemispheric-specific fashion. 84 To investigate this hypothesis we made use of data from a recent study that considered the 85 impact of stimuli paired with value salience on the modulation of oscillatory brain activity in 86 a covert attention task [38]. MEG data were recorded while participants performed a spatial 87 88 cueing task in which Chinese symbols served as targets and distractors. Prior to the 89 recordings, stimuli were paired with monetary rewards or losses. Alpha power modulation was shown to be influenced by the salience of the targets and distractors, but not their valence 90 (i.e., reward and loss had the same effect). We here re-analysed these data with the aim to 91

- 92 investigate the putative role of the subcortical brain areas in biasing alpha power modulation
- 93 during attentional shifts to stimuli paired with value-saliency. MRI data of the same
- 94 participants were processed in order to estimate volumetric asymmetries of subcortical areas,
- 95 consistent with methods employed in previous studies on clinical and healthy population
- 96 [32,34,39]. We focused on identifying the link between individual volumetric asymmetries of
- 97 the subcortical areas and individual interhemispheric bias in the ability to modulate posterior
- alpha oscillations. Crucially, we further examined whether this relationship was affected by
- 99 the degree of stimulus-value associations in the task [40].

#### 100 Results

101

102 We acquired structural and electrophysiological data from 25 participants. Participants' 103 performance was tested during a covert attention paradigm, where Chinese symbols served as 104 targets and distractors (Figure 1). During a learning phase, prior to the actual task, the stimuli 105 were associated with different values (positive, negative or neutral). In the testing phase, a 106 central cue probed an upcoming contrast variation of the target, which appeared either at 107 1450 or 2350 ms, predicting its position in 95% of the trials. Participants were instructed to 108 indicate, with button press, the direction of the contrast change, which could either increase or decrease with equal probability. MEG data, eye-tracking and behavioural responses were 109 acquired during the testing phase. Time-frequency representations of power were calculated 110 from MEG trials after preprocessing and artifacts rejection. Power modulation (MI) indices 111 were computed by contrasting power in trials where participants were validly cued to the 112 113 right (attend right trials) with trials where participants were validly cued to the left (attend 114 *left* trials) (see Eq.(1), *Materials and Methods*). As presented in the previously reported results [38], we confirmed that participants displayed a clear modulation of alpha band 115 activity in parieto-occipital sensors (MI( $\alpha$ )): when covertly orienting attention to the cued 116 117 side, alpha power decreased in the contralateral hemisphere while it increased relatively in the ipsilateral hemisphere (Figure 2A). The magnitude of alpha power modulation, as 118 119 reflected by MI( $\alpha$ ), progressively increased until the target changed contrast (Figure 2B). To best quantify the modulation, we focused our analysis on the 750 ms interval immediately 120 preceding the onset of the contrast change. Next, right and left ROIs were identified as 121 clusters of symmetric pairs of sensors showing the highest alpha lateralization values (see 122 Materials and Methods) (i.e., sensors displaying highest interhemispheric difference in alpha 123 124 modulation).

Starting from the assumption that, to a certain extent, an inter-subject variability in the ability 125 126 to modulate alpha power - in absolute value - must exist in the right compared to the left 127 hemisphere (and vice versa), we sought to quantify individual hemispheric biases in the ability to modulate alpha activity. To this purpose, hemispheric lateralized modulation of 128 alpha power (HLM( $\alpha$ )) values were then computed for each participant by summing the 129 130 average MI( $\alpha$ ) in the right and left hemisphere ROIs (see Eq.(2), Materials and Methods). As a result of this computation, positive HLM( $\alpha$ ) values would demonstrate that a given subject 131 132 was better at modulating their right, compared to left, hemisphere alpha power, while a negative index would reflect higher ability to modulate alpha power on their left, compared to 133 right, hemisphere. The histogram in Figure 2B depicts the distribution of hemispheric biases 134 related to attentional modulation of alpha power.  $HLM(\alpha)$  indices ranged from about -0.1 to 135 136 0.1 (i.e. a 20% variation) but they were normally distributed around zero across participants (Shapiro Wilk, W = .958, p = .392). 137

138

## 139 *Volumetric asymmetry of basal ganglia in relation to hemispheric lateralized alpha*

140 *modulation* 

141 The next step was to determine whether the biases in the ability to modulate left versus right hemisphere alpha (HLM( $\alpha$ )) was related to individual hemispheric lateralization of 142 143 subcortical structures. A semi-automated segmentation tool implemented in FMRIB's Software Library (FSL), was used to estimate volumes for the left and right subcortical and 144 limbic structures, namely: Globus Pallidus (GP), Nucleus Accumbens (Acb), Caudate 145 Nucleus (CN), Putamen (Pu), Hippocampus (Hpc), Amygdala (Am) and Thalamus (Th). We 146 147 then calculated the hemispheric lateralized volumes (LV) for each set of structures (see 148 Materials and Methods, Eq.(3)). Positive (or negative) LVs values, for a given participant, indicated whether a specific substructure s was larger in the right compared to the left 149

150	hemisphere (and vice versa). Further analysis revealed that, over subjects, the Acb and Th
151	were significantly left lateralized ( $z = -3.78$ , $p = 1.56 \times 10^{-4}$ and $z = -3.59$ , $p = 3.28 \times 10^{-4}$ ,
152	respectively; two-sided Wilcoxon signed rank test), whilst the CN was right lateralized ( $z =$
153	2.97, $p = .003$ ). For the other substructures, no significant lateralizations were identified.
154	These significant lateralization biases in the Acb, Th and CN are of potential interest but will
155	not be further considered in the context of this study. Given the volumetric variability in the
156	set of substructures considered for the segmentation protocol, we performed a cross
157	correlation analysis between the different substructures, including left and right volumes, to
158	query about whether there might be a bias in the segmentation protocol. No significant effects
159	were found (positive or negative correlations, all <i>p-values</i> >0.688; highest negative
160	correlation $R$ =084) indicating that, if a given structure is larger for a given subject, this
161	doesn't imply a bias in the segmentation protocol (e.g. to the expense of neighbouring,
162	allegedly smaller areas).

To investigate whether individual subcortical asymmetries (LVs, as defined in Eq. (3)) 163 predicted differences in hemispheric lateralized modulation of alpha power (HLM( $\alpha$ )), we 164 implemented a GLM, where LV indices were included as multiple explanatory variables for 165 166 the response variable (individual HLM( $\alpha$ )). A significant regression was found: when considering the grand average of all conditions, a linear combination of the subcortical LVs 167 was able to explain HLM( $\alpha$ ) values ( $F_{7,17} = 3.37$ , p = .019, adjusted  $R^2 = .409$ ). When 168 assessing each predictor individually, only the beta coefficients for  $LV_{GP}$  and  $LV_{Th}$  were 169 170 found to be significantly higher than zero (partial correlation: p = .004 and p = .028) (Figure 4A). Hence, when controlling for the other explanatory variables in the model, only GP and 171 TH asymmetry (LV<sub>GP</sub>, LV<sub>TH</sub>) significantly contributed to explain biases in hemispheric 172 lateralized alpha band modulation ( $\beta = 1.768$  and  $\beta = 1.924$ , respectively). The independent 173 174 contribution of GP and TH lateralization is visible in Figure 4B,C showing the partial regression plots for LV<sub>GP</sub> and LV<sub>TH</sub> in relation to the HLM( $\alpha$ ) values. We conclude that 175 hemispheric biases in GP and TH volume are predictive of the individual abilities to 176 177 modulate left versus right hemisphere alpha. Precisely, subjects presenting a larger GP 178 volume in the left hemisphere compared to the right, also displayed a higher ability to 179 modulate alpha power (in absolute value) in the left visual hemisphere compared to the right 180 (and vice versa); the same association holding for the Th in relation to HLM( $\alpha$ ) values.

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182 Hemispheric asymmetry of globus pallidus correlates selectively with power modulation in183 the alpha band

In order to better interpret the GLM results, we assessed whether the linear relationship
arising from the model was restricted to the alpha band: to this end, a non-parametric
approach was implemented to further explore the LV<sub>GP</sub> and LV<sub>TH</sub> in relation to HLM(α).
This method allows circumvention of the multiple comparison problem over frequency and

time points by evaluating the full low-frequency spectrum (2-30 Hz) from -750 to 0ms [41]. 188 189 We therefore conducted a cluster-based permutation test using a dependent samples 190 regression *t*-statistic to evaluate the effect (linear association between LV<sub>GP/TH</sub> indices and HLM over all frequencies) at the sample level. A *p*-value of .05 was chosen for thresholding 191 192 the *t*-statistic of the permutation distribution and a critical value corresponding to alpha = 193 .025 (two tailed) was considered for the cluster-level regression test statistic. As depicted in Figure 5A, we observed a significant cluster (p = .004) extending for the entire 750 ms 194 195 window of interest (i.e., when covert attention was deployed to the cued stimulus before the 196 contrast changed), which confirmed a positive linear association (positive *t*-value) between LV<sub>GP</sub> asymmetry and hemispheric lateralized modulation (HLM) of power constrained to the 197 198 alpha frequency range. When applying the same analysis to the Th asymmetry in relation to 199 HLM, no significant clusters of sensors were identified.

200

### 201 *Hemisphere specific relations between alpha modulation and GP asymmetry.*

Given the specific association found between  $LV_{GP}$  and  $HLM(\alpha)$ , arising from the previous 202 203 analysis, we decided to further investigate the hemisphere-specific influence of GP 204 volumetric asymmetry on alpha modulation indices. For this purpose, we sought to compare 205 average left and right hemisphere MI( $\alpha$ )s of participants according to the direction of GP lateralization. This was done by means of median split of the LV<sub>GP</sub> distribution, hence 206 207 resulting in two subgroups, that either had a bias towards a larger left than right GP volume or vice versa (see *Materials and Methods*). A topographical representation of MI( $\alpha$ ) values 208 together with a bar plot of  $MI(\alpha)$  averaged across right and left hemisphere ROIs per each 209 210 subgroup is shown in Figure 1S. Consistent with the GLM results, participants with a larger 211 right than left GP, also displayed a higher modulation of alpha band (in absolute value) in the right hemisphere compared to the left. Given that the assumption of normality, necessary to 212

perform a mixed-effect ANOVA, was not met for the distribution of  $MI(\alpha)$  indices in the two 213 214 subgroups, we implemented a non-parametric cluster-based permutation test to compare the  $MI(\alpha)$  between the two aforementioned subgroups (averaged across specific time and 215 frequency band of interest), employing an independent sample t-test score, and then 216 comparing it with the resulting permutation distribution. This allowed us to explore whether 217 218 there was a hemispheric-specific difference in the two subgroups in the extent of absolute 219 alpha modulation. The test indicated a significant cluster of sensors over right posterior channels (p= .027), hence including the previously defined right ROI and denoting a 220 significant difference in the right hemisphere absolute alpha modulation (MI( $\alpha$ )) between the 221 two subgroups. These results might suggest that the linear association arising from the GLM 222 (Figure 4A, B) in relation to the association between  $LV_{GP}$  and  $HLM(\alpha)$ , was largely driven 223 224 by right hemisphere alpha modulation. We conducted the analogous analysis performing a median split of the distribution of LV<sub>TH</sub> indices. In that case we did not find interhemispheric 225 226 dominance in alpha modulation indices related to lateralization of the thalamus in the right 227 compared to left hemisphere.

228

229 The involvement of globus pallidus and thalamus in relation to stimulus-value associations Crucially, we aimed at assessing whether the level of value-saliency occurrences (VO) in a 230 231 given trial influenced the association between the structural and functional lateralization 232 indices arisen from the GLM. We first calculated HLM( $\alpha$ ) (see Eq.(2), Materials and 233 *Methods*) values for each participant, separately for the three VO levels, namely two, one and 234 zero value saliency occurrences (see Materials and Methods). We then examined Pearson correlations between HLM( $\alpha$ ) and LV values for both GP and Th, which showed a positive 235 significant  $\beta$  in the model, across the three levels considered (Figure 6). LV<sub>GP</sub> significantly 236 237 correlated with HLM( $\alpha$ ) only in trials where both target and distractors had value-salience

(two VO) (r = .68,  $p=1.75 \times 10^{-4}$ ; Figure 6A). This denotes that, in trials with two value-salient 238 239 items presented, participants exhibiting a right lateralized GP volume, also displayed a stronger alpha modulation in the right compared to the left hemisphere, and vice versa.  $LV_{GP}$ 240 241 did not significantly correlate with HLM( $\alpha$ ) when only one or none of the stimuli presented were associated with a salient value (p = .144 and p = .314, respectively: Figure 6A). 242 243 In order to statistically quantify the influence of the stimulus-value association on the relationship between  $LV_{GP}$  and  $HLM(\alpha)$ , we compared *robust correlations* in the three 244 245 conditions according to the bootstrap method described in [42] for dependent overlapping correlations (see *Materials and Methods*). The correlation between  $LV_{GP}$  and  $HLM(\alpha)$  in 246 trials with two occurrences of value-salience, significantly differed both from the condition 247 characterized by one (95% CI [.106, .672]) and zero occurrences (95% CI [.125, .897]). This 248 249 confirmed that the association between lateralized GP volume and alpha modulation bias significantly increased as a function of the number of value-salient occurrences in the task 250 251 (Figure 6B). We performed the same analysis in order to assess whether value-saliency occurrences mediated also the association between  $LV_{TH}$  and  $HLM(\alpha)$ . When considering the 252 253 correlation indices in the three conditions separately, no significant linear relationship was 254 found between the two indices (Figure 7A). Also in this case, when comparing robust 255 correlations between the three conditions, according to the same method above, no significant 256 difference was found. This suggested that the relationship between thalamus volumetric 257 lateralization and alpha modulation arising from the model in Eq.(3), was not driven by the number of value-salient occurrences in the task. 258

259

260 Behavioural analysis

261 We also investigated whether subjects displayed a spatial bias in task performance,

262 irrespective of the value-saliency levels. To this end we performed a paired t-test to assess

whether participants' performance differed between left and right cued trials, in both reaction 263 264 times (RT) and accuracy measures. No behavioural spatial bias was found neither in RT 265 (p=.341) nor in accuracy (p=.572) values. Secondly, we examined whether value-salient 266 occurrences (VO) levels, modulated participants' behavioural performance. 267 We then compared mean RT and accuracy for the three VOs levels (see Materials and 268 *Methods*). There were no statistically significant differences between the three groups, as determined by one-way ANOVA, in RT ( $F_{(2,72)} = .004$ , p = .995) (Figure 8A) nor in accuracy 269  $(F_{(2,72)}=.003, p=.996)$  (Figure 8C). We then tested whether a behavioural spatial bias occurred 270 271 across value saliency occurrences (i.e., whether subjects displayed a difference in RT or 272 accuracy asymmetry across VOs). We computed measures of behavioural asymmetry in 273 accuracy (BA<sub>ACC</sub>) and reaction times (BA<sub>RT</sub>) (see Eq.(5), *Materials and Methods*). 274 Analogously to the method used to compute  $HLM(\alpha)$ , we created asymmetry indices for 275 every subject by contrasting behavioural measures for *attend right* with *attend left* trials. As 276 such, a positive BA<sub>RT</sub> would indicate that subjects were faster when cued to the left compared to the right hemisphere, and vice versa. Similarly, positive BA<sub>ACC</sub> indices reflected higher 277 accuracy when cued to the right compared to the left hemisphere. With the method 278 aforementioned, we performed a one-way ANOVA to assess whether a significant difference 279 280 in behavioural bias occurred across the three VO conditions. Neither BART nor BAACC values significantly differed across VOs ( $F_{(2,72)}$ =.191, p=.826 and  $F_{(2,72)}$ =.669, p=.515, respectively) 281 (Figure 8B, 8D). With the aim of determining a potential link between lateralized indices of 282 behavioural performance and the anatomical (LVs) and functional (HLM( $\alpha$ )) lateralization 283 indices of interest, we employed three separate GLMs to assess whether a linear combination 284 of BA<sub>RT</sub> and BA<sub>ACC</sub> values could explain LV<sub>GP</sub>, LV<sub>TH</sub> and/or HLM( $\alpha$ ) indices. Neither LV<sub>GP</sub> 285 nor LV<sub>TH</sub> could be explained by the behavioral lateralized measures ( $F_{1,23}$ =.18, p=.834, 286 adjusted  $R^2$ =-.07 and  $F_{1,23}$ =.16, p=.849, adjusted  $R^2$ =-.07). The same result held for the 287

- 288 prediction of HLM( $\alpha$ ), yielding also in this case no significant regression coefficients
- 289 ( $F_{1,23}=1.17$ , p=.33, adjusted  $R^2=-.01$ ).
- 290 Last, we investigated whether individual behavioral spatial biases could be accounted for by
- a combination of the other measures examined. To this end, we considered all subcortical
- 292 LV<sub>S</sub> and HLM( $\alpha$ ) indices and specified them as regressors in a general linear model (see
- Eq.(6), *Materials and Methods*), in order to determine whether they could explain biases in
- 294 RT and accuracy (BA<sub>RT</sub> and BA<sub>ACC</sub>). No significant regression was found which could
- account for BA<sub>RT</sub> indices ( $F_{8,16}$ =.85, p=.570, adjusted  $R^2$ =-.05) nor for BA<sub>ACC</sub> indices
- 296 ( $F_{8,16}=1.07$ , p=.429, adjusted  $R^2=-.023$ , respectively). (Figure 2S). The lack of a relationship
- between spatial bias in task performance and functional and structural hemispheric
- 298 lateralization indices is likely explained by the orthogonalization of attentional orienting and
- stimulus-value associations, in line with the null findings in [38].

## 300 Discussion

301 The aim of this study was to investigate the involvement of subcortical structures in 302 modulating spatial attention to stimuli associated with contextual salience. In particular, we 303 investigated volumetric measures of subcortical structures in relation to the ability to 304 modulate visual alpha oscillations in the framework of an attentional task with a reward 305 component [43,44]. We made use of a previous dataset in which alpha activity was 306 modulated by both spatial attention and value-salience associations[38]. We first observed 307 that volumetric lateralization of subcortical areas explained individual differences in the 308 ability to modulate interhemispheric alpha power. More specifically, participants exhibiting a 309 right lateralized GP also had a better ability to modulate posterior alpha oscillations in the right compared to left hemisphere, and vice versa. The same association held for the 310 relationship between Th and alpha modulation. For the GP, we were able to show how this 311 312 association was significantly constrained to the alpha frequency band. Importantly, we 313 showed that the association between GP and alpha hemispheric lateralized modulation 314 increased as a function of value-saliency occurrences in the task: the correlation between GP lateralized volume and alpha modulation asymmetry was significantly higher in trials where 315 316 both target and distractor were represented by a salient item (reward or loss) as compared to one or zero salient items. With respect to the Th and its association to interhemispheric alpha 317 318 power modulation, no relation to saliency was found. To the best of our knowledge, this is 319 the first finding relating individual volumetric differences in BG and thalamus to the modulation of posterior alpha oscillations. 320

321

322 Subcortical areas and alpha synchronization

Our first finding is in line with a growing body of literature demonstrating a subcorticalinvolvement in high level cognitive functions, such as conscious perception [45], working

memory performance [46], cognitive control [47-49] and attentional control [50,51]. Specific 325 326 to attentional control, we showed that volumetric asymmetry of the subcortical areas 327 considered predicts individual biases in the ability to efficiently allocate attention towards a 328 cued target, as indexed by interhemispheric modulation of alpha power. This is strong 329 evidence in favor of a subcortical involvement in attentional processing, given the well-330 established role of neuronal synchronization in the alpha band into the selective gating of 331 relevant information during visuospatial covert attention tasks [52,53]. Although the 332 functional association between BG and cognitive control in the context of reward has been 333 already investigated [54,55], we here provide novel insights into the involvement of 334 subcortical regions in the modulation of posterior alpha oscillations. 335 336 Pulsed inhibition A well-recognized function of the BG is to inhibit or promote cortical activity via 337 338 GABAergic signalling, through the globus pallidus pars interna (GPi), one of its major output structures [56,57] (see below for a discussion of potential pathways). The BG might then 339 340 exercise its influence by applying control over activity in the prefrontal cortex or it might 341 directly coordinate posterior regions (as reflected by its relationship to alpha power modulation during reward processing). Our results suggest that individual differences in GP 342 volume lateralization may correspond to interhemispheric variability in GABAergic 343 signalling and thus reflect the subcortical potential to inhibit cortex. This input is likely 344 responsible for producing the mechanisms of 'pulsed inhibition' in the visual cortex [52], 345 346 reflected by interhemispheric modulation of alpha power, allowing the selective processing of stimuli. Implicitly, we assumed that the volume of the GP indirectly reflects its ability to 347 exert its top-down control over posterior areas, its size possibly representing a determinant 348 for the number of GABAergic neurons involved in the control mechanism. 349

#### 350 *GP* in relation to attentional selection and cognitive control

Interestingly, our results emphasize the specific contribution of the GP in supporting 351 352 stimulus-driven allocation of attention in a value-based context. The GPi is considered to 353 mediate the output of the BG. Previous literature has implicated this structure in voluntary 354 movement regulation: its functions have indeed been predominantly investigated in clinical 355 and animal models in association with motor functions and action control [12,58], describing, 356 for instance, reduction of hypokinetic and rigidity symptoms following pallidotomy in 357 humans [59,60] and abnormal pallidal activity in monkeys with induced parkinsonism[58]. 358 Nevertheless, recent results from single unit recordings in humans have provided indications 359 that electrophysiological activity in the GPi reflects processing of stimuli associated with different reward contingencies [61]. This is corroborated by evidence of alterations of 360 cognitive, in addition to motor, abilities, following pallidotomy in Parkinson's disease 361 362 patients [62]; In addition, GPi DBS in the treatment of Parkinson's desease has been reported 363 to be associated with several cognitive impairments, such as subtle declines in attention and concentration, although to a lesser extent when compared to subthalamic (STN) DBS [63]. 364 365 This aspect has been further addressed in clinical studies showing a link between Parkinson's 366 disease, associated with abnormal pallidal activity [60,64], and altered reward processing as well as updating [65,66]. Structural GP abnormalities have also been linked to impaired 367 suppression of distractors in ADHD [28,67] as well as psychotic symptoms in schizophrenia 368 [31,33,68], which has been related to aberrant salience attribution and reward learning 369 [34,69]. As an important output component of the reward circuit [70], the GPi might serve to 370 371 indirectly influence the cortical information flow by biasing selective processing of valuerelated stimuli. Our data suggest that this influence is further reflected by a modulation of 372 373 alpha band activity.

#### 374 *Right lateralization of the association between GP and alpha modulation*

Interestingly, as visible in Figure 1S, the association between GP lateralization and
interhemispheric alpha power was largely related to right hemisphere differences in absolute
alpha modulation between subjects exhibiting a right, as compared to left, lateralized GP
volume. This finding possibly reflects and is explained by the right hemisphere dominance
allegedly characterizing spatial attention processes [71], corroborated by the right lateralized
feature of the ventral attentional network, which has been described as specifically involved
in the processing of behaviourally salient stimuli [43]

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## 383 Differential role of GP and Th in relation to posterior alpha modulation

Our results show that GP and Th lateralizations were related to the interhemispheric bias in 384 alpha modulation during selective allocation of attention. However, only GP lateralization, 385 and not Th lateralization, was related to the value-saliency pairings in the task. The different 386 387 contribution from GP and Th in relation to saliency occurrences is likely to reflect different roles of the two networks in the top-down control of attentional processing. The GP provides 388 389 a modulatory signal related to the processing of stimuli that draw attention due to their strong 390 saliency associations. The perceptual competition resulting from attending to a salient target whilst required to suppress an equally salient distractor, might be resolved by a network 391 392 involving the GP. Increased midbrain activity has indeed been shown to accompany attentional suppression of a highly rewarding distractor carrying a strong perceptual 393 competition with the target [72], suggesting that dopaminergic networks might flexibly 394 395 modulate attentional selection in reward-related contexts. The correlation between Th lateralization and attention-related alpha modulation, which was 396

irrespective of the saliency component in the current task, is in line with the notion that

thalamic activity, particularly arising from its largest nucleus, the pulvinar, modulates the

399	alpha rhythm in extended visual areas [36,37,73–75]. The pulvinar was first shown to
400	contribute to the generation of the posterior alpha rhythm in dogs [36] and also to regulate
401	synchronized activity between visual cortical areas to support the allocation of attention in
402	human and nonhuman primates [74-77]. Our findings, therefore, add to the growing body of
403	evidence suggesting that thalamo-cortical interactions play a fundamental role in shaping
404	cognitive processing [23,75,78,79]

405

406 Pallido-cortical pathways

407 Through which route does the GP influence visual alpha oscillations? A possibility is that the 408 GP modulates prefrontal activity which in turn engages and affects dorsal attentional networks [11,80]. The dorsal attention network, with the intraparietal sulcus (IPS) and frontal 409 eye-fields (FEF) as its major hubs, has been suggested to mediate top-down allocation of 410 411 attention. Supporting this notion, both the IPS and FEF have been causally implicated in the 412 control over posterior alpha oscillations in relation to attentional shifts [6-8,43,81]. With our 413 results, we propose the existence of a brain network which allows salience driven signals 414 from the BG to influence the prefrontal cortex in biasing the competition among posterior 415 regions. The idea of a BG-cortico loop involved in stimulus driven reorienting of attention has been already introduced [16,82] and is consistent with the notion of a 'salience network', 416 417 which integrates behaviourally relevant input in order to bias and guide cognitive control [83–86]. Within this framework, the BG, through their main output via the GPi, are thought 418 to influence the connectivity between frontoparietal regions by updating goal-directed 419 420 behaviour, in order to adapt to changes in the environment [87]. 421 The influence of GP on posterior alpha oscillations could be mediated through indirect

422 projections via the thalamus. The major target of GPi projections is the motor thalamus,

423 including ventrolateral and ventral anterior thalamic nuclei, which innervates motor and

premotor cortex [56,88,89]. However, cortical projections from thalamic nuclei receiving 424 425 input from the BG might be more diverse and also target prefrontal areas [90], which would 426 enable an indirect modulation of frontoparietal networks by the GPi via the thalamus. 427 Additionally, intra-thalamic connectivity [91,92] as well as complex interactions between the 428 thalamic reticular nucleus and thalamic nuclei [93,94] may provide multiple alternative 429 pathways to convey influence of the GPi on cortical areas and modulate behavior [95]. Note 430 that these pallido-thalamo-cortical pathways are not necessarily related to the volumetric 431 hemispheric lateralization of the thalamus reported here, but might instead represent 432 independent pathways. 433 Another 'pallido-frontal' pathway has recently been suggested by Saunders et al. [96], 434 describing specific connections between the external Globus Pallidus (GPe) and prefrontal areas. The authors suggests to extend traditional BG-prefrontal cortex models, by the 435 introduction of a subdivision of GPe cells based on their differential cholinergic marker 436 437 expression. Employing in vivo extracellular recordings in mice coupled with optogenetics, they demonstrate a direct modulation of frontal cortex by non-cholinergic GPe neurons. Such 438 439 a projection bypasses canonical BG-cortical networks involving thalamic nuclei. It is 440 interesting to note that the paradigm employed in [96] focused on reward-related behaviour (water reward upon pressure of a lever), hence corroborating our findings relating GP to 441 saliency components of the task. This view is in line with recent evidence in favour of an 442 extension of GPe concept from its well-known 'relay station' role within the indirect 443 pathway, to a crucial function in the coordination of neuronal activity in the BG network 444 445 [97]. On the other hand, attempting to parse specific and exclusive pathways within the BG is likely not the optimal approach given the high level of intra-connectivity patterns within 446 these nuclei [97]. Nevertheless, future investigations might benefit from a more in-depth 447 examination of the role of the subthalamic nucleus in such networks. 448

These proposed models provide a theoretical framework in favor of a flexible subcortical modulation of top-down regulation of attentional allocation, which for the GP appears to be specifically engaged in tasks involving value-saliency processing. Nevertheless, the aforementioned possible modulatory routes should not be considered as mutually exclusive: a more comprehensive model of attentional control should instead account for multiple cortical and subcortical pathways operating in parallel, which would allow optimization of the organism's interaction with the environment.

## 457 Materials and Methods

458

## 459 Participants

In the present study, we re-analysed the previously acquired dataset described in [38], where 460 twenty-eight healthy volunteers participated in the study (mean age:  $23\pm2.7$  years; 17 female; 461 462 all right handed). All participant reported normal or corrected-to-normal vision and no prior knowledge of Chinese language. Of these, datasets from three participants were excluded 463 464 from the analysis (due to respectively: technical error during acquisition, excessive eye 465 movements during MEG recording and structural MRI data not acquired), leaving 25 participants. The experiment was conducted in compliance with the Declaration of Helsinki 466 and was approved by the local ethics board (CMO region Arnhem-Nijmegen, 467 CMO2001/095). 468 469

470 *Experimental procedure* 

471 The experiment consisted of two phases: in the learning phase, participants were trained to

472 memorize associations between 6 Chinese characters and 3 different values (positive,

473 negative, neutral). Conditioning was implemented by means of visual and auditory feedback:

two symbols were associated with reward (+80 cents and a 'kaching' sound), two with loss ( -474 475 80 cents and a 'buzz' sound) and two with no value (0 cents and a 'beep' sound) (see Figure 476 1A for an example stimulus-reward association). The stimulus-reward pairing was 477 randomized across participants. Each trial started with the display of three fixation crosses 478 (1000ms), followed by the presentation of a Chinese character (1000ms), together with its 479 matching visual and auditory feedback (Figure 1B). Stimuli were displayed on a grey 480 background, each of them was presented twelve times in a randomized order. The learning 481 phase was conducted in a laboratory with attenuated sound and light and without MEG 482 recording. With the aim of reducing extinction, upon completion of this phase participants 483 were informed that the learnt stimulus-feedback associations would be signalling real reward outcomes throughout the testing phase (i.e. the presentation of a Chinese character, 484 irrespective of its role as target or distractor, would result in a financial reward, loss or none). 485 After the learning phase, participants performed a testing phase (Figure 1C), when they were 486 487 required to perform a covert spatial attention tasks including the stimuli previously associated with a monetary outcome, while ongoing electromagnetic activity was recorded with MEG. 488 489 In the testing phase, participants performed 8 blocks of 72 trials. Each trial started with the 490 presentation of three fixation crosses for 1000 ms (pre-trial interval), whose contrast subsequently decreased, as a preparatory cue indicating imminent stimuli presentation. After 491 500ms, two symbols were presented to the left and right of the screen (8 degrees visual angle) 492 respectively, together with a central fixation cross flanked by two arrows, indicating the 493 target side. Participants were instructed to covertly attend the symbol on the cued side 494 495 ('target') and to ignore the other one ('distractor'), until one of them changed contrast. The contrast change either increased or decreased with equal probability, with onset after 750 ms 496 (13% trials), 1450 ms (47% trials, 'short interval trials') or 2350 ms (40%, 'long interval 497 498 trials') from stimulus presentation. Participants were asked to report the direction of the

contrast change at the targeted ('cued') location as quickly as possible by button press, using 499 500 the index or middle finger of the right hand to indicate their choice (finger-direction mapping 501 was randomized across participants). Participants were instructed to refrain from responding 502 when the distractor changed contrast. Shorter intervals of 750 ms were used to ensure that 503 participants would start covertly directing their attention rapidly after the cue; these trials 504 were not included in the analysis. The target changed contrast on 95% of the trials (valid 505 trials), whereas in the remaining trials the distractor did (invalid trials). The approximate 506 duration of the full task in the MEG was 50 minutes. 507 As a result of the conditioning manipulation in the learning phase, targets and distractors in 508 the task would be associated with either a salient (positive or negative) or a neutral value,

resulting in three categories of trials of interest, as represented by different levels of value-

salience, namely: zero (target and distractor neutral), one (target or distractor salient) or two

511 (target and distractor salient) value-salience levels.

512

## 513 *MEG data acquisition*

514 Electromagnetic brain activity was recorded from participants while seated, using a CTF 275-515 channels whole-head MEG system with axial gradiometers (CTF MEG Systems, VSM MedTech Ltd.). The data were sampled at 1200Hz, following an antialiasing filter set at 516 300Hz. Head position was constantly monitored throughout the experiment via online head-517 localization software. This had access to the position of the three head localization coils 518 placed at anatomical fiducials (nasion, left and right ear), allowing, if necessary, readjustment 519 520 of the participant's position between blocks [98]. Horizontal and vertical EOG and ECG electrodes were recorded with bipolar Ag/AgCl electrodes. 521

#### 522 *MEG data analysis*

523 MEG data analysis was performed using the FieldTrip Toolbox running in MATLAB [99]. 524 Continuous data were segmented in epochs, centred at the onset of the target contrast change, 525 encompassing the preceding 1500 ms and the following 200 ms (this way covering the full 526 stimulus presentation window for short trials). A notch filter was applied at 50, 100, 150 Hz 527 to remove line noise, the mean was subtracted and the linear trend removed. Automatic artifact rejection was implemented for detection and removal of trials containing eye blinks 528 529 and horizontal eye movements (detected with EOG), MEG sensor jumps and muscle artifacts. 530 We produced virtual planar gradiometers by computing spatial derivatives of the magnetic 531 signal recorded with axial gradiometers [100]. The method has the advantage of improving 532 the interpretation of the topographic mapping since neural sources would produce a gradient field directly above them. Time-frequency representations (TFR) of power were then 533 calculated for the resulting pairs of orthogonal planar gradiometers, before summing the 534 535 power values at each sensor. The analysis was performed by sliding a fixed time window of 500 ms in steps of 50 ms. The resulting data segments were multiplied by a Hanning taper 536 537 and a fast Fourier transform was applied in the 2 - 30Hz frequency range, in steps of 2Hz. 538 This procedure was applied only for correct valid trials, separately for left and right cued 539 conditions.

For each participant, TFRs were averaged across trials and a Modulation Index (MI) was computed for each sensor k and over all time points t belonging to the time window of interest -750 - 0 ms, according to the formula:

$$MI(f)_{k,t} = \frac{Power(f)_{k,t_{attright}} - Power(f)_{k,t_{att left}}}{Power(f)_{k,t_{attright}} + Power(f)_{k,t_{att left}}}$$
(1)

Where Power(f)<sub>k,t att left</sub> represents the power at a given frequency f in the condition
'attend left' and Power (f)<sub>k,t att right</sub> is the power of the same frequency in the condition
'attend right'. As a result, positive (or negative) MI values, at a given sensor k and given
timepoint t, indicate higher power at a given frequency f when attention was covertly directed
towards the right (or left) hemifield.
Two clusters of sensors were then derived, by selecting the twenty symmetrical occipito-

parietal sensors (i.e. ten pairs of sensors) showing the highest interhemispheric difference in alpha modulation indices, when considering the grand average over all conditions (see Figure 2A) averaged over the previously defined time window of interest. These clusters constituted the regions of interests (ROIs) on which subsequent analysis was focused. Subsequently, in order to quantify individual hemispheric-specific bias with respect to modulation indices in the alpha range (MI( $\alpha$ )), we calculated the Hemispheric Lateralized Modulation (HLM) index per participant:

$$HLM(\alpha) = \frac{1}{n_{right}} \sum_{k_{right}=1}^{n_{right}} MI(\alpha)_{k_{right}} + \frac{1}{n_{right}} \sum_{k_{left}=1}^{n_{left}} MI(\alpha)_{k_{left}}$$
(2)

556 Where  $k_{left}$  and  $k_{right}$  denote sensors belonging to the aforementioned and previously 557 defined left and right clusters, respectively. Please note that  $MI(\alpha)_k$  indices in Eq.2 (for both 558  $k=1, ..., n_{right}$  and  $k=1, ..., n_{left}$ ) are already a result of an average over timepoints of 559 interest *t*. Since MI( $\alpha$ ) values were obtained by subtracting alpha power in 'attend left' trials 560 from 'attend right' trials, and given that, as a result of attentional allocation, alpha power is 561 suppressed in the hemisphere contralateral to the attended hemifield, a positive HLM( $\alpha$ )

562	value indicated that a given participant displayed higher modulation of absolute magnitude of
563	alpha power in the right compared to the left hemisphere, and vice versa (see Figure 2B).
564	Structural data acquisition
565	T1-weighted images of three out of twenty-five participants were acquired on a 3 T MRI
566	scanner (Magnetom TIM Trio, Siemens Healthcare, Erlangen, Germany), acquisition
567	parameters: TR/TE= 2300/3.03 ms; FA=8°; FoV= 256 × 256 mm; slice thickness= 1 mm;
568	Acquisition matrix= $0 \times 256 \times 256 \times 0$ . For the remaining participants, a 1.5T MRI scanner was
569	used (Magnetom AVANTO, Siemens Healthcare, Erlangen, Germany). Acquisition
570	parameters: TR/TE= 2250/2.95 ms; FA=15°; FoV= 256 × 256 mm; slice thickness= 1 mm;
571	Acquisition matrix= $0 \times 256 \times 256 \times 0$ .
572	
573	Analysis
574	Structural analyses were conducted using the Integrated Registration and Segmentation Tool
575	(FIRST) within FMRIB's Software Library (FSL) v5.0.9 ( <u>www.fmrib.ox.ac.uk/fsl/</u> , Oxford
576	Centre for Functional MRI of the Brain, Oxford, UK). A standard 12 degrees of freedom
577	affine registration to MNI152 space was applied to individual T1 images, adjusted with
578	optimal sub-cortical weighting. Bayesian models implemented in the software are derived
579	from a training based on previous manual segmentation of 336 datasets (provided by the
580	Center for Morphometric Analysis (CMA, MGH, Boston) and applied to registered images to
581	extract subcortical volumetric outputs for left and right hemispheres (see Figure 3A).
582	Given the reward components of the task we then focused on regions of the basal ganglia
583	identified by the algorithm namely the Globus Pallidus (GP), Nucleus Accumbens (Acb),
584	Caudate (CN), Putamen (Pu), as well as other regions potentially involved in the
585	mechanisms, namely Hippocampus (Hpc), Amygdala (Am) and Thalamus (Th). To compute
586	hemispheric Lateralized Volume indices $(LV)$ for each substructure of interest $s$ , we used the

following formula, which controls for individual differences in specific subcortical volumes
via normalization by total bilateral volume, commonly employed to evaluate structural brain
asymmetries [34,39]:

$$LV(s) = \frac{V(s)_{right} - V(s)_{left}}{V(s)_{right} + V(s)_{left}}$$
(3)

590 Where  $V_{S_{right}}$  and  $V_{S_{left}}$  represent respectively the anatomical right and left volumes (in

591 voxels) for a given substructure s. Analogously to Eq.(2), a positive (or negative)  $LV_s$  index,

in a given participant, indicated a greater right (or left) volume for a given substructure *s* (see

593 Figure 3B).

594 *Statistics* 

595 Generalized Linear Model

596 In order to determine the relationship between Basal Ganglia Lateralized Volumes (LVs) and

597 electromagnetic indices (HLM( $\alpha$ )) we applied a generalized linear regression model (GLM),

598 specifying subcortical volumes lateralization (LV<sub>s</sub> values) as regressors and individual HLM

599 values as the response vector, according to the formula:

$$HLM(\alpha) \sim \beta_0 + \beta_1 LV_{GP} + \beta_2 LV_{NAcc} + \beta_3 LV_{CN} + \beta_4 LV_{Pu} + \beta_5 LV_{HPC} + \beta_6 LV_{Am} + \beta_7 LV_{TH} + \varepsilon$$
(4)

600 All subsequent analysis on the relationship between volumetric and oscillatory data

601 specifically focused only on the subcortical structure(s) associated with a significant  $\beta$ 

602 coefficient in the model in Eq.(4), below referred as  $LV_s$ .

#### 603 *Cluster based permutation test*

604 To evaluate whether the linear association between LVs and HLM was effectively limited to 605 the alpha band, a cluster based permutation approach [41] was employed over the full time 606 frequency spectrum of interest. This method effectively allows to statistically control for 607 multiple comparisons over all time and frequency points of interest. After selecting the a-608 *priori* sensors belonging to the formerly specified ROIs, we considered a permutation 609 distribution of regression coefficients derived from randomly pairing participants' LVs value 610 (independent variable) and modulation indices (HLM(f)) 1000 times. At every time-by-611 frequency point, the actual regression coefficient was evaluated against the aforementioned 612 distribution by means of a specified critical  $\alpha$  value. Afterwards, a time-frequency map of the cluster level statistics was derived showing sets of sensors associated with a significant 613 effect. 614 An equivalent approach was later applied to investigate possible hemisphere-specific 615 616 differences in alpha modulation between participants showing a right or left lateralized substructure s. Directionality of lateralization was determined by median split of the 617 618 distribution of LV<sub>s</sub> per participant, producing two subgroups of N=12, representing subjects 619 with a larger left or right volume of substructure s. After having a-priori averaged across the

620 time-frequency spectrum of interest ([-750 0] ms, 8-13Hz), MI( $\alpha$ ) values at every sensor were

621 compared between the two subgroups (right vs left lateralized substructure). The actual t-

622 value was then compared with a permutation distribution of t-statistic derived from randomly

partitioning indices between the two groups 1000 times. As a result, a topography map was

624 plotted displaying eventual cluster(s) of sensors associated with a significant t-value (i.e. a

625 significant difference in MI( $\alpha$ ) between subgroups).

623

#### 626 Comparison between Pearson's correlation coefficients

627 Finally, we aimed at comparing the association between the derived structural and functional 628 lateralization indices in different value salience occurrences. To this end, we calculated 629  $HLM(\alpha)$  values for each participant separately for the three reward-related contingencies and 630 computed the Pearson's correlations with LVs indices which displayed a significant  $\beta$  as arising from the model in Eq.(4). We statistically assessed the difference in correlation 631 coefficients between the three experimental conditions considered, according to the method 632 633 described in [101]. The test implements a percentile resampling technique by generating a 634 bootstrap sample of the difference of the correlation coefficients between the overlapping variable  $LV_{GP}(Y)$  and the two variables representing the  $HLM(\alpha)$  for the two experimental 635 conditions (VO levels) to be compared  $(X_1, X_2)$ . As suggested in the method, we used a 636 Winsorized correlation to achieve a robust measure of association between variables. This 637 638 transformation has been shown to effectively control for the influence of outliers on the 639 correlation estimate [102]. A confidence interval was then computed on the resulting bootstrap distribution, to assess the statistical significance of the actual difference between 640 641 correlation coefficients describing the different VOs.

642

## 643 Behavioural data analysis

To assess whether subjects displayed a spatial bias during the task, we first averaged across left and right cued trials separately, averaged across all conditions (i.e., irrespective of valuesaliency occurrences (VO)). We then employed paired t-test on the derived reaction times (RT) and accuracy (ACC) (expressed as percentage of correct responses) measures for the left and right cued trials. Secondly, we divided trials according to VO pairings, averaging left and right cued trials, to determine whether behavioural performance varied as a function of saliency in both RT and ACC. We here employed one-way repeated measures ANOVA to

assess whether group means in the three conditions significantly differ from each other. We
also considered individual lateralized measures of RT and ACC across different VO
conditions. To this end, behavioural asymmetries in performance (BA) for both measures
were calculated according to:

$$BA_{RT/ACC} = \frac{BA_{RT/ACC}_{right} - BA_{RT/ACC}_{left}}{BA_{RT/ACC}_{right} + BA_{RT/ACC}_{left}}$$
(5)

655 Where  $BA_{RT right}$  and  $BA_{RT left}$  represent mean reaction times for 'attend right' and 'attend left' 656 trials, respectively. A positive  $BA_{RT}$  for a given subject indicated faster responses when a 657 participant was validly cued to the left compared to the right hemisphere, while negative 658 values indicated the opposite pattern. Consequently, positive  $BA_{ACC}$  values indicated higher 659 accuracy on 'attend right' trials compared to 'left attend' trials, and vice versa.

660 A one-way repeated measures ANOVA was employed to test the difference across group

661 means in the three VO conditions examined.

662 In a next step, we sought to investigate the possible association of behavioural performance

663 with structural and functional hemispheric lateralization, we used Pearson's correlation to

664 examine the association of individual asymmetries in accuracy (BA<sub>ACC</sub>) and reaction times

665 (BA<sub>RT</sub>) with individual HLM( $\alpha$ ) and LV values of subcortical structures which showed

666 significant correlation with HLM( $\alpha$ ).

667 In a last step, we employed a general linear model (GLM) in order to assess whether spatial

biases in behavioural performance could be explained by a combination of the other

669 variables, namely HLM( $\alpha$ ) and the LV indices of the subcortical areas considered, according

670 to the formula:

$$BA_{RT/ACC} \sim \beta_0 + \beta_1 LV_{GP} + \beta_2 LV_{NAcc} + \beta_3 LV_{CN} + \beta_4 LV_{Pu} + \beta_5 LV_{HPC} + \beta_6 LV_{Am} + \beta_7 LV_{TH} + \beta_4 HLM(\alpha) + \varepsilon$$
(6)

## 671 *Data availability*

- 672 The preprocessed MEG and MRI anonymised dastasets that support the findings of this study
- are available as downloadable online data collection in the Donders Data Repository
- 674 (https://data.donders.ru.nl), with persistent identifier: <u>11633/di.dccn.DSC 3016045.01 337</u>,
- 675 upon reasonable request to the corresponding author.
- 676

## 677 Acknowledgements

- 678 The authors gratefully acknowledge the support of the Netherlands Organisation for
- 679 Scientific Research (NWO, VICI grants 453-09-002 and 453-14-015 and the James S.
- 680 McDonnell Foundation (grants 220020328 and 220020448). We also would like to thank
- 681 Sebastiaan den Boer for his in contribution in the data collection process and experimental
- 682 design.

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#### 993 Figure 1. Illustration of selective attention task: stimuli and reward manipulation.

994 (A) Six Chinese symbols served as stimuli for the task and were associated with three values: two paired with reward, two 995 with loss and two with no financial change (neutral). (B) Representative trial of the learning phase. Symbols were displayed 996 for 1000ms, systematically paired with the corresponding (positive, negative or neutral) value, via visual and auditory 997 feedback. Characters presentation was alternated with a 1000ms fixation period. During the training phase, participants learned 998 associations between the stimuli and their reward value. C. Representative trial of the testing phase. After a 1000ms pretrial 999 interval, participants were primed with a 500ms preparatory cue signalling the upcoming stimuli. Two characters were then 1000 presented to the left and right hemifield, together with a spatial cue, instructing participants to covertly attend the symbol on 1001 the cued side (target) and ignore the other one (distractor). Participants' task was to report when the target stimulus changed 1002 contrast. Contrast change could either occur after 750ms (13% of trials), 1450ms (47% of trials) or 2350ms (40% of the trials). 1003 In 95% of the trials, the target changed contrast (valid trials), whilst in 5% of the trials, the distractor changed contrast (invalid 1004 trials). Figure adapted from [38].



#### 1005 Figure 2. Grand average MI and HLM distribution across participants. 1006 (A) Time-frequency representations of power (TFRs) and topographical plot showing contrast between the 'attention right' -1007 'attention left' trials. A clear modulation is visible at posterior sensors in the alpha band (8 - 13Hz) in the -750 - 0ms interval 1008 (this time window being considered for the computation of $HLM(\alpha)$ indices in (B)). Sensors included in the left and right ROIs 1009 are marked as dots. Trials are locked to the onset of the contrast change (t = 0). (B) Side panels show the temporal evolution 1010 of modulation indices in the alpha range (MI( $\alpha$ )), averaged over sensors within left and right hemisphere ROIs. The magnitude 1011 (absolute value) of $MI(\alpha)$ progressively increased in the stimulus interval until the onset of the contrast change. Middle: 1012 distribution of HLM( $\alpha$ ) indices across participants, computed over the ROIs and 8 – 13 Hz frequency band (see Materials and 1013 Methods). A normal density function is superimposed, denoting no hemispheric bias in lateralized modulation values across 1014 participants (Shapiro Wilk, W = .958, p = .392).



1015 Figure 3. Basal Ganglia volumes resulting from semiautomated subcortical segmentation implemented.

(A) Orthogonal view and 3D rendering. Subcortical volumes are overlaid as meshes on the anatomical MRI of one of theparticipants (following defacing procedure in Freesurfer, where voxels outside the brain mask with identifiable facial features

1018 were excluded [103]). (B) Histograms with superimposition of normal density function, showing the distribution of subcortical

- 1019 lateralization indices for each substructure. In our sample, NAcb and Th volumes were left lateralized (p = .0001 and p = .0003,
- 1020 respectively) while CN showed a right lateralization (p = .0029).

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1021 Figure 4. Lateralization of individual subcortical structures in relation to alpha hemispheric lateralized modulation (HLM) in 1022 the task. (A) Bar plot displays the Beta coefficients associated with a general linear model where LV values were defined as 1023 explanatory variables for HLM( $\alpha$ ). Error bars indicate standard error of the mean. Asterisks denote statistical significance; 1024 \*\*p < .01. (B) Partial regression plot showing the association between LV<sub>a</sub> and HLM( $\alpha$ ), while controlling for the other 1025 regressors in the model in (A). (C) Partial regression plot showing the association between  $LV_n$  and  $HLM(\alpha)$ , while controlling 1026 for the other regressors in the model in (A). Given Eqs.(1) and (2) (see *Materials and Methods*), positive HLM( $\alpha$ ) values 1027 indicate stronger modulation of alpha power in the right compared to the left hemisphere, and vice versa; similarly, positive 1028 (or negative) LVs indices denote greater right(or left) volume for a given substructure s. The dotted curves in (B) and (C) 1029 indicate 95% confidence bounds for the regression line, fitted on the plot in black.



**1030** Figure 5. Time-frequency representation of regression coefficient t-statistics on the linear relationship between lateralized **1031** alpha modulation and  $LV_{GP}$  (A) and  $LV_{Th}$  (B) indices, averaged over ROIs (see Fig. 2A). A black outline is used to highlight **1032** the significant time-frequency cluster found. For the  $LV_{GP}$ , the analysis revealed a clear  $\alpha$ -band-limited association between **1033** the variables across the full time-window of interest (see *Materials and Methods*).



1034 Figure 6. Linear association between GP volumetric asymmetry and alpha modulation asymmetry as a function of 1035 value-saliency occurrences in the task. (A) Correlation between GP volume lateralization and HLM( $\alpha$ ), grouped accordingly 1036 to the number of value-salient stimuli in the trials (see Materials and Methods). From left to right, respectively, two, one and 1037 zero value-saliency occurrences are displayed. GP asymmetry significantly explained HLM( $\alpha$ ) only when value-salient stimuli 1038 featured as both target and distractors, irrespective of their valence (r = .68, significant at the p < .001 level after Bonferroni 1039 correction for three comparisons). (B) The association between  $HLM(\alpha)$  and GP volume lateralization increased as a function 1040 of value saliency in the task: the linear relationship was stronger when two value-salient stimuli were presented, when 1041 compared to conditions characterized by either one or value-salience pairings (95% CI [.106, .672] and [.125, .897], 1042 respectively for the two comparisons). This suggests that, when both target and distractor were associated with a salient value, 1043 participants exhibiting bigger GP volume in the left hemisphere than in the right hemisphere, were also better at modulating 1044 alpha oscillations in the left compared to the right hemisphere. Asterisks denote statistical significance; \*\*p < .01.



1045Figure 7. Linear association between Th volumetric asymmetry and alpha modulation asymmetry as a function of1046value-saliency occurrences in the task. (A) Correlation between TH volume lateralization and HLM( $\alpha$ ), grouped accordingly1047to the number of value-salient stimuli in the trials (see *Materials and Methods*). From left to right, respectively, two, one and1048zero value-saliency occurrences are displayed. When considering individual correlations between Th asymmetry and HLM( $\alpha$ ),1049no significant linear relationship was found. (B) The association between the two measures also didn't significantly differ as1050a function of saliency in the trials.



# Figure 8. Mean and lateralized reaction times (RT) and accuracy values across the three value-saliency occurrences in the task.

Mean RT (A) and accuracy (C) values averaged across participants in the three value-salient occurrences conditions in the task. Error bars indicate standard error of the means. No significant difference was found between groups by means of oneway repeated measures ANOVA, indicating that different levels of value-saliency pairings didn't influence behavioural performance. No significant difference emerged also when comparing average lateralized values of RT (B) and accuracy (D) across the same conditions, and by means of same statistical analysis, indicating that the behavioural spatial bias was not affected by the different levels of value-saliency pairings.

#### 1059 Supplementary material





**Figure 1S. Alpha modulation indices for left and right hemispheres associated with two subgroups of the sample**. (A) Topographical plot of MI( $\alpha$ ) values for the two participants groups, clustered according to directionality of GP lateralization (right vs left lateralized GP). Left and right sensors of interest are marked as dots and correspond to the same ROIs as in Figure 2. (B) Bar graph showing mean MI( $\alpha$ ) averaged over ROIs in the two subgroups. As indicated in the cluster-based permutation results, a difference is particularly observable for right hemisphere alpha modulation between the two groups, being higher in participants exhibiting a right lateralized GP. Error bars represent standard error of the mean. Horizontal lines in the indicate the average HLM( $\alpha$ ) indices for each subgroup.



Figure 2S. General linear model displaying combined lateralized subcortical volumes and hemispheric lateralized
 modulation as multiple regressors for the prediction of spatial behavioural bias in accuracy (A) and RT (B). No significant
 regression was found which could account for either the lateralized accuracy or RTs (*p*=.429 and *p*=.570, respectively).