Received: 27 July 2022 | Revised: 4 February 2023 | Accepted: 9 March 2023

DOI: 10.1111/ejn.15968

RESEARCH REPORT

EJN European Journal of Neuroscience FENS WILEY

# Alpha-tACS alters attentional control but not cognitive functions as video games do: A psychophysical investigation based on the theory of visual attention

**Yannik Hilla**[1,2,3] | **Fabian Link**[1] | **Paul Sauseng**[1]

[1]Department of Psychology, Ludwig-Maximilians-Universität (LMU), Munich, Germany

[2]Allgemeine Psychologie, Universität der Bundeswehr München, Neubiberg, Germany

[3]Graduate School of Systemic Neurosciences, Department of Biology II Neurobiology, Ludwig-Maximilians-Universität (LMU), Planegg, Germany

**Correspondence**
Yannik Hilla, Allgemeine Psychologie, Universität der Bundeswehr München, Werner-Heisenberg-Weg 39, 85577, Neubiberg, Germany.
Email: yannik.hilla@unibw.de

**Funding information**
This work was supported by Deutsche Forschungsgemeinschaft (grant number SA 1872/2–2).

Edited by: Gregor Thut

## Abstract

Video game players' faster speed of information processing has been shown to coincide with altered posterior alpha power modulation, that is, brain oscillatory activity around 10 Hz. Thus, it was proposed that improved cognitive processing in video game players may be related to differential alpha activity. However, a causal relationship thereof has not yet been established. We addressed this by conducting a non-invasive brain stimulation study to demonstrate that modulating alpha power using transcranial alternating current stimulation (tACS) may impact on speed of information processing. Furthermore, we aimed to show that this effect correlated with altered attentional control, for example, visuospatial attention and/or top-down control processing, given that this has been suggested to contribute to video gaming effects. Therefore, we recruited 19 non-video game players to undergo one of five brain stimulation conditions while performing a visual short-term memory task at five different days, respectively. Thus, we applied tACS either at 10 Hz (alpha frequency) or at 16.18 Hz (control frequency) either over their left or right posterior parietal cortex (PPC) or a sham stimulation. Individuals' speed of information processing, visuospatial attention and top-down control processing were operationalised using a computational modelling approach based on the theory of visual attention. We found that alpha-tACS applied over individuals' left PPC altered their visuospatial attention orientation but not their speed of information processing. Thus, we were not able to establish a causal relationship between speed of information processing and altered visuospatial

**Abbreviations:** AICc, Second-Order Akaike Information Criterion; AOH, Activation-Orientation Hypothesis; $BF_{10}$, Bayes Factor (in Support of H1); BH, Benjamini-Hochberg (Method); BIC, Bayesian Information Criterion; DBSCAN, Density-Based Spatial Clustering of Applications with Noise; IAF, Individual Alpha Frequency; PPC, Posterior Parietal Cortex; rTMS, repetitive Transcranial Magnetic Stimulation; tACS, transcranial Alternating Current Stimulation; TVA, Theory of Visual Attention.

The work was conducted in a laboratory of the Department of Psychology at LMU.

attention processing through alpha power modulation using non-invasive brain stimulation.

**KEYWORDS**
attentional control, brain stimulation, computational modeling, transfer effects

## 1 | INTRODUCTION

Video game players, that is, individuals who regularly play video games for several hours a week, appear to develop superior cognitive processing skills through playing video games. For instance, they have been shown to outperform non-video game players, that is, individuals not sharing this habit, in psychometric tasks operationalising attentional processing (Bediou et al., 2018; Green & Bavelier, 2003), perception (Li et al., 2010; Pohl et al., 2014), executive control (Cain et al., 2012; Green et al., 2012), memory (Blacker & Curby, 2013; McDermott et al., 2014) and probabilistic inference (Green et al., 2010; Schenk et al., 2017). Moreover, non-video game players displayed similar cognitive improvements after having participated in a video game training (Bejjanki et al., 2014; Blacker et al., 2014; Green et al., 2010; Green & Bavelier, 2003; Strobach et al., 2012). Thus, video gaming seems to impact not only on individuals' gaming performance but also inadvertently on their cognitive functions—a phenomena known as *transfer effect* (Perkins & Salomon, 1992).

The underlying mechanism thereof is not yet fully understood. Bavelier, Green, et al. (2012), for instance, suggested that video games might train individuals in developing efficient cognitive strategies by improving their *probabilistic inference*, that is, the ability to learn statistical regularities. Attentional control, the conjunction between attention and executive control functions to enable individuals to focus on processing relevant information while being able to suppress irrelevant information, may play a considerable role in this regard (Bavelier & Green, 2019). Bejjanki et al. (2014), for instance, showed that video game players did not outperform non-video game players in a psychometric task from the start on but after time on task; and that this effect, in turn, correlated with an increasing signal-to-noise ratio during information processing.

Furthermore, in support of this, video game players' superior cognitive processing correlated with alterations in neural substrates of attentional control functions (Bavelier, Achtman, et al., 2012; Föcker et al., 2018, 2019; Krishnan et al., 2013; Mishra et al., 2011; Tanaka et al., 2013; Wu et al., 2012). Hilla et al. (2020), for instance, found that video game players' faster speed of information processing was associated with an increase in posterior parietal alpha amplitude attenuation in the course of time on task. Alpha activity refers to brain oscillatory activity around 10 Hz. It is widely considered as a neural substrate of attention processing given that its amplitude modulation coincides with differential information processing. Hereby, attenuated alpha activity appears to be associated with better and increased alpha activity with worse information processing, respectively (Capotosto et al., 2009; Jensen & Mazaheri, 2010; Peylo et al., 2021; Thut et al., 2006). Thus, Hilla and colleagues' (Hilla et al., 2020) results indicate that video game players' faster information processing might be related to them having been able to learn to deploy attention more efficiently than control individuals (see, Bavelier & Green, 2019).

However, this was just a correlational finding. Thus, it is not clear yet whether alpha power modulation may indeed impact on individuals' speed of information processing.

Furthermore, this alpha power modulation did not provide information which and how attentional control functions contributed to enhanced information processing (Hilla et al., 2020). To address these issues, we conducted a non-invasive brain stimulation study where non-video game players performed a visual short-term memory task at five different days and experienced one of five different stimulation conditions at each day. The aim of this study was to demonstrate that modulating posterior alpha activity using *transcranial alternating current stimulation* (tACS) may affect individuals' speed of information processing by impacting on their attentional control functions. Thus, we would imitate the video gaming effect previously described (Hilla et al., 2020) and acquire indirect evidence indicating that the conjunction between alpha power modulation and altered attentional control may account for enhanced cognitive processing as observed in video game players (Bavelier & Green, 2019). We used tACS therefore because it represents an established non-invasive brain stimulation method to alter brain oscillatory activity (Herrmann et al., 2016). Moreover, applied at alpha frequency over the posterior parietal cortex (PPC), it has been shown to reliably modulate visuospatial attention processing—an essential cognitive control function (Helfrich et al., 2014;

Kemmerer et al., 2022; Vogeti et al., 2022). Furthermore, similar to Hilla and colleagues (Hilla et al., 2020), we operationalised individuals' speed of information processing by means of a computational modelling approach based on the *theory of visual attention* (TVA) (Bundesen et al., 2015; Dyrholm et al., 2011; Kyllingsbæk, 2006). Likewise, their attentional control functions were operationalised by means of TVA visuospatial attention and top-down control parameter values.

Besides that, we modelled and investigated individuals' TVA visual short-term memory capacity. This was because TVA visual short-term memory capacity was likely affected by tACS as well given that, firstly, short-term memory performance has been shown to be related to alpha activity (Riddle et al., 2020; Sauseng et al., 2009). Secondly, TVA speed of information processing and short-term memory capacity are highly correlated (Finke et al., 2005). Thus, differential TVA visual short-term memory capacity likely coincides with altered speed of information processing through alpha power modulation. In this regard, in particular right hemispheric brain stimulation might induce alterations in TVA cognitive processing. In support of this, Hung et al. (2005), Kraft et al. (2015) and Moos et al. (2012) showed that TVA visual short-term memory capacity and top-down control were modulated by right but not left hemispheric posterior brain stimulation.

Thus, we hypothesised that tACS applied at alpha frequency (10 Hz) over individuals' PPC would alter their TVA speed of information processing (**H1**) (Hilla et al., 2020). Moreover, we expected this effect to be related to alterations in TVA visuospatial attention and/or top-down control processing (**H2**) (Bavelier & Green, 2019; Kemmerer et al., 2022). In addition to that, we anticipated that differential TVA short-term memory capacity may coincide with these effects (**H3**) (Finke et al., 2005; Riddle et al., 2020; Sauseng et al., 2009). Furthermore, we expected that these effects might be more pronounced as result of right than left hemispheric tACS application (**H4**) (Hung et al., 2005; Kraft et al., 2015; Moos et al., 2012).

## 2 | METHODS

### 2.1 | Participants

We estimated that 18 individuals were required to achieve a statistically significant effect, assuming a moderate effect size ($eta_p^2 = .10$) with a statistical power of 80% and a chance of committing a Type I error of 5% in a repeated measures design where each individual's performance would be measured five times (Campbell & Thompson, 2012). Thus, we recruited 19 healthy volunteers to participate in experiments at five different days; that is, 95 test sessions were run in total ($N_{\text{female}} = 9$; $N_{\text{male}} = 10$). At each day, they performed a visual short-term memory task and experienced one of five different brain stimulation conditions. Participants were between 19 and 30 years old ($M = 23$; $SD = 2.54$). All except for one individual with mixed handedness were right handed (Veale, 2014). Moreover, most of them were undergraduate students ($N_{\text{Undergraduate}} = 10$; $N_{\text{Bachelor's Degree}} = 6$; $N_{\text{Training}} = 1$; $N_{\text{Master's Degree}} = 1$; $N_{\text{PhD}} = 1$) and pursued studies foremost in Social Sciences, for example, Psychology ($N_{\text{Social Sciences}} = 11$; $N_{\text{Medicine}} = 4$; $N_{\text{Humanities}} = 1$; $N_{\text{Natural Sciences}} = 1$; $N_{\text{Technology}} = 1$; $N_{\text{Not a student}} = 1$). The local ethics review board approved this study. All volunteers provided written informed consent in line with the Declaration of Helsinki, and all volunteers were compensated for their participation either with money or student lab tokens.

### 2.2 | Materials and procedures

#### 2.2.1 | Inclusion criteria and demographic data acquisition

Only healthy individuals between 18 and 40 years of age with normal or corrected-to-normal vision who fulfilled the criteria of non-video game players were eligible to participate in this study (Green et al., 2017; Large et al., 2019). All individuals were thoroughly screened for (1) any history of seizures, epilepsy, fainting or traumatic brain injury, (2) any type of metal objects in their body (though retainers and dental fillings were allowed) and (3) residual risk factors, such as a history of surgery on their spine, drug/alcohol or medication intake, tinnitus, pregnancy or sleep deprivation. Only if none of these factors applied to an individual were they allowed to participate in the experiments.

#### 2.2.2 | Task

We developed a visual short-term memory task by means of *Python*'s *Tkinter* library[1] and run it using the *Spyder* IDE[2] on a computer with an AMD AthlonTM II X2 B24 processor (AMD, Sunnyvale, CA, United States) and a 64-Bit Windows 7 operating system (Microsoft, Redmond, WA, United States). Stimuli were presented on a 17″/43 cm monitor (Acer Group, Taiwan) with a refresh

---

[1] https://wiki.python.org/moin/TkInter

[2] https://www.spyder-ide.org/

rate of 60 Hz, whereas participants sat approximately 80 cm distant from this screen on a comfortable chair in a darkened room.

The participants performed the same visual short-term memory task at each day while one of five different brain stimulation protocols was applied simultaneously. The visual short-term memory task comprised a training and two blocks of experimental trials where individuals had to memorise two white shapes that were depicted on a virtual circle (radius of 2.72° of visual angle) either in the left or right visual field, either with or without black shapes as distractors at one of three different exposure durations. In detail, each trial started with the presentation of a blank screen. After 1002 ms, a white fixation cross (.72° × .72° of visual angle) appeared in the centre of the screen. We asked the participants to focus their attention to this fixation cross. After additional 1002 ms, a memory display was depicted. A memory display always contained two unique white shapes and in half of the trials two unique white shapes and four unique black shapes (approximately 2.08° × 2.08° of visual angle). We asked the participants only to memorise white and to ignore black shapes. These shapes could be an ellipse, a diamond, a pentagon, a rhombus, a square, a trapezoid or a triangle. Shapes were depicted at 210°, 270° and 330° in the left or at 30°, 90° and 150° in the right visual field, respectively. But white shapes were presented either only in the right or left visual field. After 66.8, 100.2 or 133.6 ms, a memory display was substituted by a mask display. This comprised white squares at each location where a shape could have been presented with random black polygons depicted on them (2.29° × 2.29° of visual angle). After another 501 ms, the participants were instructed to report which shapes they memorised by pressing keys marked with the corresponding shapes. Therefore, we marked keys with luminescent stickers. Thus, an ellipse was glued on key “f”, a diamond on key “g”, a pentagon on key “h”, a rhombus on key “j”, a square on key “v”, a trapezoid on key “b” and a triangle on key “n”, respectively. These stickers served as a reference guide.

Thus, the participants were not required to learn button-to-stimulus response mappings. The participants were not supposed to guess. They were allowed to refrain and could indicate between one and two shapes. There was no response time limit. The participants started the next trial by pressing the space key. For a visualisation of the task, see Figure 1. One training comprised 24 trials. Training trials differed from experimental ones by providing feedback after each response: if the participants refrained or indicated at least one incorrect shape during a training, a black “X” (.93° × .93° of visual angle) was presented in the centre of the screen for 501 ms after the space key had been pressed. But this was not the case during the experiment. Individuals were allowed to conduct up to two trainings at the first day and one training on each following testing session. Then, the participants performed two blocks of 252 experimental trials, that is, 504 experimental trials in total. There were 21 unique combinations how shape stimuli could have been paired in a memory display (e.g. ellipse and square). These pairs could then either be presented in the left or right visual field and either on their own or with four additional black distracting shapes. To ensure that each shape was equally often presented at each position in the visual field, target pairs were displayed according to three conditions in each visual field both in normal and reversed order, for example, ellipse at the upper and square at the lower position of the left visual field, and vice versa. Thus, there were 504 possible memory display combinations (42 shape pairings [normal and reversed order] distributed across six location conditions [three in both visual fields] and presented either on their own or with distractors). Presenting each memory display at each exposure duration would have resulted in 1512 experimental trials. On average, individuals would have worked for 3 h on this task. Moreover, individuals would have undergone approximately 3 h of brain stimulation—which we considered unreasonable. Therefore, memory displays were randomly but evenly associated with exposure durations. Thus, all participants performed 252 trials where memory displays had been presented with targets in either the left or right visual field and with or without distractors at each testing session, respectively. Moreover, all participants performed 168 trials where memory displays had been presented at 66.8, 100.2 or 133.6 ms. Note that the trial number of each condition (e.g. memory displays with targets presented in the left visual field without distractors at the longest exposure duration) differed slightly within and between individuals and between testing sessions given that exposure durations were randomly assigned to memory displays. Crucially, these differences were not significant.[3] Thus, potential performance differences across conditions were unlikely related to different numbers of trials of experimental conditions. Furthermore, the order of memory displays was always random. Thus, the participants were not able to anticipate either the identity or location of target shapes or the condition or exposure duration of a memory display.

The participants had sufficient opportunities to make breaks. This was because, firstly, there was no response time limit but a new trial was started by pressing the space key. Secondly, we asked the participants to make a

---

[3] Please review the **Task** section of our supporting information for more details on conditional trial distributions.

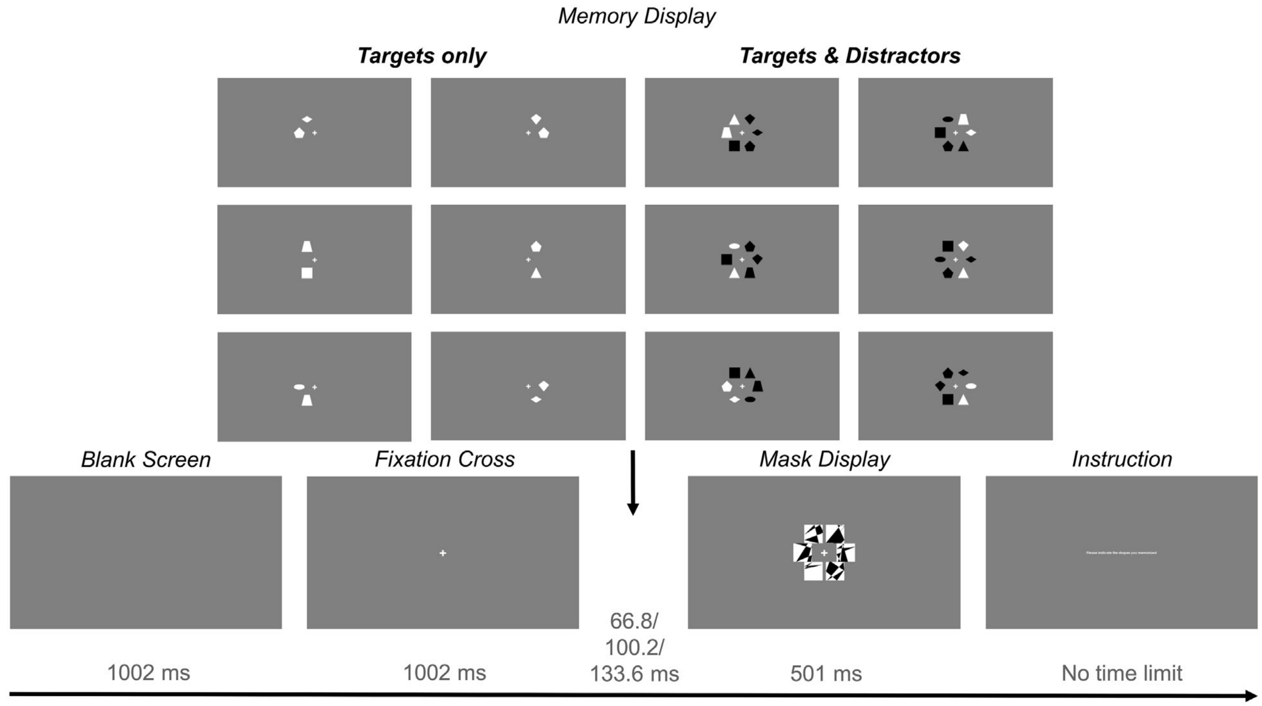

**FIGURE 1** Participants performed a visual short-term memory task where they memorised white shapes depicted on an invisible circle either in the left or right visual field, either with or without black shapes as distractors at one of three different exposure durations. There were always two white shapes regardless of memory display condition. Memory displays were subsequently masked by white squares with random black polygons depicted on them to prevent afterimages. At the end of each trial, the participants were asked to indicate which shapes they memorised by pressing keys on a regular keyboard marked with corresponding shapes. There was no response time limit. Each new trial was initiated by pressing the space key. At the onset of each trial, a blank gray screen was shown. After 1002 ms, a white "+" was depicted in the centre of the screen to which the participants were supposed to focus their gaze to. After 1002 ms, a new memory display was shown.

longer break between experimental blocks. No brain stimulation was applied during these longer breaks.

## 2.3 | Theory of visual attention cognitive functions

### 2.3.1 | Parameter value estimation

We operationalised visual short-term memory capacity ($K$), visual speed of information processing ($C$), a temporal threshold for conscious information processing (effective exposure duration; $t0$), top-down control ($\alpha$) and visuospatial attentional processing (*spatial bias*) by means of a computational modelling approach based on TVA (Bundesen et al., 2015; Dyrholm et al., 2011; Kyllingsbæk, 2006). Parameter values reflecting these cognitive functions were estimated based on performance in different task conditions using maximum likelihood method.

$K$ parameter values (visual short-term memory capacity) were computed from accuracy data in response to memory displays presented at different exposure durations and based on different set sizes using a mass function as described in Equation (1) (Dyrholm et al., 2011; Kyllingsbæk, 2006). Hereby, $i$ indicates an individual, $j$ the number of items that may be memorised, $n$ the total number of items presented in the visual field and $P$ the probability for memorising $j$ items.

$$K_i = \sum\nolimits_{j=1}^{n} P(j) \times j \tag{1}$$

$C$ and $t0$ parameter values (speed of information processing; effective exposure duration) were computed from accuracy data in response to memory displays presented at different exposure durations as well (Dyrholm et al., 2011; Kyllingsbæk, 2006). The idea underlying the modelling approach of these three parameters is that the number of memorised items should increase exponentially as a function of exposure duration: the longer the exposure duration, the easier the encoding, the more likely targets may be memorised.

Thus, the probabilities $P$ for memorising $j$ items depend on how many items $j$ had been correctly recalled at each exposure duration (but see, Dyrholm et al. [2011], for more information on this relationship). Consequentially, the asymptotic level of this function indicates the visual short-term memory capacity, *K*; its starting point the minimum exposure duration required for conscious information processing, *t0*; and the gradient parameter of its slope line visual speed of information processing, *C*. Temporal precision is crucial here. Thus, we applied masks to prevent visual afterimages. On top of that, we controlled for temporal imprecision related to operations run on non-real time operating systems by computing the mode value of distributions of difference values between predicted and observed time delays between stimuli applying the *default_timer* function of *Python*'s *timeit* library.[4] Thus, we corrected for temporal imprecision by adding respective mode difference values to the predicted exposure durations. Consequentially, 66.8, 100.2 and 133.6 ms were changed to 71.2, 106.8, and 126.8 ms for computational modelling (see Hilla et al. (2020) for a similar approach).

TVA $\alpha$ parameter values (top-down control) were computed from differences in accuracy data in response to trials where either only targets or targets and distractors had been displayed in memory displays, see Equation (2) (Dyrholm et al., 2011; Kyllingsbæk, 2006). An individual *i* with high top-down control should allocate attention resources *w* stronger to targets than distractors resulting in a larger ratio between the two conditions as compared to an individual *i* with lower top-down control. Thus, $\alpha$ values range between 0 and 1 with 0 indicating high top-down control and 1 similar attentional weighting in both conditions. We then applied a log10-transformation on $\alpha$ values after adding 1 as a constant to enable linear comparisons. As a result, $\alpha$ values ranged between 0 and .30 with 0 suggesting high and .30 low top-down control.

$$\alpha_i = \frac{w_{\text{distractors}_i}}{w_{\text{targets}_i}} \tag{2}$$

TVA *spatial bias* values were computed from differences in accuracy data in response to targets presented at different spatial locations in memory displays (Dyrholm et al., 2011; Kyllingsbæk, 2006). Hereby, attentional weights *w* were estimated for every position depending on how well the participants responded to these spatial locations. We then put the attentional weights of stimuli presented in the left visual field in relation to those displayed in the right to compute a *spatial bias*, see Equation (3). Hereby, *i* indicates an individual and *w* an attentional weight of either the left (*j*) or right (*k*) visual field. Values > .5 indicate a leftward and values < .5 a rightward *spatial bias*.

$$\textit{Spatial Bias}_i = \frac{\sum_{j=1}^{3} w_{ji}}{\sum_{j=1}^{3} w_{ji} + \sum_{k=1}^{3} w_{ki}} \tag{3}$$

### 2.3.2 | Differential model assumptions: balanced vs. biased visuospatial attentional processing

TVA parameter values may be estimated under the assumptions that attentional resources are either distributed homogeneously, that is, *balanced*, or *biased* in the visual field. In theory, healthy individuals' performances should fit well to a *balanced* model given that they should be able to allocate attentional resources homogeneously in the visual field. Nevertheless, it has also been frequently reported that healthy individuals display a visuospatial bias (Brooks et al., 2014). Thus, their performance may be fit to both model assumptions.

However, such model fit assumptions may impact on TVA parameter estimation beyond attentional resource allocation resulting in divergent parameter estimates. *K* parameter estimation, for instance, depends on set sizes of memory displays (Dyrholm et al., 2011; Kyllingsbæk, 2006). Given a *balanced* model, probabilities *P* for memorising *j* items may be computed based on the assumption that individuals memorise up to two targets irrespective of their spatial location in the visual field. In contrast, provided a *biased* model, these probabilities *P* may be computed based on the assumptions that targets had been presented at six different locations and either with or without distractors. Consequentially, probabilities *P* might be largest for memorising 0, 1 or 2 items given a *balanced* model, whereas they may be largest for memorising more than two items provided a *biased* model. Thus, *K* parameter values may be overestimated given a *biased* as compared to a *balanced* model. Furthermore, for similar reasons TVA $\alpha$ parameter value estimates might differ depending on model assumptions. These are computed based on performance in response to memory displays with targets only as compared to targets and distractors. Given a *balanced* model, combinations of these conditions (e.g., targets presented at six different spatial locations) may be neglected. In contrast, provided a *biased* model, attentional weighting towards targets presented at different spatial locations and either with or without distractors is accounted for. Thus, $\alpha$ estimates might diverge. Therefore, we conducted a series of control analyses to determine which

---

[4] https://docs.python.org/3.7/library/timeit.html

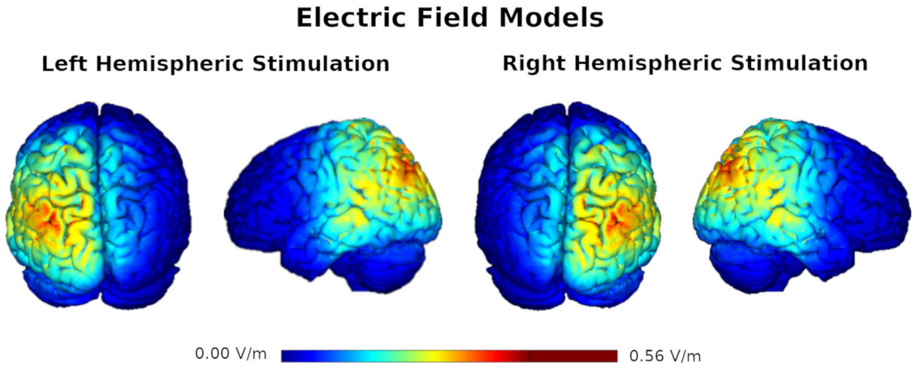

**FIGURE 2** Electric field model(s). (left side) Simulation of an electric field generated in the left hemisphere by mounting a stimulation electrode at P3 and return electrodes at Oz, Cz and T7, respectively. (right side) Simulation of an electric field generated in the right hemisphere by mounting a stimulation electrode at P4 and return electrodes at Oz, Cz and T8, respectively. The magnitude of the electric field is indicated in $|E|$.

estimates (based on a *balanced* or *biased* model) should be used for further analyses.[5]

As a result, we chose to use TVA estimates based on the *biased* TVA model because individuals' performances fit best to this model (as determined based on *AICc* values). However, there were three exceptions: (1) *K* parameter estimates were based on the *balanced* model because they appeared to have been overestimated based on the *biased* model; (2) data of three testing sessions fit better to the *balanced* than the *biased* model; and (3) there were five cases where the deviation between estimates given a *biased* and a *balanced* model were unreasonably large because of extreme values of the *biased* model (two cases for *t0* and three cases for *C* estimates). Therefore, we substituted these estimates by estimates of the *balanced* model.

### 2.3.3 | Brain stimulation

We used a NE® starstim tACS device (Neuroelectrics®, Barcelona, Spain) and four electrodes mounted in a neoprene cap to apply tACS *online* at 2000 μA (zero-to-peak intensity). There were five different stimulation conditions: *Condition 1*: 10-Hz stimulation applied to the left PPC; *Condition 2*: 10-Hz stimulation applied to the right PPC; *Condition 3*: 16.18-Hz stimulation applied to the left PPC; *Condition 4*: 16.18-Hz stimulation applied to the right PPC; and *Condition 5*: sham stimulation applied over the medial superior parietal cortex. *Online* means that the stimulation was applied throughout the whole time while participants performed the task. The stimulation started directly before the participants started performing experimental trials and was stopped after they had performed the last experimental trial. Each stimulation was applied on a different day. Hereby, we determined all possible unique combinations of conditions per day and randomly selected one such stimulation protocol for each participant. Thus, each participant experienced a unique stimulation protocol. There was no indication that either one of the stimulation conditions was applied more frequently on a specific day as compared to other days. Thus, it is rather unlikely that order effects confounded our data. For left hemispheric stimulation, the stimulation electrode was mounted at electrode site P3, and return electrodes were mounted at electrode sites Oz, Cz and T7. In contrast for right hemispheric stimulation, the stimulation electrode was mounted at electrode site P4 and return electrodes were mounted at electrode sites Oz, Cz and T8.[6] As can be inferred from Figure 2, these protocols should have resulted in a fairly focal stimulation of the parietal cortex (Bender et al., 2019; Helfrich et al., 2014; Moliadze et al., 2019; Wolinski et al., 2018). For sham stimulation, the stimulation electrode was positioned at electrode site Cz and return electrodes were mounted at electrode sites P3, Oz and T7. Hereby, a stimulation of 16.18 Hz was ramped up at the onset of experimental trials but ramped down again after 3 s and did not further continue throughout the experiment. After their final session, the participants were informed of the aim of this study and asked to indicate at which day sham stimulation may have been applied. None of the individuals were able to correctly indicate this. Moreover, none of the individuals reported differential sensations during testing sessions. Thus, we are confident that their

---

[5] See **Methods** in supporting information for more details.

[6] For the interested reader, see **Brain Stimulation** in supporting information, for a discussion why alpha-tACS applied at 10 Hz as compared to an individual alpha frequency (IAF) was sufficient for our research purpose.

performance had been unlikely affected by expectation effects.

## 2.4 | Statistical analyses

### 2.4.1 | Model fitting

We computed hierarchical generalised (linear/additive) regression models to test our hypotheses. Hereby, *stimulation condition* (Condition 1 vs. Condition 2 vs. Condition 3 vs. Condition 4 vs. Condition 5), *target position* (left vs. right), *trial type condition* (targets only vs. targets and distractors), *exposure duration* (71.2 ms vs. 106.8 ms vs. 128.6 ms), TVA $K$ (short-term memory capacity), $C$ (speed of information processing), $t0$ (effective exposure duration), $\alpha$ (top-down control), and *spatial bias* (visuospatial attention) parameter values and individuals' *error rate* represented variables of interest.

However, we only analysed $t0$ for exploratory reasons given that we had no strong hypothesis how tACS might impact on this parameter. We determined the significance of a model by comparing its second-order Akaike information criterion (*AICc*) value to the *AICc* value of a reference model. Smaller *AICc* values indicate a better model fit than larger ones. Thus, $\Delta AICc$ values $> 2$ suggest a significant model fit difference (Burnham & Anderson, 2004). For instance, in order to test whether there were differential effects of tACS conditions on TVA speed of information processing, one would compare the *AICc* value of a model comprising *stimulation condition* as predictor variable and TVA $C$ parameter values as criterion variable with the *AICc* value of a model without predictor variable. The latter is also referred to as *intercept* model given that its model fit depends on its mean/intercept value only. If the *AICc* value of the former model was at least two units smaller than the *AICc* value of the latter model, this would indicate that *stimulation condition* explained a significant portion of the variance of TVA $C$ parameter values. In contrast, in order to test whether an interaction between two predictors, for example, *target position* and *exposure duration*, explained a significant portion of a criterion variable, for example, *error rate*, one would need to compare a model comprising both the main effects *target position* and *exposure duration* and the interaction term between *target position* and *exposure duration* to a model comprising only the main effect terms *target position* and *exposure duration*. Thus, it would be possible to disentangle the interaction effect from the main effects. Furthermore, it is possible to introduce random effects to these models. Random effects represent variables that may possibly explain some variance of the criterion variable but are not of primary research interest. For instance, there may be intra-individual differences between testing sessions given that individuals' activity levels may fluctuate or because some are faster learners than others. Introducing these variables, for example, *subject* and *day*, to a model allows to control for their contribution to the dependent variable, meaning that the influence of predictors of interest may be estimated more precisely. This is because, the influence of *stimulation condition* would not only be estimated based on different levels of *stimulation condition* but also depending on individuals' performance in general and the performance displayed at different days. In addition to that, random effects may also be considered for slope estimations in models with metric predictors, for example, with TVA $C$ parameter values as predictor and TVA $K$ parameter values as criterion variables. Thus, the relationship between TVA parameter values would be estimated by allowing for differential relationships for each individual and/or at each day. Importantly, for comparing models with random effects, both the reference model and model of interest need to contain the random effects. Besides that, model fits between different models may be compared to each other to determine which model explains a criterion best.

### 2.4.2 | Bayesian statistics

In addition to that, we computed *Bayes factors* ($BF_{10}$) based on *Bayes information criterion* (*BIC*) values in order to determine how strong the data favoured a model of interest over a reference model using Equation (4) by Wagenmakers (2007). For instance, $BF_{10} = 3$ indicates that data fit three times more likely to a model of interest as compared to the corresponding reference model. However, model fits as operationalised by means of $\Delta AICc$ and $BF_{10}$ values do not necessarily match since *BIC* values are differently penalised than *AICc* values (Stoica & Selen, 2004). Thus, we considered a model fit as significant only if $\Delta AICc > 2$ and $BF_{10} > 1$.

$$BF_{10} = \exp((BIC_{\text{reference}} - BIC_{\text{model of interest}})/2) \quad (4)$$

### 2.4.3 | Post-hoc processing

The range of most plausible estimates of linear regression coefficients was then determined by computing two-tailed confidence intervals whose significance level, $\alpha = .05$, was adjusted by means of *Benjamini-Hochberg* (*BH*) procedure if necessary, see Equation (5)

(Benjamini & Hochberg, 1995).[7] Moreover, the significance of condition-specific smooth terms was determined by means of $F$-test statistics where $p$-values were also corrected by applying the $BH$-procedure if necessary.

$$CI_{BH} = \left[\bar{y} \pm t_{\left(1 - -\frac{\mathrm{rank} \times \alpha}{n_{\mathrm{tests}} \times 2}; n_{\mathrm{observations}} - \left(df_{\mathrm{parametric}} + df_{\mathrm{smooth}}\right) - 1\right)} \times \mathrm{se(y)}\right] \tag{5}$$

The range of most plausible average estimates reported, for example, for descriptive statistical reasons, were determined by computing two-tailed confidence intervals with a significance level of .1%, see Equation (6).

$$CI_{\mathrm{descriptive}} = \left[\bar{y} \pm t_{(1-\frac{\alpha}{2}; n_{\mathrm{observations}} - 1} \times \mathrm{se(y)}\right] \tag{6}$$

### 2.4.4 | Model assumptions and constraints

We controlled for outliers in regression models with smooth terms by applying the *density-based spatial clustering of applications with noise* (*DBSCAN*) algorithm (Ester et al., 1996). Hereby, clusters contained at least five data points, and their radius was constrained to distance values $< Q_3 + 3 * IQR$. We only analysed models further if there were less than 5% outliers.

Moreover, we only reported models if their model fits were significant, $\Delta AICc > 2$ and $BF_{10} > 1$, based on both full data and data without outliers.

Furthermore, we controlled if residuals were fairly symmetrically distributed applying the following procedure: at first, we estimated location and scale parameter values given a normal distribution based on residual values using maximum likelihood method. Then, we determined the frequency of each residual value rounded to the second decimal. Afterwards, we computed the probability of these residual values by dividing these frequencies by the total amount of unique residual values. In a next step, we accumulated these probabilities in an ascending order corresponding to the order of the residual values to model the progression of a cumulative distribution function. Subsequently, we indeed modelled a normal cumulative distribution function based on the location and scale parameter estimates we had acquired using maximum likelihood method. Thus, we were able to determine the most plausible deviation between observed and predicted cumulative probabilities of residual values given a normal distribution assumption using confidence intervals with a significance level of 5% ($CI_{\mathrm{Gauss}}$). We did not determine the model fit based on whether 0 was among these most plausible values. Firstly, this approach would be counter-intuitive to frequentistic testing. Secondly, 0 may be unlikely among the most plausible values the better the model fit given that the corresponding standard error may be small and hence the range of the confidence interval narrow. Alternatively, we will report the size of the range of the most plausible values ($range\ size_{\mathrm{Gauss}}$). There is no rule of thumb which range size indicates a good model fit and thus implies symmetrically distributed residuals. Nevertheless, we believe that a range size of up to 5% may suggest a very good, between 5% and 10% a good, and between 10% and 15% an acceptable fit.

On top of that, we controlled whether residuals were homoscedastic using the following approach: we fitted generalised additive models with $z$-standardised residuals as criterion and $z$-standardised predicted values as predictor variables with random intercepts and slopes for each individual and each day (if applicable) and compared the model fit to a reference model with random intercepts and slopes for each individual and each day (if applicable). If $\Delta AICc > 2$ and $BF_{10} > 1$, we considered a model as problematic and did not report it.

### 2.4.5 | Individuals' performance

We then investigated which stimulation and conditional factors impacted on individuals' performance in the visual short-term memory task the most. For this, we conducted hierarchical regression analyses with *error rate* as criterion variable, and *stimulation condition* (Condition 1 vs. Condition 2 vs. Condition 3 vs. Condition 4 vs. Condition 5), *target position* (left vs. right), *trial type condition* (targets only vs. targets and distractors) and *exposure duration* (71.2 ms vs. 106.8 ms vs. 126.8 ms) as predictor variables with random intercepts for each individual and for each day.

### 2.4.6 | TVA parameter values

Furthermore, we analysed whether different brain stimulation protocols impacted on TVA cognitive functions relative to sham condition by conducting hierarchical regression analyses with $K$ (short-term memory capacity), $C$ (speed of information processing), $t0$ (effective exposure duration), $\alpha$ (top-down control) and *spatial bias* parameter values as criterion variables and *stimulation*

---

[7] Note that we did not consider intercepts for these computations as we were primarily interested in significant differences between conditions.

*condition* (Condition 1 vs. Condition 2 vs. Condition 3 vs. Condition 4 vs. Condition 5) as predictor variable with random intercepts for each individual and for each day.

### 2.4.7 | Associations between TVA parameter values

Moreover, we investigated whether associations between TVA parameter values were differently affected by stimulation condition as compared to sham condition. For this, we computed hierarchical generalised additive models with $K$, $C$, $t0$, $\alpha$ and *spatial bias* parameter values as criterion variable, either one of the remaining parameter values as predictor variable, and *stimulation condition* (Condition 1 vs. Condition 2 vs. Condition 3 vs. Condition 4 vs. Condition 5) as grouping variable with random intercepts and slopes for each individual. We also conducted these analyses with *day* (1 vs. 2 vs. 3 vs. 4 vs. 5) as grouping variable. If the latter model fits were significant, we did not include *day* as a random effect variable.

### 2.4.8 | Software

Data analyses were conducted using *R* (R Core Team, 2022; Version 4.2.2). Data were (pre-)processed using the *dplyr* and *tidyr* packages (Wickham, 2021; Wickham et al., 2021). Binomial tests were conducted using the *rstatix* package (Kassambara, 2021) (see supporting information for application examples).

Regression models were fit and processed by means of the *mgcv* and *tidymv* packages (Coretta, 2021; Wood, 2011). *AICc* values were computed using the *MuMIn* package (Barton, 2020). To employ outlier detection, we used the *dbscan* and *factoextra* packages (Hahsler et al., 2019; Kassambara & Mundt, 2020). To estimate location and scale parameters of a normal distribution using maximum likelihood method, we applied the *optim* algorithm of *R*'s *stats* package (R Core Team, 2022). For data visualisation, we used the *ggplot2*, *patchwork*, *RColorBrewer*, and *kableExtra* packages (Neuwirth, 2014; Pedersen, 2020; Wickham, 2016; Zhu, 2021).

## 3 | RESULTS

### 3.1 | Individuals' performance

Individuals' performance was best explained by a model comprising *target position*, *trial type condition* and *exposure duration* as interaction term with random intercepts for each individual and each day irrespective of the stimulation protocol ($\Delta AICc = 69.54$, $BF_{10} > 100$, $CI_{\text{Gauss}} = [.00; .02]$, $range\ size_{\text{Gauss}} = 1.63\%$).[8] On average, they displayed the lowest mean error rate of between 1.67 and 7.97% in response to targets presented in the right visual field without distractors at the longest exposure duration. Their mean error rate was on average between .36 and 5.69% larger in response to memory displays with distractors. Moreover, their mean error rate was on average between 1.50 and 7.13% larger in response to memory displays presented at the shortest exposure duration. In addition to that, their mean error rate increased further by on average between 5.29 and 13.93% if targets had been presented in the left visual field at the shortest exposure duration. All remaining effect terms were unlikely to contribute to explaining individuals' performance as the respective confidence intervals contained 0, see Table 1. For a visualisation of these effects, see Figure 3.

### 3.2 | TVA parameter values

Only the model with *spatial bias* values as criterion variable and *stimulation condition* as categorical predictor variable with random intercepts for each individual and each day reached significance ($\Delta AICc = 4.19$, $BF_{10} = 2.22$, $CI_{\text{Gauss}} = [.01; .03]$, $range\ size_{\text{Gauss}} = 1.99\%$). Individuals' spatial bias values ranged on average between .04 and .35 in the sham condition. Thus, the participants seemed to have deployed attentional resources stronger to the right visual field given that spatial bias values $< .5$ indicate a rightward and values $> .5$ a leftward bias. Interestingly, only tACS applied to the left PPC at alpha frequency (10 Hz) modulated this effect as individuals' spatial bias values were on average between .02 and .18 values larger in Condition 1 as compared to Condition 5. Thus, left hemispheric alpha-tACS applied to the left PPC appeared to have caused a reduction of a rightward spatial bias towards more balanced attentional processing in the majority of subjects. For a visualisation of this effect, see Figure 4.[9]

### 3.3 | Associations between TVA parameter values

Moreover, only the model comprising $\alpha$ values as criterion variable and *spatial bias* values as predictor

---

[8] $\Delta AICc$ and $BF_{10}$ values were computed in comparison to $AICc$ and $BIC$ values of two different second best models.

[9] For a visualization of the impact of all tACS protocols on *spatial bias* values, see **Results** in supporting information.

**TABLE 1** Generalised linear model with error rate as criterion and target position (left vs. right), trial type condition (targets only vs. targets and distractors) and exposure duration (71.2 ms vs. 106.8 ms vs 126.8 ms) as predictors and subject and day as random effects.

| Regression coefficients | Lower bound | Upper bound |
|---|---|---|
| Target position (left) × exposure duration (71.2 ms) | .05289 | .13931 |
| Exposure duration (71.2 ms) | .01504 | .07130 |
| Trial type condition (targets and distractors) | .00362 | .05687 |
| Target position (left) × trial type condition (targets and distractors) × exposure duration (71.2 ms) | −.00334 | .09879 |
| Trial type condition (targets an distractors) × exposure duration (71.2 ms) | −.00658 | .06308 |
| Target position (left) × trial type condition (targets and distractors) | −.01011 | .05745 |
| Target position (left) × exposure duration (106.8 ms) | −.01057 | .05517 |
| Trial type condition (targets and distractors) × exposure duration (106.8 ms) | −.00999 | .05415 |
| Target position (left) × trial type condition (targets and distractors) × exposure duration (106.8 ms) | −.02975 | .05891 |
| Exposure duration (106.8 ms) | −.01530 | .02810 |
| Target position (left) | −.01538 | .02717 |

*Note*: Lower/upper bound: Benjamini–Hochberg-corrected confidence interval boundaries.

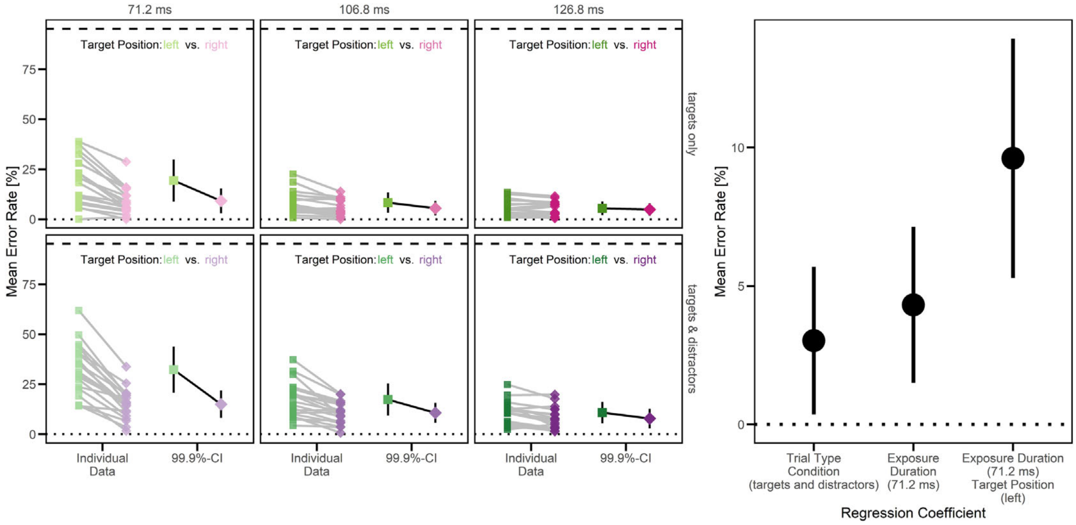

**FIGURE 3** Individuals' performance. Performance was operationalised by (mean) error rate. Individuals' error rates in response to stimuli presented at different positions in the visual field (left vs. right), without and with distractors (targets only vs. targets and distractors) and at different exposure durations (71.2 ms vs. 106.8 ms vs. 126.8 ms) are illustrated by different colours, shapes, luminance and transparency values. Target position contrasts are indicated by green squares and pink diamonds; trial type condition contrasts by differences in luminance; and exposure duration contrasts by different levels of transparency. The black dashed line indicates *P* (at least one incorrect). (left panel) Individuals' mean error rate in each condition averaged over stimulation conditions and corresponding 99.9% confidence intervals. (right panel) Regression coefficients: individuals' error rate increased in response to memory displays with distractors and in response to memory displays presented at the shortest exposure duration—in particular if targets had been presented in the left visual field. Dots indicate averages, and whiskers Benjamini–Hochberg-corrected confidence intervals.

variable with random intercepts and slopes for each individual reached significance when fit for each *stimulation condition*, separately ($\Delta AICc = 10.76$, $BF_{10} > 100$, $CI_{\text{Gauss}} = [-.01;\ .12]$, $range\ size_{\text{Gauss}} = 12.27\%$). Hereby, all conditional fits were significant, $ps_{BH} < .001$. As can be inferred from Figure 5, there appeared to be a linear association between the two variables in Condition 5 (sham condition). This indicates that on average individuals allocated attentional resources stronger to targets than distractors if presented in the right visual field than the left one at the baseline. Interestingly, there were very similar trajectories describing the association between the two variables for each brain stimulation condition. Thus, tACS

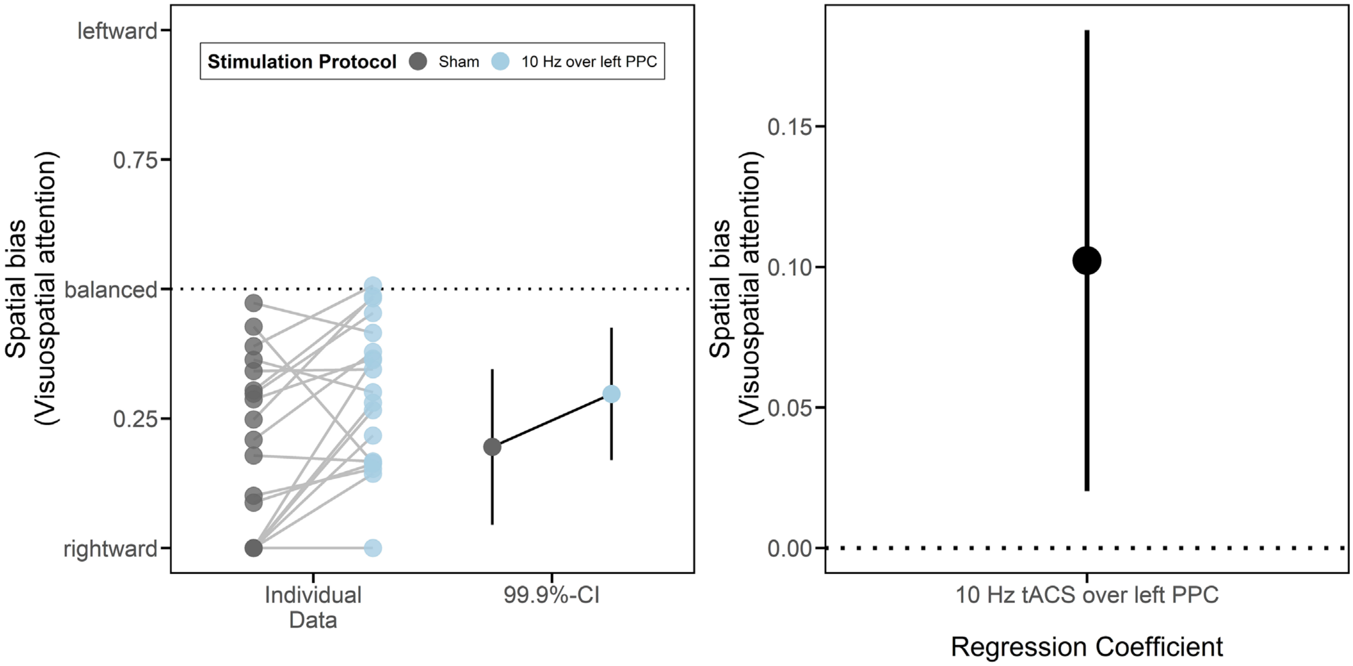

**FIGURE 4** Effect of transcranial alternating current stimulation (tACS) at alpha frequency (10 Hz) on theory of visual attention *spatial bias* values. Values between 0 and .5 indicate a rightward, and between .5 and 1 a leftward *spatial bias*. Individuals' *spatial bias* values during sham stimulation served as baseline and are indicated as dark grey dots. Individuals' *spatial bias* values during alpha-tACS applied to the left posterior parietal cortex (PPC) are visualised as light blue dots. (left panel) Individuals' *spatial bias* values and corresponding 99.9%-confidence intervals. (right panel) Significant main effect of 10 Hz-tACS over left PPC: on average, individuals' *spatial bias* values were < .5 in the sham condition, and larger after 10 Hz-tACS had been applied over the left PPC in most of the individuals. Thus, alpha tACS to the left PPC seemed to have reduced most individuals' rightward *spatial bias* compared to baseline. The dot indicates the average, and whiskers the Benjamini–Hochberg-corrected confidence interval.

unlikely or just weakly modulated this association. Similar effects were found when grouped by *day*, see supporting information.

## 4 | DISCUSSION

The aim of this study was to demonstrate that modulating (right hemispheric **[H4]** [Hung et al., 2005; Kraft et al., 2015; Moos et al., 2012]) posterior parietal alpha activity using tACS may affect individuals' speed of information processing **(H1)** (Hilla et al., 2020) and short-term memory capacity **(H3)** (Finke et al., 2005) by impacting on their attentional control functions **(H2)** (Bavelier & Green, 2019; Helfrich et al., 2014; Kemmerer et al., 2022; Riddle et al., 2020; Sauseng et al., 2009; Vogeti et al., 2022). However, the participants displayed similar speed of information processing and short-term memory capacity regardless of stimulation condition. In addition to that, alpha-tACS applied over individuals' *left* but not right PPC impacted on their visuospatial attention orientation. Thus, our data support **H2** but not **H1**, **H3** and **H4**.

### 4.1 | Inter-hemispheric competition and visuospatial attentional processing

We did not expect our participants to attend stronger to the right than the left visual field. In fact, previous research indicated that healthy individuals prevalently demonstrate a visuospatial bias towards the *left* and not the right visual field—a phenomenon established as *pseudoneglect* (Brooks et al., 2014). According to the *activation-orientation hypothesis* (AOH) such an attentional bias may be related to differential hemispheric activation with stronger biases emerging contralateral to the hemisphere with the higher excitation level (Reuter-Lorenz et al., 1990). Thus, *pseudoneglect* might be a consequence of higher excitation in the right as compared to the left hemisphere during visuospatial attentional processing (Siman-Tov et al., 2007). In line with this, Loftus and Nicholls (2012) showed that individuals exhibited a significant reduction in *pseudoneglect* after anodal (excitatory) transcranial direct current stimulation had been applied to the left PPC. The authors suggested that this effect might be related to inter-hemispheric competition where the imbalance in excitation levels between the

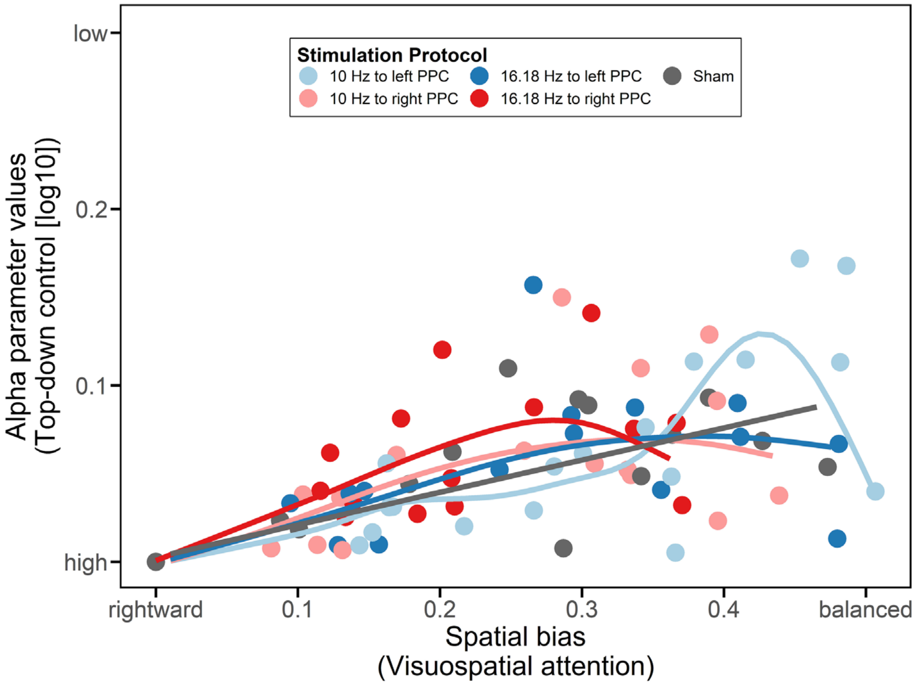

**FIGURE 5** Association between theory of visual attention $\alpha$ (top-down control) and *spatial bias* values (visuospatial attention) in different brain stimulation conditions. $\alpha$ values close to zero indicate high top-down control and close to .30 no differentiation between targets and distractors. *Spatial bias* values < .5 suggest a rightward, and values > .5 a leftward spatial bias. Five different stimulation protocols were applied. Differential hemispheric stimulation is indicated by different colours (left hemispheric tACS: blue, right hemispheric tACS: red). Stimulation frequencies are indicated by different levels of luminance (10 Hz: bright, 16.18 Hz: dark). Sham stimulation is indicated by dark grey dots. Model fits were significant in each condition; and overall, there appeared to be (a tendency for) a linear association between the two variables in all conditions. PPC: posterior parietal cortex.

right and the left hemisphere might have been altered by anodal stimulation analogously shifting attention away from the left and more towards the right visual field.

Thus, the question of why participants in this study demonstrated nevertheless a *rightward* spatial bias needs to be addressed. One explanation for this may be an imbalance in alpha power between hemispheres. Alpha brain oscillatory activity is widely considered as a neural substrate of visuospatial attentional processing provided that lower/larger activity seems to coincide with processing states more/less favourable for information processing in line with the focus of attention, respectively (Jensen & Mazaheri, 2010; Klimesch, 2012; Peylo et al., 2021; Thut et al., 2006). Regarding the AOH (Reuter-Lorenz et al., 1990), one would then expect that attention would be biased towards a visual hemifield contralateral to the hemisphere with the lowest and ipsilateral to the hemisphere with the highest alpha oscillatory activity. Our data partially support this account given that alpha-tACS applied to the left PPC coincided with an attentional shift away from the right visual hemifield. But the question remains why our participants exhibited a rightward and not a leftward visuospatial bias in the sham condition in the first place? One explanation may be that individuals might have demonstrated an increased alpha activity in the right as compared to the left hemisphere during visuospatial attentional processing. In support of this, Gallotto et al. (2020) found that individuals exhibited a larger alpha power in the right as compared to the left hemisphere in neutral conditions while performing a spatial orientation task. This implies that individuals may display an imbalance in hemispheric alpha activity even in conditions where attention is not cued towards one particular hemifield. Furthermore, individuals displayed larger differences in alpha activity between neutral and cued trials in the left as compared to the right hemisphere. This indicates that there may be a larger potential for alpha power modulation in the left than the right hemisphere. Thus, our participants' visuospatial attention bias towards the right visual field might have been driven by a larger alpha activity in the right hemisphere. Moreover, this effect may only have been altered by left hemispheric alpha-tACS application provided that there may have been a larger propensity for modulation in the left hemisphere. However, further research on alpha oscillatory activity during this task execution will be required to test these hypotheses.

## 4.2 | Association between TVA spatial bias and $\alpha$ values

Furthermore, we did not expect a significant relationship between TVA $\alpha$ and *spatial bias* values. This was because Wiegand et al. (2018) demonstrated that TVA visuospatial attentional processing and top-down control were related to distinct electrophysiological mechanisms which implied that these parameters were independent. In contrast, our findings suggest an association between these two parameters such that individuals' ability of target enhancement may be stronger if visuospatial attention was directed to the right visual field. One explanation for this may be that visuospatial attention may be deployed to facilitate target enhancement foremost in challenging conditions. In support of this, we observed that individuals displayed a larger error rate in response to targets presented in the left visual field as compared to the right one in particular if stimuli had been presented at the shortest exposure duration. But their performance was better in response to memory displays with targets only than targets and distractors irrespective of the remaining conditions. This indicates that visuospatial attention rather than target enhancement may be deployed to deal with challenging circumstances, for example, processing information presented at very short exposure duration. Moreover, Shalev et al. (2018) showed that individuals' TVA top-down control could be increased by directing visuospatial attention towards the right visual field using a lateralised sustained attention task.[10] Thus, TVA *spatial bias* and $\alpha$ parameter values may indeed reflect distinct cognitive functions. Nevertheless, these might interact.

## 4.3 | Video gaming effects

If we had been able to demonstrate that modulating alpha activity using tACS impacted on TVA speed of information processing through alterations in attentional control functions, we would have been able to imitate an effect previously observed in video game players, that is, that video game players' faster visual information processing coincided with alpha amplitude modulation (Hilla et al., 2020). Furthermore, this effect would have provided indirect evidence in favour of alpha power modulation potentially representing a causal mechanism of this effect. In addition to that, we would have been able to infer to some extent which attention control function, for example, target enhancement and/or visuospatial attention processing, may have contributed to the effect. On top of that, combined, these effects would have provided indirect evidence in favour of the hypothesis according to which video games may train individuals in learning to deploy attention control such that they may develop efficient cognitive strategies (Bavelier & Green, 2019).

However, we had only been able to show that modulating alpha activity using tACS impacted on individuals' visuospatial attention orientation. Thus, one might conclude from this effect that alpha power modulation might not represent a neural substrate of TVA speed of information processing. In addition to that, one might doubt if alpha power modulation indeed contributed to video game players' faster information processing (Hilla et al., 2020). We believe that such a conclusion may be premature given that we may not have been able to imitate the exact the same neural modulation as observed in video game players using tACS. This is because alpha-tACS rather increases brain oscillatory activity (Helfrich et al., 2014; Kemmerer et al., 2022). In contrast, video game players' faster speed of information processing correlated with alpha amplitude attenuation time-locked to memory display processing (Hilla et al., 2020). The issue here may be not so much that tACS increases brain oscillatory activity (because even opposite effects, that is, slower speed of information processing related to increased alpha activity, would have supported our hypotheses) but rather that alpha-tACS would have been required to alter alpha power modulation specifically related to memory display processing. Hung et al. (2005), for instance, showed that 10-Hz repetitive transcranial magnetic stimulation (rTMS) time-locked to memory displays applied over individuals' right hemispheric PPC altered their TVA top-down control. In this context, rTMS represents a non-invasive brain stimulation method employing a different mechanism to alter brain oscillatory activity as compared to tACS. Nevertheless, both methods appear to induce similar effects (Veniero et al., 2015). Thus, a temporally more precise application of (a different) brain stimulation at alpha frequency may be suitable to impact on TVA speed of information processing via altered TVA top-down control. But further research will be required to prove this hypothesis.

Besides speed of information processing, we expected alpha-tACS to impact on TVA short-term memory capacity $K$. We derived this hypothesis from the observation that short-term memory performance was related to alpha power modulation (Riddle et al., 2020; Sauseng et al., 2009) and TVA speed of information processing and short-term memory capacity commonly correlate (Finke et al., 2005). Moreover, video game players have been frequently shown to demonstrate enhanced

---

[10] However, this effect did only manifest as a result of high-frequency transcranial random-noise stimulation to both hemispheres.

short-term memory processing (Blacker & Curby, 2013; McDermott et al., 2014; Tanaka et al., 2013). Thus, if our results had been in line with our hypotheses (**H1** and **H2**), this may have indirectly implied that alpha power modulation may account for video gaming effects—therefore also for differential short-term memory processing in video game players (Blacker & Curby, 2013; McDermott et al., 2014; Tanaka et al., 2013). However, we had not been successful in establishing such a relationship. We speculate that one explanation for this may be that short-term memory processing may be stronger related to theta oscillatory activity around 5 Hz rather than alpha power (Lisman, 2010; Riddle et al., 2020; Sauseng et al., 2009). For instance, Jaušovec et al. (2014), Bender et al. (2019) and Wolinski et al. (2018) showed that individuals' short-term memory capacity could be increased by means of theta-tACS applied over their PPC. Furthermore, Kraft et al. (2015) found that individuals' TVA short-term memory capacity could be altered by applying 6-Hz rTMS time-locked to memory displays over individuals' right precuneus. Thus, TVA *K* parameter values may be more likely affected by modulating theta as compared to alpha activity. But further research will be required to establish this.

## 5 | CONCLUSION

The aim of this study was to demonstrate that modulating posterior parietal alpha activity using tACS may impact on individuals' speed of information processing by alternating their attentional control functions. If our results had been in line with this, we would have been able to imitate an effect previously observed in video game players, that is, that video game players' faster visual information processing coincided with alpha amplitude modulation (Hilla et al., 2020). Thus, this effect would have indirectly indicated that alpha power modulation might represent a neural substrate of video gaming effects. However, we only managed to change individuals' visuospatial attention orientation by applying tACS at alpha frequency over their left PPC. This indicates that mere alterations in visuospatial attention processing related to alpha oscillatory activity unlikely account for differential cognitive processing as observed in video game players.

## AUTHOR CONTRIBUTIONS

**Yannik Hilla:** Conceptualisation; methodology; project administration; investigation; data curation; formal analysis; visualisation; software; writing–original draft preparation; writing–review and editing. **Fabian Link:** Investigation; data curation. **Paul Sauseng:** Conceptualisation; funding acquisition; methodology; resources; supervision; validation; writing–review and editing.

## ACKNOWLEDGEMENTS

We would like to thank our colleagues Anna Lena Biel, Elisabeth V.C. Friedrich, Charline Peylo and Jörg von Mankowski for their helpful advice to improve our project. Open Access funding enabled and organized by Projekt DEAL.

## CONFLICT OF INTEREST STATEMENT

The authors declare no competing interests.

## DATA AVAILABILITY STATEMENT

Data supporting the findings of this study will be openly available in a repository on Open Science Framework (https://osf.io/rp2n6/).

## ETHICAL STATEMENT

Studies involving human participants were reviewed and approved by the local ethics review board. The participants provided their written informed consent to participate in this study.

## ORCID

*Yannik Hilla* https://orcid.org/0000-0002-4870-7051

## PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/ejn.15968.

## REFERENCES

Barton, K. (2020). *MuMIn: Multi-model inference*. Retrieved from https://CRAN.R-project.org/package=MuMIn

Bavelier, D., Achtman, R. L., Mani, M., & Föcker, J. (2012). Neural bases of selective attention in action video game players. *Vision Research*, *61*, 132–143. https://doi.org/10.1016/j.visres.2011.08.007

Bavelier, D., & Green, C. S. (2019). Enhancing attentional control: Lessons from action video games. *Neuron*, *104*(1), 147–163. https://doi.org/10.1016/j.neuron.2019.09.031

Bavelier, D., Green, C. S., Pouget, A., & Schrater, P. (2012). Brain plasticity through the life span: Learning to learn and action video games. *Annual Review of Neuroscience*, *35*, 391–416. https://doi.org/10.1146/annurev-neuro-060909-152832

Bediou, B., Adams, D. M., Mayer, R. E., Tipton, E., Green, C. S., & Bavelier, D. (2018). Correction: Meta-analysis of action video game impact on perceptual, attentional, and cognitive skills [psychological bulletin]. *Psychological Bulletin*, *144*(9), 978–979.

Bejjanki, V. R., Zhang, R., Li, R., Pouget, A., Green, C. S., Lu, Z.-L., & Bavelier, D. (2014). Action video game play facilitates the development of better perceptual templates. *Proceedings of the National Academy of Sciences*, *111*(47), 16961–16966. https://doi.org/10.1073/pnas.1417056111

Bender, M., Romei, V., & Sauseng, P. (2019). Slow theta tACS of the right parietal cortex enhances contralateral visual working memory capacity. *Brain Topography*, *32*(3), 477–481. https://doi.org/10.1007/s10548-019-00702-2

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B: Methodological*, *57*(1), 289–300.

Blacker, K. J., & Curby, K. M. (2013). Enhanced visual short-term memory in action video game players. *Attention, Perception, & Psychophysics*, *75*(6), 1128–1136. https://doi.org/10.3758/s13414-013-0487-0

Blacker, K. J., Curby, K. M., Klobusicky, E., & Chein, J. M. (2014). Effects of action video game training on visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(5), 1992–2004. https://doi.org/10.1037/a0037556

Brooks, J. L., Della Sala, S., & Darling, S. (2014). Representational pseudoneglect: A review. *Neuropsychology Review*, *24*(2), 148–165. https://doi.org/10.1007/s11065-013-9245-2

Bundesen, C., Vangkilde, S., & Petersen, A. (2015). Recent developments in a computational theory of visual attention (TVA). *Vision Research*, *116*, 210–218. https://doi.org/10.1016/j.visres.2014.11.005

Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. *Sociological Methods & Research*, *33*(2), 261–304. https://doi.org/10.1177/0049124104268644

Cain, M. S., Landau, A. N., & Shimamura, A. P. (2012). Action video game experience reduces the cost of switching tasks. *Attention, Perception, & Psychophysics*, *74*(4), 641–647. https://doi.org/10.3758/s13414-012-0284-1

Campbell, J. I., & Thompson, V. A. (2012). MorePower 6.0 for ANOVA with relational confidence intervals and Bayesian analysis. *Behavior Research Methods*, *44*(4), 1255–1265.

Capotosto, P., Babiloni, C., Romani, G. L., & Corbetta, M. (2009). Frontoparietal cortex controls spatial attention through modulation of anticipatory alpha rhythms. *Journal of Neuroscience*, *29*(18), 5863–5872.

Coretta, S. (2021). *Tidymv: Tidy model visualisation for generalised additive models*. Retrieved from https://CRAN.R-project.org/package=tidymv

Dyrholm, M., Kyllingsbæk, S., Espeseth, T., & Bundesen, C. (2011). Generalizing parametric models by introducing trial-by-trial parameter variability: The case of TVA. *Journal of Mathematical Psychology*, *55*(6), 416–429. https://doi.org/10.1016/j.jmp.2011.08.005

Ester, M., Kriegel, H.-P., Sander, J., & Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. *Kdd*, *96*, 226–231.

Finke, K., Bublak, P., Krummenacher, J., KyllingsbÆk, S., Müller, H. J., & Schneider, W. X. (2005). Usability of a theory of visual attention (TVA) for parameter-based measurement of attention i: Evidence from normal subjects. *Journal of the International Neuropsychological Society*, *11*(7), 832–842. https://doi.org/10.1017/S1355617705050976

Föcker, J., Cole, D., Beer, A. L., & Bavelier, D. (2018). Neural bases of enhanced attentional control: Lessons from action video game players. *Brain and Behavior: a Cognitive Neuroscience Perspective*, *8*(7), e01019. https://doi.org/10.1002/brb3.1019

Föcker, J., Mortazavi, M., Khoe, W., Hillyard, S. A., & Bavelier, D. (2019). Neural correlates of enhanced visual attentional control in action video game players: An event-related potential study. *Journal of Cognitive Neuroscience*, *31*(3), 377–389. https://doi.org/10.1162/jocn_a_01230

Gallotto, S., Duecker, F., Ten Oever, S., Schuhmann, T., De Graaf, T. A., & Sack, A. T. (2020). Relating alpha power modulations to competing visuospatial attention theories. *NeuroImage*, *207*, 116429. https://doi.org/10.1016/j.neuroimage.2019.116429

Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature*, *423*(6939), 534–537. https://doi.org/10.1038/nature01647

Green, C. S., Kattner, F., Eichenbaum, A., Bediou, B., Adams, D. M., Mayer, R. E., & Bavelier, D. (2017). Playing some video games but not others is related to cognitive abilities: A critique of Unsworth et al.(2015). *Psychological Science*, *28*(5), 679–682.

Green, C. S., Pouget, A., & Bavelier, D. (2010). Improved probabilistic inference as a general learning mechanism with action video games. *Current Biology*, *20*(17), 1573–1579. https://doi.org/10.1016/j.cub.2010.07.040

Green, C. S., Sugarman, M. A., Medford, K., Klobusicky, E., & Bavelier, D. (2012). The effect of action video game experience on task-switching. *Computers in Human Behavior*, *28*(3), 984 994–984 994. https://doi.org/10.1016/j.chb.2011.12.020

Hahsler, M., Piekenbrock, M., & Doran, D. (2019). Dbscan: Fast density-based clustering with R. *Journal of Statistical Software*, *91*(1), 1–30. https://doi.org/10.18637/jss.v091.i01

Helfrich, R. F., Schneider, T. R., Rach, S., Trautmann-Lengsfeld, S. A., Engel, A. K., & Herrmann, C. S. (2014). Entrainment of brain oscillations by transcranial alternating current stimulation. *Current Biology*, *24*(3), 333–339. https://doi.org/10.1016/j.cub.2013.12.041

Herrmann, C. S., Strüber, D., Helfrich, R. F., & Engel, A. K. (2016). EEG oscillations: From correlation to causality. *International Journal of Psychophysiology*, *103*, 12–21.

Hilla, Y., von Mankowski, J., Föcker, J., & Sauseng, P. (2020). Faster visual information processing in video gamers is associated with EEG alpha amplitude modulation. *Frontiers in Psychology*, *11*, 3333.

Hung, J., Driver, J., & Walsh, V. (2005). Visual selection and posterior parietal cortex: Effects of repetitive transcranial magnetic stimulation on partial report analyzed by Bundesen's theory of visual attention. *Journal of Neuroscience*, *25*(42), 9602–9612. https://doi.org/10.1523/JNEUROSCI.0879-05.2005

Jaušovec, N., Jaušovec, K., & Pahor, A. (2014). The influence of theta transcranial alternating current stimulation (tACS) on working memory storage and processing functions. *Acta Psychologica*, *146*, 1–6. https://doi.org/10.1016/j.actpsy.2013.11.011

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: Gating by inhibition. *Frontiers in Human Neuroscience*, *4*, 186. https://doi.org/10.3389/fnhum.2010.00186

Kassambara, A. (2021). *Rstatix: Pipe-friendly framework for basic statistical tests*. Retrieved from https://CRAN.R-project.org/package=rstatix

Kassambara, A., & Mundt, F. (2020). *Factoextra: Extract and visualize the results of multivariate data analyses*. Retrieved from https://CRAN.R-project.org/package=factoextra

Kemmerer, S., Sack, A., de Graaf, T., Ten Oever, S., De Weerd, P., & Schuhmann, T. (2022). Frequency-specific transcranial neuromodulation of alpha power alters visuospatial attention performance. *Brain Research*, *1782*, 147834. https://doi.org/10.1016/j.brainres.2022.147834

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, *16*(12), 606–617. https://doi.org/10.1016/j.tics.2012.10.007

Kraft, A., Dyrholm, M., Kehrer, S., Kaufmann, C., Bruening, J., Kathmann, N., Bundesen, C., Irlbacher, K., & Brandt, S. A. (2015). TMS over the right precuneus reduces the bilateral field advantage in visual short term memory capacity. *Brain Stimulation*, *8*(2), 216–223. https://doi.org/10.1016/j.brs.2014.11.004

Krishnan, L., Kang, A., Sperling, G., & Srinivasan, R. (2013). Neural strategies for selective attention distinguish fast-action video game players. *Brain Topography*, *26*(1), 83–97. https://doi.org/10.1007/s10548-012-0232-3

Kyllingsbæk, S. (2006). Modeling visual attention. *Behavior Research Methods*, *38*(1), 123–133. https://doi.org/10.3758/BF03192757

Large, A. M., Bediou, B., Cekic, S., Hart, Y., Bavelier, D., & Green, C. S. (2019). Cognitive and behavioral correlates of achievement in a complex multi-player video game. *Media and Communication*, *7*(4), 198–212. https://doi.org/10.17645/mac.v7i4.2314

Li, R., Polat, U., Scalzo, F., & Bavelier, D. (2010). Reducing backward masking through action game training. *Journal of Vision*, *10*(14), 1–13. https://doi.org/10.1167/10.14.33

Lisman, J. (2010). Working memory: The importance of theta and gamma oscillations. *Current Biology*, *20*(11), R490–R492. https://doi.org/10.1016/j.cub.2010.04.011

Loftus, A. M., & Nicholls, M. E. (2012). Testing the activation–orientation account of spatial attentional asymmetries using transcranial direct current stimulation. *Neuropsychologia*, *50*(11), 2573–2576. https://doi.org/10.1016/j.neuropsychologia.2012.07.003

McDermott, A. F., Bavelier, D., & Green, C. S. (2014). Memory abilities in action video game players. *Computers in Human Behavior*, *34*, 69–78. https://doi.org/10.1016/j.chb.2014.01.018

Mishra, J., Zinni, M., Bavelier, D., & Hillyard, S. A. (2011). Neural basis of superior performance of action videogame players in an attention-demanding task. *Journal of Neuroscience*, *31*(3), 992–998. https://doi.org/10.1523/JNEUROSCI.4834-10.2011

Moliadze, V., Sierau, L., Lyzhko, E., Stenner, T., Werchowski, M., Siniatchkin, M., & Hartwigsen, G. (2019). After-effects of 10 Hz tACS over the prefrontal cortex on phonological word decisions. *Brain Stimulation*, *12*(6), 1464–1474. https://doi.org/10.1016/j.brs.2019.06.021

Moos, K., Vossel, S., Weidner, R., Sparing, R., & Fink, G. R. (2012). Modulation of top-down control of visual attention by cathodal tDCS over right IPS. *Journal of Neuroscience*, *32*(46), 16360–16368. https://doi.org/10.1523/JNEUROSCI.6233-11.2012

Neuwirth, E. (2014). *RColorBrewer: ColorBrewer palettes*. Retrieved from https://CRAN.R-project.org/package=RColorBrewer

Pedersen, T. L. (2020). Patchwork: The composer of plots. Retrieved from https://CRAN.R-project.org/package=patchwork

Perkins, D. N., & Salomon, G. (1992). Transfer of learning. In T. Husén & T. N. Postlethwaite (Eds.), *The international encyclopedia of education* (Vol. 2, pp. 425–441). Pergamon.

Peylo, C., Hilla, Y., & Sauseng, P. (2021). Cause or consequence? Alpha oscillations in visuospatial attention. *Trends in Neurosciences*, *44*(9), 705–713. https://doi.org/10.1016/j.tins.2021.05.004

Pohl, C., Kunde, W., Ganz, T., Conzelmann, A., Pauli, P., & Kiesel, A. (2014). Gaming to see: Action video gaming is associated with enhanced processing of masked stimuli. *Frontiers in Psychology*, *5*, 70. https://doi.org/10.3389/fpsyg.2014.00070

R Core Team. (2022). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Reuter-Lorenz, P. A., Kinsbourne, M., & Moscovitch, M. (1990). Hemispheric control of spatial attention. *Brain and Cognition*, *12*(2), 240–266.

Riddle, J., Scimeca, J. M., Cellier, D., Dhanani, S., & D'Esposito, M. (2020). Causal evidence for a role of theta and alpha oscillations in the control of working memory. *Current Biology*, *30*(9), 1748–1754. https://doi.org/10.1016/j.cub.2020.02.065

Sauseng, P., Klimesch, W., Heise, K. F., Gruber, W. R., Holz, E., Karim, A. A., Glennon, M., Gerloff, C., Birbaumer, N., & Hummel, F. C. (2009). Brain oscillatory substrates of visual short-term memory capacity. *Current Biology*, *19*(21), 1846–1852. https://doi.org/10.1016/j.cub.2009.08.062

Schenk, S., Lech, R. K., & Suchan, B. (2017). Games people play: How video games improve probabilistic learning. *Behavioural Brain Research*, *335*, 208–214. https://doi.org/10.1016/j.bbr.2017.08.027

Shalev, N., De Wandel, L., Dockree, P., Demeyere, N., & Chechlacz, M. (2018). Beyond time and space: The effect of a lateralized sustained attention task and brain stimulation on spatial and selective attention. *Cortex*, *107*, 131–147. https://doi.org/10.1016/j.cortex.2017.09.009

Siman-Tov, T., Mendelsohn, A., Schonberg, T., Avidan, G., Podlipsky, I., Pessoa, L., Gadoth, N., Ungerleider, L. G., & Hendler, T. (2007). Bihemispheric leftward bias in a visuospatial attention-related network. *Journal of Neuroscience*, *27*(42), 11271–11278. https://doi.org/10.1523/JNEUROSCI.0599-07.2007

Stoica, P., & Selen, Y. (2004). Model-order selection: A review of information criterion rules. *IEEE Signal Processing Magazine*, *21*(4), 36–47. https://doi.org/10.1109/MSP.2004.1311138

Strobach, T., Frensch, P. A., & Schubert, T. (2012). Video game practice optimizes executive control skills in dual-task and task switching situations. *Acta Psychologica*, *140*(1), 13–24. https://doi.org/10.1016/j.actpsy.2012.02.001

Tanaka, S., Ikeda, H., Kasahara, K., Kato, R., Tsubomi, H., Sugawara, S. K., Mori, M., Hanakawa, T., Sadato, N., Honda, M., & Watanabe, K. (2013). Larger right posterior parietal volume in action video game experts: A behavioral and voxel-based morphometry (VBM) study. *PLoS ONE*, *8*(6), e66998. https://doi.org/10.1371/journal.pone.0066998

Thut, G., Nietzel, A., Brandt, S. A., & Pascual-Leone, A. (2006). $\alpha$-band electroencephalographic activity over occipital cortex indexes visuospatial attention bias and predicts visual target detection. *Journal of Neuroscience*, *26*(37), 9494–9502. https://doi.org/10.1523/JNEUROSCI.0875-06.2006

Veale, J. F. (2014). Edinburgh handedness inventory–short form: A revised version based on confirmatory factor analysis. *Laterality: Asymmetries of Body, Brain and Cognition*, *19*(2), 164–177. https://doi.org/10.1080/1357650X.2013.783045

Veniero, D., Vossen, A., Gross, J., & Thut, G. (2015). Lasting EEG/-MEG aftereffects of rhythmic transcranial brain stimulation: Level of control over oscillatory network activity. *Frontiers in Cellular Neuroscience*, *9*, 477. https://doi.org/10.3389/fncel.2015.00477

Vogeti, S., Boetzel, C., & Herrmann, C. S. (2022). Entrainment and spike-timing dependent plasticity—A review of proposed mechanisms of transcranial alternating current stimulation. *Frontiers in Systems Neuroscience*, *16*, 827353. https://doi.org/10.3389/fnsys.2022.827353

Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems of p values. *Psychonomic Bulletin & Review*, *14*(5), 779–804. https://doi.org/10.3758/BF03194105

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag. Retrieved from https://ggplot2.tidyverse.org

Wickham, H. (2021). *Tidyr: Tidy messy data*. Retrieved from https://CRAN.R-project.org/package=tidyr

Wickham, H., François, R., Henry, L., & Müller, K. (2021). *Dplyr: A grammar of data manipulation*. Retrieved from https://CRAN.R-project.org/package=dplyr

Wiegand, I., Napiórkowski, N., Töllner, T., Petersen, A., Habekost, T., Müller, H. J., & Finke, K. (2018). Event-related electroencephalographic lateralizations mark individual differences in spatial and nonspatial visual selection. *Journal of Cognitive Neuroscience*, *30*(4), 482–497. https://doi.org/10.1162/jocn_a_01221

Wolinski, N., Cooper, N. R., Sauseng, P., & Romei, V. (2018). The speed of parietal theta frequency drives visuospatial working memory capacity. *PLoS Biology*, *16*(3), e2005348. https://doi.org/10.1371/journal.pbio.2005348

Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society, Series B: Statistical Methodology*, *73*(1), 3–36. https://doi.org/10.1111/j.1467-9868.2010.00749.x

Wu, S., Cheng, C. K., Feng, J., D'angelo, L., Alain, C., & Spence, I. (2012). Playing a first-person shooter video game induces neuroplastic change. *Journal of Cognitive Neuroscience*, *24*(6), 1286–1293. https://doi.org/10.1162/jocn_a_00192

Zhu, H. (2021). *kableExtra: Construct complex table with 'kable' and pipe syntax*. Retrieved from https://CRAN.R-project.org/package=kableExtra

## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Hilla, Y., Link, F., & Sauseng, P. (2023). Alpha-tACS alters attentional control but not cognitive functions as video games do: A psychophysical investigation based on the theory of visual attention. *European Journal of Neuroscience*, *57*(10), 1705–1722. https://doi.org/10.1111/ejn.15968