

**Towards Optimized Methodological Parameters for Maximizing
the Behavioral Effects of Transcranial Direct Current Stimulation**

Tyler Santander^{1,2}, Sara Leslie², Luna J. Li², Henri E. Skinner², Jessica M. Simonson^{1,2}, Patrick
Sweeney², Kaitlyn P. Deen², Michael B. Miller^{1,2}, & Tad T. Brunye^{3,4}

¹ Institute for Collaborative Biotechnologies, University of California, Santa Barbara, Santa Barbara, CA
93106 USA

² Department of Psychological and Brain Sciences, University of California, Santa Barbara, Santa
Barbara, CA 93106 USA

³ U. S. Army DEVCOM Soldier Center, 15 General Greene Ave., Natick, MA 01760 USA

⁴ Center for Applied Brain and Cognitive Sciences, Tufts University, 177 College Ave., Suite 090,
Medford, MA 02155 USA

*Corresponding author: Tad Brunye, tbrunye01@tufts.edu

Funding Statement. This research was sponsored by the U.S. Army DEVCOM Soldier Center under
contract #W911NF-D-19-0001 to the Institute for Collaborative Biotechnologies at the University of
California, Santa Barbara. The opinions expressed herein are those of the authors and do not reflect
those of the United States government. The U.S. government is authorized to reproduce and distribute
reprints for Government purposes notwithstanding any copyright notation herein.

Author Contributions. T.S. and T.T.B. wrote and edited the manuscript. T.S. performed formal
analyses. T.S., S.L., L.J.L., H.E.S., J.M.S., P.S., and K.P.D. performed data acquisition and coding.
M.B.M. and T.T.B. secured funding.

Conflicts of Interest. The authors declare no competing financial interests.

Abstract

Transcranial direct current stimulation (tDCS) administers low-intensity direct current electrical stimulation to brain regions via electrodes arranged on the surface of the scalp. The core promise of tDCS is its ability to modulate brain activity and affect performance on diverse cognitive functions (affording *causal* inferences regarding regional brain activity and behavior), but the optimal methodological parameters for maximizing behavioral effects remain to be elucidated. Here we sought to examine the effects of 10 stimulation and experimental design factors across a series of five cognitive domains: motor performance, visual search, working memory, vigilance, and response inhibition. The objective was to identify a set of optimal parameter settings that consistently and reliably maximized the behavioral effects of tDCS within each cognitive domain. To that end, we surveyed tDCS effects on these various cognitive functions in healthy young adults, ultimately resulting in 721 effects across 106 published reports. Hierarchical Bayesian meta-regression models were fit to characterize how (and to what extent) these design parameters differentially predict the likelihood of positive/negative behavioral outcomes. Consistent with many previous meta-analyses of tDCS effects, extensive variability was observed across tasks and measured outcomes. Consequently, most design parameters did not confer consistent advantages or disadvantages to behavioral effects—a domain-general model suggested an advantage to using within-subjects designs (versus between-subjects) and the tendency for cathodal stimulation (relative to anodal stimulation) to produce reduced behavioral effects, but these associations were scarcely-evident in domain-specific models. Together, these findings highlight the urgent need for tDCS studies to more systematically probe the effects of these parameters on behavior to fulfill the promise of identifying causal links between brain function and cognition.

Keywords: non-invasive brain stimulation, transcranial direct current stimulation, meta-analysis, meta-regression, research methods

Towards Optimized Methodological Parameters for Maximizing the Behavioral Effects of Transcranial Direct Current Stimulation

1. Introduction

Non-invasive brain stimulation (NIBS) involves the introduction of exogenous energy (including magnetic, electrical, or ultrasonic) to cortical and subcortical brain regions to modify neuronal activity and draw causal links between regional brain function, cognition, emotion, and behavior (1-3). Transcranial direct current stimulation (tDCS) is one of the most popular and widely-used NIBS methods, offering the ability to induce transient and subthreshold modulation of neuronal membrane potentials, with downstream consequences for the activity of neuronal populations and neural networks, neuroplasticity, and/or behavior (1, 4). While tDCS is a promising neuromodulatory tool, the precise mechanisms by which it exerts effects on physiology and behavior are still being discovered (1, 2, 5, 6). Emerging mechanistic models suggest that tDCS induces shifts of neuronal membrane potentials; that the nature of this shift (i.e., hyperpolarizing, depolarizing) is related to the orientation of neurons relative to the induced electrical field; that tDCS can induce large-scale oscillatory changes of brain activity; and that lasting after-effects of tDCS are related to changes in synaptic plasticity (6-8). However, much uncertainty still exists about how electrical current propagates through human tissue, which structures are effectively modulated by various electrode montages, how to effectively individualize stimulation protocols, and how various study design features might influence tDCS effects on observed outcomes (1, 4, 9).

Ambiguity regarding tDCS mechanisms of action can make it difficult for researchers to select from myriad methodological parameters when designing experiments. An *a priori* review of related literature can complicate the issue due to heterogeneity of stimulation procedures and observed outcomes across studies, laboratories, and cognitive domains (1, 9, 10). Indeed, published tDCS research varies widely in stimulation methods, study designs, and statistical methods employed; variation along each of these dimensions is likely to shape the effects of tDCS on brain physiology and behavior, and they likely interact in yet unknown ways. Herein we describe a meta-analytic, meta-regression modeling approach intended to provide an initial breadth-first understanding of relationships between methodological parameters employed in tDCS studies and behavioral outcomes across five cognitive domains, focusing only on studies examining healthy, neurotypical participants. We focused our analysis on 10 parameters of interest, including 7 stimulation-specific parameters and 3 experimental

parameters (detailed in **Table 1**). These parameters were selected because they were relatively well represented in the literature across our outcome domains.

The scope of our approach builds upon prior reviews and meta-analyses that are often focused on specific cognitive domains and behavioral outcomes, or alternatively, on specific neural/physiological responses to stimulation. Mixed or otherwise inconclusive patterns of results have been well-characterized across *many* disparate areas of neurostimulation research (11-35). However, the most popular approach to quantifying and describing heterogeneity is—understandably—rather piecemeal. Past studies addressing potential moderating factors (e.g., the polarity of stimulation, or the laterality of a target region) typically either parse out effects for separate analyses (e.g., looking at trends for left vs. right hemisphere stimulation independently, rather than modeling the contrast) or perform meta-regression based on small subsets of features (11-18). Our goal, in contrast, is to consider a wider breadth of tasks, experiment parameters, and domains to explicitly quantify systematic differences in behavioral outcomes associated with these design factors.

Table 1. The 10 independent variables considered under our meta-regression models, including the category, name, and a brief description of each.

Parameter Category	Parameter Name	Description
Stimulation	Target	The intended brain target of the stimulation electrode montage.
Stimulation	Laterality	The laterality of the brain target (i.e., left or right hemisphere, or bilateral stimulation of homotopic regions).
Stimulation	Electrode count	The number of stimulation electrodes used in the experiment, ranging from 2 to 10.
Stimulation	Individualization	Whether the experiment used a standardized or participant-specific electrode montage (i.e., MRI-guided targeting).
Stimulation	Intensity	The raw intensity of stimulation applied, ranging from 0.25 to 5 mA.
Stimulation	Polarity	Whether anodal or cathodal stimulation was applied.
Stimulation	Duration	The duration of stimulation applied, ranging from 5 to 30 minutes.
Experimental	Timing	Whether stimulation was administered prior to or during task execution (or some combination thereof).
Experimental	Session count	The number of stimulation sessions completed by participants, ranging from 1 to 20.
Experimental	Design	Whether the experiment used a within-subjects or between-subjects design.

1.1. Stimulation Parameters

One critical consideration for experimenters is determining the arrangement of electrodes on the

scalp to effectively target a brain region of interest. When doing so, experiments tend to rely upon methods demonstrated as effective in extant research, and/or on results derived from models of predicted current flow (5, 36-39). Researchers typically arrange electrodes on the scalp in reference to an anatomical coordinate system, such as the International 10-20 System (40), and/or based on outcomes from neuronavigation or peak activations identified in functional tests (e.g., motor-evoked potentials). In all cases, the intent is to maximize current density at a brain target believed to be functionally-relevant for a cognitive process or behavioral outcome of interest (41-43). The target brain regions identified in our review included the dorsolateral prefrontal cortex (DLPFC), posterior parietal cortex (PPC), and primary motor cortex (M1), as well as a number of other diverse stimulation targets spanning nearly the whole brain.

The targeted brain regions were variably lateralized, with most reported effects (418 out of 721 total) localized to the left hemisphere and a minority of effects derived through bilateral stimulation of homotopic regions (59 total). When referring to laterality of stimulation, it is typically the case that the anodal electrode is placed over the targeted region (e.g., left DLPFC), and a reference cathodal electrode is placed over the contralateral hemisphere (e.g., right supraorbital area) or on an ipsilateral or contralateral extracephalic area (e.g., shoulder, bicep). While often treated as a relatively trivial decision in practice, it is important to realize that the placement of the cathode likely carries important implications for physiological and behavioral influences of tDCS (44).

Most studies we identified used two saline-soaked sponges, one anode and one cathode, to administer tDCS; other studies used multi-electrode montages that are assumed to provide higher focality and maximize current density at both superficial and relatively medial targets (37). We also found that most studies tended to use a consistent electrode positioning across individuals, whereas a minority used individualized montages based on structural and/or functional magnetic resonance imaging (MRI) scans. Individualized montages are becoming more commonplace and are thought to compensate for varied brain morphology, functional neuroanatomy, and head sizes and shapes (9, 45, 46).

Stimulation procedures often involve a slow ramp-up (e.g., over a 30-second window) to a target intensity, maintaining that peak intensity level for a specific duration (e.g., 20 minutes), and then a slow ramp-down to terminate stimulation (47, 48). Peak stimulation intensity is typically between 0.5-2.0 milliamperes (mA; with the conventional limit being 2 mA) (49), with one meta-analysis demonstrating a mean tDCS stimulation intensity of 1.5 mA when considering studies done in the cognitive domain

(18). Modeling and experimental work suggests that stimulation intensity can have paradoxical, nonlinear effects on neuronal activity and behavioral effects of tDCS (50-52). For example, 1 mA stimulation intensity can produce hyperpolarization whereas 2 mA can produce depolarization of motor neurons (50). One meta-analysis suggests that on the aggregate, higher intensity stimulation (operationalized as current density under the anode) is more likely to benefit task accuracy during DLPFC stimulation (17). In our review, however, we focused primarily on raw stimulation intensity (as opposed to current density) and found studies administering stimulation as low as 0.25 mA intensity and as high as 5 mA.

The duration of peak stimulation intensity is typically between 5-30 minutes (as seen in our review), with one meta-analysis demonstrating an average tDCS stimulation duration of 15.2 minutes when considering studies performed in cognitive domains (18). Some of the nonlinear responses found with stimulation intensity can interact in unexpected ways with stimulation duration. For example, 1 mA of tDCS can induce depolarization during the first 13 minutes of stimulation, but hyperpolarization during a latter 13 minutes of stimulation (53).

A further critical decision point in designing a tDCS study is whether to deliver anodal or cathodal stimulation to the target site. Some mechanistic models of tDCS, namely *sliding scale* models, suggest that stimulation polarity influences whether tDCS can increase or decrease neural activity (1, 5). Specifically, neuronal populations residing in brain regions underlying the anode will experience depolarization, and populations under the cathode will experience hyperpolarization. This simplistic model has been repeatedly challenged (1, 4, 54, 55), but remains as a strong motivator for scientists who compare (experimentally and statistically) anodal versus cathodal stimulation over a target brain region, typically in reference to a sham condition.

Thus, stimulation parameters are variably selected and applied across studies. It is known that variation of certain parameters can elicit unexpected and nonlinear effects on brain physiology and behavior, and it is likely that many of these parameters interact in ways that have yet to be discovered. Here we focus primarily on additive, main effects due to the combinatorial explosion in model parameter space when exploring interactions between our 10 predictors of interest. However, it is still of central interest to uncover how these various factors might jointly-modulate one another in any given neurostimulation experiment.

1.2. Experimental & Statistical Parameters

In addition to stimulation parameters, our model also considered the influence of 3 experimental

design parameters. Across studies, tDCS is variably administered either before task performance (offline), during task performance (online), or a mixture of both (offline-online) (16, 46). Original research and meta-analyses suggest that offline stimulation is more likely than online stimulation to enhance performance on working memory tasks (15, 56, 57), but that the opposite might be true for skill acquisition (58) and visuospatial tasks (59). In our review, we indeed found that offline stimulation was employed more frequently than online stimulation (347 vs. 276 effects, respectively), with comparatively fewer studies using a mixed-timing design. Furthermore, while many studies use a single-session design involving only one (e.g., 20-minute) administration of tDCS during a single visit to the laboratory, some studies involve the repeated administration of tDCS over the course of successive visits. While repeated sessions of tDCS are a common design feature in clinical research and are associated with higher treatment efficacy relative to single-session studies (31, 33, 60, 61), they are used less frequently in studies with healthy neurotypical adults. When such a design is used, it is typically in the context of studies examining the effects of tDCS on cognitive training or skill acquisition paradigms. In general, it is thought that repeated tDCS can facilitate memory consolidation (62, 63), and meta-analyses suggest there may be insufficient evidence to evaluate any potential advantage of repeated- versus single-session tDCS on cognitive function (19).

In tDCS studies, within-participants designs are generally preferred to between-participants design given the inherent challenges associated with inter-participant variation in tDCS experiments, including factors such as the brain's morphology and function, genetic attributes, consumption patterns (e.g., caffeine), menstrual cycle, aptitudes, and other trait-based variables (27, 64). They are also considered the more powerful design for detecting differences among conditions because analyses partition out between-participants variance and reduce error (65). That said, many studies use between-participants designs, typically for scheduling efficiency (tDCS sessions are typically separated by at least 24 hours), to avoid carryover effects, or because the associated large sample size helps afford analyses of individual differences. Some studies balance power, efficiency, and scale by using mixed designs, which include one or more within- *and* between-participants factors. However, estimation of mixed effects, particularly in the context of the models described here (which generally focus on binary comparisons between conditions rather than factorial comparisons), is less straightforward. We therefore focus on studies using *either* a between-subjects or within-subjects design, which were represented fairly equivalently across the domains considered in our review.

1.3. Performance Domains

The meta-analytic model was designed to understand how the 10 stimulation and experimental parameters are associated with performance outcomes across 5 cognitive domains, including vigilance, working memory, visual search, response inhibition, and motor performance. We chose these five domains because they have all received considerable attention in the scientific literature and exhibit variability in the brain regions targeted, the stimulation methods, and/or the experimental and statistical methods employed. Moreover, and perhaps most importantly, these 5 domains tend to underlie performance in many applied settings of interest including driving, aviation, and military.

Vigilance refers to a sustained focus of attention on stimulus detection tasks over lengthy periods of time (66-68), such as when continuously monitoring a radar screen. Maintaining vigilance is stressful and places high demands on attentional resources, resulting in vigilance decrements (i.e., reduced detection of critical stimuli) over time (68, 69). Given its reliance on arousal and alertness, sustained attention, and information processing, many brain systems have been implicated in vigilance performance. These include the prefrontal cortex, reticular formation, thalamus, and basal forebrain cholinergic system (70). In general, anodal tDCS targeting the DLPFC appears to reduce vigilance decrements (71, 72), though one study showed that the same tDCS increased the rate of mind wandering during a vigilance task (73). From our review of the literature, we included 93 effects derived from tDCS experiments on vigilance, primarily involving DLPFC stimulation.

Working memory refers to mechanisms responsible for temporarily storing, processing, and manipulating task-relevant information in memory (74, 75). Working memory plays a pervasive role in daily life and is a critical process underlying performance on planning, reasoning and problem solving, and decision-making tasks (76-79). It has also been a topic of interest among cognitive neuroscientists interested in mapping working memory processes to brain regions and networks, which has found strong evidence that the lateral prefrontal cortex is involved in the temporary maintenance of task-relevant information, and that the distribution of brain activity across widespread networks is dependent on many task-related parameters such as the sensory modality being used (e.g., visual, auditory), the nature of stimuli (e.g., verbal, spatial, motor, faces) being maintained or manipulated, and whether the information is retrospective or prospective (80). In general, the prefrontal cortex appears to be a critical node in a distributed working memory network that coordinates the involvement of other brain regions more specialized in specific functions (e.g., sensory, representational, and action-related) (81). The effects of tDCS on working memory performance have engendered some debate in the scientific literature, with some meta-analyses suggesting improvement of working memory (in accuracy or response times) with

anodal tDCS targeting the left or right DLPFC (13-15, 17), and another meta-analysis suggesting no evidence for improvement (19). From our review of the literature, we included 115 effects of tDCS on working memory, also primarily involving PFC stimulation.

Visual search refers to the process of finding a visual target among distractors, and is typically assumed to involve interactions between preattentive processing and focal attention (82-84). Visual search is extremely common in applied and daily tasks, such as searching for a weapon in luggage, finding lung nodules on a radiograph, identifying suspects in a crowd, or simply finding a matching pair of socks (83). It also recruits a wide range of brain regions including ventral and dorsal regions of the prefrontal cortex (and frontal eye fields; FEF) (85), multiple areas of the parietal cortex (86), and the occipital cortex (87). Studies suggest that anodal and cathodal tDCS over the left FEF can improve target detection during a visual search task (88), that cathodal stimulation of the right posterior parietal cortex (but not FEF) can reduce the benefits of practice in a visual search task (89), and that anodal stimulation of the right inferior frontal or posterior parietal cortex can enhance performance on a task involving searching for threats in complex scenes (90, 91). From our review of the literature, we included 176 tDCS effects on visual search, primarily involving PFC and parietal stimulation.

Inhibitory control refers to the ability to suppress thoughts or behaviors that are not relevant or conducive to task performance, and is considered a critical executive function that enables adaptive behavior (92, 93). Response inhibition enables the adaptive control of cognitive processes and motor behavior, and failure of response inhibition is thought to underlie both clinical and subclinical impulsivity (94). In applied and daily tasks, response inhibition enables people to inhibit prepotent behavioral responses across a range of settings—such as firing or not firing a weapon (95), swinging or not swinging a baseball bat (96), or not eating a second piece of cake (97). Dominant theories of inhibitory control emphasize the role of several regions of the prefrontal cortex, including the dorsolateral, inferior, and orbital frontal cortex (98, 99). While some debate exists regarding the modular versus distributed roles of prefrontal brain regions in inhibitory processes (100), particular emphasis has been given to the right inferior frontal gyrus given results of functional neuroimaging, lesion, and transcranial magnetic stimulation (TMS) studies (98, 101). With tDCS, a recent meta-analysis demonstrated generally small but significant effect of tDCS on inhibitory control outcomes (including go-/no-go task and stop-signal task), especially with right inferior frontal gyrus stimulation (12). From our review of the literature, we included 84 effects on inhibitory control, primarily involving PFC stimulation.

Finally, motor performance here refers to the process of acquiring new abilities to perform novel sequences of skilled behaviors to accomplish a goal, from typing on a keyboard to riding a bike. Acquiring a new skill relies upon experience-dependent neuroplasticity in the brain, often tied to practice and consolidation (102, 103), which can occur over the course of hours, days, or weeks (104). Neuroplastic changes associated with motor skill acquisition are often considered the locus of the primary motor cortex (102, 105, 106). In addition to the motor cortex, the cerebellum has received attention due to its potential involvement in the initiation of limb movements and the improvement of motor skills (107-110). Studies using tDCS to influence motor skill acquisition variably target the primary motor cortex and cerebellum. Reviews and meta-analyses suggest that anodal tDCS targeting the primary motor cortex can improve motor learning and motor function (111), and both anodal and cathodal tDCS targeting the cerebellum can accelerate motor learning, motor adaptation, and procedural learning (11). This domain represented the largest in our survey of the literature, spanning 253 effects related to motor and procedural skill acquisition.

2. Methods

2.1. Study Search & Selection

A literature search was performed by authors S.L. and P.S. using PsycINFO, PubMed, Google Scholar, and the tDCS Database (<http://tdcsdatabase.com/>). The key search terms were [tDCS] or [HD-tDCS] in combination with any of the following domain-specific terms: [motor skill], [motor learning], [procedural learning], [implicit learning], [skill learning], [working memory], [vigilance], [endurance], [visual search], and [inhibition]. Unions of key terms (using the AND function) were queried using the options for All Fields or Any Field for three of the selected databases (PubMed, PsycINFO, and the tDCS Database); when searching Google Scholar, key search terms were queried in the full text, and due to the high search yield only the first 300 results were included for screening. Searches were not restricted by publication date.

Because we sought to model specific effects of experimental design parameters on behavioral performance outcomes, we applied strict inclusion criteria to narrow down relevant studies. Beyond the basic requirement of publication in a peer-reviewed scientific journal, these included: 1) no studies focused exclusively on minors, older adults, or individuals with neuropsychiatric conditions (we extracted *only* effects related to healthy younger adults in studies based on these comparisons); 2) application of tDCS and not tACS/tRNS (although again, in cases where these were compared, we

extracted *only* tDCS-related effects); 3) ability to extract simple within-subject or between-subject effects; 4) binary comparisons between either anodal or cathodal stimulation vs. sham stimulation (i.e., no anodal vs. cathodal comparisons, or comparisons between active stimulation conditions across different intensities); 5) stimulation targeted over a specific brain region (e.g., focused on DLPFC alone rather than a ‘network-like’ approach to neuromodulation, exciting both frontal and parietal areas); 6) reporting of behavioral outcomes (i.e., we did not include effects on fMRI or EEG-derived brain activity); and 7) sufficiently clear reporting of all stimulation parameters/procedures. This yielded 42 studies in the motor domain (253 total effects) (112-153), 18 visual search studies (176 effects) (88-90, 142, 154-167), 16 working memory studies (115 effects) (57, 168-182), 15 vigilance studies (93 effects) (71, 168, 169, 183-194), and 15 inhibition studies (84 effects) (178, 181, 186, 195-206). A summary flowchart of search and screening procedures is shown in **Figure 1**; the studies included in each domain are listed for convenience in **Supplementary Table 1**. We note that this represents only a subset of all published studies under each domain (some of which employed multiple tasks capturing various cognitive constructs) and is not intended to be exhaustive; however, we suggest the total number of effects considered affords a reasonable estimation of how various stimulation and study design parameters might modulate behavior.

2.2. Data Extraction, Effect Size Estimation, & Parameter Coding

Whenever possible, we extracted exact descriptive statistics (means and standard deviations, or standard errors) from the reported text. However, in many cases, this information was only presented graphically. We therefore used the WebPlotDigitizer (<https://automeris.io/WebPlotDigitizer/>) to convert graphical displays into numerical data. Effects were excluded here if error bars were visually indistinguishable and/or if their endpoints could not be reliably identified. For each study, we attempted to extract as much behaviorally-relevant information as possible, particularly when multiple effects were reported across different experiment blocks or outcome variables (e.g., accuracy and/or reaction time), allowing us to better capture variability in the effects of tDCS on performance—which may be transient over the course of a task. Irrelevant, non-task-related measures were excluded (e.g., self-reported side effects), as were ancillary task-related measures that did not inform the cognitive domains of interest (e.g., for inhibition, we excluded reaction times to ‘congruent’ trials in Stroop tasks).

Effect sizes and their standard errors were estimated using Hedges’ *g*. For between-subject designs where group means, standard deviations, and sample sizes are known, this is trivial; however,

for within-subject designs, the standard deviation around the mean difference depends upon the correlation between repeated measures. No study in our survey of the literature provided this information. We ultimately chose to assume a moderate correlation ($r = 0.50$) for all within-subject effects (equivalently, taking an average of the variances)—a common practice in power analyses when the within-subject correlation is not known *a priori*. Furthermore, to enable more generalized assessments of behavioral outcomes regardless of the exact task paradigm or behavioral construct being measured, each effect size was assigned a positive or negative sign depending on whether the relevant comparison indicated an improvement or detriment to behavior, respectively. For example, faster reaction times during active stimulation vs. sham were assigned a positive sign, whereas higher error rates earned a negative sign. Thus, under the model, we could assess whether certain experiment design parameters conferred positive or negative effects *on average* for a given domain, irrespective of specific tasks or outcomes.

Each effect was coded alongside the 10 stimulation and experiment parameters summarized in **Table 1**. The stimulation target parameter was given as the intended brain region targeted by the electrode montage. In cases where some brain regions were poorly-represented (i.e., were only targeted in one or two studies, or constituted an exceptionally small proportion of the total number of effects), we attempted to collapse them into an ‘Other’ category grouped with other anatomically-proximal regions. Target laterality was coded as either Left, Right, or Bilateral (in the latter case, when stimulation was applied to homotopic regions in both the left and right hemisphere). We also recorded the number of electrodes used in the montage and whether the placement of electrodes was individualized (e.g., guided by an anatomical MRI for each subject; coded as a binary Yes or No). Individualized target montages were exceedingly rare, occurring primarily in the motor performance domain. Raw stimulation intensity was recorded in milliamperes and polarity coded as either Anodal or Cathodal (always in comparison to a sham stimulation condition). The duration of stimulation was given in minutes and coded as Online (applied during task performance), Offline (prior to task performance), or Mixed (for cases when online stimulation was applied for only a portion of task performance). The total number of stimulation sessions completed by participants was also given for each effect. Finally, we recorded whether each comparison was made under a within-subjects or between-subjects framework. A summary of how these parameters were represented under each domain can be found in **Supplementary Table 2**.

As an additional supplementary analysis, we also attempted to extract or estimate current *density* over the target brain region (in mA / cm²). This was possible for all studies included in the visual

search and vigilance domains, but it resulted in some loss of data for the motor, working memory, and inhibition domains (due to, e.g., the use of customized or otherwise more complex multielectrode arrays for which it was not possible to reliably estimate current density). We found that this parameter did not inform variability in behavioral outcomes and generally exhibited much greater posterior uncertainty; thus, given our already-strict inclusion criteria, we do not use it in the models and results described below. For completeness, however, we visualize these models in **Supplementary Figure 1**.

2.3. Hierarchical Bayesian Meta-Regression: Model Specification and Estimation

Given that nearly all studies reported multiple behavioral outcomes as a function of their tDCS manipulations, we used a hierarchical Bayesian meta-regression framework to model the average magnitude of behavioral effects associated with our design parameters of interest, accounting for both *intra*- and *inter*-study variability in the effects of neurostimulation across all reported comparisons. We elected to use a Bayesian framework over a comparable frequentist framework for several reasons. First, Bayesian methods afford probabilistic estimates in favor of hypotheses and the existence of an effect by computing full posterior distributions given the observed data, which in turn allow for more direct estimates of *uncertainty* surrounding an effect. Second, Bayesian methods allow us to be pragmatic in incorporating our prior beliefs (or perhaps alternatively, our lack of strong prior convictions) into a model and help us control for potential bias by retaining identical prior assumptions regardless of the data or cognitive domain. Finally, Bayesian methods allow for principled, probabilistic model comparison, useful for exploratory analyses and quantifying uncertainty in performance between models using different sets of parameters.

All models were specified and estimated using Stan (<https://mc-stan.org>) and brms (207) in R. For consistency, and to avoid the possibility that any given model could be unduly influenced by arbitrary prior specifications, key parameters for all models were estimated under the same set of weakly-informative priors:

$$\text{Intercept} \sim \text{Normal}(0, 1)$$

$$\text{Slopes} \sim \text{Normal}(0, 2.5)$$

$$\text{Random effect } SD \sim \text{Half-Cauchy}(0, 0.5)$$

Note that, because we obtained standard errors around each recorded effect size, we could incorporate these values directly into the model likelihoods, precluding the need to estimate noise variance as an additional free parameter. These priors were selected based on previous recommendations for Bayesian meta-analysis (208, 209) with one notable change. Typically, a traditional meta-analysis only models an

intercept (capturing the average effect size pooled across studies): a Normal(0, 1) prior for this term is arguably quite sensible in these situations (this assumes with 95% probability that the ‘true’ pooled effect lies somewhere between $g = [-2, 2]$). However, here we are not just pooling effect sizes on average, but also determining the extent to which effect sizes are systematically moderated by differences in experiment design factors (that is, we also need to model slopes). Given that we do not necessarily have a good *a priori* guess as to how, for example, effect size might differ on average between Anodal and Cathodal stimulation, we use a wider, weaker prior.

In constructing the design matrix for each model, categorical regressors (e.g., stimulation polarity) were coded using sum-to-zero deviation contrasts, which enable more traditional ‘ANOVA-like’ comparisons of mean differences between a given factor level and a reference level. Continuous regressors (e.g., stimulation intensity) were centered about their respective means. We further specified a random intercept term to account for variation in reported effects across studies. Random slopes were omitted, both to minimize model complexity (and thereby ensure convergence) and because many comparisons are empirically unidentifiable within a given study (e.g., many studies reported *either* anodal vs. sham or cathodal vs. sham stimulation designs, so one cannot estimate differential effects between the two on an individual study level). Thus, using Wilkinson notation, an additive model containing all predictors may be written as:

```
hedgesG|se(stdErrorG) ~ stimPolarity + targetRegion + individualizedTarget +
targetLaterality + numSessStim + stimDurationPerSess + stimIntensity +
stimOnlineOffline + numElectrodes + designType + (1|studyID)
```

Continuous predictors such as stimulation intensity imply a single slope, while categorical factors such as stimulation polarity imply $k - 1$ contrasts, where k is the number of factor levels (so, for example, the polarity term tests for differences associated with Anodal vs. Cathodal stimulation, whereas the stimulation timing term may imply two fit parameters: one for Offline vs. Mixed comparisons, and one for Online vs. Mixed).

Robust exploration of the posterior space for all models was performed via Hamiltonian Monte Carlo, with four independent chains of 15000 iterations each (5000 of which were used as warm-up samples). We ensured that all models properly converged to equilibrium for all parameters using classical benchmarks, including: the effective sample size (considering the autocorrelation between independent posterior draws); the Monte Carlo standard error (relative to the posterior *SD*); *R*-hat (the variance ratio between each chain relative to *all* chains); and no divergent Monte Carlo transitions after warm-up.

For statistical inference, we consider 95% credibility intervals (using the highest posterior density interval) around the posterior median parameter estimates along with the ‘probability of direction’ (p_d), capturing the proportion of the posterior density above or below zero. Here, p_d can range from 0.50 (indicating that the posterior is centered at zero, i.e., half its density lies above zero and half below zero) to 1 (in the most extreme case, that *no* proportion of the posterior density intersects zero)—thus, values of p_d closer to 1 indicate more evidence for the presence of a directional/nonzero effect, and $p_d > 0.95$ can *roughly* be thought of as a Bayesian analogue to the frequentist p -value, such that less than 5% of the full posterior distribution intersects zero (210). However, an important point here is that we do not wish to frame these results in terms of ‘statistical significance’, but rather a simple consideration of *evidence* for nonzero differences given the posterior densities for each parameter. Bayes factors are not reported due to their sensitivity to priors and because they often (regrettably) encourage the sorts of binary thinking about hypotheses that Bayesian methods are meant to circumvent. Instead, we compute a Bayesian analogue of Cohen’s d for categorical predictors by taking the posterior draws for each regressor and dividing them by the square root of the summed residual variances and random effects variances (as per convention for hierarchical linear models) (211), yielding a posterior distribution for each non-continuous model-level effect. Finally, fit indices were computed using the conditional R^2 over the full model (taking both fixed and random effects together), and the marginal R^2 capturing variance that can be attributed to the fixed effects alone (212).

2.4. Exploratory Modeling of Interaction Effects

The models described above focused simply on additive, main effects for each predictor of interest—we did not have any *a priori* hypotheses related to how these various experiment design parameters might interact to produce differential behavioral outcomes. However, it is likely that interaction effects *do* exist between these factors. One general challenge with modeling these potential effects in an exploratory fashion is combinatorial explosion: given the number of parameters under consideration, the possible model space is massive and may include models with many higher-order interactions that are uninterpretable.

In an effort to perform an exploratory search in a restricted, albeit principled and maximally-unbiased fashion, we focused on models containing either two-way or three-way interactions (the latter of which included all three marginal two-way interactions) constructed on a dataset comprised of *all* domains combined. This would allow us to identify interaction models that appear to generalize across

domains and subsequently test the extent to which they inform domain-specific models. To assess the performance of candidate models against the ‘base model’ (i.e., solely including additive, main effects), we used Bayesian approximate leave-one-out cross validation with Pareto-smoothed importance sampling (PSIS) (213-215). In brief, this approach takes advantage of our fully Bayesian modeling framework to circumvent typically-costly cross-validation routines requiring many model re-fits, instead using PSIS to imagine the likelihood our model would assign to each datapoint *as if* they were held-out, yielding a new cross-validated posterior predictive distribution over the data (*a pointwise predictive density*). We can then directly quantify the difference in predictive performance between candidate and base models by comparing their mean, expected log pointwise predictive densities (*ELPDs*), which has an associated standard error: the ratio of the *ELPD* differential to the standard error of the difference (akin to a *Z*-statistic) is a simple summary metric that can inform us whether the addition of putative interaction terms significantly improves predictive performance above the base, additive model (a fairly liberal criterion is to check whether the absolute value $|ELPD_{Diff} / SE_{Diff}| > 2$, similar to a two-tailed test at $\alpha = 0.05$).

Under this framework, we first performed a comprehensive sweep over all possible inclusions of a single two-way interaction term (28 models total). None of these candidate models, however, suggested a significant improvement in predictive performance above the base model (**Supplementary Table 3**). We then performed a similarly exhaustive sweep over 56 candidate three-way interaction models, and here, there were three models that suggested significant improvement over the base model (**Supplementary Table 4**), each with the following terms: 1) Design Type (Within- vs. Between-Subjects) x Number of Electrodes in Montage x Stim Intensity (mA); 2) Design Type x Number of Electrodes x Stim Duration per Session (min); and 3) Design Type x Number of Electrodes x Stim Duration. Notably, there was considerable overlap in the relevant factors for each candidate interaction—we therefore fit a four-way interaction model that provided, at best, a marginal improvement over the base model and did not significantly outperform any of the individual three-way models (**Table 2**).

Table 2. Differences in candidate model predictive performance derived via Bayesian approximate leave-one-out cross-validation. The four-way interaction model provided the best performance overall and thus differences in fit are presented with respect to this model. $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive densities (negative values shown here indicate decrements in predictive performance relative to the top model); SE_{Diff} gives the standard error of the difference. The top model significantly differs in performance from any other model where $|ELPD_{Diff} / SE_{Diff}| > 2$.

Candidate Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Design Type x Stim Intensity x Stim Duration x Num Electrodes	—	—	—
Design Type x Num Electrodes x Stim Intensity	-10.984	7.330	-1.499
Design Type x Stim Intensity x Stim Duration	-16.034	10.357	-1.548
Design Type x Num Electrodes x Stim Duration	-18.334	10.245	-1.790
Base Model (Only Additive Terms)	-33.532	16.581	-2.022

Because the four-way model did not confer a particular advantage over any individual three-way model, we excluded it from further testing and instead consider the various three-way models noted above to be *competitive*. These were subsequently applied to each individual domain to assess the extent to which they may inform domain-specific differences in behavioral effects above and beyond their respective base, additive models.

3. Results

3.1. Motor Performance

Under a simple additive model, analysis of 253 effects across 42 studies in the motor domain revealed little consistency in the relationships between stimulation/experiment parameters and the likelihood of conferring positive or negative behavioral effects (**Figure 2A; Table 3**). However, there was a considerable advantage when using a within-subjects design vs. a between-subjects design, such that within-subjects designs were consistently associated with stronger positive effects ($d = 1.35$, 95CI = [0.93, 1.78]; $b = 1.11$ $SD = 0.22$, 95CI = [0.68, 1.55], $p_d = 1$). We also observed some evidence for target-specific effects, such that stimulating DLPFC tended to yield smaller behavioral differences, relative to the more motor-relevant cerebellum ($d = -0.53$, 95CI = [-1.13, 0.002]; $b = -0.43$, $SD = 0.22$, 95CI = [-0.86, -0.01], $p_d = 0.977$), although the credibility intervals for this effect lightly-intersect zero. We note that, due to restrictions on the number of possible contrasts one can uniquely-estimate for a given factor, there remain many potential comparisons that are not reflected under the model fit. However, given that this is a Bayesian framework, it is possible to ‘simulate’ new data under the generative model and derive *posterior predictive distributions* that describe the expected value (i.e., the likely effect size) one would observe under certain stimulation/experiment parameters. By integrating out other factors from these predictive distributions, we can approximate the *average marginal effect* (AME) one might expect for novel comparisons. This here reveals potential benefits to stimulating M1

vs. DLPFC (Median predictive difference = 0.35, 95CI = [0.11, 0.58]) as well as a potential detriment to stimulating online vs. offline (Median predictive difference = -0.20, 95CI = [-0.39, -0.01]).

Applying the candidate interaction terms described previously to the motor domain did not reveal any significant increases in performance relative to the base model (**Supplementary Table 5**). The three-way interaction model including Design Type x Num Electrodes x Stim Duration provided the best overall predictive accuracy—however, this was not meaningfully different from the cross-validated performance of the base model with only additive terms ($ELPD_{Diff} = -33.53$, $SE_{Diff} = 16.58$, $ELPD_{Diff} / SE_{Diff} = -1.88$). That being said, while the highest-performing candidate model did not significantly outperform the base model, it nevertheless suggested the presence of potential interaction effects including (most importantly) the full three-way interaction ($b = 0.76$, $SD = 0.28$, 95CI = [0.21, 1.31], $p_d = 0.996$). It is unclear whether the increase in model complexity is justifiable given the nonsignificant difference in predictive performance, but we report the full set of parameter estimates for this model in **Supplementary Table 6**.

3.2. Visual Search

The visual search model spanned 176 effects across 18 studies (**Figure 2B; Table 4**). One challenge of this domain was the lack of variability in stimulation target sites. The posterior parietal cortex (PPC) was highly overrepresented as a stimulation target in this sample, comprising 110/176 effects; conversely, only four effects were derived from visual cortex stimulation. The remaining regions spanned various areas of the prefrontal cortex, including the FEF (14 effects) and DLPFC (16 effects). We elected to retain the visual cortex target as its own factor level (although this estimate is highly unreliable, as reflected by the wide credibility interval) and collapse all PFC regions into one group, yielding 62 total effects. Bilateral stimulation (14/176 effects) and mixed online/offline stimulation designs (15/176 effects) were also underrepresented here.

Despite the disparities across several of these parameters, we observed evidence for a moderate effect of stimulation polarity: cathodal stimulation was associated with smaller behavioral effects in these studies relative to anodal stimulation ($d = -0.55$, 95CI = [-1.14, -0.08]; $b = -0.22$, $SD = 0.08$, 95CI = [-0.37, -0.06], $p_d = 0.996$). Perhaps counterintuitively, we also saw evidence for moderately weaker behavioral effects when targeting PPC compared to the combined grouping of all PFC targets ($d = -0.58$, 95CI = [-1.29, -0.004]; $b = -0.23$, $SD = 0.10$, 95CI = [-0.42, -0.03], $p_d = 0.988$), although this effect is

difficult to interpret given the lack of specificity in PFC regions. No additional trends were observed for other fixed effects or predictive AMEs in this domain.

With respect to potential interaction effects, here the base model provided the best predictive performance—strongly exceeding candidate interaction models with the exception of a model including a Design Type x Stim Intensity x Stim Duration interaction, with which it was tightly competitive ($ELPD_{Diff} = -0.10$, $SE_{Diff} = 1.59$, $ELPD_{Diff} / SE_{Diff} = -0.06$; **Supplementary Table 7**). Notably, however, despite the similarity in predictive performance, neither the three-way interaction term nor any of the marginal two-way interaction terms for this model provided clear evidence for nonzero effects. We observed, at best, an inconclusive trend for a two-way interaction between stimulation intensity and duration where the 95% credibility interval over the posterior included zero ($b = 0.05$, $SD = 0.03$, $95CI = [-0.003, 0.11]$, $p_d = 0.969$). Beyond this, we only observed evidence for an effect of stimulation polarity in the same direction as seen in the base model (i.e., such that cathodal stimulation was associated with reduced behavioral effects on average; $d = -0.95$, $95CI = [-3.24, -0.02]$; $b = -0.23$, $SD = 0.08$, $95CI = [-0.39, -0.07]$, $p_d = 0.998$). The full summary of statistics for this competitive interaction model are compiled in **Supplementary Table 8**.

3.3. Working Memory

We next assessed 115 effects reported in 16 working memory studies (**Figure 2C**; **Table 5**). Here we faced similar difficulties with unbalanced representation of target brain regions, with montages focused on the DLPFC in 90/115 reported effects. Other sparsely-represented regions (including the cerebellum, PPC, and temporal lobe) were therefore grouped into a ‘Non-DLPFC’ category. This domain was also the only other to employ subject-specific, individualized targeting—although this occurred only in one study with 5 reported effects. Furthermore, unlike other domains which applied anodal and cathodal stimulation fairly evenly, these studies almost exclusively applied anodal stimulation (103/115 effects). Bilateral stimulation also failed to be represented in this domain. Ultimately, none of the available contrasts suggested a reliable advantage or disadvantage to working memory performance, nor did examination of posterior predictive AMEs. Removal of highly-unbalanced factors also had no effect on the results, so we retain them here for transparency.

Turning to our model comparison set, the best performing model included a three-way interaction between Design Type x Stim Intensity x Stim Duration—but again, this failed to significantly beat the base model in terms of predictive performance ($ELPD_{Diff} = -3.10$, $SE_{Diff} = 2.50$,

$ELPD_{Diff} / SE_{Diff} = -1.24$; **Supplementary Table 9**). Furthermore, this particular candidate model, while ostensibly offering the highest predictive utility, also demonstrated more degenerate behavior during sampling, consistently yielding several divergent Monte Carlo transitions regardless of numerous attempts at adjusting sampling behavior. While these make up an extremely small proportion of the total number of MCMC iterations run, it nevertheless suggests a more unwieldy posterior geometry, and this in turn can hamper the interpretability/reliability of parameter estimates. Here we see several potential effects that were not apparent in the base model, including a potential advantage for using larger electrode montages ($b = 0.14$, $SD = 0.06$, $95CI = [0.02, 0.27]$, $p_d = 0.989$) and some evidence trending towards a two-way interaction between stimulation intensity and duration ($b = -0.15$, $SD = 0.05$, $95CI = [-0.25, -0.04]$, $p_d = 0.991$). The full set of parameter estimates for this model can be found in **Supplementary Table 10**, although we urge some caution in their interpretation given the aforementioned challenges with convergence.

3.4. Vigilance

The effects of tDCS on performance in vigilance tasks were modeled over 15 studies reporting 93 effects (**Figure 2D**; **Table 6**). Similar to working memory, most studies here employed anodal stimulation designs (83 effects) focused on the DLPFC (51 effects). Additional brain regions were grouped into ‘Other PFC’ and ‘Temporal-Parietal’ categories. Most design parameters did not suggest any associations with behavioral outcomes; however, we observed a small positive relationship with the number of electrodes used in the montage ($b = 0.08$, $SD = 0.04$, $95CI = [0.01, 0.15]$, $p_d = 0.983$). We note that this may have been driven by two studies using a more complex montage comprised of 10 electrodes (yielding 11 effects)—other studies employed between 2 and 5 electrodes. Thus, we caution against overinterpreting this particular effect. Further comparisons of posterior predictive densities and AMEs did not reveal additional associations beyond the estimated contrasts.

The base model further demonstrated the best performance relative to all candidate interaction models; however, it was not *significantly better* than any candidate model. The closest contender was again the model including a Design Type x Stim Intensity x Stim Duration interaction ($ELPD_{Diff} = -0.67$, $SE_{Diff} = 1.48$, $ELPD_{Diff} / SE_{Diff} = -0.45$; **Supplementary Table 11**)—although no individual main effects or interaction effects under this model yielded any nonzero effects (**Supplementary Table 12**). Thus, the inclusion of interaction terms does not inform differences under this domain any more than those scantily observed in the base model.

3.5. Inhibition

A survey of 84 effects across 15 inhibition studies did not reveal any meaningful associations between any stimulation or experiment parameters and behavior (**Figure 2E; Table 7**). Again, there was little variability in brain regions targeted for stimulation: 75/84 effects were localized to the DLPFC. The remaining effects spanned the inferior frontal junction and parietal cortex and were therefore collapsed into an ‘Other’ term during the original model fit. Removing this predictor from the model did not affect the results. There was also less variability in target laterality (no effects under bilateral stimulation) and the number of stimulation sessions (only one session reported per subject). Assessments of posterior predictive densities and AMEs did not reveal any other potential effects not captured in the base model. Although several parameters trended towards a nonzero effect, there is inconclusive evidence for any reliable differences in behavioral performance given variation in design parameters under this domain.

Here we again saw superior performance for the base model over candidate interaction models. This time, however, the base model consistently, significantly beat all three potential candidates—no exploratory model provided competitive predictive performance (**Supplementary Table 13**).

3.6. Combined Model

Finally, we considered a domain-general model combining all 106 studies and 721 effects across all domains (**Figure 2F; Table 8**). Here we omitted the individualized target parameter (due to its scarce representation beyond motor performance tasks) as well as the regional target parameter to instead focus on broader trends related to stimulation and experiment design. Taken together, there was considerable heterogeneity across all relevant effects, with stimulation polarity and within- vs. between-subject designs providing inconclusive evidence for domain-general associations with behavior: cathodal stimulation tended to produce somewhat smaller behavioral effects on average ($d = -0.19$, $95\text{CI} = [-0.39, 0.02]$; $b = -0.07$, $SD = 0.04$, $95\text{CI} = [-0.15, 0]$, $p_d = 0.971$), while within-subjects designs produced larger effects ($d = 0.32$, $95\text{CI} = [0, 0.65]$; $b = 0.13$, $SD = 0.07$, $95\text{CI} = [0, 0.26]$, $p_d = 0.973$). Posterior predictive AMEs further suggested that online stimulation may yield smaller effects than offline stimulation (Median predictive difference = -0.14 , $95\text{CI} = [-0.24, -0.04]$).

As described previously, the competing set of three-way interaction models was originally defined by concatenating together the data from all domains. Thus, each candidate model significantly

outperformed the base model (**Supplementary Table 4**) while remaining competitive with each other (**Supplementary Table 14**). The best-performing candidate included a strong three-way interaction between Design Type x Num Electrodes x Stim Intensity ($b = -0.49$, $SD = 0.10$, $95CI = [-0.69, -0.29]$, $p_d = 1$), which suggested that the montages with more electrodes may produce larger behavioral effects as raw stimulation intensity increases under *between-subjects* designs—but this relationship is reversed in *within-subjects* designs, such that one might expect increasingly-diminishing returns with more complex montages and stronger stimulation intensities (**Supplementary Figure 2; Supplementary Table 15**). The second-best model included a three-way interaction for Design Type x Stim Intensity x Stim Duration ($b = -0.11$, $SD = 0.03$, $95CI = [-0.17, -0.06]$, $p_d = 1$): here, we saw similar trends as in the previous model, such that longer and stronger applications of tDCS may confer an advantage in between-subjects studies, but this is again reversed for within-subjects designs (**Supplementary Figure 3; Supplementary Table 16**). Finally, the third candidate model provided evidence for a three-way interaction between Design Type x Num Electrodes x Stim Duration ($b = 0.06$, $SD = 0.02$, $95CI = [0.03, 0.09]$, $p_d = 1$), where longer stimulation durations coupled with larger montages may provide a specific benefit to within-subject designs, whereas between-subject designs are relatively invariant to combined changes in these factors (**Supplementary Figure 4; Supplementary Table 17**).

4. Discussion

When designing a neurostimulation experiment, researchers are presented with a vast decision tree. For example, one must determine where in the brain to apply stimulation; to what intensity and for how long; whether to apply it *online* (as subjects are performing a task) or *offline*; and whether to apply ‘excitatory’ or ‘inhibitory’ stimulation. The net effect of neurostimulation ultimately depends on a complex constellation of these factors—and while some of these decisions have clear theoretical/empirical guides (e.g., targeting brain regions previously known to be associated with task performance), many others remain open to the subjective preferences of the researcher, and there is no clear consensus or standardization of the optimal approach. In this report, we sought to identify which of these stimulation and experimental design factors confer the strongest likelihood of behavioral effects in tDCS studies, using a hierarchical, Bayesian meta-regression approach across five cognitive domains.

We observed considerable heterogeneity in these associations, with little consensus between domains. When combining all studies and effects under a purely-additive, domain-general model, only two factors emerged with a modicum of consistency: 1) the polarity of stimulation, with cathodal vs.

sham designs often producing reduced behavioral effects relative to anodal vs. sham designs (perhaps in line with the naïve notion that cathodal stimulation is primarily *inhibitory*), and 2) within-subject experimental designs conferring larger effects than between-subject designs (which may be unsurprising given that within-subject comparisons are generally considered to be more powerful—which is to say, for an identical assumed effect size *a priori*, within-subject manipulations require fewer subjects to reach the same level of power relative to between-subjects). These associations were modest at best when considering the full range of variance in reported effects; however, stronger associations with polarity and statistical design were seen across visual search and motor performance tasks, respectively.

The results of our exploratory interaction analyses are also somewhat difficult to interpret, given that no candidate model significantly generalized to individual cognitive domains—the improvements in predictive performance when including various three-way interaction terms were most appreciable when combining data across domains. However, there are several notable trends that may be worthy of consideration. For example, the use of between- vs within-subject designs was consistently a relevant factor in each candidate model. In cases where this factor interacted with Stimulation Intensity x Num Electrodes (**Supplementary Figure 1; Supplementary Table 15**) and Stimulation Intensity x Stim Duration (**Supplementary Figure 2; Supplementary Table 16**), it appeared that the benefit of larger montages and longer stimulation durations (respectively) reversed for between- vs. within-subject designs—however, this switch primarily occurred out in the tails of the observed stimulation intensities (i.e., at least 3 mA or more). While such high intensities were seen in our review, they are *not* necessarily representative of most tDCS studies on the whole. At lower, more traditional stimulation intensities (e.g., ~1 mA), within-subjects designs generally still held an advantage over between-subjects. Furthermore, it is worth noting that factors such as stimulation intensity generally only informed differences in behavioral outcomes when included in an interaction—this seems reasonable given that the effectiveness of a given intensity may critically depend upon the duration of stimulation and/or the extent of an electrode montage. However, deeper interpretation of these results is made somewhat difficult given that raw intensity alone does not necessarily reflect the *dosage* of stimulation applied to the target (typically operationalized as current density), nor does the three-way interaction identified here. We attempted to model this factor in each domain (**Supplementary Figure 1**), but it was not reliably estimable for all studies (resulting in loss of data) and otherwise did not appear to be predictive of outcome variability. There are a number of potential reasons for this (e.g., individual differences in brain anatomy mediating differences in the effective current density at the target) which

warrant future investigation, and it is similarly critical for other empirical work to report this information in their Methods sections to help aid in the interpretation of results. In sum, while it nevertheless remains unclear as to whether (or to what extent) specific stimulation or experimental parameters can reliably induce desired behavioral outcomes, these findings may provide a useful reference for researchers designing future behavioral studies in addition to more systematic investigations of how various tDCS parameters may interact to modulate behavior.

A growing number of published meta-analyses have attempted to quantify and characterize patterns of uncertainty and variability in neurostimulation-related effects on cognition and behavior. However, to date, many of these previous efforts have taken a more piecemeal approach, focused on specific tasks/domains, individual behavioral measures (e.g., accuracy or reaction time), or a limited range of stimulation parameters (e.g., particular target brain regions, or differentiating between anodal or cathodal stimulation alone) (11-18). Our goal, by contrast, was to take a more holistic view capturing a broad range of design factors and behaviors. This presented a number of challenges, including uneven representation of some stimulation/experimental parameters across domains, making it difficult to robustly contrast certain effects. In a sense, these imbalances could be interpreted as a *de facto* consensus on which brain regions ‘should’ be targeted, or which type of stimulation to apply, etc., when probing behaviors under a given domain. Yet, our analyses demonstrate that there is still a profound degree of heterogeneity across these parameters, suggesting the need for deeper consideration when planning and designing tDCS studies.

4.1. Uncontrollable Sources of Variability

The design elements under investigation here are generally considered to be *controllable* sources of variability in neurostimulation studies (i.e., easily-manipulated by experimenters in a systematic fashion), but there nevertheless remain a host of *uncontrollable* sources of variability that may further hamper one’s ability to elicit behavioral effects and contribute to inconsistent results across studies. Critically among these are a number of neuroanatomical factors that likely influence the propagation of electrical current through the brain and the degree to which stimulation actually produces the presumed effects on neuronal activity. For example, neurons running parallel to an applied electric field generally appear to exhibit the hypothesized excitatory and inhibitory effects of anodal and cathodal stimulation (respectively), but neurons running orthogonally to the field may not (7, 216). Inter-individual variability in the local orientation of neurons within a target brain region might therefore preclude

1 effective neuromodulation during tDCS. Other variables such as head size, head fat content, skull
2 thickness, and sulcal depth can also mediate the effectiveness of tDCS (217-220), which together could
3 manifest as further individual differences in behavior, washing out a mean difference between one
4 stimulation/task condition and another.

5 The development of improved, neuroanatomically-informed current modeling techniques,
6 particularly with respect to individual-specific optimization of electrode placements and stimulation
7 dosage, may be able to mitigate some of these factors (9, 45, 46, 221). Recent advances in electrical
8 field modeling, including the Realistic Volumetric Approach to Simulate Transcranial Electrical
9 Stimulation (ROAST) software (222), the dose-target determination index (DTDI) (223), and other
10 novel approaches combining meta-analysis with simulation of electrical fields (35) have highlighted that
11 it is not sufficient to simply place an electrode montage over a given brain area and assume that it is
12 receiving focal stimulation. The frequently-observed mixed findings across tDCS studies may in large
13 part be due to variability and suboptimality in the actual strength/focality of electric fields over the
14 desired target brain region (35). We advocate strongly for the use of these field modeling techniques
15 whenever possible as an additional control over stimulation targeting.

16 Finally, and more generally, there remain many other challenging sources of variability (e.g.,
17 baseline cognitive abilities, neurochemistry, circadian rhythms, blood pressure, genetic factors, etc.)
18 (224-226) which, while not necessarily *impossible* to control for, are frequently impractical or
19 unrealistic for any given study to measure and factor into their analyses. Because these variables are
20 often so difficult to quantify (and as such, are rarely reported), the sum total of their influence on the
21 heterogenous nature of effects modeled here cannot be ascertained. Nevertheless, a more complete
22 understanding of these issues is imperative as the field moves forward.

23 24 *4.2. Limitations of This Study*

25 As aforementioned, we applied highly-restrictive inclusion criteria when collating data for this
26 meta-analysis. While this was necessary to enable more straightforward tests of our key stimulation and
27 experimental parameters, these findings may not be fully-representative of the literature on the whole
28 (although the high degree of variability observed is in line with prior work). One critical omission of
29 note spans studies using customized/individualized stimulation protocols beyond target placement alone:
30 for example, paradigms which vary stimulation intensity on an individual basis to standardize the dosage
31 (current density) applied to the target. Our models required stimulation intensity to be held constant for a

1 given reported effect, but such individualized approaches are becoming increasingly more
2 commonplace. Thus, while our results may reflect historical trends in stimulation outcomes (especially
3 with respect to conventional designs), they may not adequately account for present trends using more
4 sophisticated methods. Future meta-analytic work would benefit from more direct comparisons between
5 conventional and contemporary approaches to stimulation designs.

6 As an additional limitation, we desired to identify more generalizable trends in how these design
7 parameters relate to behavioral outcomes, both within and between domains—but collapsing across
8 multiple task paradigms and performance metrics may actually obscure reliable effects that would
9 otherwise be apparent in a more focal meta-analysis. Even when simplifying behavioral effects to
10 ‘positive’ and ‘negative’ outcomes, it is unlikely that any given study tests/measures a particular
11 psychological construct in the same way, which might amplify the inherent noise variance under the
12 model.

13 Finally, while we attempted to explore potential interactions between various experiment design
14 factors, this was still somewhat limited in scope—to limit complexity and reduce the putative model
15 space, we considered at most the inclusion of a single three-way interaction term (along with its
16 marginal two-way interactions) and performed this selection based on data combined across domains
17 rather than within each domain. While on the one hand this allowed us to assess generalizability of the
18 identified candidate models, it is also possible that each domain may produce different sets of candidate
19 interactions. Furthermore, in order to be consistent with our base, additive models across all domains,
20 we retained the same sets of weakly-informative priors: but in a Bayesian model comparison and variable
21 selection scenario, sparsity-inducing priors (e.g., a regularized horseshoe) may be preferable. These are
22 often extremely delicate in the context of hierarchical models, though, and may produce degenerate
23 sampling behavior and difficulties with convergence. Future experimental work would greatly benefit
24 from systematic investigations of these parameters and the potential ways in which they jointly-
25 modulate behavioral performance outcomes, and this modeling framework could also potentially be
26 combined with tDCS simulation methods (35) to further inform experimental design principles for
27 neurostimulation researchers.

28 29 *4.3. Conclusion*

30 In conclusion, our comprehensive meta-analysis across five cognitive domains reveals a complex
31 and heterogenous landscape of associations between neurostimulation and behavioral outcomes. While

some trends emerge, such as the advantage of within-subject designs and the influence of stimulation polarity, overall, there is little consensus on the optimal stimulation and experimental parameters for reliably inducing desired behavioral outcomes using tDCS. The field of neurostimulation research faces the challenge of contending with uncontrollable sources of variability, including various neuroanatomical and individual difference factors, which may further contribute to the inconsistency observed across studies. This study underscores the need for deeper consideration and standardization of experimental design in tDCS studies and highlights the importance of developing neuroanatomically-informed current modeling techniques to better understand and control for sources of variability. Future research should continue to investigate the complex interplay of these parameters and their potential interactions to advance our understanding of the effects of tDCS on cognitive and behavioral performance.

References

1. Bestmann S, de Berker AO, Bonaiuto J. Understanding the behavioural consequences of noninvasive brain stimulation. *Trends Cogn Sci.* 2015;19(1):13-20.
2. Dayan E, Censor N, Buch ER, Sandrini M, Cohen LG. Noninvasive brain stimulation: from physiology to network dynamics and back. *Nat Neurosci.* 2013;16(7):838-44.
3. Polania R, Nitsche MA, Ruff CC. Studying and modifying brain function with non-invasive brain stimulation. *Nat Neurosci.* 2018;21(2):174-87.
4. de Berker AO, Bikson M, Bestmann S. Predicting the behavioral impact of transcranial direct current stimulation: issues and limitations. *Front Hum Neurosci.* 2013;7:613.
5. Bikson M, Name A, Rahman A. Origins of specificity during tDCS: anatomical, activity-selective, and input-bias mechanisms. *Front Hum Neurosci.* 2013;7:688.
6. Bikson M, Paulus W, Esmaeilpour Z, Kronberg G, Nitsche MA. Mechanisms of Acute and After Effects of Transcranial Direct Current Stimulation. In: Knotkova H, Nitsche M, Bikson M, Woods A, editors. *Practical Guide to Transcranial Direct Current Stimulation*: Springer; 2019. p. 81-113.
7. Lafon B, Rahman A, Bikson M, Parra LC. Direct Current Stimulation Alters Neuronal Input/Output Function. *Brain Stimul.* 2017;10(1):36-45.
8. Nitsche MA, Knotkova H, Woods AJ, Bikson M. Challenges, Open Questions and Future Direction in Transcranial Direct Current Stimulation Research and Applications. In: Knotkova H, Nitsche M, Bikson M, Woods A, editors. *Practical Guide to Transcranial Direct Current Stimulation*: Springer; 2019. p. 627-39.
9. Datta A, Truong D, Minhas P, Parra LC, Bikson M. Inter-Individual Variation during Transcranial Direct Current Stimulation and Normalization of Dose Using MRI-Derived Computational Models. *Front Psychiatry.* 2012;3:91.
10. Horvath JC, Carter O, Forte JD. Transcranial direct current stimulation: five important issues we aren't discussing (but probably should be). *Front Syst Neurosci.* 2014;8:2.
11. Oldrati V, Schutter D. Targeting the Human Cerebellum with Transcranial Direct Current Stimulation to Modulate Behavior: a Meta-Analysis. *Cerebellum.* 2018;17(2):228-36.

12. Schroeder PA, Schwippel T, Wolz I, Svaldi J. Meta-analysis of the effects of transcranial direct current stimulation on inhibitory control. *Brain Stimul.* 2020;13(5):1159-67.
13. Brunoni AR, Vanderhasselt MA. Working memory improvement with non-invasive brain stimulation of the dorsolateral prefrontal cortex: a systematic review and meta-analysis. *Brain Cogn.* 2014;86:1-9.
14. Mancuso LE, Ilieva IP, Hamilton RH, Farah MJ. Does Transcranial Direct Current Stimulation Improve Healthy Working Memory?: A Meta-analytic Review. *J Cogn Neurosci.* 2016;28(8):1063-89.
15. Hill AT, Fitzgerald PB, Hoy KE. Effects of Anodal Transcranial Direct Current Stimulation on Working Memory: A Systematic Review and Meta-Analysis of Findings From Healthy and Neuropsychiatric Populations. *Brain Stimul.* 2016;9(2):197-208.
16. Imburgio MJ, Orr JM. Effects of prefrontal tDCS on executive function: Methodological considerations revealed by meta-analysis. *Neuropsychologia.* 2018;117:156-66.
17. Dedoncker J, Brunoni AR, Baeken C, Vanderhasselt MA. A Systematic Review and Meta-Analysis of the Effects of Transcranial Direct Current Stimulation (tDCS) Over the Dorsolateral Prefrontal Cortex in Healthy and Neuropsychiatric Samples: Influence of Stimulation Parameters. *Brain Stimul.* 2016;9(4):501-17.
18. Jacobson L, Koslowsky M, Lavidor M. tDCS polarity effects in motor and cognitive domains: a meta-analytical review. *Exp Brain Res.* 2012;216(1):1-10.
19. Horvath JC, Forte JD, Carter O. Quantitative Review Finds No Evidence of Cognitive Effects in Healthy Populations From Single-session Transcranial Direct Current Stimulation (tDCS). *Brain Stimul.* 2015;8(3):535-50.
20. Horvath JC, Carter O, Forte JD. No significant effect of transcranial direct current stimulation (tDCS) found on simple motor reaction time comparing 15 different stimulation protocols. *Neuropsychologia.* 2016;91:544-52.
21. Horvath JC, Forte JD, Carter O. Evidence that transcranial direct current stimulation (tDCS) generates little-to-no reliable neurophysiologic effect beyond MEP amplitude modulation in healthy human subjects: A systematic review. *Neuropsychologia.* 2015;66:213-36.
22. Horvath JC, Vogrin SJ, Carter O, Cook MJ, Forte JD. Effects of a common transcranial direct current stimulation (tDCS) protocol on motor evoked potentials found to be highly variable within individuals over 9 testing sessions. *Exp Brain Res.* 2016;234(9):2629-42.
23. Heroux ME, Loo CK, Taylor JL, Gandevia SC. Questionable science and reproducibility in electrical brain stimulation research. *PLoS One.* 2017;12(4):e0175635.
24. Vannorsdall TD, van Steenburgh JJ, Schretlen DJ, Jayatilake R, Skolasky RL, Gordon B. Reproducibility of tDCS Results in a Randomized Trial: Failure to Replicate Findings of tDCS-Induced Enhancement of Verbal Fluency. *Cogn Behav Neurol.* 2016;29(1):11-7.
25. Koenigs M, Ukeberuwa D, Campion P, Grafman J, Wassermann E. Bilateral frontal transcranial direct current stimulation: Failure to replicate classic findings in healthy subjects. *Clin Neurophysiol.* 2009;120(1):80-4.
26. Lopez-Alonso V, Cheeran B, Rio-Rodriguez D, Fernandez-Del-Olmo M. Inter-individual variability in response to non-invasive brain stimulation paradigms. *Brain Stimul.* 2014;7(3):372-80.
27. Lopez-Alonso V, Fernandez-Del-Olmo M, Costantini A, Gonzalez-Henriquez JJ, Cheeran B. Intra-individual variability in the response to anodal transcranial direct current stimulation. *Clin Neurophysiol.* 2015;126(12):2342-7.
28. Wiethoff S, Hamada M, Rothwell JC. Variability in response to transcranial direct current stimulation of the motor cortex. *Brain Stimul.* 2014;7(3):468-75.

- 1 29. Chew T, Ho KA, Loo CK. Inter- and Intra-individual Variability in Response to Transcranial
2 Direct Current Stimulation (tDCS) at Varying Current Intensities. *Brain Stimul.* 2015;8(6):1130-7.
- 3 30. Falcone M, Bernardo L, Wileyto EP, Allenby C, Burke AM, Hamilton R, et al. Lack of effect of
4 transcranial direct current stimulation (tDCS) on short-term smoking cessation: Results of a randomized,
5 sham-controlled clinical trial. *Drug Alcohol Depend.* 2019;194:244-51.
- 6 31. Loo CK, Alonzo A, Martin D, Mitchell PB, Galvez V, Sachdev P. Transcranial direct current
7 stimulation for depression: 3-week, randomised, sham-controlled trial. *Br J Psychiatry.* 2012;200(1):52-
8 9.
- 9 32. Loo CK, Husain MM, McDonald WM, Aaronson S, O'Reardon JP, Alonzo A, et al. International
10 randomized-controlled trial of transcranial Direct Current Stimulation in depression. *Brain Stimul.*
11 2018;11(1):125-33.
- 12 33. Loo CK, Sachdev P, Martin D, Pigot M, Alonzo A, Malhi GS, et al. A double-blind, sham-
13 controlled trial of transcranial direct current stimulation for the treatment of depression. *Int J*
14 *Neuropsychopharmacol.* 2010;13(1):61-9.
- 15 34. Rassovsky Y, Dunn W, Wynn JK, Wu AD, Iacoboni M, Hellemann G, et al. Single transcranial
16 direct current stimulation in schizophrenia: Randomized, cross-over study of neurocognition, social
17 cognition, ERPs, and side effects. *PLoS One.* 2018;13(5):e0197023.
- 18 35. Wischniewski M, Mantell KE, Opitz A. Identifying regions in prefrontal cortex related to
19 working memory improvement: A novel meta-analytic method using electric field modeling. *Neurosci*
20 *Biobehav Rev.* 2021;130:147-61.
- 21 36. Bikson M, Rahman A, Datta A. Computational models of transcranial direct current stimulation.
22 *Clin EEG Neurosci.* 2012;43(3):176-83.
- 23 37. Datta A, Bansal V, Diaz J, Patel J, Reato D, Bikson M. Gyri-precise head model of transcranial
24 direct current stimulation: improved spatial focality using a ring electrode versus conventional
25 rectangular pad. *Brain Stimul.* 2009;2(4):201-7, 7 e1.
- 26 38. Ramaraju S, Roula MA, McCarthy PW. Modelling the effect of electrode displacement on
27 transcranial direct current stimulation (tDCS). *J Neural Eng.* 2018;15(1):016019.
- 28 39. Rich TL, Gillick BT. Electrode Placement in Transcranial Direct Current Stimulation-How
29 Reliable Is the Determination of C3/C4? *Brain Sci.* 2019;9(3).
- 30 40. DaSilva AF, Volz MS, Bikson M, Fregni F. Electrode positioning and montage in transcranial
31 direct current stimulation. *J Vis Exp.* 2011(51).
- 32 41. Miranda PC, Faria P, Hallett M. What does the ratio of injected current to electrode area tell us
33 about current density in the brain during tDCS? *Clin Neurophysiol.* 2009;120(6):1183-7.
- 34 42. Rich TL, Menk JS, Rudser KD, Chen M, Meekins GD, Pena E, et al. Determining Electrode
35 Placement for Transcranial Direct Current Stimulation: A Comparison of EEG- Versus TMS-Guided
36 Methods. *Clin EEG Neurosci.* 2017;48(6):367-75.
- 37 43. Sadleir RJ, Vannorsdall TD, Schretlen DJ, Gordon B. Target optimization in transcranial direct
38 current stimulation. *Front Psychiatry.* 2012;3:90.
- 39 44. Bikson M, Datta A, Rahman A, Scaturro J. Electrode montages for tDCS and weak transcranial
40 electrical stimulation: role of "return" electrode's position and size. *Clin Neurophysiol.*
41 2010;121(12):1976-8.
- 42 45. Kim JH, Kim DW, Chang WH, Kim YH, Kim K, Im CH. Inconsistent outcomes of transcranial
43 direct current stimulation may originate from anatomical differences among individuals: electric field
44 simulation using individual MRI data. *Neurosci Lett.* 2014;564:6-10.
- 45 46. Woods AJ, Antal A, Bikson M, Boggio PS, Brunoni AR, Celnik P, et al. A technical guide to
46 tDCS, and related non-invasive brain stimulation tools. *Clin Neurophysiol.* 2016;127(2):1031-48.

- 1 47. Gandiga PC, Hummel FC, Cohen LG. Transcranial DC stimulation (tDCS): a tool for double-
2 blind sham-controlled clinical studies in brain stimulation. *Clin Neurophysiol.* 2006;117(4):845-50.
- 3 48. Nitsche MA, Paulus W. Excitability changes induced in the human motor cortex by weak
4 transcranial direct current stimulation. *J Physiol.* 2000;527 Pt 3(Pt 3):633-9.
- 5 49. Nitsche MA, Bikson M. Extending the parameter range for tDCS: Safety and tolerability of 4
6 mA stimulation. *Brain Stimul.* 2017;10(3):541-2.
- 7 50. Batsikadze G, Moliadze V, Paulus W, Kuo MF, Nitsche MA. Partially non-linear stimulation
8 intensity-dependent effects of direct current stimulation on motor cortex excitability in humans. *J*
9 *Physiol.* 2013;591(7):1987-2000.
- 10 51. Bonaiuto JJ, Bestmann S. Understanding the nonlinear physiological and behavioral effects of
11 tDCS through computational neurostimulation. *Prog Brain Res.* 2015;222:75-103.
- 12 52. Esmaeilpour Z, Marangolo P, Hampstead BM, Bestmann S, Galletta E, Knotkova H, et al.
13 Incomplete evidence that increasing current intensity of tDCS boosts outcomes. *Brain Stimul.*
14 2018;11(2):310-21.
- 15 53. Monte-Silva K, Kuo MF, Hessenthaler S, Fresnoza S, Liebetanz D, Paulus W, et al. Induction of
16 late LTP-like plasticity in the human motor cortex by repeated non-invasive brain stimulation. *Brain*
17 *Stimul.* 2013;6(3):424-32.
- 18 54. Bestmann S, Walsh V. Transcranial electrical stimulation. *Curr Biol.* 2017;27(23):R1258-R62.
- 19 55. Jackson MP, Rahman A, Lafon B, Kronberg G, Ling D, Parra LC, et al. Animal models of
20 transcranial direct current stimulation: Methods and mechanisms. *Clin Neurophysiol.*
21 2016;127(11):3425-54.
- 22 56. Friehs MA, Frings C. Offline beats online: transcranial direct current stimulation timing
23 influences on working memory. *Neuroreport.* 2019;30(12):795-9.
- 24 57. Zivanovic M, Paunovic D, Konstantinovic U, Vulic K, Bjekic J, Filipovic SR. The effects of
25 offline and online prefrontal vs parietal transcranial direct current stimulation (tDCS) on verbal and
26 spatial working memory. *Neurobiol Learn Mem.* 2021;179:107398.
- 27 58. Martin DM, Liu R, Alonzo A, Green M, Loo CK. Use of transcranial direct current stimulation
28 (tDCS) to enhance cognitive training: effect of timing of stimulation. *Exp Brain Res.*
29 2014;232(10):3345-51.
- 30 59. Oldrati V, Colombo B, Antonietti A. Combination of a short cognitive training and tDCS to
31 enhance visuospatial skills: A comparison between online and offline neuromodulation. *Brain Res.*
32 2018;1678:32-9.
- 33 60. Boggio PS, Nunes A, Rigonatti SP, Nitsche MA, Pascual-Leone A, Fregni F. Repeated sessions
34 of noninvasive brain DC stimulation is associated with motor function improvement in stroke patients.
35 *Restor Neurol Neurosci.* 2007;25(2):123-9.
- 36 61. Fregni F, Boggio PS, Lima MC, Ferreira MJ, Wagner T, Rigonatti SP, et al. A sham-controlled,
37 phase II trial of transcranial direct current stimulation for the treatment of central pain in traumatic
38 spinal cord injury. *Pain.* 2006;122(1-2):197-209.
- 39 62. Marshall L, Kirov R, Brade J, Molle M, Born J. Transcranial electrical currents to probe EEG
40 brain rhythms and memory consolidation during sleep in humans. *PLoS One.* 2011;6(2):e16905.
- 41 63. Reis J, Schambra HM, Cohen LG, Buch ER, Fritsch B, Zarahn E, et al. Noninvasive cortical
42 stimulation enhances motor skill acquisition over multiple days through an effect on consolidation. *Proc*
43 *Natl Acad Sci U S A.* 2009;106(5):1590-5.
- 44 64. Vergallito A, Feroldi S, Pisoni A, Romero Lauro LJ. Inter-Individual Variability in tDCS
45 Effects: A Narrative Review on the Contribution of Stable, Variable, and Contextual Factors. *Brain Sci.*
46 2022;12(5).

- 1 65. Kirk R. Experimental Design: Procedures for the Behavioral Sciences. Thousand Oaks,
2 California 2013. Available from: <https://methods.sagepub.com/book/experimental-design>.
- 3 66. Hancock PA. On the Nature of Vigilance. *Hum Factors*. 2017;59(1):35-43.
- 4 67. Parasuraman R. Consistency of individual differences in human vigilance performance: an
5 abilities classification analysis. *J Appl Psychol*. 1976;61(4):486-92.
- 6 68. Warm JS, Parasuraman R, Matthews G. Vigilance requires hard mental work and is stressful.
7 *Hum Factors*. 2008;50(3):433-41.
- 8 69. Grier RA, Warm JS, Dember WN, Matthews G, Galinsky TL, Parasuraman R. The vigilance
9 decrement reflects limitations in effortful attention, not mindlessness. *Hum Factors*. 2003;45(3):349-59.
- 10 70. Parasuraman R, Warm JS, See JE. Brain systems of vigilance. *The attentive brain*. Cambridge,
11 MA, US: The MIT Press; 1998. p. 221-56.
- 12 71. McIntire LK, McKinley RA, Goodyear C, Nelson J. A comparison of the effects of transcranial
13 direct current stimulation and caffeine on vigilance and cognitive performance during extended
14 wakefulness. *Brain Stimul*. 2014;7(4):499-507.
- 15 72. Nelson JT, McKinley RA, Golob EJ, Warm JS, Parasuraman R. Enhancing vigilance in operators
16 with prefrontal cortex transcranial direct current stimulation (tDCS). *Neuroimage*. 2014;85 Pt 3:909-17.
- 17 73. Axelrod V, Rees G, Lavidor M, Bar M. Increasing propensity to mind-wander with transcranial
18 direct current stimulation. *Proc Natl Acad Sci U S A*. 2015;112(11):3314-9.
- 19 74. Baddeley A. Working memory. *Science*. 1992;255(5044):556-9.
- 20 75. Miyake A, Shah P. Models of working memory: Mechanisms of active maintenance and
21 executive control. In: Miyake A, Shah P, editors. *Models of working memory: Mechanisms of active
22 maintenance and executive control*. New York, NY, US: Cambridge University Press; 1999. p. 1-27.
- 23 76. Davidson JE, Sternberg RJ. *The psychology of problem solving*. New York, NY, US: Cambridge
24 University Press; 2003.
- 25 77. Gilhooly KJ. Working Memory and Planning. In: Morris R, Ward G, editors. *The cognitive
26 psychology of planning*. London: Routledge; 2004. p. 71-88.
- 27 78. Hinson JM, Jameson TL, Whitney P. Impulsive decision making and working memory. *J Exp
28 Psychol Learn Mem Cogn*. 2003;29(2):298-306.
- 29 79. Kyllonen PC, Christal RE. Reasoning ability is (little more than) working-memory capacity?!
30 *Intelligence*. 1990;14(4):389-433.
- 31 80. D'Esposito M. From cognitive to neural models of working memory. *Philos Trans R Soc Lond B
32 Biol Sci*. 2007;362(1481):761-72.
- 33 81. Postle BR. Working memory as an emergent property of the mind and brain. *Neuroscience*.
34 2006;139(1):23-38.
- 35 82. Chan LKH, Hayward WG. Visual search. *WIREs Cognitive Science*. 2013;4(4):415-29.
- 36 83. Eckstein MP. Visual search: a retrospective. *J Vis*. 2011;11(5).
- 37 84. Wolfe JM. Visual search. *Curr Biol*. 2010;20(8):R346-9.
- 38 85. Anderson EJ, Mannan SK, Husain M, Rees G, Sumner P, Mort DJ, et al. Involvement of
39 prefrontal cortex in visual search. *Exp Brain Res*. 2007;180(2):289-302.
- 40 86. Donner T, Kettermann A, Diesch E, Ostendorf F, Villringer A, Brandt SA. Involvement of the
41 human frontal eye field and multiple parietal areas in covert visual selection during conjunction search.
42 *Eur J Neurosci*. 2000;12(9):3407-14.
- 43 87. Nobre AC, Coull JT, Walsh V, Frith CD. Brain activations during visual search: contributions of
44 search efficiency versus feature binding. *Neuroimage*. 2003;18(1):91-103.

- 1 88. Nelson JM, McKinley RA, McIntire LK, Goodyear C, Walters C. Augmenting visual search
2 performance with transcranial direct current stimulation (tDCS). *Military Psychology*. 2015;27(6):335-
3 47.
- 4 89. Ball K, Lane AR, Smith DT, Ellison A. Site-dependent effects of tDCS uncover dissociations in
5 the communication network underlying the processing of visual search. *Brain Stimul*. 2013;6(6):959-65.
- 6 90. Callan DE, Falcone B, Wada A, Parasuraman R. Simultaneous tDCS-fMRI Identifies Resting
7 State Networks Correlated with Visual Search Enhancement. *Front Hum Neurosci*. 2016;10:72.
- 8 91. Falcone B, Coffman BA, Clark VP, Parasuraman R. Transcranial direct current stimulation
9 augments perceptual sensitivity and 24-hour retention in a complex threat detection task. *PLoS One*.
10 2012;7(4):e34993.
- 11 92. Chambers CD, Garavan H, Bellgrove MA. Insights into the neural basis of response inhibition
12 from cognitive and clinical neuroscience. *Neurosci Biobehav Rev*. 2009;33(5):631-46.
- 13 93. Congdon E, Mumford JA, Cohen JR, Galvan A, Canli T, Poldrack RA. Measurement and
14 reliability of response inhibition. *Front Psychol*. 2012;3:37.
- 15 94. Horn NR, Dolan M, Elliott R, Deakin JF, Woodruff PW. Response inhibition and impulsivity: an
16 fMRI study. *Neuropsychologia*. 2003;41(14):1959-66.
- 17 95. Biggs AT, Cain MS, Mitroff SR. Cognitive Training Can Reduce Civilian Casualties in a
18 Simulated Shooting Environment. *Psychol Sci*. 2015;26(8):1164-76.
- 19 96. Nakamoto H, Mori S. Experts in fast-ball sports reduce anticipation timing cost by developing
20 inhibitory control. *Brain Cogn*. 2012;80(1):23-32.
- 21 97. Appelhans BM. Neurobehavioral inhibition of reward-driven feeding: implications for dieting
22 and obesity. *Obesity (Silver Spring)*. 2009;17(4):640-7.
- 23 98. Aron AR, Robbins TW, Poldrack RA. Inhibition and the right inferior frontal cortex. *Trends*
24 *Cogn Sci*. 2004;8(4):170-7.
- 25 99. Duncan J, Owen AM. Common regions of the human frontal lobe recruited by diverse cognitive
26 demands. *Trends Neurosci*. 2000;23(10):475-83.
- 27 100. Hampshire A, Sharp DJ. Contrasting network and modular perspectives on inhibitory control.
28 *Trends Cogn Sci*. 2015;19(8):445-52.
- 29 101. Aron AR, Robbins TW, Poldrack RA. Inhibition and the right inferior frontal cortex: one decade
30 on. *Trends Cogn Sci*. 2014;18(4):177-85.
- 31 102. Karni A, Meyer G, Rey-Hipolito C, Jezard P, Adams MM, Turner R, et al. The acquisition of
32 skilled motor performance: fast and slow experience-driven changes in primary motor cortex. *Proc Natl*
33 *Acad Sci U S A*. 1998;95(3):861-8.
- 34 103. Robertson EM, Pascual-Leone A, Miall RC. Current concepts in procedural consolidation. *Nat*
35 *Rev Neurosci*. 2004;5(7):576-82.
- 36 104. Korman M, Raz N, Flash T, Karni A. Multiple shifts in the representation of a motor sequence
37 during the acquisition of skilled performance. *Proc Natl Acad Sci U S A*. 2003;100(21):12492-7.
- 38 105. Karni A, Meyer G, Jezard P, Adams MM, Turner R, Ungerleider LG. Functional MRI evidence
39 for adult motor cortex plasticity during motor skill learning. *Nature*. 1995;377(6545):155-8.
- 40 106. Sanes JN, Donoghue JP. Plasticity and primary motor cortex. *Annu Rev Neurosci*. 2000;23:393-
41 415.
- 42 107. Gilbert PF, Thach WT. Purkinje cell activity during motor learning. *Brain Res*. 1977;128(2):309-
43 28.
- 44 108. Houk JC, Buckingham JT, Barto AG. Models of the cerebellum and motor learning. *Behavioral*
45 *and Brain Sciences*. 1996;19(3):368-83, 503-27.

- 1 109. Kitazawa S, Kimura T, Yin PB. Cerebellar complex spikes encode both destinations and errors
2 in arm movements. *Nature*. 1998;392(6675):494-7.
- 3 110. Thach WT. On the specific role of the cerebellum in motor learning and cognition: Clues from
4 PET activation and lesion studies in man. *Behavioral and Brain Sciences*. 1996;19(3):411-33.
- 5 111. Reis J, Fritsch B. Modulation of motor performance and motor learning by transcranial direct
6 current stimulation. *Curr Opin Neurol*. 2011;24(6):590-6.
- 7 112. Apsvalka D, Ramsey R, Cross ES. Anodal tDCS over Primary Motor Cortex Provides No
8 Advantage to Learning Motor Sequences via Observation. *Neural Plast*. 2018;2018:1237962.
- 9 113. Antal A, Nitsche MA, Kincses TZ, Kruse W, Hoffmann KP, Paulus W. Facilitation of visuo-
10 motor learning by transcranial direct current stimulation of the motor and extrastriate visual areas in
11 humans. *Eur J Neurosci*. 2004;19(10):2888-92.
- 12 114. Ambrus GG, Chaieb L, Stilling R, Rothkegel H, Antal A, Paulus W. Monitoring transcranial
13 direct current stimulation induced changes in cortical excitability during the serial reaction time task.
14 *Neurosci Lett*. 2016;616:98-104.
- 15 115. Zimerman M, Heise KF, Gerloff C, Cohen LG, Hummel FC. Disrupting the ipsilateral motor
16 cortex interferes with training of a complex motor task in older adults. *Cereb Cortex*. 2014;24(4):1030-
17 6.
- 18 116. von Rein E, Hoff M, Kaminski E, Sehm B, Steele CJ, Villringer A, et al. Improving motor
19 performance without training: the effect of combining mirror visual feedback with transcranial direct
20 current stimulation. *J Neurophysiol*. 2015;113(7):2383-9.
- 21 117. Vollmann H, Conde V, Sewerin S, Taubert M, Sehm B, Witte OW, et al. Anodal transcranial
22 direct current stimulation (tDCS) over supplementary motor area (SMA) but not pre-SMA promotes
23 short-term visuomotor learning. *Brain Stimul*. 2013;6(2):101-7.
- 24 118. Vines BW, Cerruti C, Schlaug G. Dual-hemisphere tDCS facilitates greater improvements for
25 healthy subjects' non-dominant hand compared to uni-hemisphere stimulation. *BMC Neurosci*.
26 2008;9:103.
- 27 119. Toth AJ, Ramsbottom N, Constantin C, Milliet A, Campbell MJ. The effect of expertise, training
28 and neurostimulation on sensory-motor skill in esports. *Computers in Human Behavior*.
29 2021;121:106782.
- 30 120. Tecchio F, Zappasodi F, Assenza G, Tombini M, Vollaro S, Barbati G, et al. Anodal transcranial
31 direct current stimulation enhances procedural consolidation. *J Neurophysiol*. 2010;104(2):1134-40.
- 32 121. Talimkhani A, Abdollahi I, Mohseni-Bandpei MA, Ehsani F, Khalili S, Jaberzadeh S.
33 Differential Effects of Unihemispheric Concurrent Dual-Site and Conventional tDCS on Motor
34 Learning: A Randomized, Sham-Controlled Study. *Basic Clin Neurosci*. 2019;10(1):59-72.
- 35 122. Spampinato DA, Satar Z, Rothwell JC. Combining reward and M1 transcranial direct current
36 stimulation enhances the retention of newly learnt sensorimotor mappings. *Brain Stimul*.
37 2019;12(5):1205-12.
- 38 123. Shilo G, Lavidor M. Non-linear effects of cathodal transcranial direct current stimulation (tDCS)
39 of the primary motor cortex on implicit motor learning. *Exp Brain Res*. 2019;237(4):919-25.
- 40 124. Sevilla-Sanchez M, Hortobágyi T, Fogelson N, Iglesias-Soler E, Carballeira E, Fernandez-del-
41 Olmo M. Small Enhancement of Bimanual Typing Performance after 20 Sessions of tDCS in Healthy
42 Young Adults. *Neuroscience*. 2021;466:26-35.
- 43 125. Saucedo Marquez CM, Zhang X, Swinnen SP, Meesen R, Wenderoth N. Task-specific effect of
44 transcranial direct current stimulation on motor learning. *Front Hum Neurosci*. 2013;7:333.

126. Samaei A, Ehsani F, Zoghi M, Hafez Yosephi M, Jaberzadeh S. Online and offline effects of cerebellar transcranial direct current stimulation on motor learning in healthy older adults: a randomized double-blind sham-controlled study. *Eur J Neurosci.* 2017;45(9):1177-85.
127. Rumpf JJ, Wegscheider M, Hinselmann K, Fricke C, King BR, Weise D, et al. Enhancement of motor consolidation by post-training transcranial direct current stimulation in older people. *Neurobiol Aging.* 2017;49:1-8.
128. Rocha K, Marinho V, Magalhaes F, Carvalho V, Fernandes T, Ayres M, et al. Unskilled shooters improve both accuracy and grouping shot having as reference skilled shooters cortical area: An EEG and tDCS study. *Physiol Behav.* 2020;224:113036.
129. Prichard G, Weiller C, Fritsch B, Reis J. Effects of different electrical brain stimulation protocols on subcomponents of motor skill learning. *Brain Stimul.* 2014;7(4):532-40.
130. Pollok B, Keitel A, Foerster M, Moshiri G, Otto K, Krause V. The posterior parietal cortex mediates early offline-rather than online-motor sequence learning. *Neuropsychologia.* 2020;146:107555.
131. Pixa NH, Steinberg F, Doppelmayr M. High-definition transcranial direct current stimulation to both primary motor cortices improves unimanual and bimanual dexterity. *Neurosci Lett.* 2017;643:84-8.
132. Parma JO, Profeta V, Andrade AGP, Lage GM, Apolinario-Souza T. TDCS of the Primary Motor Cortex: Learning the Absolute Dimension of a Complex Motor Task. *J Mot Behav.* 2021;53(4):431-44.
133. Nguemni C, Stiehl A, Hiew S, Zeller D. No Impact of Cerebellar Anodal Transcranial Direct Current Stimulation at Three Different Timings on Motor Learning in a Sequential Finger-Tapping Task. *Front Hum Neurosci.* 2021;15:631517.
134. Naros G, Geyer M, Koch S, Mayr L, Ellinger T, Grimm F, et al. Enhanced motor learning with bilateral transcranial direct current stimulation: Impact of polarity or current flow direction? *Clin Neurophysiol.* 2016;127(4):2119-26.
135. Minarik T, Sauseng P, Dunne L, Berger B, Sterr A. Effects of anodal transcranial direct current stimulation on visually guided learning of grip force control. *Biology (Basel).* 2015;4(1):173-86.
136. Leite J, Carvalho S, Fregni F, Goncalves OF. Task-specific effects of tDCS-induced cortical excitability changes on cognitive and motor sequence set shifting performance. *PLoS One.* 2011;6(9):e24140.
137. Jin Y, Lee J, Kim S, Yoon B. Noninvasive brain stimulation over M1 and DLPFC cortex enhances the learning of bimanual isometric force control. *Hum Mov Sci.* 2019;66:73-83.
138. Hashemirad F, Fitzgerald PB, Zoghi M, Jaberzadeh S. Single-Session Anodal tDCS with Small-Size Stimulating Electrodes Over Frontoparietal Superficial Sites Does Not Affect Motor Sequence Learning. *Front Hum Neurosci.* 2017;11:153.
139. Furuya S, Klaus M, Nitsche MA, Paulus W, Altenmuller E. Ceiling effects prevent further improvement of transcranial stimulation in skilled musicians. *J Neurosci.* 2014;34(41):13834-9.
140. Fujiyama H, Hinder MR, Barzideh A, Van de Vijver C, Badache AC, Manrique CM, et al. Preconditioning tDCS facilitates subsequent tDCS effect on skill acquisition in older adults. *Neurobiol Aging.* 2017;51:31-42.
141. Focke J, Kemmet S, Krause V, Keitel A, Pollok B. Cathodal transcranial direct current stimulation (tDCS) applied to the left premotor cortex (PMC) stabilizes a newly learned motor sequence. *Behav Brain Res.* 2017;316:87-93.
142. Filmer HL, Lyons M, Mattingley JB, Dux PE. Anodal tDCS applied during multitasking training leads to transferable performance gains. *Sci Rep.* 2017;7(1):12988.

- 1 143. Ferrucci R, Brunoni AR, Parazzini M, Vergari M, Rossi E, Fumagalli M, et al. Modulating
2 human procedural learning by cerebellar transcranial direct current stimulation. *Cerebellum*.
3 2013;12(4):485-92.
- 4 144. Fehring DJ, Illipparampil R, Acevedo N, Jaberzadeh S, Fitzgerald PB, Mansouri FA. Interaction
5 of task-related learning and transcranial direct current stimulation of the prefrontal cortex in modulating
6 executive functions. *Neuropsychologia*. 2019;131:148-59.
- 7 145. Fan J, Voisin J, Milot MH, Higgins J, Boudrias MH. Transcranial direct current stimulation over
8 multiple days enhances motor performance of a grip task. *Ann Phys Rehabil Med*. 2017;60(5):329-33.
- 9 146. Ehsani F, Bakhtiary AH, Jaberzadeh S, Talimkhani A, Hajihasani A. Differential effects of
10 primary motor cortex and cerebellar transcranial direct current stimulation on motor learning in healthy
11 individuals: A randomized double-blind sham-controlled study. *Neurosci Res*. 2016;112:10-9.
- 12 147. Dumel G, Bourassa ME, Charlebois-Plante C, Desjardins M, Doyon J, Saint-Amour D, et al.
13 Multisession anodal transcranial direct current stimulation induces motor cortex plasticity enhancement
14 and motor learning generalization in an aging population. *Clin Neurophysiol*. 2018;129(2):494-502.
- 15 148. Dumel G, Bourassa ME, Charlebois-Plante C, Desjardins M, Doyon J, Saint-Amour D, et al.
16 Motor Learning Improvement Remains 3 Months After a Multisession Anodal tDCS Intervention in an
17 Aging Population. *Front Aging Neurosci*. 2018;10:335.
- 18 149. Doppelmayr M, Pixa NH, Steinberg F. Cerebellar, but not Motor or Parietal, High-Density
19 Anodal Transcranial Direct Current Stimulation Facilitates Motor Adaptation. *J Int Neuropsychol Soc*.
20 2016;22(9):928-36.
- 21 150. Cantarero G, Spampinato D, Reis J, Ajagbe L, Thompson T, Kulkarni K, et al. Cerebellar direct
22 current stimulation enhances on-line motor skill acquisition through an effect on accuracy. *J Neurosci*.
23 2015;35(7):3285-90.
- 24 151. Boggio PS, Castro LO, Savagim EA, Braite R, Cruz VC, Rocha RR, et al. Enhancement of non-
25 dominant hand motor function by anodal transcranial direct current stimulation. *Neurosci Lett*.
26 2006;404(1-2):232-6.
- 27 152. Ballard HK, Eakin SM, Maldonado T, Bernard JA. Using high-definition transcranial direct
28 current stimulation to investigate the role of the dorsolateral prefrontal cortex in explicit sequence
29 learning. *PLoS One*. 2021;16(3):e0246849.
- 30 153. Ballard HK, Goen JRM, Maldonado T, Bernard JA. Effects of cerebellar transcranial direct
31 current stimulation on the cognitive stage of sequence learning. *J Neurophysiol*. 2019;122(2):490-9.
- 32 154. Nydam AS, Sewell DK, Dux PE. Cathodal electrical stimulation of frontoparietal cortex disrupts
33 statistical learning of visual configural information. *Cortex*. 2018;99:187-99.
- 34 155. Cosman JD, Atreya PV, Woodman GF. Transient reduction of visual distraction following
35 electrical stimulation of the prefrontal cortex. *Cognition*. 2015;145:73-6.
- 36 156. Sung K, Gordon B. Transcranial direct current stimulation (tDCS) facilitates overall visual
37 search response times but does not interact with visual search task factors. *PLoS One*.
38 2018;13(3):e0194640.
- 39 157. Clark VP, Coffman BA, Mayer AR, Weisend MP, Lane TD, Calhoun VD, et al. TDCS guided
40 using fMRI significantly accelerates learning to identify concealed objects. *Neuroimage*.
41 2012;59(1):117-28.
- 42 158. Lanina AA, Feurra M, Gorbunova ES. No Effect of the Right Posterior Parietal Cortex tDCS in
43 Dual-Target Visual Search. *Front Psychol*. 2018;9:2112.
- 44 159. Falcone B, Wada A, Parasuraman R, Callan DE. Individual differences in learning correlate with
45 modulation of brain activity induced by transcranial direct current stimulation. *PLoS One*.
46 2018;13(5):e0197192.

- 1 160. Filmer HL, Varghese E, Hawkins GE, Mattingley JB, Dux PE. Improvements in Attention and
2 Decision-Making Following Combined Behavioral Training and Brain Stimulation. *Cereb Cortex*.
3 2017;27(7):3675-82.
- 4 161. Coffman BA, Trumbo MC, Flores RA, Garcia CM, van der Merwe AJ, Wassermann EM, et al.
5 Impact of tDCS on performance and learning of target detection: interaction with stimulus
6 characteristics and experimental design. *Neuropsychologia*. 2012;50(7):1594-602.
- 7 162. Ellison A, Ball KL, Moseley P, Dowsett J, Smith DT, Weis S, et al. Functional interaction
8 between right parietal and bilateral frontal cortices during visual search tasks revealed using functional
9 magnetic imaging and transcranial direct current stimulation. *PLoS One*. 2014;9(4):e93767.
- 10 163. Reinhart RM, Woodman GF. Enhancing long-term memory with stimulation tunes visual
11 attention in one trial. *Proc Natl Acad Sci U S A*. 2015;112(2):625-30.
- 12 164. Wagner J, Lo Monaco S, Conto F, Parrott D, Battelli L, Rusconi E. Effects of transcranial direct
13 current stimulation over the posterior parietal cortex on novice X-ray screening performance. *Cortex*.
14 2020;132:1-14.
- 15 165. Grasso PA, Tonolli E, Miniussi C. Effects of different transcranial direct current stimulation
16 protocols on visuo-spatial contextual learning formation: evidence of homeostatic regulatory
17 mechanisms. *Sci Rep*. 2020;10(1):4622.
- 18 166. Bolognini N, Fregni F, Casati C, Olgiati E, Vallar G. Brain polarization of parietal cortex
19 augments training-induced improvement of visual exploratory and attentional skills. *Brain Res*.
20 2010;1349:76-89.
- 21 167. Ellison A, Ball KL, Lane AR. The Behavioral Effects of tDCS on Visual Search Performance
22 Are Not Influenced by the Location of the Reference Electrode. *Front Neurosci*. 2017;11:520.
- 23 168. Nikolin S, Loo CK, Bai S, Dokos S, Martin DM. Focalised stimulation using high definition
24 transcranial direct current stimulation (HD-tDCS) to investigate declarative verbal learning and memory
25 functioning. *Neuroimage*. 2015;117:11-9.
- 26 169. Naka M, Matsuzawa D, Ishii D, Hamada H, Uchida T, Sugita K, et al. Differential effects of
27 high-definition transcranial direct current stimulation on verbal working memory performance according
28 to sensory modality. *Neurosci Lett*. 2018;687:131-6.
- 29 170. Pupikova M, Simko P, Gajdos M, Rektorova I. Modulation of Working Memory and Resting-
30 State fMRI by tDCS of the Right Frontoparietal Network. *Neural Plast*. 2021;2021:5594305.
- 31 171. Murphy OW, Hoy KE, Wong D, Bailey NW, Fitzgerald PB, Segrave RA. Transcranial random
32 noise stimulation is more effective than transcranial direct current stimulation for enhancing working
33 memory in healthy individuals: Behavioural and electrophysiological evidence. *Brain Stimul*.
34 2020;13(5):1370-80.
- 35 172. Karthikeyan R, Smoot MR, Mehta RK. Anodal tDCS augments and preserves working memory
36 beyond time-on-task deficits. *Sci Rep*. 2021;11(1):19134.
- 37 173. Caulfield KA, Indahlastari A, Nissim NR, Lopez JW, Fleischmann HH, Woods AJ, et al. Electric
38 Field Strength From Prefrontal Transcranial Direct Current Stimulation Determines Degree of Working
39 Memory Response: A Potential Application of Reverse-Calculation Modeling? *Neuromodulation*.
40 2022;25(4):578-87.
- 41 174. Asseondi S, Hu R, Eskes G, Pan X, Zhou J, Shapiro K. Impact of tDCS on working memory
42 training is enhanced by strategy instructions in individuals with low working memory capacity.
43 *Scientific Reports*. 2021;11(1):5531.
- 44 175. Ankri YLE, Braw Y, Luboshits G, Meiron O. The effects of stress and transcranial direct current
45 stimulation (tDCS) on working memory: A randomized controlled trial. *Cogn Affect Behav Neurosci*.
46 2020;20(1):103-14.

176. Abellaneda-Perez K, Vaque-Alcazar L, Perellon-Alfonso R, Bargallo N, Kuo MF, Pascual-Leone A, et al. Differential tDCS and tACS Effects on Working Memory-Related Neural Activity and Resting-State Connectivity. *Front Neurosci.* 2019;13:1440.
177. Zwissler B, Sperber C, Aigeldinger S, Schindler S, Kissler J, Plewnia C. Shaping memory accuracy by left prefrontal transcranial direct current stimulation. *J Neurosci.* 2014;34(11):4022-6.
178. Hussey EK, Fontes EB, Ward N, Westfall DR, Kao SC, Kramer AF, et al. Combined and Isolated Effects of Acute Exercise and Brain Stimulation on Executive Function in Healthy Young Adults. *J Clin Med.* 2020;9(5).
179. Chrysikou EG, Gorey C, Aupperle RL. Anodal transcranial direct current stimulation over right dorsolateral prefrontal cortex alters decision making during approach-avoidance conflict. *Soc Cogn Affect Neurosci.* 2017;12(3):468-75.
180. Boehringer A, Macher K, Dukart J, Villringer A, Pleger B. Cerebellar transcranial direct current stimulation modulates verbal working memory. *Brain Stimul.* 2013;6(4):649-53.
181. Baumert A, Buchholz N, Zinkernagel A, Clarke P, MacLeod C, Osinsky R, et al. Causal underpinnings of working memory and Stroop interference control: Testing the effects of anodal and cathodal tDCS over the left DLPFC. *Cogn Affect Behav Neurosci.* 2020;20(1):34-48.
182. Au J, Katz B, Buschkuehl M, Bunarjo K, Senger T, Zabel C, et al. Enhancing Working Memory Training with Transcranial Direct Current Stimulation. *J Cogn Neurosci.* 2016;28(9):1419-32.
183. van Schouwenburg MR, Sligte IG, Giffin MR, Günther F, Koster D, Spronkers FS, et al. Effects of Midfrontal Brain Stimulation on Sustained Attention. *Journal of Cognitive Enhancement.* 2021;5(1):62-72.
184. Ironside M, O'Shea J, Cowen PJ, Harmer CJ. Frontal Cortex Stimulation Reduces Vigilance to Threat: Implications for the Treatment of Depression and Anxiety. *Biol Psychiatry.* 2016;79(10):823-30.
185. Hanken K, Bosse M, Mohrke K, Eling P, Kastrup A, Antal A, et al. Counteracting Fatigue in Multiple Sclerosis with Right Parietal Anodal Transcranial Direct Current Stimulation. *Front Neurol.* 2016;7:154.
186. Plewnia C, Zwissler B, Langst I, Maurer B, Giel K, Kruger R. Effects of transcranial direct current stimulation (tDCS) on executive functions: influence of COMT Val/Met polymorphism. *Cortex.* 2013;49(7):1801-7.
187. McIntire LK, McKinley RA, Nelson JM, Goodyear C. Transcranial direct current stimulation versus caffeine as a fatigue countermeasure. *Brain Stimul.* 2017;10(6):1070-8.
188. Manuel AL, David AW, Bikson M, Schnider A. Frontal tDCS modulates orbitofrontal reality filtering. *Neuroscience.* 2014;265:21-7.
189. Luna FG, Roman-Caballero R, Barttfeld P, Lupianez J, Martin-Arevalo E. A High-Definition tDCS and EEG study on attention and vigilance: Brain stimulation mitigates the executive but not the arousal vigilance decrement. *Neuropsychologia.* 2020;142:107447.
190. Jacoby N, Lavidor M. Null tDCS Effects in a Sustained Attention Task: The Modulating Role of Learning. *Front Psychol.* 2018;9:476.
191. Filmer HL, Ehrhardt SE, Bollmann S, Mattingley JB, Dux PE. Accounting for individual differences in the response to tDCS with baseline levels of neurochemical excitability. *Cortex.* 2019;115:324-34.
192. Coulborn S, Bowman H, Miall RC, Fernandez-Espejo D. Effect of tDCS Over the Right Inferior Parietal Lobule on Mind-Wandering Propensity. *Front Hum Neurosci.* 2020;14:230.
193. Brunnauer A, Segmiller FM, Loschner S, Grun V, Padberg F, Palm U. The Effects of Transcranial Direct Current Stimulation (tDCS) on Psychomotor and Visual Perception Functions Related to Driving Skills. *Front Behav Neurosci.* 2018;12:16.

- 1 194. Borragan G, Gilson M, Guerrero-Mosquera C, Di Ricci E, Slama H, Peigneux P. Transcranial
2 Direct Current Stimulation Does Not Counteract Cognitive Fatigue, but Induces Sleepiness and an Inter-
3 Hemispheric Shift in Brain Oxygenation. *Front Psychol.* 2018;9:2351.
- 4 195. Angius L, Santarnecchi E, Pascual-Leone A, Marcora SM. Transcranial Direct Current
5 Stimulation over the Left Dorsolateral Prefrontal Cortex Improves Inhibitory Control and Endurance
6 Performance in Healthy Individuals. *Neuroscience.* 2019;419:34-45.
- 7 196. Thomas F, Pixa NH, Berger A, Cheng MY, Doppelmayr M, Steinberg F. Neither Cathodal nor
8 Anodal Transcranial Direct Current Stimulation on the Left Dorsolateral Prefrontal Cortex alone or
9 Applied During Moderate Aerobic Exercise Modulates Executive Function. *Neuroscience.* 2020;443:71-
10 83.
- 11 197. Oldrati V, Patricelli J, Colombo B, Antonietti A. The role of dorsolateral prefrontal cortex in
12 inhibition mechanism: A study on cognitive reflection test and similar tasks through neuromodulation.
13 *Neuropsychologia.* 2016;91:499-508.
- 14 198. Kuehne M, Schmidt K, Heinze HJ, Zaehle T. Modulation of Emotional Conflict Processing by
15 High-Definition Transcranial Direct Current Stimulation (HD-TDCS). *Front Behav Neurosci.*
16 2019;13:224.
- 17 199. Hammer A, Mohammadi B, Schmicker M, Saliger S, Munte TF. Errorless and errorful learning
18 modulated by transcranial direct current stimulation. *BMC Neurosci.* 2011;12:72.
- 19 200. Gomez-Ariza CJ, Martin MC, Morales J. Tempering Proactive Cognitive Control by
20 Transcranial Direct Current Stimulation of the Right (but Not the Left) Lateral Prefrontal Cortex. *Front*
21 *Neurosci.* 2017;11:282.
- 22 201. Gladwin TE, den Uyl TE, Fregni FF, Wiers RW. Enhancement of selective attention by tDCS:
23 interaction with interference in a Sternberg task. *Neurosci Lett.* 2012;512(1):33-7.
- 24 202. Friedrich J, Beste C. Paradoxical, causal effects of sensory gain modulation on motor inhibitory
25 control - a tDCS, EEG-source localization study. *Sci Rep.* 2018;8(1):17486.
- 26 203. Edgcumbe DR, Thoma V, Rivolta D, Nitsche MA, Fu CHY. Anodal transcranial direct current
27 stimulation over the right dorsolateral prefrontal cortex enhances reflective judgment and decision-
28 making. *Brain Stimul.* 2019;12(3):652-8.
- 29 204. Dubreuil-Vall L, Chau P, Ruffini G, Widge AS, Camprodon JA. tDCS to the left DLPFC
30 modulates cognitive and physiological correlates of executive function in a state-dependent manner.
31 *Brain Stimul.* 2019;12(6):1456-63.
- 32 205. Denis G, Zory R, Radel R. Testing the role of cognitive inhibition in physical endurance using
33 high-definition transcranial direct current stimulation over the prefrontal cortex. *Hum Mov Sci.*
34 2019;67:102507.
- 35 206. Boudewyn M, Roberts BM, Mizrak E, Ranganath C, Carter CS. Prefrontal transcranial direct
36 current stimulation (tDCS) enhances behavioral and EEG markers of proactive control. *Cogn Neurosci.*
37 2019;10(2):57-65.
- 38 207. Bürkner P-C. brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of*
39 *Statistical Software.* 2017;80(1):1 - 28.
- 40 208. Williams DR, Rast P, Burkner P. Bayesian meta-analysis with weakly informative prior
41 distributions. *PsyArXiv.* 2018:1-19.
- 42 209. Reis DJ, Kaizer AM, Kinney AR, Bahraini NH, Holliday R, Forster JE, et al. A practical guide to
43 random-effects Bayesian meta-analyses with application to the psychological trauma and suicide
44 literature. *Psychol Trauma.* 2023;15(1):121-30.
- 45 210. Makowski D, Ben-Shachar MS, Chen SHA, Ludecke D. Indices of Effect Existence and
46 Significance in the Bayesian Framework. *Front Psychol.* 2019;10:2767.

211. Westfall J, Kenny DA, Judd CM. Statistical power and optimal design in experiments in which samples of participants respond to samples of stimuli. *J Exp Psychol Gen.* 2014;143(5):2020-45.
212. Gelman A, Goodrich B, Gabry J, Vehtari A. R-squared for Bayesian Regression Models. *The American Statistician.* 2019;73(3):307-9.
213. Vehtari A, Simpson D, Gelman A, Yao Y, Gabry J. Pareto smoothed importance sampling. *Journal of Machine Learning Research.* 2024;25:1-58.
214. Paananen T, Piironen J, Bürkner PC, Vehtari A. Implicitly adaptive importance sampling. *Stat Comput.* 2021;31(2).
215. Vehtari A, Gelman A, Gabry J. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Stat Comput.* 2017;27(5):1413-32.
216. Rahman A, Reato D, Arlotti M, Gasca F, Datta A, Parra LC, et al. Cellular effects of acute direct current stimulation: somatic and synaptic terminal effects. *J Physiol.* 2013;591(10):2563-78.
217. Bikson M, Grossman P, Thomas C, Zannou AL, Jiang J, Adnan T, et al. Safety of Transcranial Direct Current Stimulation: Evidence Based Update 2016. *Brain Stimul.* 2016;9(5):641-61.
218. Kessler SK, Minhas P, Woods AJ, Rosen A, Gorman C, Bikson M. Dosage considerations for transcranial direct current stimulation in children: a computational modeling study. *PLoS One.* 2013;8(9):e76112.
219. Opitz A, Paulus W, Will S, Antunes A, Thielscher A. Determinants of the electric field during transcranial direct current stimulation. *Neuroimage.* 2015;109:140-50.
220. Truong DQ, Magerowski G, Blackburn GL, Bikson M, Alonso-Alonso M. Computational modeling of transcranial direct current stimulation (tDCS) in obesity: Impact of head fat and dose guidelines. *Neuroimage Clin.* 2013;2:759-66.
221. Saturnino GB, Siebner HR, Thielscher A, Madsen KH. Accessibility of cortical regions to focal TES: Dependence on spatial position, safety, and practical constraints. *Neuroimage.* 2019;203:116183.
222. Huang Y, Datta A, Bikson M, Parra LC. Realistic volumetric-approach to simulate transcranial electric stimulation-ROAST-a fully automated open-source pipeline. *J Neural Eng.* 2019;16(5):056006.
223. Kashyap R, Bhattacharjee S, Arumugam R, Bharath RD, Udupa K, Oishi K, et al. Focality-Oriented Selection of Current Dose for Transcranial Direct Current Stimulation. *J Pers Med.* 2021;11(9).
224. Hsu TY, Juan CH, Tseng P. Individual Differences and State-Dependent Responses in Transcranial Direct Current Stimulation. *Front Hum Neurosci.* 2016;10:643.
225. Li LM, Uehara K, Hanakawa T. The contribution of interindividual factors to variability of response in transcranial direct current stimulation studies. *Front Cell Neurosci.* 2015;9:181.
226. Rosen DS, Erickson B, Kim YE, Mirman D, Hamilton RH, Kounios J. Anodal tDCS to Right Dorsolateral Prefrontal Cortex Facilitates Performance for Novice Jazz Improvisers but Hinders Experts. *Front Hum Neurosci.* 2016;10:579.

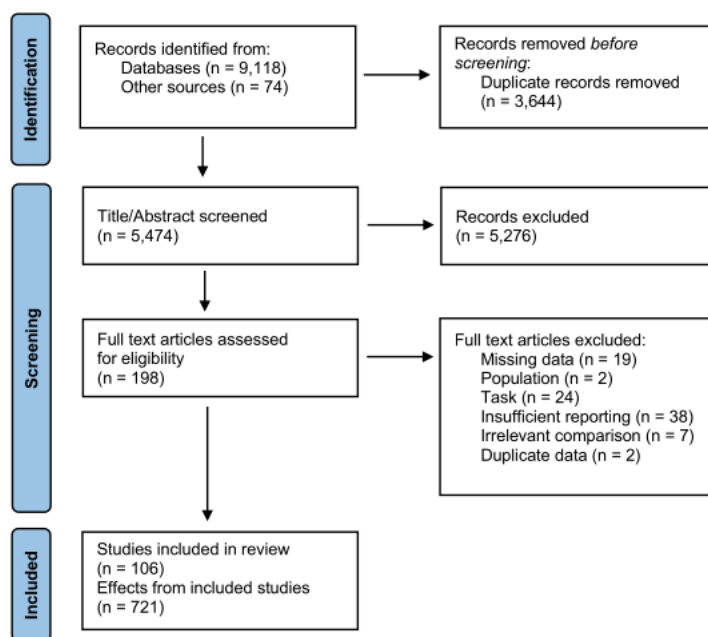


Figure 1. Summary flowchart of literature search and screening procedure.

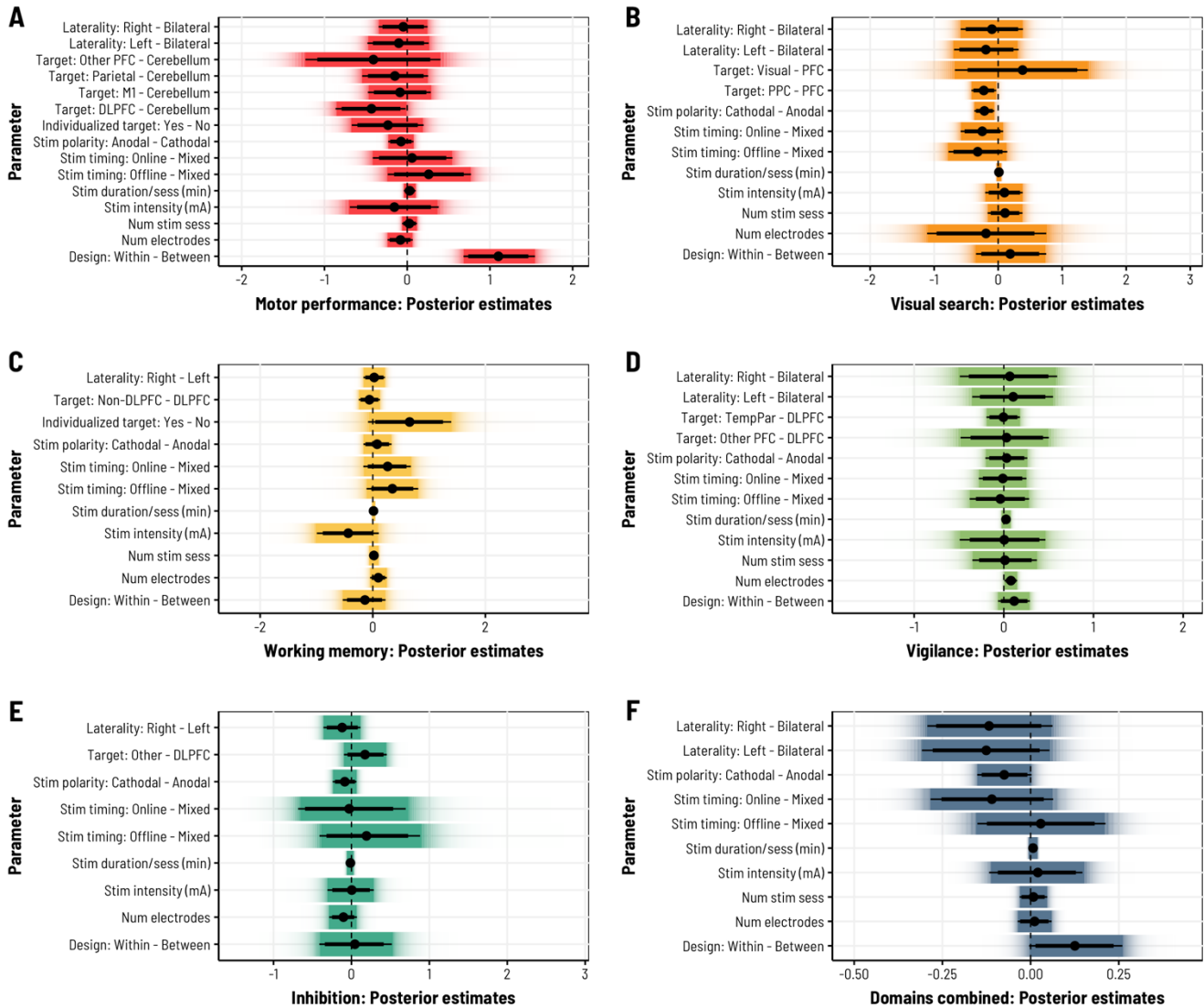


Figure 2. Contrasting estimates of multiple neurostimulation and experimental parameters on behavioral performance outcomes, both within-domain and between-domain. For categorical predictors (e.g., target laterality), contrasts were specified in an $A - B$ fashion, such that level B served as the reference point. Thus, positive values suggest larger effect sizes (on average) for level A compared to B ; negative values indicate the reverse. For continuous predictors (e.g., stimulation intensity), positive values suggest larger effect sizes with increasing values of the predictor (e.g., stronger stimulation dosages); negative values suggest the inverse association. Values closer to zero indicate weak or no association with performance outcomes, either at the level of mean differences between factor levels or a linear relationship with continuous predictors. Point intervals give 90-95% credibility intervals (i.e., highest density intervals) around the median posterior estimates (thick lines = 90% CI; thin lines = 95% CI; solid gradient areas indicate the 95% CI). (A) Motor performance, (B) Visual search, (C) Working memory, (D) Vigilance, (E) Inhibition, (F) Domain-General.

1

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)	2 3	Table 3. Summary of meta- regression parameters for motor
Intercept	-0.04	0.62	-1.32 – 1.22 (.524)	4 5	
Polarity: Anodal - Cathodal	-0.07	0.08	-0.23 – 0.08 (.829)	6 7	
Target: DLPFC - Cerebellum	-0.43	0.22	-0.86 – -0.01 (.977)		
Target: M1 - Cerebellum	-0.09	0.19	-0.47 – 0.29 (.672)		
Target: Parietal - Cerebellum	-0.15	0.20	-0.55 – 0.25 (.767)		
Target: Other PFC - Cerebellum	-0.41	0.42	-1.24 – 0.41 (.838)		
Individualized target: Yes - No	-0.23	0.22	-0.68 – 0.19 (.854)		
Laterality: Left - Bilateral	-0.10	0.19	-0.48 – 0.26 (.709)		
Laterality: Right - Bilateral	-0.05	0.15	-0.34 – 0.25 (.627)		
Number of stimulation sessions	0.02	0.04	-0.06 – 0.12 (.718)		
Stimulation duration/session (min)	0.03	0.03	-0.04 – 0.10 (.801)		
Stimulation intensity (mA)	-0.16	0.26	-0.71 – 0.36 (.725)		
Stimulation timing: Offline - Mixed	0.26	0.25	-0.24 – 0.77 (.844)		
Stimulation timing: Online - Mixed	0.06	0.24	-0.42 – 0.55 (.591)		
Number of electrodes in montage	-0.08	0.07	-0.24 – 0.06 (.863)		
Design: Within - Between	1.11	0.22	0.68 – 1.55 (1.00)		
Random Effects (N studies = 42)					
σ_{StudyID} (Intercept)	0.82	0.14	0.58 – 1.14		
N total effects = 253					
Marginal $R^2 = 0.25$ [0.16, 0.34]					
Conditional $R^2 = 0.41$ [0.34, 0.47]					

performance.

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39

1 **Table 4.** Summary of meta-regression parameters for visual search.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)	2
Intercept	0.25	0.98	-1.86 – 2.29 (.599)	3
Polarity: Anodal - Cathodal	-0.22	0.08	-0.37 – -0.06 (.996)	4
Target: PPC - PFC	-0.23	0.10	-0.42 – -0.03 (.988)	5
Target: Visual - PFC	0.38	0.50	-0.67 – 1.40 (.773)	6
Laterality: Left - Bilateral	-0.19	0.26	-0.70 – 0.31 (.777)	7
Laterality: Right - Bilateral	-0.10	0.25	-0.59 – 0.38 (.658)	8
Number of stimulation sessions	0.11	0.13	-0.16 – 0.38 (.801)	9
Stimulation duration/session (min)	0.01	0.02	-0.02 – 0.05 (.751)	10
Stimulation intensity (mA)	0.10	0.15	-0.20 – 0.38 (.743)	11
Stimulation timing: Offline - Mixed	-0.32	0.23	-0.79 – 0.13 (.920)	12
Stimulation timing: Online - Mixed	-0.25	0.17	-0.59 – 0.08 (.928)	13
Number of electrodes in montage	-0.19	0.44	-1.11 – 0.76 (.664)	14
Design: Within - Between	0.19	0.26	-0.36 – 0.74 (.760)	15
Random Effects (N studies = 18)				16
σ_{StudyID} (Intercept)	0.40	0.11	0.23 – 0.65	17
N total effects = 176				18
Marginal $R^2 = 0.36$ [0.10, 0.49]				19
Conditional $R^2 = 0.50$ [0.39, 0.59]				20

36
37
38
39
40
41
42
43
44
45
46

1 **Table 5.** Summary of meta-regression parameters for working memory.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (pd)	2
Intercept	0.67	0.41	-0.20 – 1.58 (.943)	3
Polarity: Anodal - Cathodal	0.08	0.13	-0.17 – 0.34 (.725)	4
Target: Non-DLPFC - DLPFC	-0.06	0.10	-0.25 – 0.13 (.734)	5
Individualized target: Yes - No	0.65	0.35	-0.08 – 1.40 (.963)	6
Laterality: Right - Left	0.03	0.10	-0.16 – 0.22 (.605)	7
Number of stimulation sessions	0.02	0.04	-0.07 – 0.10 (.692)	8
Stimulation duration/session (min)	0.01	0.01	-0.01 – 0.04 (.835)	9
Stimulation intensity (mA)	-0.44	0.26	-1.01 – 0.09 (.953)	10
Stimulation timing: Offline - Mixed	0.35	0.21	-0.11 – 0.81 (.941)	11
Stimulation timing: Online - Mixed	0.26	0.19	-0.16 – 0.69 (.906)	12
Number of electrodes in montage	0.10	0.07	-0.05 – 0.25 (.921)	13
Design: Within - Between	-0.14	0.18	-0.54 – 0.23 (.786)	14
Random Effects (N studies = 16)				15
σ_{StudyID} (Intercept)	0.22	0.11	0.04 – 0.47	16
<i>N</i> total effects = 115				17
Marginal $R^2 = 0.16$ [0.06, 0.31]				18
Conditional $R^2 = 0.14$ [0.07, 0.21]				19

34
35
36
37
38
39
40
41
42
43
44
45
46

1 **Table 6.** Summary of meta-regression parameters for vigilance.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (pd)	2
Intercept	-0.81	0.67	-2.19 – 0.57 (.883)	3
Polarity: Anodal - Cathodal	0.03	0.12	-0.20 – 0.26 (.607)	4
Target: Other PFC - DLPFC	0.03	0.23	-0.48 – 0.50 (.552)	5
Target: Temporal-Parietal - DLPFC	-0.00	0.09	-0.19 – 0.18 (.526)	6
Laterality: Left - Bilateral	0.10	0.21	-0.35 – 0.55 (.687)	7
Laterality: Right - Bilateral	0.07	0.26	-0.50 – 0.58 (.601)	8
Number of stimulation sessions	0.01	0.17	-0.35 – 0.37 (.528)	9
Stimulation duration/session (min)	0.02	0.02	-0.03 – 0.08 (.841)	10
Stimulation intensity (mA)	0.00	0.22	-0.49 – 0.46 (.507)	11
Stimulation timing: Offline - Mixed	-0.04	0.16	-0.38 – 0.28 (.595)	12
Stimulation timing: Online - Mixed	-0.01	0.13	-0.28 – 0.25 (.536)	13
Number of electrodes in montage	0.08	0.04	0.01 – 0.15 (.982)	14
Design: Within - Between	0.12	0.09	-0.07 – 0.29 (.892)	15
Random Effects (<i>N</i> studies = 15)				16
σ_{StudyID} (Intercept)	0.13	0.09	0.01 – 0.35	17
<i>N</i> total effects = 93				18
Marginal $R^2 = 0.40$ [0.23, 0.53]				19
Conditional $R^2 = 0.41$ [0.26, 0.52]				20

36
37
38
39
40
41
42
43
44
45
46

1 **Table 7.** Summary of meta-regression parameters for inhibition.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (pd)
Intercept	0.71	0.62	-0.53 – 2.14 (.879)
Polarity: Anodal - Cathodal	-0.09	0.08	-0.24 – 0.07 (.865)
Target: Other - DLPFC	0.17	0.14	-0.10 – 0.45 (.892)
Laterality: Right - Left	-0.12	0.12	-0.36 – 0.12 (.836)
Stimulation duration/session (min)	-0.01	0.02	-0.06 – 0.03 (.751)
Stimulation intensity (mA)	0.00	0.14	-0.31 – 0.29 (.514)
Stimulation timing: Offline - Mixed	0.19	0.30	-0.39 – 0.90 (.745)
Stimulation timing: Online - Mixed	-0.03	0.33	-0.65 – 0.73 (.534)
Number of electrodes in montage	-0.10	0.08	-0.29 – 0.07 (.900)
Design: Within - Between	0.04	0.21	-0.40 – 0.53 (.581)
Random Effects (N studies = 15)			
σ_{StudyID} (Intercept)	0.35	0.14	0.14 – 0.68
<i>N</i> total effects = 84			
Marginal $R^2 = 0.23$ [0.09, 0.40]			
Conditional $R^2 = 0.36$ [0.22, 0.50]			

30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46

1 **Table 8.** Summary of meta-regression parameters across all domains.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (<i>p</i> _d)	2
Intercept	-0.01	0.15	-0.31 – 0.29 (.532)	3
Polarity: Anodal - Cathodal	-0.07	0.04	-0.15 – 0.00 (.971)	4
Laterality: Left - Bilateral	-0.13	0.09	-0.31 – 0.06 (.914)	5
Laterality: Right - Bilateral	-0.12	0.09	-0.30 – 0.06 (.904)	6
Number of stimulation sessions	0.01	0.02	-0.03 – 0.05 (.660)	7
Stimulation duration/session (min)	0.01	0.01	-0.01 – 0.02 (.866)	8
Stimulation intensity (mA)	0.02	0.07	-0.11 – 0.15 (.619)	9
Stimulation timing: Offline - Mixed	0.03	0.09	-0.15 – 0.21 (.624)	10
Stimulation timing: Online - Mixed	-0.11	0.09	-0.28 – 0.06 (.893)	11
Number of electrodes in montage	0.01	0.02	-0.04 – 0.06 (.681)	12
Design: Within - Between	0.13	0.07	0.00 – 0.26 (.972)	13
Random Effects (<i>N</i> studies = 106)				14
σ_{StudyID} (Intercept)	0.39	0.04	0.32 – 0.46	15
<i>N</i> total effects = 721				16
Marginal $R^2 = 0.05$ [0.02, 0.09]				17
Conditional $R^2 = 0.29$ [0.25, 0.33]				18

32
33
34
35
36
37
38
39
40
41
42
43

Supplementary Information

Table S1. Studies included under each cognitive domain with reference numbers corresponding to their appearance in the full text.

Motor Performance

Ref no.	Citation
112	Apsvalka D, Ramsey R, Cross ES. Anodal tDCS over Primary Motor Cortex Provides No Advantage to Learning Motor Sequences via Observation. <i>Neural Plast.</i> 2018;2018:1237962.
113	Antal A, Nitsche MA, Kincses TZ, Kruse W, Hoffmann KP, Paulus W. Facilitation of visuo-motor learning by transcranial direct current stimulation of the motor and extrastriate visual areas in humans. <i>Eur J Neurosci.</i> 2004;19(10):2888-92.
114	Ambrus GG, Chaieb L, Stilling R, Rothkegel H, Antal A, Paulus W. Monitoring transcranial direct current stimulation induced changes in cortical excitability during the serial reaction time task. <i>Neurosci Lett.</i> 2016;616:98-104.
115	Zimmerman M, Heise KF, Gerloff C, Cohen LG, Hummel FC. Disrupting the ipsilateral motor cortex interferes with training of a complex motor task in older adults. <i>Cereb Cortex.</i> 2014;24(4):1030-6.
116	von Rein E, Hoff M, Kaminski E, Sehm B, Steele CJ, Villringer A, et al. Improving motor performance without training: the effect of combining mirror visual feedback with transcranial direct current stimulation. <i>J Neurophysiol.</i> 2015;113(7):2383-9.
117	Vollmann H, Conde V, Sewerin S, Taubert M, Sehm B, Witte OW, et al. Anodal transcranial direct current stimulation (tDCS) over supplementary motor area (SMA) but not pre-SMA promotes short-term visuomotor learning. <i>Brain Stimul.</i> 2013;6(2):101-7.
118	Vines BW, Cerruti C, Schlaug G. Dual-hemisphere tDCS facilitates greater improvements for healthy subjects' non-dominant hand compared to uni-hemisphere stimulation. <i>BMC Neurosci.</i> 2008;9:103.
119	Toth AJ, Ramsbottom N, Constantin C, Milliet A, Campbell MJ. The effect of expertise, training and neurostimulation on sensory-motor skill in esports. <i>Computers in Human Behavior.</i> 2021;121:106782.
120	Tecchio F, Zappasodi F, Assenza G, Tombini M, Vollaro S, Barbati G, et al. Anodal transcranial direct current stimulation enhances procedural consolidation. <i>J Neurophysiol.</i> 2010;104(2):1134-40.
121	Talimkhani A, Abdollahi I, Mohseni-Bandpei MA, Ehsani F, Khalili S, Jaberzadeh S. Differential Effects of Unihemispheric Concurrent Dual-Site and Conventional tDCS on Motor Learning: A Randomized, Sham-Controlled Study. <i>Basic Clin Neurosci.</i> 2019;10(1):59-72.
122	Spampinato DA, Satar Z, Rothwell JC. Combining reward and M1 transcranial direct current stimulation enhances the retention of newly learnt sensorimotor mappings. <i>Brain Stimul.</i> 2019;12(5):1205-12.
123	Shilo G, Lavidor M. Non-linear effects of cathodal transcranial direct current stimulation (tDCS) of the primary motor cortex on implicit motor learning. <i>Exp Brain Res.</i> 2019;237(4):919-25.
124	Sevilla-Sanchez M, Hortobágyi T, Fogelson N, Iglesias-Soler E, Carballeira E, Fernandez-del-Olmo M. Small Enhancement of Bimanual Typing Performance after 20 Sessions of tDCS in Healthy Young Adults. <i>Neuroscience.</i> 2021;466:26-35.
125	Saucedo Marquez CM, Zhang X, Swinnen SP, Meesen R, Wenderoth N. Task-specific effect of transcranial direct current stimulation on motor learning. <i>Front Hum Neurosci.</i> 2013;7:333.
126	Samaei A, Ehsani F, Zoghi M, Hafez Yosephi M, Jaberzadeh S. Online and offline effects of cerebellar transcranial direct current stimulation on motor learning in healthy older adults: a randomized double-blind sham-controlled study. <i>Eur J Neurosci.</i> 2017;45(9):1177-85.
127	Rumpf JJ, Wegscheider M, Hinselmann K, Fricke C, King BR, Weise D, et al. Enhancement of motor consolidation by post-training transcranial direct current stimulation in older people. <i>Neurobiol Aging.</i> 2017;49:1-8.

- 128 Rocha K, Marinho V, Magalhaes F, Carvalho V, Fernandes T, Ayres M, et al. Unskilled shooters
improve both accuracy and grouping shot having as reference skilled shooters cortical area: An EEG
and tDCS study. *Physiol Behav.* 2020;224:113036.
- 129 Prichard G, Weiller C, Fritsch B, Reis J. Effects of different electrical brain stimulation protocols on
subcomponents of motor skill learning. *Brain Stimul.* 2014;7(4):532-40.
- 130 Pollok B, Keitel A, Foerster M, Moshiri G, Otto K, Krause V. The posterior parietal cortex mediates
early offline-rather than online-motor sequence learning. *Neuropsychologia.* 2020;146:107555.
- 131 Pixa NH, Steinberg F, Doppelmayr M. High-definition transcranial direct current stimulation to both
primary motor cortices improves unimanual and bimanual dexterity. *Neurosci Lett.* 2017;643:84-8.
- 132 Parma JO, Profeta V, Andrade AGP, Lage GM, Apolinario-Souza T. TDCS of the Primary Motor
Cortex: Learning the Absolute Dimension of a Complex Motor Task. *J Mot Behav.* 2021;53(4):431-
44.
- 133 Nguemeni C, Stiehl A, Hiew S, Zeller D. No Impact of Cerebellar Anodal Transcranial Direct Current
Stimulation at Three Different Timings on Motor Learning in a Sequential Finger-Tapping Task. *Front
Hum Neurosci.* 2021;15:631517.
- 134 Naros G, Geyer M, Koch S, Mayr L, Ellinger T, Grimm F, et al. Enhanced motor learning with bilateral
transcranial direct current stimulation: Impact of polarity or current flow direction? *Clin
Neurophysiol.* 2016;127(4):2119-26.
- 135 Minarik T, Sauseng P, Dunne L, Berger B, Sterr A. Effects of anodal transcranial direct current
stimulation on visually guided learning of grip force control. *Biology (Basel).* 2015;4(1):173-86.
- 136 Leite J, Carvalho S, Fregni F, Goncalves OF. Task-specific effects of tDCS-induced cortical excitability
changes on cognitive and motor sequence set shifting performance. *PLoS One.* 2011;6(9):e24140.
- 137 Jin Y, Lee J, Kim S, Yoon B. Noninvasive brain stimulation over M1 and DLPFC cortex enhances the
learning of bimanual isometric force control. *Hum Mov Sci.* 2019;66:73-83.
- 138 Hashemirad F, Fitzgerald PB, Zoghi M, Jaberzadeh S. Single-Session Anodal tDCS with Small-Size
Stimulating Electrodes Over Frontoparietal Superficial Sites Does Not Affect Motor Sequence
Learning. *Front Hum Neurosci.* 2017;11:153.
- 139 Furuya S, Klaus M, Nitsche MA, Paulus W, Altenmuller E. Ceiling effects prevent further
improvement of transcranial stimulation in skilled musicians. *J Neurosci.* 2014;34(41):13834-9.
- 140 Fujiyama H, Hinder MR, Barzideh A, Van de Vijver C, Badache AC, Manrique CM, et al.
Preconditioning tDCS facilitates subsequent tDCS effect on skill acquisition in older adults.
Neurobiol Aging. 2017;51:31-42.
- 141 Focke J, Kemmet S, Krause V, Keitel A, Pollok B. Cathodal transcranial direct current stimulation
(tDCS) applied to the left premotor cortex (PMC) stabilizes a newly learned motor sequence. *Behav
Brain Res.* 2017;316:87-93.
- 142 Filmer HL, Lyons M, Mattingley JB, Dux PE. Anodal tDCS applied during multitasking training leads to
transferable performance gains. *Sci Rep.* 2017;7(1):12988.
- 143 Ferrucci R, Brunoni AR, Parazzini M, Vergari M, Rossi E, Fumagalli M, et al. Modulating human
procedural learning by cerebellar transcranial direct current stimulation. *Cerebellum.*
2013;12(4):485-92.
- 144 Fehring DJ, Illipparampil R, Acevedo N, Jaberzadeh S, Fitzgerald PB, Mansouri FA. Interaction of
task-related learning and transcranial direct current stimulation of the prefrontal cortex in
modulating executive functions. *Neuropsychologia.* 2019;131:148-59.
- 145 Fan J, Voisin J, Milot MH, Higgins J, Boudrias MH. Transcranial direct current stimulation over
multiple days enhances motor performance of a grip task. *Ann Phys Rehabil Med.* 2017;60(5):329-
33.
- 146 Ehsani F, Bakhtiary AH, Jaberzadeh S, Talimkhani A, Hajihasani A. Differential effects of primary
motor cortex and cerebellar transcranial direct current stimulation on motor learning in healthy
individuals: A randomized double-blind sham-controlled study. *Neurosci Res.* 2016;112:10-9.
- 147 Dumel G, Bourassa ME, Charlebois-Plante C, Desjardins M, Doyon J, Saint-Amour D, et al.
Multisession anodal transcranial direct current stimulation induces motor cortex plasticity
enhancement and motor learning generalization in an aging population. *Clin Neurophysiol.*
2018;129(2):494-502.

- 148 Dumel G, Bourassa ME, Charlebois-Plante C, Desjardins M, Doyon J, Saint-Amour D, et al. Motor Learning Improvement Remains 3 Months After a Multisession Anodal tDCS Intervention in an Aging Population. *Front Aging Neurosci.* 2018;10:335.
- 149 Doppelmayr M, Pixa NH, Steinberg F. Cerebellar, but not Motor or Parietal, High-Density Anodal Transcranial Direct Current Stimulation Facilitates Motor Adaptation. *J Int Neuropsychol Soc.* 2016;22(9):928-36.
- 150 Cantarero G, Spampinato D, Reis J, Ajagbe L, Thompson T, Kulkarni K, et al. Cerebellar direct current stimulation enhances on-line motor skill acquisition through an effect on accuracy. *J Neurosci.* 2015;35(7):3285-90.
- 151 Boggio PS, Castro LO, Savagim EA, Braitte R, Cruz VC, Rocha RR, et al. Enhancement of non-dominant hand motor function by anodal transcranial direct current stimulation. *Neurosci Lett.* 2006;404(1-2):232-6.
- 152 Ballard HK, Eakin SM, Maldonado T, Bernard JA. Using high-definition transcranial direct current stimulation to investigate the role of the dorsolateral prefrontal cortex in explicit sequence learning. *PLoS One.* 2021;16(3):e0246849.
- 153 Ballard HK, Goen JRM, Maldonado T, Bernard JA. Effects of cerebellar transcranial direct current stimulation on the cognitive stage of sequence learning. *J Neurophysiol.* 2019;122(2):490-9.

Visual Search

Ref no. Citation

- 88 Nelson JM, McKinley RA, McIntire LK, Goodyear C, Walters C. Augmenting visual search performance with transcranial direct current stimulation (tDCS). *Military Psychology.* 2015;27(6):335-47.
- 89 Ball K, Lane AR, Smith DT, Ellison A. Site-dependent effects of tDCS uncover dissociations in the communication network underlying the processing of visual search. *Brain Stimul.* 2013;6(6):959-65.
- 90 Callan DE, Falcone B, Wada A, Parasuraman R. Simultaneous tDCS-fMRI Identifies Resting State Networks Correlated with Visual Search Enhancement. *Front Hum Neurosci.* 2016;10:72.
- 142 Filmer HL, Lyons M, Mattingley JB, Dux PE. Anodal tDCS applied during multitasking training leads to transferable performance gains. *Sci Rep.* 2017;7(1):12988.
- 154 Nydam AS, Sewell DK, Dux PE. Cathodal electrical stimulation of frontoparietal cortex disrupts statistical learning of visual configural information. *Cortex.* 2018;99:187-99.
- 155 Cosman JD, Atreya PV, Woodman GF. Transient reduction of visual distraction following electrical stimulation of the prefrontal cortex. *Cognition.* 2015;145:73-6.
- 156 Sung K, Gordon B. Transcranial direct current stimulation (tDCS) facilitates overall visual search response times but does not interact with visual search task factors. *PLoS One.* 2018;13(3):e0194640.
- 157 Clark VP, Coffman BA, Mayer AR, Weisend MP, Lane TD, Calhoun VD, et al. TDCS guided using fMRI significantly accelerates learning to identify concealed objects. *Neuroimage.* 2012;59(1):117-28.
- 158 Lanina AA, Feurra M, Gorbunova ES. No Effect of the Right Posterior Parietal Cortex tDCS in Dual-Target Visual Search. *Front Psychol.* 2018;9:2112.
- 159 Falcone B, Wada A, Parasuraman R, Callan DE. Individual differences in learning correlate with modulation of brain activity induced by transcranial direct current stimulation. *PLoS One.* 2018;13(5):e0197192.
- 160 Filmer HL, Varghese E, Hawkins GE, Mattingley JB, Dux PE. Improvements in Attention and Decision-Making Following Combined Behavioral Training and Brain Stimulation. *Cereb Cortex.* 2017;27(7):3675-82.
- 161 Coffman BA, Trumbo MC, Flores RA, Garcia CM, van der Merwe AJ, Wassermann EM, et al. Impact of tDCS on performance and learning of target detection: interaction with stimulus characteristics and experimental design. *Neuropsychologia.* 2012;50(7):1594-602.
- 162 Ellison A, Ball KL, Moseley P, Dowsett J, Smith DT, Weis S, et al. Functional interaction between right parietal and bilateral frontal cortices during visual search tasks revealed using functional magnetic imaging and transcranial direct current stimulation. *PLoS One.* 2014;9(4):e93767.

- 163 Reinhart RM, Woodman GF. Enhancing long-term memory with stimulation tunes visual attention in
one trial. *Proc Natl Acad Sci U S A*. 2015;112(2):625-30.
- 164 Wagner J, Lo Monaco S, Conto F, Parrott D, Battelli L, Rusconi E. Effects of transcranial direct
current stimulation over the posterior parietal cortex on novice X-ray screening performance.
Cortex. 2020;132:1-14.
- 165 Grasso PA, Tonolli E, Miniussi C. Effects of different transcranial direct current stimulation protocols
on visuo-spatial contextual learning formation: evidence of homeostatic regulatory mechanisms. *Sci
Rep*. 2020;10(1):4622.
- 166 Bolognini N, Fregni F, Casati C, Olgiati E, Vallar G. Brain polarization of parietal cortex augments
training-induced improvement of visual exploratory and attentional skills. *Brain Res*. 2010;1349:76-
89.
- 167 Ellison A, Ball KL, Lane AR. The Behavioral Effects of tDCS on Visual Search Performance Are Not
Influenced by the Location of the Reference Electrode. *Front Neurosci*. 2017;11:520.

Working Memory

- | Ref no. | Citation |
|---------|--|
| 57 | Zivanovic M, Paunovic D, Konstantinovic U, Vulic K, Bjekic J, Filipovic SR. The effects of offline and
online prefrontal vs parietal transcranial direct current stimulation (tDCS) on verbal and spatial
working memory. <i>Neurobiol Learn Mem</i> . 2021;179:107398. |
| 168 | Nikolin S, Loo CK, Bai S, Dokos S, Martin DM. Focalised stimulation using high definition
transcranial direct current stimulation (HD-tDCS) to investigate declarative verbal learning and
memory functioning. <i>Neuroimage</i> . 2015;117:11-9. |
| 169 | Naka M, Matsuzawa D, Ishii D, Hamada H, Uchida T, Sugita K, et al. Differential effects of high-
definition transcranial direct current stimulation on verbal working memory performance
according to sensory modality. <i>Neurosci Lett</i> . 2018;687:131-6. |
| 170 | Pupikova M, Simko P, Gajdos M, Rektorova I. Modulation of Working Memory and Resting-State
fMRI by tDCS of the Right Frontoparietal Network. <i>Neural Plast</i> . 2021;2021:5594305. |
| 171 | Murphy OW, Hoy KE, Wong D, Bailey NW, Fitzgerald PB, Segrave RA. Transcranial random noise
stimulation is more effective than transcranial direct current stimulation for enhancing working
memory in healthy individuals: Behavioural and electrophysiological evidence. <i>Brain Stimul</i> .
2020;13(5):1370-80. |
| 172 | Karthikeyan R, Smoot MR, Mehta RK. Anodal tDCS augments and preserves working memory
beyond time-on-task deficits. <i>Sci Rep</i> . 2021;11(1):19134. |
| 173 | Caulfield KA, Indahlstari A, Nissim NR, Lopez JW, Fleischmann HH, Woods AJ, et al. Electric Field
Strength From Prefrontal Transcranial Direct Current Stimulation Determines Degree of Working
Memory Response: A Potential Application of Reverse-Calculation Modeling? <i>Neuromodulation</i> .
2022;25(4):578-87. |
| 174 | Asseconci S, Hu R, Eskes G, Pan X, Zhou J, Shapiro K. Impact of tDCS on working memory training is
enhanced by strategy instructions in individuals with low working memory capacity. <i>Scientific
Reports</i> . 2021;11(1):5531. |
| 175 | Ankri YLE, Braw Y, Luboshits G, Meiron O. The effects of stress and transcranial direct current
stimulation (tDCS) on working memory: A randomized controlled trial. <i>Cogn Affect Behav Neurosci</i> .
2020;20(1):103-14. |
| 176 | Abellaneda-Perez K, Vaque-Alcazar L, Perellon-Alfonso R, Bargallo N, Kuo MF, Pascual-Leone A, et
al. Differential tDCS and tACS Effects on Working Memory-Related Neural Activity and Resting-
State Connectivity. <i>Front Neurosci</i> . 2019;13:1440. |
| 177 | Zwissler B, Sperber C, Aigeldinger S, Schindler S, Kissler J, Plewnia C. Shaping memory accuracy by
left prefrontal transcranial direct current stimulation. <i>J Neurosci</i> . 2014;34(11):4022-6. |
| 178 | Hussey EK, Fontes EB, Ward N, Westfall DR, Kao SC, Kramer AF, et al. Combined and Isolated
Effects of Acute Exercise and Brain Stimulation on Executive Function in Healthy Young Adults. <i>J
Clin Med</i> . 2020;9(5). |

- Chrysikou EG, Gorey C, Aupperle RL. Anodal transcranial direct current stimulation over right dorsolateral prefrontal cortex alters decision making during approach-avoidance conflict. *Soc Cogn Affect Neurosci*. 2017;12(3):468-75.
- Boehringer A, Macher K, Dukart J, Villringer A, Pleger B. Cerebellar transcranial direct current stimulation modulates verbal working memory. *Brain Stimul*. 2013;6(4):649-53.
- Baumert A, Buchholz N, Zinkernagel A, Clarke P, MacLeod C, Osinsky R, et al. Causal underpinnings of working memory and Stroop interference control: Testing the effects of anodal and cathodal tDCS over the left DLPFC. *Cogn Affect Behav Neurosci*. 2020;20(1):34-48.
- Au J, Katz B, Buschkuehl M, Bunarjo K, Senger T, Zabel C, et al. Enhancing Working Memory Training with Transcranial Direct Current Stimulation. *J Cogn Neurosci*. 2016;28(9):1419-32.

Vigilance

Ref no. Citation

- McIntire LK, McKinley RA, Goodyear C, Nelson J. A comparison of the effects of transcranial direct current stimulation and caffeine on vigilance and cognitive performance during extended wakefulness. *Brain Stimul*. 2014;7(4):499-507.
- Nikolin S, Loo CK, Bai S, Dokos S, Martin DM. Focalised stimulation using high definition transcranial direct current stimulation (HD-tDCS) to investigate declarative verbal learning and memory functioning. *Neuroimage*. 2015;117:11-9.
- Naka M, Matsuzawa D, Ishii D, Hamada H, Uchida T, Sugita K, et al. Differential effects of high-definition transcranial direct current stimulation on verbal working memory performance according to sensory modality. *Neurosci Lett*. 2018;687:131-6.
- van Schouwenburg MR, Sligte IG, Giffin MR, Günther F, Koster D, Spronkers FS, et al. Effects of Midfrontal Brain Stimulation on Sustained Attention. *Journal of Cognitive Enhancement*. 2021;5(1):62-72.
- Ironsides M, O'Shea J, Cowen PJ, Harmer CJ. Frontal Cortex Stimulation Reduces Vigilance to Threat: Implications for the Treatment of Depression and Anxiety. *Biol Psychiatry*. 2016;79(10):823-30.
- Hanken K, Bosse M, Mohrke K, Eling P, Kastrup A, Antal A, et al. Counteracting Fatigue in Multiple Sclerosis with Right Parietal Anodal Transcranial Direct Current Stimulation. *Front Neurol*. 2016;7:154.
- Plewnia C, Zwissler B, Langst I, Maurer B, Giel K, Kruger R. Effects of transcranial direct current stimulation (tDCS) on executive functions: influence of COMT Val/Met polymorphism. *Cortex*. 2013;49(7):1801-7.
- McIntire LK, McKinley RA, Nelson JM, Goodyear C. Transcranial direct current stimulation versus caffeine as a fatigue countermeasure. *Brain Stimul*. 2017;10(6):1070-8.
- Manuel AL, David AW, Bikson M, Schnider A. Frontal tDCS modulates orbitofrontal reality filtering. *Neuroscience*. 2014;265:21-7.
- Luna FG, Roman-Caballero R, Barttfeld P, Lupianez J, Martin-Arevalo E. A High-Definition tDCS and EEG study on attention and vigilance: Brain stimulation mitigates the executive but not the arousal vigilance decrement. *Neuropsychologia*. 2020;142:107447.
- Jacoby N, Lavidor M. Null tDCS Effects in a Sustained Attention Task: The Modulating Role of Learning. *Front Psychol*. 2018;9:476.
- Filmer HL, Ehrhardt SE, Bollmann S, Mattingley JB, Dux PE. Accounting for individual differences in the response to tDCS with baseline levels of neurochemical excitability. *Cortex*. 2019;115:324-34.
- Coulborn S, Bowman H, Miall RC, Fernandez-Espejo D. Effect of tDCS Over the Right Inferior Parietal Lobule on Mind-Wandering Propensity. *Front Hum Neurosci*. 2020;14:230.
- Brunnauer A, Segmiller FM, Loschner S, Grun V, Padberg F, Palm U. The Effects of Transcranial Direct Current Stimulation (tDCS) on Psychomotor and Visual Perception Functions Related to Driving Skills. *Front Behav Neurosci*. 2018;12:16.
- Borragan G, Gilson M, Guerrero-Mosquera C, Di Ricci E, Slama H, Peigneux P. Transcranial Direct Current Stimulation Does Not Counteract Cognitive Fatigue, but Induces Sleepiness and an Inter-Hemispheric Shift in Brain Oxygenation. *Front Psychol*. 2018;9:2351.

Inhibition**Ref no. Citation**

- 178 Hussey EK, Fontes EB, Ward N, Westfall DR, Kao SC, Kramer AF, et al. Combined and Isolated Effects of Acute Exercise and Brain Stimulation on Executive Function in Healthy Young Adults. *J Clin Med*. 2020;9(5).
- 181 Baumert A, Buchholz N, Zinkernagel A, Clarke P, MacLeod C, Osinsky R, et al. Causal underpinnings of working memory and Stroop interference control: Testing the effects of anodal and cathodal tDCS over the left DLPFC. *Cogn Affect Behav Neurosci*. 2020;20(1):34-48.
- 186 Plewnia C, Zwissler B, Langst I, Maurer B, Giel K, Kruger R. Effects of transcranial direct current stimulation (tDCS) on executive functions: influence of COMT Val/Met polymorphism. *Cortex*. 2013;49(7):1801-7.
- 195 Angius L, Santarnecchi E, Pascual-Leone A, Marcora SM. Transcranial Direct Current Stimulation over the Left Dorsolateral Prefrontal Cortex Improves Inhibitory Control and Endurance Performance in Healthy Individuals. *Neuroscience*. 2019;419:34-45.
- 196 Thomas F, Pixa NH, Berger A, Cheng MY, Doppelmayr M, Steinberg F. Neither Cathodal nor Anodal Transcranial Direct Current Stimulation on the Left Dorsolateral Prefrontal Cortex alone or Applied During Moderate Aerobic Exercise Modulates Executive Function. *Neuroscience*. 2020;443:71-83.
- 197 Oldrati V, Patricelli J, Colombo B, Antonietti A. The role of dorsolateral prefrontal cortex in inhibition mechanism: A study on cognitive reflection test and similar tasks through neuromodulation. *Neuropsychologia*. 2016;91:499-508.
- 198 Kuehne M, Schmidt K, Heinze HJ, Zaehle T. Modulation of Emotional Conflict Processing by High-Definition Transcranial Direct Current Stimulation (HD-TDCS). *Front Behav Neurosci*. 2019;13:224.
- 199 Hammer A, Mohammadi B, Schmicker M, Saliger S, Munte TF. Errorless and errorful learning modulated by transcranial direct current stimulation. *BMC Neurosci*. 2011;12:72.
- 200 Gomez-Ariza CJ, Martin MC, Morales J. Tempering Proactive Cognitive Control by Transcranial Direct Current Stimulation of the Right (but Not the Left) Lateral Prefrontal Cortex. *Front Neurosci*. 2017;11:282.
- 201 Gladwin TE, den Uyl TE, Fregni FF, Wiers RW. Enhancement of selective attention by tDCS: interaction with interference in a Sternberg task. *Neurosci Lett*. 2012;512(1):33-7.
- 202 Friedrich J, Beste C. Paradoxical, causal effects of sensory gain modulation on motor inhibitory control - a tDCS, EEG-source localization study. *Sci Rep*. 2018;8(1):17486.
- 203 Edgcumbe DR, Thoma V, Rivolta D, Nitsche MA, Fu CHY. Anodal transcranial direct current stimulation over the right dorsolateral prefrontal cortex enhances reflective judgment and decision-making. *Brain Stimul*. 2019;12(3):652-8.
- 204 Dubreuil-Vall L, Chau P, Ruffini G, Widge AS, Camprodon JA. tDCS to the left DLPFC modulates cognitive and physiological correlates of executive function in a state-dependent manner. *Brain Stimul*. 2019;12(6):1456-63.
- 205 Denis G, Zory R, Radel R. Testing the role of cognitive inhibition in physical endurance using high-definition transcranial direct current stimulation over the prefrontal cortex. *Hum Mov Sci*. 2019;67:102507.
- 206 Boudewyn M, Roberts BM, Mizrak E, Ranganath C, Carter CS. Prefrontal transcranial direct current stimulation (tDCS) enhances behavioral and EEG markers of proactive control. *Cogn Neurosci*. 2019;10(2):57-65.

1

2

Table S2. Occurrence and central tendency of each stimulation/design parameter (given as number of effects for categorical factors and the median, min, and max for numeric variables).

Parameter Name	Motor Performance	Visual Search	Working Memory	Vigilance	Inhibition
Target	Cerebellum: 30 DLPFC: 33 M1: 160 Parietal: 14 PFC: 16	DLPFC: 16 FEF: 14 IFC: 6 MFC: 6 MFG: 4 PFC: 16 PPC: 110 Visual: 4	Cerebellum: 2 DLPFC: 90 MFG: 1 MTL: 2 PPC	DLPFC: 51 IPL: 10 MTL: 2 PFC: 2 Parietal: 2 PFC: 10 PPC: 12 Temporal: 2	DLPFC: 75 IFC: 8 Parietal: 1
Laterality	Bilateral: 33 Left: 151 Right: 69	Bilateral: 14 Left: 88 Right: 74	Left: 78 Right: 37	Bilateral: 12 Left: 41 Right: 40	Left: 60 Right: 24
Electrode count	M = 2 Min = 2 Max = 9	M = 2 Min = 2 Max = 3	M = 2 Min = 2 Max = 5	M = 3 Min = 2 Max = 10	M = 2 Min = 2 Max = 5
Individualization	No: 208 Yes: 45	NA	No: 110 Yes: 5	NA	NA
Intensity (mA)	M = 1 Min = 0.25 Max = 2.1	M = 1 Min = 0.61 Max = 3	M = 1 Min = 1 Max = 2	M = 1.5 Min = 0.7 Max = 2	M = 1.75 Min = 1 Max = 5
Polarity	Anodal: 191 Cathodal: 62	Anodal: 91 Cathodal: 85	Anodal: 103 Cathodal: 12	Anodal: 83 Cathodal: 10	Anodal: 56 Cathodal: 28
Duration (min)	M = 20 Min = 10 Max = 30	M = 15 Min = 10 Max = 30	M = 15 Min = 5 Max = 30	M = 20 Min = 9 Max = 30	M = 20 Min = 10 Max = 30
Timing	Mixed: 20 Offline: 138 Online: 95	Mixed: 15 Offline: 93 Online: 68	Mixed: 27 Offline: 41 Online: 47	Mixed: 14 Offline: 31 Online: 48	Mixed: 22 Offline: 44 Online: 18
Session count	M = 1 Min = 1 Max = 20	M = 1 Min = 1 Max = 4	M = 1 Min = 1 Max = 10	M = 1 Min = 1 Max = 3	M = 1 Min = 1 Max = 1
Design	Between: 130 Within: 123	Between: 108 Within: 68	Between: 64 Within: 51	Between: 37 Within: 56	Between: 42 Within: 42

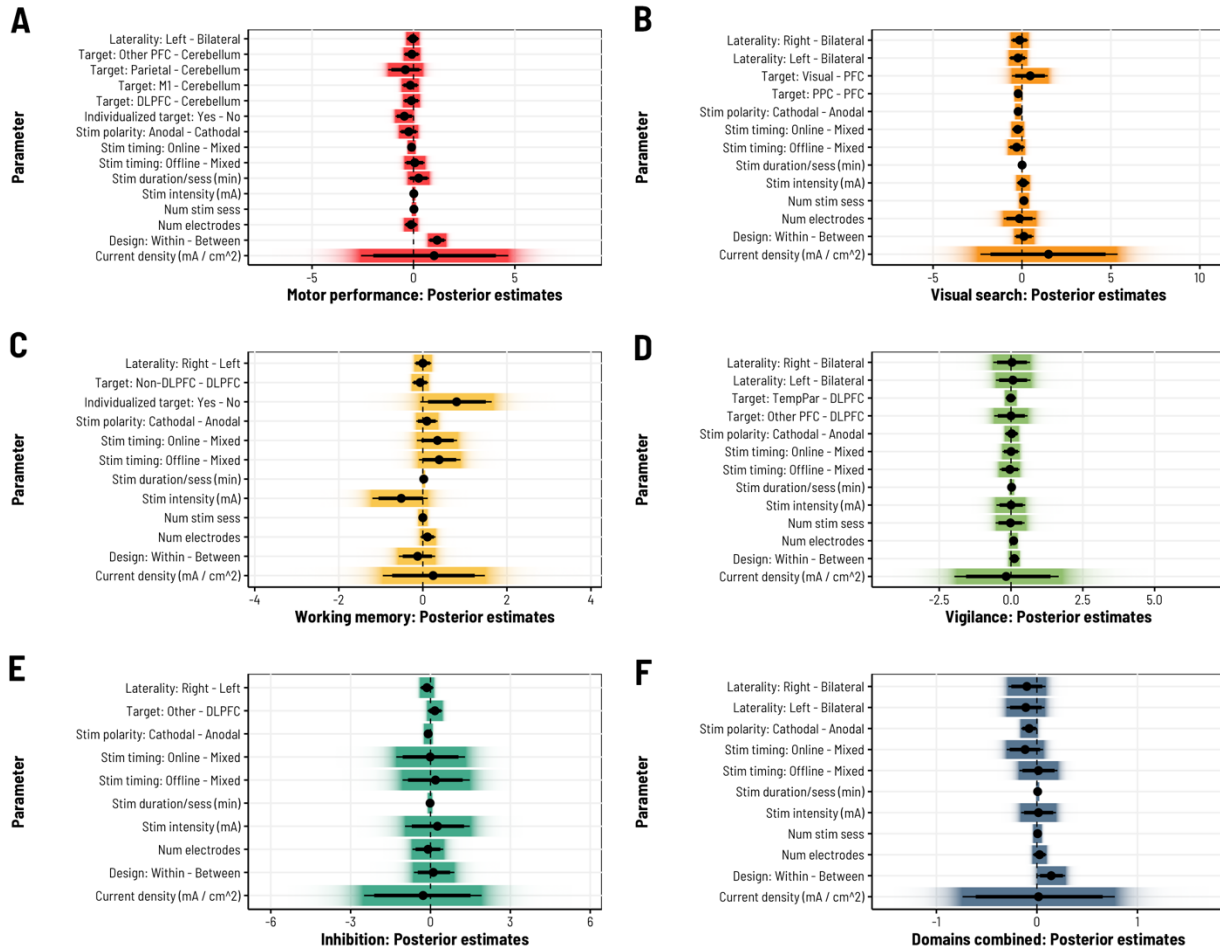


Figure S1. Contrasting estimates of multiple neurostimulation and experimental parameters on behavioral performance outcomes, both within-domain and between-domain. Here we include estimated current density over the target brain region (in mA / cm²) for each domain, where it was possible to calculate. Point intervals give 90-95% credibility intervals (i.e., highest density intervals) around the median posterior estimates (thick lines = 90% CI; thin lines = 95% CI; solid gradient areas indicate the 95% CI). Generally-speaking, current density did not show any relationship with behavioral outcomes and had the most posterior uncertainty, relative to other parameters. **(A)** Motor performance, **(B)** Visual search, **(C)** Working memory, **(D)** Vigilance, **(E)** Inhibition, **(F)** Domain-General.

Table S3. Summary of model comparison outcomes for two-way interaction models. For each exploratory model, $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive density derived through Bayesian approximate leave-one-out cross validation. Positive values indicate a preference for the proposed interaction model (i.e., better predictive performance); negative values indicate a preference for the base model with only additive terms. SE_{Diff} gives the standard error of the difference, and the ratio of the two can be used to approximate the significance of the difference (akin to a Z-statistic, where values > 2 indicate a nontrivial improvement in predictive performance when adding the proposed interaction term). No two-way interaction model met this criterion.

Candidate Model	Top Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Stim Polarity x Target Laterality	Base Model	-0.694	0.977	-0.710
Num Stim Sess x Target Laterality	Base Model	-2.387	1.767	-1.351
Stim Duration x Target Laterality	Interaction Model	0.127	1.873	0.068
Stim Intensity x Target Laterality	Base Model	-0.963	1.011	-0.952
Stim Timing x Target Laterality	Base Model	-0.720	2.750	-0.262
Num Electrodes x Target Laterality	Base Model	-0.428	2.128	-0.201
Design Type x Target Laterality	Interaction Model	0.646	3.396	0.190
Num Stim Sess x Stim Polarity	Interaction Model	0.968	1.528	0.633
Stim Duration x Stim Polarity	Base Model	-0.325	0.919	-0.353
Stim Intensity x Stim Polarity	Base Model	-0.882	0.344	-2.562
Stim Timing x Stim Polarity	Base Model	-1.582	0.920	-1.719
Num Electrodes x Stim Polarity	Base Model	-0.136	0.896	-0.152
Design Type x Stim Polarity	Interaction Model	0.358	1.047	0.342
Stim Duration x Num Stim Sess	Interaction Model	0.905	3.161	0.286
Stim Intensity x Num Stim Sess	Interaction Model	0.290	0.932	0.311
Stim Timing x Num Stim Sess	Base Model	-1.661	2.073	-0.801
Num Electrodes x Num Stim Sess	Base Model	-0.057	0.634	-0.090
Design Type x Num Stim Sess	Base Model	-0.148	0.993	-0.149
Stim Intensity x Stim Duration	Base Model	-0.287	0.483	-0.595
Stim Timing x Stim Duration	Base Model	-0.370	0.859	-0.431
Num Electrodes x Stim Duration	Interaction Model	0.117	0.700	0.167
Design Type x Stim Duration	Interaction Model	0.183	0.396	0.463
Stim Timing x Stim Intensity	Base Model	-0.238	1.311	-0.182
Num Electrodes x Stim Intensity	Interaction Model	0.046	0.232	0.199
Design Type x Stim Intensity	Interaction Model	4.930	2.821	1.748
Num Electrodes x Stim Timing	Interaction Model	5.844	4.449	1.313
Design Type x Stim Timing	Interaction Model	1.005	1.625	0.618
Design Type x Num Electrodes	Interaction Model	1.880	2.074	0.906

Table S4. Summary of model comparison outcomes for three-way interaction models. For each exploratory model, $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive density derived through Bayesian approximate leave-one-out cross validation. Positive values indicate a preference for the proposed interaction model (i.e., better predictive performance); negative values indicate a preference for the base model with only additive terms. SE_{Diff} gives the standard error of the difference, and the ratio of the two can be used to approximate the significance of the difference (akin to a Z-statistic, where values > 2 indicate a nontrivial improvement in predictive performance when adding the proposed interaction term). Several three-way interaction models met this criterion, bolded and italicized below.

Candidate Model	Top Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Num Stim Sess x Stim Polarity x Target Laterality	Base Model	-4.571	3.309	-1.381
Stim Duration x Stim Polarity x Target Laterality	Base Model	-4.467	2.638	-1.693
Stim Intensity x Stim Polarity x Target Laterality	Base Model	-7.466	1.242	-6.010
Stim Timing x Stim Polarity x Target Laterality	Base Model	-11.922	3.865	-3.085
Num Electrodes x Stim Polarity x Target Laterality	Base Model	-23.571	5.509	-4.279
Design Type x Stim Polarity x Target Laterality	Interaction Model	0.266	4.516	0.059
Num Stim Sess x Stim Duration x Target Laterality	Base Model	-6.457	3.970	-1.626
Num Stim Sess x Stim Intensity x Target Laterality	Base Model	-5.816	2.655	-2.190
Num Stim Sess x Stim Timing x Target Laterality	Base Model	-200.353	17.132	-11.694
Design Type x Num Stim Sess x Target Laterality	Base Model	-2.469	5.892	-0.419
Stim Intensity x Stim Duration x Target Laterality	Base Model	-176.908	11.665	-15.166
Stim Duration x Stim Timing x Target Laterality	Base Model	-150.205	11.004	-13.650
Num Electrodes x Stim Duration x Target Laterality	Base Model	-3.442	3.453	-0.997
Design Type x Stim Duration x Target Laterality	Interaction Model	1.157	6.778	0.171
Num Stim Sess x Stim Duration x Stim Polarity	Interaction Model	2.945	3.102	0.949
Num Stim Sess x Stim Intensity x Stim Polarity	Base Model	-0.436	2.061	-0.211
Num Stim Sess x Stim Timing x Stim Polarity	Base Model	-5.463	2.610	-2.093
Num Electrodes x Num Stim Sess x Stim Polarity	Base Model	-31.651	5.982	-5.291
Design Type x Num Stim Sess x Stim Polarity	Interaction Model	2.354	2.943	0.800
Stim Intensity x Stim Duration x Stim Polarity	Base Model	-3.496	1.130	-3.093
Stim Duration x Stim Timing x Stim Polarity	Base Model	-3.041	2.814	-1.081
Design Type x Stim Duration x Stim Polarity	Interaction Model	0.859	2.143	0.401
Stim Intensity x Stim Timing x Stim Polarity	Base Model	-6.102	2.116	-2.884
Num Electrodes x Stim Intensity x Stim Polarity	Base Model	-1.830	1.729	-1.059

Design Type x Stim Intensity x Stim Polarity	Interaction Model	3.941	2.964	1.330
Num Electrodes x Stim Timing x Stim Polarity	Base Model	-31.402	7.316	-4.292
Design Type x Stim Timing x Stim Polarity	Base Model	-1.868	2.570	-0.727
Design Type x Num Electrodes x Stim Polarity	Base Model	-7.386E+18	7.386E+18	-1.000
Num Stim Sess x Stim Intensity x Stim Duration	Base Model	-2.939	4.150	-0.708
Num Stim Sess x Stim Duration x Stim Timing	Base Model	-4.119	5.562	-0.741
Num Electrodes x Num Stim Sess x Stim Duration	Base Model	-0.501	3.193	-0.157
Design Type x Num Stim Sess x Stim Duration	Base Model	-1.412	3.299	-0.428
Num Stim Sess x Stim Intensity x Stim Timing	Base Model	-1.017	3.134	-0.324
Num Electrodes x Num Stim Sess x Stim Intensity	Interaction Model	0.022	0.909	0.024
Design Type x Num Stim Sess x Stim Intensity	Interaction Model	5.329	3.683	1.447
Num Electrodes x Num Stim Sess x Stim Timing	Base Model	-31.620	17.935	-1.763
Design Type x Num Stim Sess x Stim Timing	Base Model	-105.643	14.833	-7.122
Num Electrodes x Num Stim Sess x Target Laterality	Base Model	-93.958	10.411	-9.025
Design Type x Num Electrodes x Num Stim Sess	Interaction Model	0.424	3.069	0.138
Stim Intensity x Stim Duration x Stim Timing	Base Model	-1.888	2.311	-0.817
Num Electrodes x Stim Intensity x Stim Duration	Interaction Model	0.147	1.058	0.139
Design Type x Stim Intensity x Stim Duration	Interaction Model	16.448	7.352	2.237
Num Electrodes x Stim Duration x Stim Timing	Interaction Model	3.564	4.495	0.793
Design Type x Stim Duration x Stim Timing	Base Model	-0.735	2.137	-0.344
Design Type x Num Electrodes x Stim Duration	Interaction Model	15.818	7.363	2.148
Num Electrodes x Stim Intensity x Target Laterality	Base Model	-5.671	2.856	-1.986
Design Type x Stim Intensity x Target Laterality	Interaction Model	4.538	5.985	0.758
Stim Intensity x Stim Timing x Target Laterality	Base Model	-172.785	11.626	-14.862
Num Electrodes x Stim Intensity x Stim Timing	Interaction Model	4.357	7.482	0.582
Design Type x Stim Intensity x Stim Timing	Interaction Model	6.276	5.111	1.228
Design Type x Num Electrodes x Stim Intensity	Interaction Model	23.287	11.403	2.042
Num Electrodes x Stim Timing x Target Laterality	Base Model	-165.216	11.660	-14.169
Design Type x Stim Timing x Target Laterality	Base Model	-132.073	14.904	-8.861
Design Type x Num Electrodes x Stim Timing	Interaction Model	13.369	8.243	1.622
Design Type x Num Electrodes x Target Laterality	Base Model	-1.369	4.901	-0.279

	Num Electrodes x Stim Duration x Stim Polarity	Base Model	-319.103	19.998	-15.957
1					
2					
3					
4					

Table S5. Differences in candidate model predictive performance for the Motor domain, derived via Bayesian approximate leave-one-out cross-validation. Differences in fit are presented with respect to the top listed model. $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive densities (negative values thus indicate decrements in predictive performance relative to the top model); SE_{Diff} gives the standard error of the difference. The top model significantly differs in performance from any other model where $|ELPD_{Diff} / SE_{Diff}| > 2$.

Candidate Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Design Type x Num Electrodes x Stim Duration	—	—	—
Design Type x Num Electrodes x Stim Intensity	-1.678	2.126	-0.789
Design Type x Stim Intensity x Stim Duration	-5.079	3.190	-1.592
Base Model (Only Additive Terms)	-13.796	7.331	-1.882

1 **Table S6.** Model summary for top motion performance candidate.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)
Intercept	-13.94	5.96	-25.69 – -1.99 (.988)
Polarity: Anodal - Cathodal	-0.07	0.08	-0.22 – 0.09 (.805)
Target: DLPFC - Cerebellum	-0.35	0.20	-0.75 – 0.06 (.954)
Target: M1 - Cerebellum	-0.03	0.18	-0.39 – 0.33 (.563)
Target: Parietal - Cerebellum	-0.02	0.20	-0.42 – 0.37 (.546)
Target: Other PFC - Cerebellum	-0.54	0.38	-1.31 – 0.22 (.920)
Individualized target: Yes - No	-0.22	0.19	-0.61 – 0.16 (.871)
Laterality: Left - Bilateral	-0.12	0.18	-0.47 – 0.24 (.748)
Laterality: Right - Bilateral	-0.11	0.15	-0.40 – 0.18 (.765)
Number of stimulation sessions	-0.03	0.03	-0.09 – 0.04 (.801)
Stimulation duration/session (min)	0.70	0.28	0.13 – 1.26 (.991)
Stimulation intensity (mA)	-0.18	0.19	-0.56 – 0.21 (.820)
Stimulation timing: Offline - Mixed	0.24	0.23	-0.22 – 0.68 (.850)
Stimulation timing: Online - Mixed	0.12	0.22	-0.32 – 0.55 (.699)
Number of electrodes in montage	7.10	2.97	1.14 – 12.99 (.984)
Design: Within - Between	30.37	11.57	7.22 – 53.53 (.994)
Design: Within - Between x Number of electrodes in montage	-15.38	5.77	-26.90 – -3.80 (.995)
Design: Within - Between x Stimulation duration/session	-1.51	0.55	-2.62 – -0.41 (.996)
Number of electrodes in montage x Stimulation duration/session	-0.35	0.14	-0.63 – -0.06 (.991)
Design: Within - Between x Number of electrodes in montage x Stimulation duration/session	0.76	0.27	0.21 – 1.31 (.996)
Random Effects (N studies = 42)			
σ_{StudyID} (Intercept)	0.56	0.08	0.42 – 0.74

N total effects = 253	1
Marginal $R^2 = 0.23$ [0.16, 0.32]	2
	3
Conditional $R^2 = 0.44$ [0.38, 0.50]	4
	5

6
7
8
9
10
11
12

Table S7. Differences in candidate model predictive performance for the Visual Search domain, derived via Bayesian approximate leave-one-out cross-validation. Differences in fit are presented with respect to the top listed model. $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive densities (negative values thus indicate decrements in predictive performance relative to the top model); SE_{Diff} gives the standard error of the difference. The top model significantly differs in performance from any other model where $|ELPD_{Diff} / SE_{Diff}| > 2$.

Candidate Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Base Model (Only Additive Terms)	—	—	—
Design Type x Stim Intensity x Stim Duration	-0.099	1.589	-0.062
Design Type x Num Electrodes x Stim Duration	-624.797	6.581	-94.946
Design Type x Num Electrodes x Stim Intensity	-654.956	9.758	-67.119

1 **Table S8.** Model summary for top visual search candidate.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)	2
Intercept	1.36	0.89	-0.74 – 3.34 (.916)	3
Polarity: Anodal - Cathodal	-0.23	0.08	-0.39 – -0.07 (.998)	4
Target: PPC - PFC	-0.18	0.10	-0.38 – 0.01 (.968)	5
Target: Visual - PFC	0.37	0.39	-0.45 – 1.25 (.830)	6
Laterality: Left - Bilateral	-0.35	0.27	-0.87 – 0.19 (.899)	7
Laterality: Right - Bilateral	-0.25	0.26	-0.75 – 0.27 (.828)	8
Number of stimulation sessions	0.07	0.10	-0.15 – 0.29 (.751)	9
Stimulation duration/session (min)	-0.07	0.04	-0.17 – 0.03 (.936)	10
Stimulation intensity (mA)	-0.91	0.47	-1.90 – 0.10 (.963)	11
Stimulation timing: Offline - Mixed	-0.33	0.20	-0.75 – 0.05 (.955)	12
Stimulation timing: Online - Mixed	-0.19	0.16	-0.52 – 0.12 (.878)	13
Number of electrodes in montage	0.03	0.35	-0.76 – 0.83 (.536)	14
Design: Within - Between	-0.20	1.24	-2.91 – 2.64 (.567)	15
Design: Within - Between x Stimulation intensity	0.36	0.90	-1.63 – 2.29 (.655)	16
Design: Within - Between x Stimulation duration/session	0.04	0.09	-0.15 – 0.23 (.693)	17
Stim intensity x Stimulation duration/session	0.05	0.03	-0.003 – 0.11 (.969)	18
Design: Within - Between x Stimulation intensity x Stimulation duration/session	-0.04	0.05	-0.15 – 0.08 (.762)	19
Random Effects (N studies = 18)				20
σ_{StudyID} (Intercept)	0.25	0.11	0.06 – 0.51	21
N total effects = 176				22
Marginal $R^2 = 0.47$ [0.33, 0.58]				23
Conditional $R^2 = 0.51$ [0.41, 0.60]				24

Table S9. Differences in candidate model predictive performance for the Working Memory domain, derived via Bayesian approximate leave-one-out cross-validation. Differences in fit are presented with respect to the top listed model. $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive densities (negative values thus indicate decrements in predictive performance relative to the top model); SE_{Diff} gives the standard error of the difference. The top model significantly differs in performance from any other model where $|ELPD_{Diff} / SE_{Diff}| > 2$.

Candidate Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Design Type x Stim Intensity x Stim Duration	—	—	—
Base Model (Only Additive Terms)	-3.101	2.499	-1.241
Design Type x Num Electrodes x Stim Intensity	-102.34	12.966	-7.893
Design Type x Num Electrodes x Stim Duration	-473.343	25.129	-18.837

1 **Table S10.** Model summary for top working memory candidate.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)	2 3
Intercept	-2.85	1.22	-5.43 – 0.04 (.973)	4
Polarity: Anodal - Cathodal	0.19	0.12	-0.04 – 0.43 (.942)	5 6
Target: Non-DLPFC - DLPFC	-0.03	0.10	-0.22 – 0.16 (.620)	7 8
Individualized target: Yes - No	0.69	0.29	0.09 – 1.29 (.986)	9
Laterality: Right - Left	0.02	0.09	-0.16 – 0.21 (.597)	10 11
Number of stimulation sessions	0.04	0.03	-0.03 – 0.11 (.889)	12 13
Stimulation duration/session (min)	0.27	0.08	0.08 – 0.44 (.992)	14
Stimulation intensity (mA)	1.78	0.77	-0.05 – 3.38 (.973)	15 16
Stimulation timing: Offline - Mixed	0.08	0.20	-0.34 – 0.53 (.647)	17 18
Stimulation timing: Online - Mixed	0.02	0.20	-0.42 – 0.46 (.544)	19 20
Number of electrodes in montage	0.14	0.06	0.02 – 0.27 (.989)	21
Design: Within - Between	0.37	2.24	-4.76 – 6.13 (.566)	22 23
Design: Within - Between x Stimulation intensity	-0.42	1.42	-4.10 – 2.87 (.620)	24 25
Design: Within - Between x Stimulation duration/session	0.18	0.15	-0.20 – 0.50 (.858)	26 27
Stimulation intensity x Stimulation duration/session	-0.15	0.05	-0.25 – -0.04 (.991)	28 29 30
Design: Within - Between x Stimulation intensity x Stimulation duration/session	-0.09	0.09	-0.28 – 0.13 (.829)	31 32 33
Random Effects (N studies = 16)				34
σ_{StudyID} (Intercept)	0.09	0.08	0.00 – 0.38	35 36
N total effects = 115				37 38
Marginal R^2 = 0.16 [0.08, 0.30]				39
Conditional R^2 = 0.15 [0.09, 0.22]				40 41

42

43

44

Table S11. Differences in candidate model predictive performance for the Vigilance domain, derived via Bayesian approximate leave-one-out cross-validation. Differences in fit are presented with respect to the top listed model. $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive densities (negative values thus indicate decrements in predictive performance relative to the top model); SE_{Diff} gives the standard error of the difference. The top model significantly differs in performance from any other model where $|ELPD_{Diff} / SE_{Diff}| > 2$.

Candidate Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Base Model (Only Additive Terms)	—	—	—
Design Type x Stim Intensity x Stim Duration	-0.666	1.480	-0.450
Design Type x Num Electrodes x Stim Intensity	-0.671	2.081	-0.322
Design Type x Num Electrodes x Stim Duration	-0.760	2.148	-0.354

1 **Table S12.** Model summary for top vigilance candidate.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)	2 3
Intercept	-1.70	10.12	-24.40 – 19.40 (.568)	4
Polarity: Anodal - Cathodal	0.04	0.12	-0.20 – 0.28 (.634)	5 6
Target: Other PFC - DLPFC	0.19	0.31	-0.50 – 0.89 (.732)	7 8
Target: Temporal-Parietal - DLPFC	-0.01	0.10	-0.20 – 0.18 (.528)	9 10
Laterality: Left - Bilateral	0.95	0.98	-1.01 – 3.05 (.837)	11
Laterality: Right - Bilateral	0.81	0.83	-0.93 – 2.62 (.834)	12 13
Number of stimulation sessions	0.86	0.89	-0.97 – 2.82 (.832)	14 15
Stimulation duration/session (min)	0.06	0.49	-0.96 – 1.16 (.547)	16
Stimulation intensity (mA)	0.51	5.26	-10.46 – 12.16 (.541)	17 18
Stimulation timing: Offline - Mixed	-0.03	0.23	-0.50 – 0.43 (.546)	19 20
Stimulation timing: Online - Mixed	-0.02	0.16	-0.36 – 0.31 (.557)	21
Number of electrodes in montage	0.04	0.08	-0.16 – 0.24 (.693)	22 23
Design: Within - Between	-14.06	11.56	-41.34 – 13.84 (.873)	24 25
Design: Within - Between x Stimulation intensity	9.32	6.84	-7.41 – 25.84 (.897)	26 27
Design: Within - Between x Stimulation duration/session	0.66	0.59	-0.76 – 2.02 (.855)	28 29
Stimulation intensity x Stimulation duration/session	-0.05	0.29	-0.68 – 0.55 (.567)	30 31 32
Design: Within - Between x Stimulation intensity x Stimulation duration/session	-0.43	0.33	-1.23 – 0.38 (.886)	33 34 35 36
Random Effects (N studies = 15)				37
σ_{StudyID} (Intercept)	0.17	0.15	0.01 – 0.55	38
N total effects = 93				39
Marginal R^2 = 0.43 [0.27, 0.55]				40 41
Conditional R^2 = 0.42 [0.28, 0.53]				42 43

Table S13. Differences in candidate model predictive performance for the Inhibition domain, derived via Bayesian approximate leave-one-out cross-validation. Differences in fit are presented with respect to the top listed model. $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive densities (negative values thus indicate decrements in predictive performance relative to the top model); SE_{Diff} gives the standard error of the difference. The top model significantly differs in performance from any other model where $|ELPD_{Diff} / SE_{Diff}| > 2$.

Candidate Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Base Model (Only Additive Terms)	—	—	—
Design Type x Stim Intensity x Stim Duration	-81.191	12.117	-6.701
Design Type x Num Electrodes x Stim Duration	-156.164	15.967	-9.780
Design Type x Num Electrodes x Stim Intensity	-174.519	15.943	-10.946

Table S14. Differences in candidate model predictive performance for the combined domains, derived via Bayesian approximate leave-one-out cross-validation. Differences in fit are presented with respect to the top listed model. $ELPD_{Diff}$ gives the mean difference in the expected log pointwise predictive densities (negative values thus indicate decrements in predictive performance relative to the top model); SE_{Diff} gives the standard error of the difference. The top model significantly differs in performance from any other model where $|ELPD_{Diff} / SE_{Diff}| > 2$.

Candidate Model	$ELPD_{Diff}$	SE_{Diff}	$ELPD_{Diff} / SE_{Diff}$
Design Type x Num Electrodes x Stim Intensity	—	—	—
Design Type x Stim Intensity x Stim Duration	-6.904	4.839	-1.427
Design Type x Num Electrodes x Stim Duration	-7.038	4.703	-1.497
Base Model (Only Additive Terms)	-23.029	11.329	-2.033

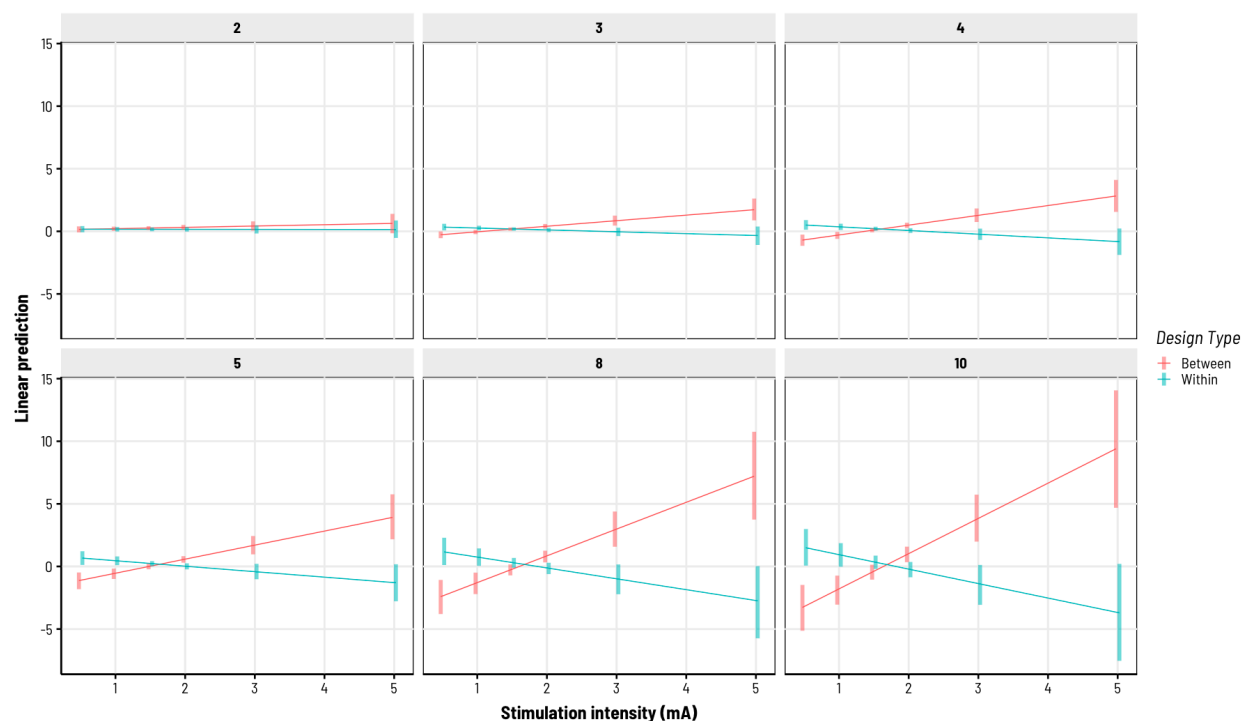


Figure S2. Posterior predictions for a three-way interaction between Design Type x Num Electrodes x Stim Intensity (all domains combined). For visualization, stimulation intensities (along the x-axis) were sampled at 0.50, 1, 1.5, 2, 3, and 5 mA; montage sizes (individual facets/tiles) were sampled at 2, 3, 4, 5, 8, and 10 electrodes. Error bars give 95% highest posterior density intervals. These trends suggest that larger montages coupled with stronger stimulation intensities may produce larger behavioral effects in between-subject designs, but this is reversed under within-subject designs.

1 **Table S15.** Model summary for top candidate model with domains combined.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)	2 3
Intercept	0.45	0.33	-0.20 – 1.10 (.914)	4
Polarity: Anodal - Cathodal	-0.07	0.04	-0.15 – 0.01 (.956)	5
Laterality: Left - Bilateral	-0.14	0.10	-0.33 – 0.05 (.920)	6
Laterality: Right - Bilateral	-0.12	0.09	-0.30 – 0.07 (.887)	7
Number of stimulation sessions	0.00	0.02	-0.05 – 0.04 (.590)	8
Stimulation duration/session (min)	0.00	0.01	-0.01 – 0.02 (.671)	9
Stimulation intensity (mA)	-0.14	0.17	-0.48 – 0.19 (.808)	10
Stimulation timing: Offline - Mixed	0.00	0.10	-0.20 – 0.19 (.519)	11
Stimulation timing: Online - Mixed	-0.12	0.09	-0.31 – 0.06 (.906)	12
Number of electrodes in montage	-0.18	0.12	-0.43 – 0.07 (.923)	13
Design: Within - Between	-1.60	0.47	-2.57 – -0.69 (1.00)	14
Design: Within - Between x Number of electrodes in montage	0.84	0.16	0.53 – 1.16 (1.00)	15
Design: Within - Between x Stimulation intensity	0.86	0.28	0.32 – 1.43 (.999)	16
Number of electrodes in montage x Stimulation intensity	0.10	0.07	-0.04 – 0.23 (.923)	17
Design: Within - Between x Number of electrodes in montage x Stimulation intensity	-0.48	0.10	-0.69 – -0.29 (1.00)	18
Random Effects (N studies = 106)				19
σ_{StudyID} (Intercept)	0.43	0.04	0.36 – 0.52	20
N total effects = 721				21
Marginal R^2 = 0.02 [0.07, 0.17]				22
Conditional R^2 = 0.33 [0.29, 0.37]				23

43

44

1

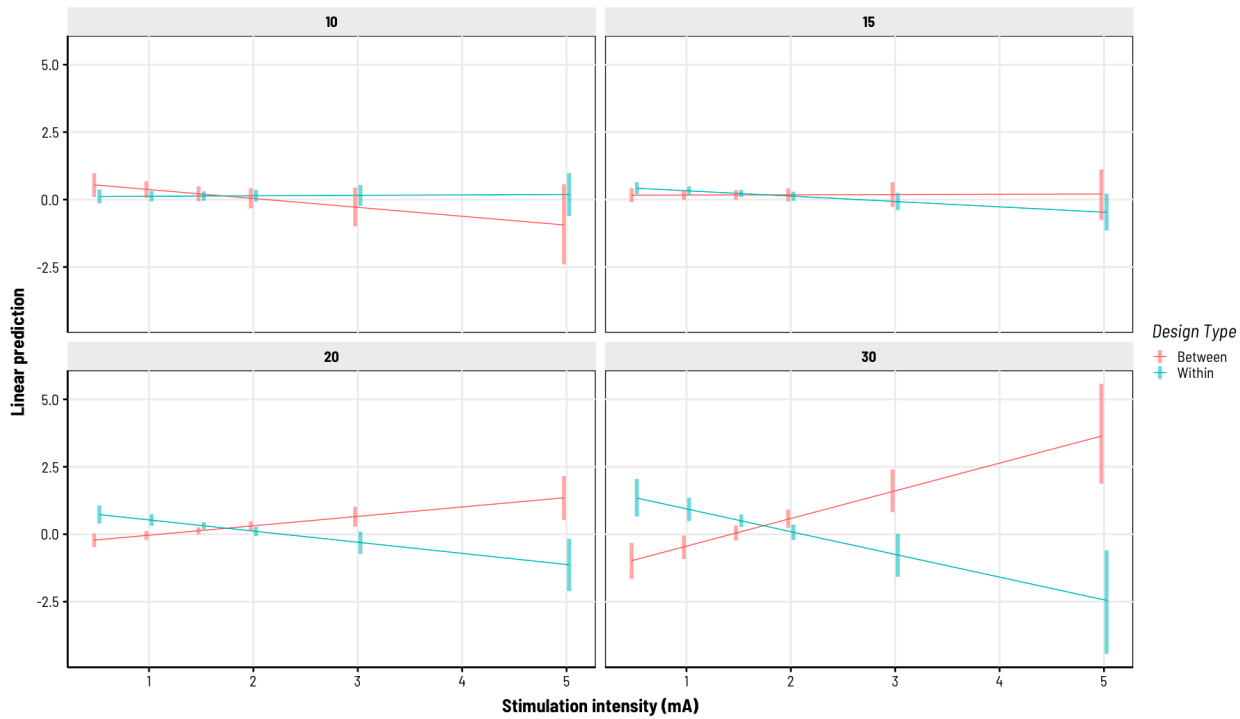


Figure S3. Posterior predictions for a three-way interaction between Design Type x Stim Intensity x Stim Duration (all domains combined). For visualization, stimulation intensities (along the x-axis) were sampled at 0.50, 1, 1.5, 2, 3, and 5 mA; stimulation durations (individual facets/tiles) were sampled at 10, 15, 20, and 30 minutes. Error bars give 95% highest posterior density intervals. These trends suggest that longer and stronger stimulation sessions may produce larger behavioral effects in between-subject designs, but this is reversed under within-subject designs.

1 **Table S16.** Model summary for second-best candidate model with domains combined.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)
Intercept	0.54	0.41	-0.25 – 1.35 (.911)
Polarity: Anodal - Cathodal	-0.08	0.04	-0.15 – 0.00 (.973)
Laterality: Left - Bilateral	-0.15	0.09	-0.33 – 0.04 (.941)
Laterality: Right - Bilateral	-0.12	0.09	-0.30 – 0.06 (.902)
Number of stimulation sessions	-0.00	0.02	-0.04 – 0.04 (.505)
Stimulation duration/session (min)	-0.01	0.02	-0.06 – 0.03 (.718)
Stimulation intensity (mA)	-0.28	0.24	-0.76 – 0.19 (.880)
Stimulation timing: Offline - Mixed	-0.01	0.10	-0.21 – 0.18 (.557)
Stimulation timing: Online - Mixed	-0.12	0.09	-0.31 – 0.06 (.910)
Number of electrodes in montage	0.00	0.03	-0.05 – 0.06 (.512)
Design: Within - Between	-2.54	0.74	-4.07 – -1.11 (1.00)
Design: Within - Between x Stimulation intensity	1.46	0.46	0.59 – 2.39 (.999)
Design: Within - Between x Stimulation duration/session	0.19	0.04	0.11 – 0.28 (1.00)
Stimulation intensity x Stimulation duration/session	0.01	0.01	-0.02 – 0.04 (.811)
Design: Within - Between x Stimulation intensity x Stimulation duration/session	-0.11	0.03	-0.17 – -0.06 (1.00)
Random Effects (N studies = 106)			
σ_{StudyID} (Intercept)	0.42	0.04	0.34 – 0.51
N total effects = 721			
Marginal R^2 = 0.13 [0.08, 0.20]			
Conditional R^2 = 0.32 [0.27, 0.36]			

43

44

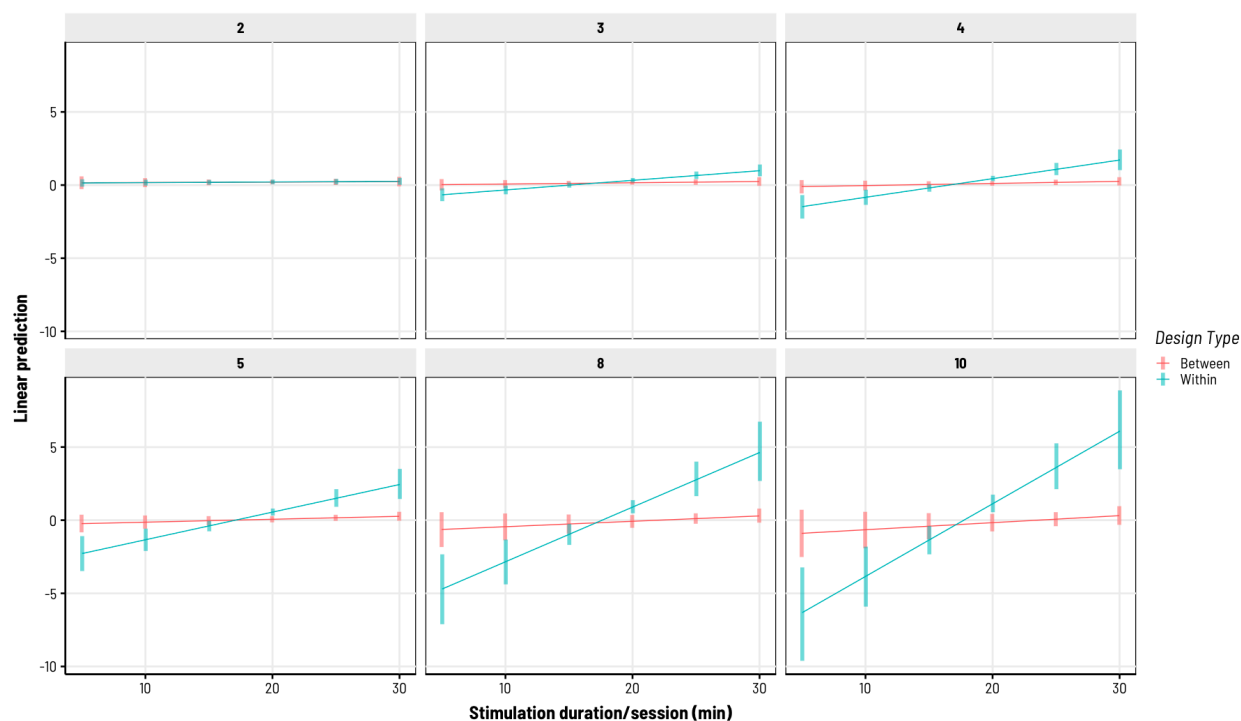


Figure S4. Posterior predictions for a three-way interaction between Design Type x Num Electrodes x Stim Duration (all domains combined). For visualization, stimulation durations (along the x-axis) were sampled at 5, 10, 15, 20, 25, and 30 minutes; montage sizes (individual facets/tiles) were sampled at 2, 3, 4, 5, 8, and 10 electrodes. Error bars give 95% highest posterior density intervals. These trends suggest that longer stimulation sessions with larger montages may benefit within-subjects designs while between-subjects designs are relatively invariant.

1 **Table S17.** Model summary for final candidate model with domains combined.

Fixed Predictors	Post. Med. Est.	Post. SD	95CI (p_d)	2 3
Intercept	1.38	0.40	0.63 – 2.20 (1.00)	
Polarity: Anodal - Cathodal	-0.08	0.04	-0.16 – 0.00 (.977)	
Laterality: Left - Bilateral	-0.20	0.10	-0.39 – -0.01 (.980)	
Laterality: Right - Bilateral	-0.18	0.09	-0.36 – 0.01 (.970)	
Number of stimulation sessions	0.01	0.02	-0.04 – 0.05 (.638)	
Stimulation duration/session (min)	-0.06	0.02	-0.10 – -0.03 (1.00)	
Stimulation intensity (mA)	0.01	0.07	-0.13 – 0.16 (.554)	
Stimulation timing: Offline - Mixed	0.02	0.10	-0.18 – 0.22 (.594)	
Stimulation timing: Online - Mixed	-0.11	0.09	-0.30 – 0.07 (.886)	
Number of electrodes in montage	-0.64	0.16	-0.97 – -0.34 (1.00)	
Design: Within - Between	1.89	0.75	0.48 – 3.44 (.996)	
Design: Within - Between x Number of electrodes in montage	-0.95	0.30	-1.57 – -0.40 (1.00)	
Design: Within - Between x Stimulation duration/session	-0.11	0.04	-0.19 – -0.04 (.999)	
Number of electrodes in montage x Stimulation duration/session	0.03	0.01	0.02 – 0.05 (1.00)	
Design: Within - Between x Number of electrodes in montage x Stimulation duration/session	0.06	0.02	0.03 – 0.09 (1.00)	
Random Effects (N studies = 106)				
σ_{StudyID} (Intercept)	0.43	0.04	0.36 – 0.52	
N total effects = 721				
Marginal R^2 = 0.11 [0.06, 0.17]				
Conditional R^2 = 0.32 [0.27, 0.36]				