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Modulating task outcome value to mitigate real-world procrastination via noninvasive brain stimulation

Zhiyi Chen[1,2,3], **Zhilin Ren**[3], **Wei Li**[3], **ZhenZhen Huo**[1,2], **ZhuanZheng Wang**[1,2], **Ye Liu**[1,2], **Bowen Hu**[1,2], **Wanting Chen**[1,2], **Ting Xu**[1,4,5], **Artemiy Leonov**[6], **Chenyan Zhang**[7], **Bernhard Hommel**[7], **Tingyong Feng**[1,2]

[1]Faculty of Psychology, Southwest University, Chongqing, China • [2]Key Laboratory of Cognition and Personality, Ministry of Education, Beijing, China • [3]Experimental Research Center for Medical and Psychological Sciences, School of Psychology, Third Military Medical University, Chongqing, China • [4]The Clinical Hospital of the Chengdu Brain Science Institute, Chengdu, China • [5]Key Laboratory for Neuroinformation, University of Electronic Science and Technology of China, Chengdu, China • [6]School of Psychology, Clark University, Worcester, United States • [7]Institute for Psychological Research, Leiden University, Leiden, Netherlands

For correspondence:
chenzhiyi@tmmu.edu.cn
fengty0@swu.edu.cn

Author notes: See page 26

Funding: See page 25

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eLife Assessment

This **valuable** cross-sectional longitudinal study leverages high-definition transcranial direct current stimulation to the left dorsolateral prefrontal cortex to examine its effect on procrastination behavior over an extended time span. The cross-sectional longitudinal study provided evidence for how stimulating DLPFC impacts reveal-world procrastination behavior. Support for the conclusions is **incomplete** owing to missing information about the analyses, and results, as well as some potential alternative interpretations.

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Abstract

Procrastination represents one of the most prevalent behavioral problems affecting individual health and societal productivity. Although it is often conceptualized as a form of self-control failure, its underlying neurocognitive mechanisms are poorly understood. A leading model posits that procrastination arises from imbalanced competing motivations: the avoidance of negative task aversiveness and the pursuit of positive task outcomes, yet this theoretical framework has not fully validated in real-world settings and not applied effectively to guide interventions. Here, we addressed this gap with a double-blind, randomized controlled trial. We applied seven sessions of high-definition transcranial direct current stimulation (HD-tDCS) to the left dorsolateral prefrontal cortex (DLPFC), a key region for self-control, in chronic procrastinators. Using the intensive experience sampling method (iESM), we assessed the effect of anodal HD-tDCS on real-world procrastination behavior at offline after-effect (2-day interval) and long-term retention (6-month follow-up). We found that this neuromodulation produced a lasting reduction in real-world procrastination, with effects sustained at a 6-month follow-up. While the intervention both decreased task aversiveness and increased perceived task outcome value, causal mediation analysis revealed a striking mechanism: the increase in task outcome value (but not task aversiveness) sufficiently mediated the entire behavioral improvement. In conclusion, these findings provide causal evidence that enhancing DLPFC function mitigates procrastination by selectively amplifying the valuation of future rewards, not by simply reducing negative feelings about the task. This establishes a precise, value-driven neurocognitive pathway to account the conceptualized roles of self-control on procrastination, and potentially offers a validated, theory-driven strategy for interventions.

Introduction

Procrastination is increasingly becoming a prevalent behavioral problem around the world, which reflects the irrational voluntary postponement of scheduled tasks albeit being worse off for such delays (Blake, 2019; Steel, 2007). In epidemiological investigations, more than 15% of adults were identified as having chronic procrastination problems, and the situation for students was worse as 70-80% of undergraduates engaged in procrastination (American College Health Association, 2022; Ferrari et al., 2005). Moreover, the behavioral genetic evidence indicates a certain heritability of procrastination in human beings as well (Gustavson et al., 2017; Gustavson et al., 2014, 2015). In addition to its prevalence, the undesirable associations between procrastination behavior and health also warrant caution. There is cumulative evidence to show the close associations between procrastination behavior and work performance, financial status, interpersonal relationships, and subjective well-being (Ferrari, 1994; Pychyl & Sirois, 2016; Steel et al., 2021). Further, as prospective cohort studies indicate, many mental health problems emerge alongside procrastination, particularly sleep problems, depression, and anxiety (Hairston & Shpitalni, 2016; Johansson et al., 2023). Even worse, chronic procrastination has been observed to impair general health, as manifested by the close associations with immune system disruption, gastrointestinal disturbance, as well as a high risk of hypertension and cardiovascular disease (Sirois, 2015; Sirois, 2016). Thus, given these critical ramifications, considerable efforts have been devoted to delve into why we procrastinate irrationally.

To probe why we procrastinate irrationally, researchers have built upon theoretical bases of procrastination from different perspectives. For instance, Steel (2007) pioneered a promising temporal motivation theory (TMT) to explicate procrastination as the failure of self-regulation. This theory suggests that individuals would procrastinate as task utility is devalued in the far future (Steel & König, 2006). Based on insights into emotional regulation, the mood repair perspective provides another explanation to elucidate that procrastination is due to the failure of self-regulation to give priority to short-term mood repair caused by doing the task rather than long-term task reward (Sirois & Pychyl, 2013). Recently, the temporal decision model (TDM) of procrastination further provides an integrative framework to explain the procrastination decisions, which highlights that procrastination is contingent on the trade-off between task aversiveness and task-outcome value (Zhang & Feng, 2020; Zhang, Liu, et al., 2019). Task aversiveness reflects how unpleasant individuals perceive tasks to be, with more unpleasant feelings making procrastination more likely (Zhang & Feng, 2020). Task outcome value indicates how much it is worth as we evaluate the benefits it provides us (e.g., keeping body health) once we complete the task before the deadline (e.g., doing scheduled exercise) (Zhang & Feng, 2020). If the task aversiveness is overvalued in this trade-off, the decision to postpone tasks would be made consistently.

It is worthwhile to note that this trade-off and resultant decisions to procrastinate are predominantly influenced by self-control capability, with higher self-control associated with less procrastination behavior (Blake, 2019; Ramzi & Saed, 2019; Zhao et al., 2021). Thus far, there have been three promising pathways attempting to clarify how self-control works in reducing procrastination: one for decreasing task aversiveness, the other one for increasing task-outcome value, and the last one for both (Zhang & Feng, 2020). As identified by both behavioral and neural evidence, procrastinators consistently report high task aversiveness when receiving scheduled tasks, and are more likely to postpone tasks so as to devalue negative task aversiveness (Blunt & Pychyl, 2000; Zhang et al., 2021). Meanwhile, the self-control was observed as powerful for downstream regulation of negative emotional stimuli (Paschke et al., 2016; Tice & Bratslavsky, 2000). Therefore, the first possible pathway is to enhance self-control by facilitating emotional regulation towards task aversiveness (Eckert et al., 2016). On the other hand, as a value-based decision, procrastination behavior is contingent on the evaluation of future outcomes (Rebetez et al., 2016; Zhang, Becker, et al., 2019). Existing evidence has shown that procrastinators generally underestimate the task-outcome value (H. Wu et al., 2016; Zhang et al., 2021). In this vein, it is hard to generate the motivation to take immediate action (Taura et al., 2015). Notably, increasing the value of future rewards has been found effective in making individuals inclined to pursue future outcomes by strengthening self-control (Cho et al., 2015; Kelley et al., 2018). Thus, another pathway worth putting forward is that procrastination behavior could be shaped by increasing future task-outcome value. Also, given the multifaceted roles of self-control, we hypothesize a third pathway whereby both decreased task aversiveness and increased task-outcome value contribute to determining procrastination simultaneously through the exertion of self-control.

Supporting this view, the left dorsolateral prefrontal cortex (DLPFC), responsible for self-control, has been frequently shown to be closely associated with procrastination. As the biomarker of self-control, the neuroanatomical changes of the left DLPFC were revealed to predict procrastination robustly (Chen et al., 2020; Hu et al., 2018; Liu & Feng, 2017). In addition to structural brain hallmarks, the neurofunctional anomalies underlying procrastination were found in DLPFC-involved circuits (Y. Wu et al., 2016; Xu et al., 2021). Furthermore, the triple brain network theory provides network-based insights to highlight the neural signature of procrastination as the self-control neural network (e.g., left DLPFC; anterior cingulate cortex, ACC), emotional regulation network (e.g., insula and orbitofrontal cortex, OFC) and episodic prospection network (e.g., hippocampus and ventromedial prefrontal cortex, vmPFC, amygdala) (Chen & Feng, 2022; Chen et al., 2020; Schlüter et al., 2018; Wypych et al., 2019). In addition to the left lateralization, there is solid evidence indicating significant associations between self-control and the right DLPFC indeed, particularly given that this region specifically functions in top-down regulation, future self-continuity representation and social decisions (Huang et al., 2025; Knoch & Fehr, 2007; Lin & Feng, 2024). Despite this case, Xu and colleagues demonstrated null effects of anodally stimulating the right DLPFC to modulate either value evaluation or emotional regulation for changing procrastination willingness (Xu et al., 2023). Moreover, a substantial amount of neural evidence supports this conclusion that DLPFC is involved in long-term reward evaluation and value encoding via top-down self-control circuits (Frost & McNaughton, 2017; Jimura et al., 2013; Smith et al., 2018). Using a neurocomputational model, Le Bouc & Pessiglione (2022) provided clear evidence indicating that dorsal PFC signaling expected effort values was significantly attenuated in procrastinators compared to healthy controls (Le Bouc & Pessiglione, 2022). In this vein, this evidence supports this conceptualization that the left DLPFC may be a domain-specific neural signature determining one's procrastination. In light of technical advances, high-resolution transcranial direct current stimulation (HD-tDCS) has been widely used to reveal the causal neurocognitive mechanism of problematic behaviors by modulating cortical excitability, blood-brain barrier permeability and even neuroplasticity (Cirillo et al., 2017; Woods et al., 2016), which is regulated by the NMDA (N-methyl-D-aspartate) system to either bolster LTP (Long-term potentiation) or LTD (Long-term depression) processes (Chrysikou et al., 2022; Shin et al., 2020). For instance, anodic HD-tDCS applied to the left DLPFC was found effective in inhibiting problematic behaviors caused by the lack of self-control (Allenby et al., 2018), showing significantly amplified local neural oscillations (Chrysikou et al., 2022). Beyond regional neuromodulation in a dose-free protocol, cumulative evidence has well-documented that the effects of tDCS for neuromodulation are highly dose-dependent and are involved in network-wise covariance (Sabé et al., 2024; Soleimani et al., 2023; Woodham et al., 2025). Thus, this study aims to provide causal evidence clarifying the brain-behavior association of procrastination and revealing how self-control works to shape one's procrastination by manipulating left DLPFC activity in a multiple-session (dose) protocol.

To clarify the causal cognitive mechanism of self-control on procrastination, we conducted a double-blind, randomized, multiple-session, placebo-controlled design, with a 2 (active HD-tDCS vs. sham control) × 2 (before first neural stimulation vs. after last neural stimulation) full factorial design (see Fig. 1). This HD-tDCS protocol consisted of 7 sessions spaced over 15 days, and each session was implemented every two days. To ensure sound ecological validity, each procrastinator was informed to report one REAL-LIFE task that he/she should complete the following day (e.g., Day 2) after the current neuromodulation session (e.g., Day 1), and was asked to report the ACTUAL performance for completing this task in that day (Day 2) (see Fig. 1). Based on the temporal decision model of procrastination (Zhang, Liu, et al., 2019), we drew on the experience sampling method (ESM) to estimate the real dynamics of task aversiveness and task-outcome value by using a parameter-free model in each session. More importantly, to clarify which pathway best explains the neurocognitive mechanism of procrastination, we built upon the mixed-effects general linear model and Quasi-Bayesian causal mediation model to test whether the changes in task aversiveness and task outcome value caused by HD-tDCS could predict decreased procrastination. Finally, the follow-up investigation for actual procrastination was conducted for 6 months after the experiment to examine the long-term retention of this neural stimulation effect.

Materials and Methods

This study fully adhered to CONSORT reporting guidelines and was originally preregistered in the OSF repository (10.17605/OSF.IO/Y3EDT). However, due to the technical constraint related to OSF account service (see SM Methods), this OSF page is no longer accessible. For transparency and best practices of open science, based on the original protocol documentations, a preregistration statement has been reconstructed to clarify a prior hypotheses, sample size determinations, and analysis plans for this study (Table S1).

Participants

Due to the lack of diagnostic criteria for clinical procrastinators, we recruited a large-scale sample (n = 1,682) to obtain a stable benchmark distribution. Thus, the procrastinators were captured once their procrastination scores were higher than 66 on General Procrastination Scale (GPS) (see Fig. 2A-B). Following this criterion, a total of 186 participants were included initially, which was in accordance with empirical evidence (i.e., 10 - 15% prevalence of procrastination) (Harriott & Ferrari, 1996). Subsequently, the semi-structured interview was performed to screen those suffering from problematic procrastination and volunteering for this study, thereby enrolling 53 participants (see SM Methods). Seven participants were eventually excluded from the analyses because they voluntarily dropped out before experimental completion. All the included participants were screened for depression and anxiety symptoms (see Tab. 1).

Table 1. Demographic information for included participants.

NM represents active neuromodulation group and sham indicates sham-control group. Anxiety symptoms were measured by State-Trait Anxiety Inventory (STAI). Depression symptoms were tested by Self-Rating Depression Scale (SDS). BF10 describes the Bayesian evidence strength to support alternative hypothesis, with ≥ 3 for a strong evidence.

	active NM		SC		*P*-value (BF_{10})
	Male	Female	Male	Female	
Gender	3	20	3	20	.99 (-)
Age	19.61 ±0.78		22.22 ± 1.44		0.08 (1.03)
SES	2.17 ±0.65		2.34 ± 0.64		0.38 (0.41)
Anxiety	48.48 ± 6.52		47.30 ± 6.87		0.56 (0.33)
Depression	47.13 ±8.27		47.50 ± 9.28		0.88 (0.29)
Procrastination	71.00 ±5.47		72.07 ± 4.77		0.26 (0.48)

A full randomized block design was used to assign participants to both groups (active neuromodulation group, NM; sham-control group, SC) (see Fig. 2C). As the pilot study probing into the effect of single-session tDCS stimulation to change procrastination willingness indicated (t = 2.38, p = .02, 95% CI [0.14, 1.49]; Xu et al., 2023), statistical power was predetermined by G*Power at a relatively medium effect size (1-β err prob = 0.80, f = 0.25), yielding the total sample size at 18 to reach acceptable power (see SM Methods and Figure. S1). All the participants reported no history for HD-tDCS or neuromodulation. No significant differences were found between groups for any demographic characteristics (see Tab. 1). This study and protocol have been fully approved by the Institutional Review Board (IRB) of the School of Psychology, Southwest University (China, IRB200301108).

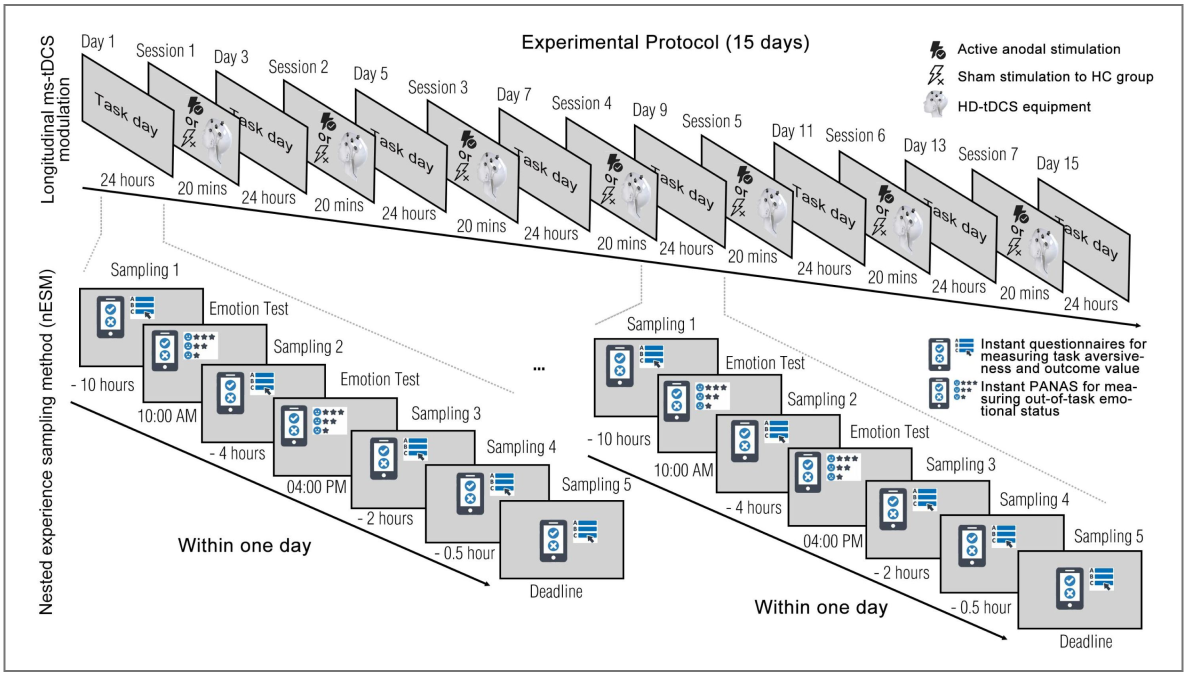


Figure 1. Experimental diagram of this study.

The upper sub-graph illustrates the whole multiple sessions tDCS neuromodulation pipeline including seven sessions (days) and eight task-demanded days. Here, the “flash” icon indicates conducting tDCS neuromodulation (active anodal stimulation for active NM group and sham stimulation for sham NM group). This “+” label means a task-demanded day, where no stimulation is required for participants but all the covariates of interests should be measured by experience sampling methods. The bottom sub-graph reflect specific pipeline in task-demanded days. Participants were required to provide response at five progressive time moments nearing deadline for task aversiveness and outcome value in task-demanded days. In this diagram, the icon of “clock” symbolize ecological momentary assessment for measuring instant task willingness and outcome value. In addition, twice tests for daily emotions (labeled by “+”) were added for participants at 10:00 and 16:00 as covariates of no interests to be adjusted.

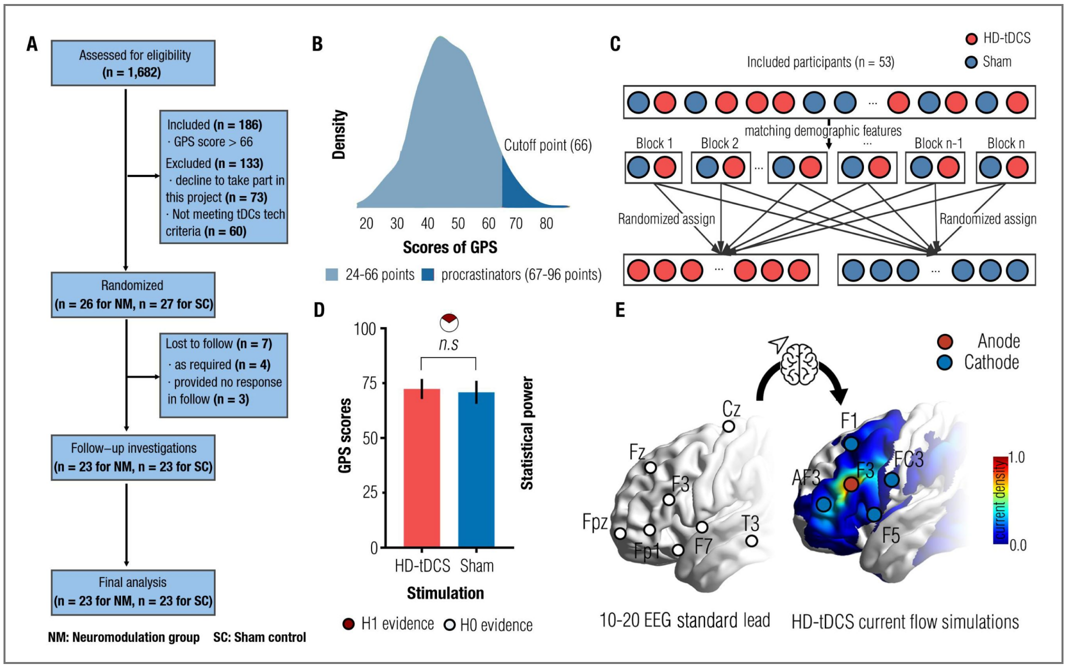


Figure 2. **Flow diagram of CONSORT (A) and partial details of randomized groups (B-D) and neural locations of electric pole (E).**

B plots the distribution of all the participants procrastination scores (GPS = general procrastination scale). C detailed what the full randomized block design is. D shows the comparison between active neuromodulation group and sham control for procrastination scores. E indicates the pipeline to determine the location of electric pole. The 10-20 EEG standard lead is used to locate the left dorsolaterial prefrontal cortex (DLPFC) initially, and the neuronavigation is further utilized to locate the exact location of this targeting region (i.e., left DLPFC).

Measurement

The General Procrastination Scale (GPS) developed by Lay (1986) was used to quantify one's chronic procrastination symptom here (Lay, 1986). This scale was widely adopted in many cross-cultural contexts, and has been reported to have good psychometric properties (Klein et al., 2019). There were two additional items that we added for lie detection, including description of "the sky is red" and "I have never taken shower". If either one was selected as "agree" by participant, his/her response would be discarded. Internal reliability of the GPS in the current study was found acceptable (Cronbach's α = 0.890). No significant difference was found between groups for GPS scores (t = -1.08, 95% CI: -4.296 1.283, p = .283; Jeffreys-Zellner-Siow Bayesian factor, BF, BF_{10} = 0.455, error = 0.020 %).

To quantify one's daily emotions, the Positive and Negative Affect Schedule (PANAS) developed by Watson et al. (1988) was adopted. This scale consists of two subscales (i.e., positive affect, PA and negative affect, NA), each containing 10 terms, where higher scores indicate stronger affective states (Terracciano et al., 2003). To control for potential confounding effects of daily emotions, both subscale scores were included as covariates of no interest in the statistical model. Additionally, this tool demonstrated good internal consistency for both sub-scales (α = 0.801 for PA, α = 0.793 for NA).

Experimental design and procedure

Nested cross-sectional longitudinal design

This study used a nested cross-sectional longitudinal design to investigate whether the multiple-session anodal HD-tDCS targeting the left DLPFC could reduce actual procrastination behavior and to probe how this effect manifests. To assess procrastination in daily life, we implemented a 15-day protocol alternating between Neuromodulation Days (Days 2, 4, 6, 8, 10, 12, 14) and Task Days (Days 1, 3, 5, 7, 9, 11, 13, 15). On the Neuromodulation days, the 20-min anodal HD-tDCS neuromodulation targeting the left DLPFC was performed for HD-tDCS active group at intervals of 2 days, while the sham-control group received sham HD-tDCS training. This HD-tDCS training was repeated for a total of seven sessions, and lasted 15 days (see Fig. 1). Crucially, to capture procrastination in ecologically valid contexts, prior to receiving either active or sham HD-tDCS (administered between 09:00-18:00), participants were instructed to specify a real-life task they were personally obligated to complete the following day, with a self-defined deadline strictly constrained to 18:00-24:00 to ensure ≥24 hours between stimulation offset and task deadline, thereby isolating offline after-effects. This task should meet the following three criteria: (a) it should be already assigned in the real-world settings; (b) deadline should be constrained to 18:00-24:00 (see above); (c) it should be more likely to induce procrastinate. By doing so, more than 300 real-life tasks were collected, spanning academic (e.g., "submit a statistics homework assignment"), occupational (e.g., "draft and email a project proposal"), administrative (e.g., "complete online application for Class C driver's license"), self-improvement (e.g., "practice guitar for ≥ 30 minutes"), domestic (e.g., "do laundry"), and health-related (e.g., "running 2,000m for exercise"). Full task list has been tabulated in the Appendix 1. As primary outcomes, all the participants were required to report task-execution willingness (TEW) (Zhang & Feng, 2020; Zhang, Liu, et al., 2019), for a real-life task 24 hours post-neuromodulation. Thus, procrastination willingness was quantified as 100-TEW score (see underneath for details). Furthermore, we asked participants to report the actual task completion rate (CR) of the task at the deadline (e.g. participant A finished 90% homework at deadline and reported this situation to us at deadline). In this vein, the actual procrastination rate (PR) was quantified as 1-CR.

On the Task day, we developed a mobile app to implement experience sampling method (ESM) for tracking one's real-time evaluation of task aversiveness and task outcome value (see Fig. 1). The task aversiveness describes how disagreeable one perceives performing a given real-life task to be, whereas outcome value refers to the subjective benefits of the task outcome brought about by completing the task before the deadline (Zhang & Feng, 2020). As theoretically conceptualized by the temporal decision model (TDM) of procrastination, the perceived task aversiveness is hyperbolically discounted when approaching deadline, showing sharply discounting when faring away from deadline but slowly discounting once nearing deadline (Zhang & Feng, 2020). Thus, considering this nonlinear dynamics inherent in this hyperbolic discounting, the five recording moments of ESM were selected per task a priori by using a log-spaced temporal sampling scheme (Myerson et al., 2001), with increasing sampling density toward the deadline, such as moments of 10:00 (earliest), 16:00, 18:00, 19:30, 20:00 (deadline). The five sampling points could meet statistical prerequisite in the hyperbolic model fitting, requiring ≥ 4 points (Green & Myerson, 2004). To do so, recording moments of tasks were individually tailored for each task per participant in this ESM procedure. To obviate the confounds of daily emotions in task aversiveness evaluation, we used the averaged scores of PANAS at 10:00 (noon) and 16:00 (afternoon) as anchoring points to quantify one's daily emotions by using this ESM app. Before each session of HD-tDCS training, each participant was required to report a real-life task whose deadline is tomorrow. To obtain the long-term effect of HD-tDCS (i.e., the interval between HD-tDCS and task completion is at least 24 hours), the task deadline that participants reported was required to be between 18:00 - 24:00. Once a sampling time reached, this app would send a digital message to require participants to fill online form for data collection.

Quantification of covariates of interests

Outcome variables of this study were twofold: one is task-execution willingness and another is procrastination rate (PR). Task-execution willingness is used to evaluate one's subjective inclination to avoid procrastination (Zhang & Feng, 2020). In this vein, we used a 100-point scale to require participants to report their task-execution willingness (0 for "I will definitely procrastinate this task" and 100 for "I will take action to complete this task immediately"). This metric was recorded 24 hours after neuromodulation to examine its long-term effects. PR is used to quantify the extent to which one task has been procrastinated, and was calculated as 1 - CR (task completion rate). Critically, at the precise deadline, the app prompted participants to (a) indicate task completion status (yes/no), and if incomplete, (b) report the percentage completed (1-99%), defined as the Task CR, while simultaneously uploading objective evidence (e.g., screenshots of submitted files, photos of physical outputs, system-generated logs, or app-exported records). If the task was actually completed before the deadline, the CR would be 100% and the PR would be calculated as 0% (1-CR). PR was recorded at the actual task deadline for each participant. We were also interested in re-investigating their actual procrastination by using PR 6 months after the last neuromodulation to test the long-term retention of this neuromodulation effect.

From what has been mentioned above, task aversiveness and outcome value were considered key factors to explain the effect of neuromodulation on reducing procrastination in the current study. To quantify one's task aversiveness, participants were required to rate their feelings towards the task by using a 100-point visual analog scale (i.e., How do you feel in the current moment when you need to complete this task before deadline, with 0 for "extremely unpleasant", 50 for "totally neutral" and 100 for "extremely pleasant"). Likewise, participants are also required to rate their outcome value by using a 100-point visual analog scale (i.e., How much do you desire to obtain incentive outcome of this task, with 0 for "extremely weak", 50 for "medium" and 100 for "extremely strong"). As articulated temporal decision theoretical model above, the task aversiveness evoked by executing a task was temporally dynamic in a hyperbolic discounting pattern, with sharply discounting in faring away from deadline but slowly discounting in nearing deadline (Zhang & Feng, 2020). To quantitatively characterize the task aversiveness with consideration for its dynamics, the model-free area under the curve (AUC) was calculated. Specifically, based on the log-spaced temporal sampling rule, task aversiveness was measured by 100-point visual analog scale at the five sampling moments. Then, the task aversiveness discounting (A) was calculated as 1- (A(t) / A(earliest)), where t(earliest) was the earliest sampling point, serving as the reference for immediate execution. Subsequently, using the GraphPad Prism software (v9, 525), the AUC was computed as the trapezoidal integration between task aversiveness discounting and time across five data points, basing on the Myerson algorithm (Myerson et al., 2001). By doing so, a higher AUC reflects stronger temporal discounting of task aversiveness along with nearing deadline, which means that participants experience a faster decline in subjective aversiveness as execution is delayed, yielding lower effective aversiveness and reduced avoidance behavior. As for the task outcome value, it was theoretically posited as a relatively stable evaluation of the task (Zhang & Feng, 2020). Therefore, it was quantified by the self-reported 100-point visual analog scale after neuromodulation at least 12 hours later, to ensure no online effect.

HD-tDCS protocol

The HD-tDCS suit (stimulater and 4 × 1 multichannel stimulation adapter, MSA) that this study used was produced by the Soterix Medical Inc., and has been widely verified safe, effective and reliable for public (Villamar et al., 2013). Based on advanced properties of 4 × 1 MSA, the targeted areas for current flow can be constrained within 2.5 cm^2 (Villamar et al., 2013).

To position electrodes into targeted areas (left DLPFC), the 10-20 international system for EEG was initially used to mark potential nodes, and determined Cz as reference point. There is compelling evidence to claim that the left F3 could be used as target node for modulating the left DLPFC (Seibt et al., 2015; Tsukuda et al., 2025). In this vein, the central anodal electrode was determined onto F3, and four return electrodes surrounded central electrode at outside of 7.5 cm, including F5, AF3, FC3 and F1 (see Fig. 2F). Ramp-up and ramp-down durations were set to 30 seconds. To further locate the targeted areas, the high-definition neuronavigation system (ANT Neuro Inc., Welbergweg, Germany) was performed. Results indicated the accurate position that we pre-determined by showing a high overlap probability over the left DLPFC (MNI Coordinate: -51 40 18, 94.33 % overlapping probability) (see SM Method and Fig. 2F). In addition, the coordinates of this targeted area were retrieved from the Brede Database (*http://neuro.imm.dtu.dk/services/*), and showed highly pertinent functions related to DLPFC.

Before stimulation, participants were informed to clean the scalp to reduce resistance. Then, cotton swabs were used to separate hair until the scalp surface become visible. Subsequently, the electrically conductive gel (about 1.5 ml) was introduced into the plastic casing facilitating constraint of current flow. Next, the Ag/AgCI sintered ring electrodes were placed onto plastic casing and covered with a cap to lock them in the right positions. To reduce discomfort, the electrode cables were taped elsewhere. Further, the above processes would be re-adjusted if any electrode resistances were found larger than 1.5 units (Villamar et al., 2013). Once all the processes had been completed, the stimulator would be launched.

Participants in the HD-tDCS training group underwent constant electric current of 2.0 mA targeting the left DLPFC for 20 minutes. Results from the simulation of electric density showed a peak current of ~0.5mA/cm^2 at the central electrode and of ~0.125 mA/cm^2 at the four return electrodes, thereby indicating the safety and effectiveness. As for the sham-controlled group, the stimulator would deliver current flow with 2.0 mA during the first and last 30 seconds to elicit sense of electric stimulation for blinding of them. To obtain the pure offline effect, these measures for task-execution willingness, task aversiveness, and outcome value were conducted after stimulation at least 12 hours (Bikson et al., 2016).

Statistics

All the statistics were implemented by *R* (*https://www.rstudio.com/*) and *R*-dependent packages.

To clarify whether multiple-session HD-tDCS neuromodulation can reduce procrastination, the generalized mixed-effects linear model (GLMM) was constructed with full factorial design for subjective procrastination willingness (i.e., self-reported visual analog scores) and actual procrastination behavior (i.e., real-world task-completion rate before deadline). Here, sex, age and socioeconomic status (SES) were modeled as covariates of no interest. As the National Bureau of Statistics (China) issued (*https://www.stats.gov.cn/sj/tjbz/gjtjbz/*), on the basis of per capita annual household income, the SES was divided into seven hierarchical tiers from 1 (poor) to 7 (rich). To obviate subjective rating bias stemming from individual daily mood, we separately measured participants' daily emotional fluctuation at 10:00 and 16:00 using a self-rating visual analog item (i.e., "How do feel for your mood today?", 0 for "completely uncomfortable" and 100 for "definitely happy"). By doing so, the averaged score of those self-rating emotions at the two time points was modeled into the GLMM as covariate of no interest, yielding the final expression of "outcome ~ Group*Treatment_Day + Age + Gender + SES + Emotions + (1 + Treatment_Day | SubjectID)" in the statistical model". This analysis was implemented using the "lme4" and "lmerTest" packages. Employing "emmeans" package, simple effects were also tested at baseline and post-last-intervention using Tukey-adjusted pairwise comparisons of estimated marginal means from the full GLMM, controlling for covariates and random-effects structure. To validate statistical robustness, instead of continuous outcomes for parametric tests, we also conducted a between-group comparison for the number of tasks that procrastination emerges by using the nonparametric x^2 test with ϕ correction or Fisher exact test. Regarding the 6-month follow-up investigation, this GLMM was also built to examine the long-term retention of neuromodulation on reducing actual procrastination.

To ascertain the neurocognitive mechanism of tDCS in reducing procrastination, the Quasi-Bayesian causal mediation analysis was used to model the association between the effects of tDCS, task aversiveness/outcome and decreased procrastination. To build upon this model, the tDCS treatments were inputted as independent variables, and the task aversiveness/outcomes were modeled as causal mediating variables by using the "Mediation" package (*https://cran.r-project.org/web/packages/mediation/*) (Imai et al., 2010). We estimated these pathway effects (i.e., averaged causal mediation effects, δ; averaged direct effects, ζ; total effects, ρ) by using Markov Chain Monte Carlo (MCMC) sampling. To improve the statistical reliability, the sequential ignorability assumption was tested by using sensitivity analysis. Details for the statistical principals and basis could be found elsewhere (Imai et al., 2010).

Results

Blinding

In both groups, almost all participants reported perceiving acceptable pain stemming from current stimulation, and believed they were receiving treatment, with 91.30% (21/23) for active neuromodulation group (NM) and with 86.95% (20/23) for sham control group (SC) ($x^2 = 0.224$, $p = .636$). All the participants were engaged in the identical experimental procedures excepting stimulation's type (active *vs* sham). In addition, statistical models excluded Session 1 and Session 4 because participants reported additional unexpected events that uncontrollably disrupt task execution in both groups (see SI Result and Tab. S2).

Multiple-sessions HD-tDCS (ms-tDCS) can alleviate procrastination

To identify whether ms-tDCS targeting the left DLPFC can alleviate subjective procrastination willingness and actual procrastination behavior, a generalized linear mixed-effects model (GLMM) with Satterwhite algorithm was built, with task-execution willingness and actual procrastination rates (PR) as primary outcomes, respectively. For procrastination willingness, results showed a statistically significant interaction effect between multi-session neuromodulations and groups ($\beta = -7.8$, SE = 1.8, DF = 45.6, $p < .001$; Fig. 3A). In the post-hoc simple effect analysis, it demonstrated a significantly increased task-execution willingness (i.e., decreased procrastination willingness) after neuromodulation in the active neuromodulation group (NM-before: 35.65 ± 30.20, NM-after: 80.43 ± 19.92, t.ratio = 5.4, $p < .0001$, Tukey correction), but no such effects were identified in the sham control group (SC-before: 37.57 ± 26.46, SC-after: 47.35 ± 30.49, t.ratio = 0.3, $p = .77$, Tukey correction) (Fig. 3B-C). A linear uptrend for task-execution willingness was further observed across multiple sessions in the active NM group, indicating gradually increasing neuromodulation effects (Fig. 3D; $p < .01$, Mann-Kendall test). For actual procrastination behavior, changes to actual procrastination rates across all the sessions have been detailed in the Fig. 3E. Similarly, a statistically significant interaction effect was identified here ($\beta = -7.4$, SE = 2.4, DF = 46.6, $p = .004$), and the simple effect analysis further revealed decreased actual procrastination rates after ms-tDCS in the active neuromodulation group (NM-before: 43.26 ± 39.09, NM-after: 0.00 ± 0.00, t.ratio = 5.1, $p < .0001$, Tukey correction), but no such prominent changes found in the sham control group

(SC-before: 46.47 ± 40.75, SC-after: 33.34 ± 37.82, *t*.ratio = 0.7, p = .48, Tukey correction) (Fig. 3F-G). Also, a significant downtrend for procrastination rates across all the sessions was identified in the active NM group (Fig. 3H; p < .01, Mann-Kendall test).

Furthermore, the nonparametric x^2 test of R × C contingency table was conducted for the count of procrastinated tasks, by treating this outcome (i.e., whether a participant actually procrastinates the task in real-world settings) as an ordinal variable. Results showed a significant reduction in group-averaged procrastination frequency in the active neuromodulation group after last-session HD-tDCS, but not in the sham control group (NM-before: 69.56% (16/23 participants), NM-after: 0.00% (0/23 participants); SC-before: 69.56% (16/23 participants), SC-after: 56.52% (13/23 participants), x^2= 10.08, p < .001), partly indicating a high statistical robustness. To systematically test the statistical robustness, we reconstructed GLMMs by iteratively removing data from the last two sessions, which showed extraordinarily high effectiveness from neuromodulation. Results showed the significant group*neuromodulation_sessions interaction effects across all those nested models (removing session #6, #7 or both, all p < .05; see SI Results and Tab. S3-4). In brief, these findings provided empirical evidence to support that ms-tDCS neuromodulation targeting the left DLPFC can be an effective way to reduce both procrastination willingness and actual procrastination.

Ms-tDCS changes task aversiveness and task-outcome value

Both task aversiveness and task outcome value serve as key pathways determining whether one would procrastinate. To this end, we further utilized a generalized linear mixed-effects model to examine the effects of ms-tDCS on changes in task aversiveness and task outcome value. Task aversiveness changes across all the sessions are shown in the Fig. 4A and 4C. We demonstrated a statistically significant decrease in task aversiveness and an increase in task outcome value via ms-tDCS in the neuromodulation group (Task aversiveness: interaction effect, β = -0.12, SE = 0.04, DF = 46.7, p = .002; simple effect, NM-before$_{(AUC)}$: 1.13 ± 0.53, NM-after$_{(AUC)}$: 1.95 ± 0.85, *t*.ratio = 4.5, p < .001, Tukey correction; Outcome value: β = -6.8, SE = 1.74, DF = 46.2, p< .001; simple effect, NM-before: 35.86 ± 27.82, NM-after: 73.08 ± 23.33, *t*.ratio = 5.0, p < .001, Tukey correction; see Fig. 4B), but not in the sham control group (Task aversiveness: SC-before $_{(AUC)}$: 1.07 ± 0.51, SC-after $_{(AUC)}$: 1.28 ± 0.46, *t*.ratio = 1.3, p = .20, Tukey correction; Outcome value: SC-before: 34.00 ± 25.17, SC-after: 40.13 ± 28.94, *t*.ratio = 0.8, p = .41, Tukey correction; see Fig. 4D). In the neuromodulation (NM) group, task aversiveness steadily decreased with the cumulative number of stimulation sessions, while perceived task outcome value increased significantly (see Fig. 4E-F, p < .05, Mann-Kendall test). Thus, it provides causal evidence clarifying that neuromodulation to left DLPFC reduces task aversiveness and enhances task-outcome value meanwhile.

Increased task outcome value but not decreased task aversiveness predicts reduced procrastination

Given the dual neurocognitive pathways identified above—reduced task aversiveness and increased task-outcome value—we proposed that these changes, conceptually driven by enhanced self-control via ms-tDCS over left DLPFC, account for how neuromodulation reduces procrastination. To this end, we utilized a generalized linear model to regress decreased task aversiveness and increased task outcome value to changes in task-execution willingness. In this model, increased task outcome value (Δ $_{\text{Outcome value}}$) significantly predicted increased task-execution willingness (Δ $_{\text{task-execution willingness}}$) ($x^2$ = 15.95, p <.01, R^2 = .40; Δ $_{\text{Outcome value}}$:β= 0.61, S.E. = 0.12, p< .001, 95% CI: 0.37 - 0.86), whereas no significant effect was observed for predicting task-execution willingness through decreased task aversiveness (Δ $_{\text{task aversiveness}}$:$\beta$= 0.10, S.E. = 0.12, p= .41, 95% CI: -0.14 - 0.34). Likewise, for actual procrastination behavior in real-world settings, increased outcome value (Δ $_{\text{Outcome value}}$) was identified to be significantly predictive, whereas decreased task aversiveness showed null effects (see Tab. 2). Collectively, these findings provide causal evidence supporting notion that the outcome-value neurocognitive pathway accounts well for procrastination reduction, rather than a dual circuits incorporating task-aversiveness.

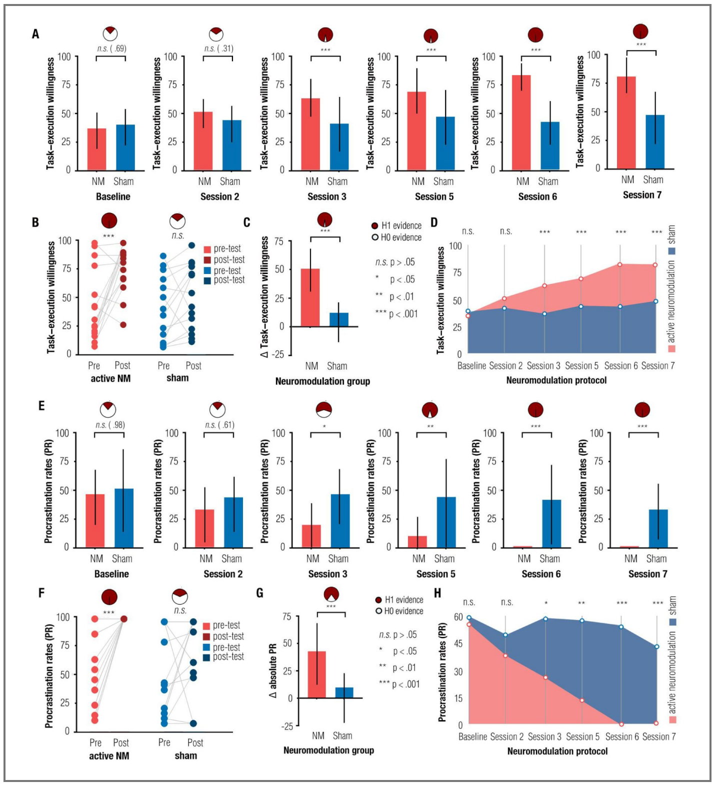


Figure 3. **Results of neuromodulation effects to task-execution willingness and procrastination rates (PR).**

A shows the effects of neuromodulation to increase task-execution willingness for both active group and sham control across sessions that included in formal analysis (session 0 (baseline), 2, 3, 5, 6, 7). B illustrates the effects of whole neuromodulation round to task-execution willingness for both group. C plots the changes of task-execution willingness for both group after neuromodulation. D provides a line chart to show the changes of task-execution willingness across each session that included in formal analysis. E shows the effects of neuromodulation to reduce PR for both active group and sham control across sessions that included in formal analysis. F illustrates the effects of whole neuromodulation round to PR for both group. G plots the absolute changes of PR for both group after neuromodulation. H provides a line chart to show the changes of PR across these sessions that included in formal analysis. Pie graph for each comparison represent the corresponding result of Bayesian factor inference, with brown piece for supporting H1 evidence and white piece for supporting H0 evidence. Each bar indicates mean value, and each line placed onto the bar reflects standard deviation (SD).

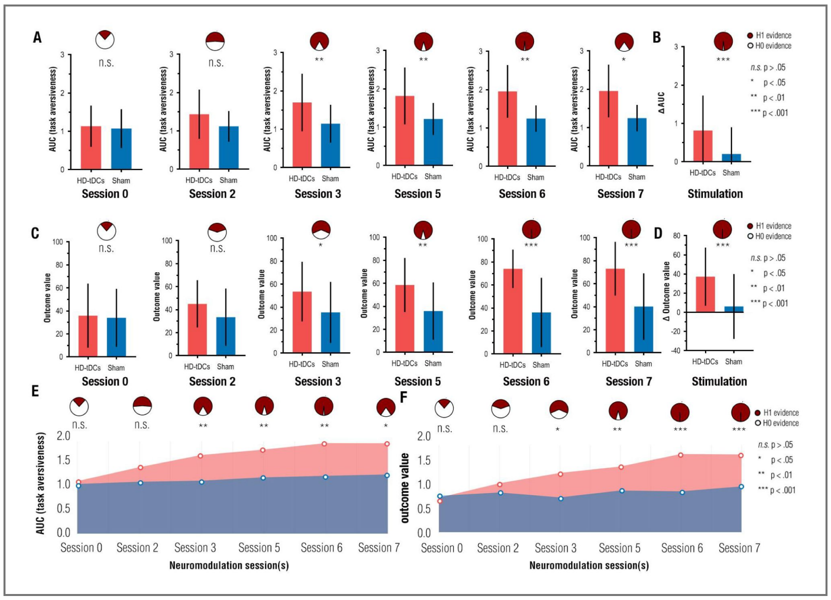


Figure 4. **Results of neuromodulation effects to task aversiveness and outcome value.**

A shows the effects of neuromodulation to increase AUC of task aversiveness for both active group and sham control across sessions that included in formal analysis (session 0 (baseline), 2, 3, 5, 6, 7). Higher AUC indicates lower task avsiveness as a given task is increasingly executed. B plots the changes of AUC of task aversiveness for both group after neuromodulation. C shows the effects of neuromodulation to increase outcome value for both active group and sham control across sessions that included in formal analysis. D plots the changes of outcome value for both group after neuromodulation. E provides a line chart to show the changes of AUC of task aversiveness across these sessions that included in formal analysis. F provides a line chart to show the changes of outcome value in the same manner. Pie graph for each comparison represent the corresponding result of Bayesian factor inference, with brown piece for supporting H1 evidence and white piece for supporting H0 evidence. Each bar indicates mean value, and each line placed onto the bar reflects standard deviation (SD).

Table 2. Summary for general linear model in predicting changes of task aversiveness and outcome value to actual procrastination.

S.E. means standard error. * p < .05.

	β	S.E	*P* value	Odd Ratio (OR)	adj R^2
Δ task aversiveness	0.62	0.42	0.13	1.85	.29
Δ outcome value	0.85*	0.42	0.04	2.34	

Increased task outcome value plays causal role to explain why ms-tDCS reduces procrastination

To clarify the causal neurocognitive mechanism of procrastination, the Quasi-Bayesian causal mediation analysis was undertaken by using White's heteroskedasticity-consistent estimator, with increased task outcome value as a mediated variable. Results demonstrated the significant causal mediated role of increased task outcome value in increasing the task-execution willingness (δ = 21.73, p < .01; ζ = 11.25, p = .07, ρ = 32.99, p < .01, simulation = 1,000; see Fig. 5A) and real-world procrastination (δ = 30.75, p < .01; ζ = 3.05, p = .52, ρ = 33.81, *p* < .01, simulation = 1,000; see Fig. 5B), as caused by ms-tDCS neuromodulation. To ensure the robustness and specificity of these findings, the sensitivity analysis was implemented by changing sampling parameters and outcome variables. By doing so, those findings were validated highly robust, as shown by replicated observations across bootstrapping sampling algorithms (see SI Results and Tab. S5-6). Moreover, the results of the control analysis further validated the specificity of these findings by showing a null causal mediated effect of this model to predict one's task aversiveness (see SI Results and Tab. S7). In summary, these findings demonstrated a mechanistic pathway underlying procrastination: the self-control that was conceptualized to be governed by left DLPFC mitigate procrastination by plausibly increasing task-outcome value.

Long-term effects of ms-tDCS

We have also attempted to conduct a follow-up investigation to test the long-term retention of ms-tDCS in reducing actual procrastination. Almost all the participants had undergone follow-up except one in the neuromodulation group after last neuromodulation for 6 months (N_{NM} = 22, N_{SC} = 23). Thus, the GLMM was constructed, with the PR before first neuromodulation vs. PR after last neuromodulation for 6 months as covariates of interest. Results showed the statistically significant group*time interaction effects (β = 16.5, SE = 9.9, *p* = .049). Simple-effect model demonstrated a decrease in actual procrastination rates in the active neuromodulation group after last stimulation for 6 months compared to baseline (β = -22.05, SE = 10.0, *p* = .038, Tukey correction; NM-before: 40.68 ± 37.96, NM-after$_{6\text{-months}}$: 18.63 ± 29.80), and revealed null effects in the SC group (β= 1.26, SE = 9.78, *p* = .99, Tukey correction; SC-before: 46.47 ± 40.75, SC-after$_{6\text{-months}}$: 47.73 ± 39.18) (see Fig. 6).. Furthermore, using a nonparametric x^2 test to compare differences in the number of procrastinated tasks, we still found a statistically significant reduction in procrastination frequency in NM group after neuromodulation for 6 months compared to baseline (x^2 = 3.30, *p* = .035, NM-before: 68.19% (15/22), NM-after$_{6\text{-months}}$: 40.91% (9/22)), while no significant changes were observed in the SC group (x^2 = 0.11, *p* = .74, SC-before: 69.56% (16/23), SC-after$_{6\text{-months}}$: 73.91% (17/23)). Therefore, beyond short-term effects, the benefits of ms-tDCS neuromodulation to reduce procrastination pose the long-term retention.

Discussion

In the current study, by performing anodal ms-tDCS neuromodulation on the left DLPFC, both procrastination willingness and actual procrastination behavior were significantly decreased in real life. Additionally, a 6-month follow-up investigation revealed the long-term retention of such effects. Furthermore, this neuromodulation was found to decrease task aversiveness and increase outcome values; notably, only increased task-outcome value could predict decreased

Figure 5. **Results of Quasi-Bayesian causal model for the medicated role of increased task outcome value in the association between neuromodulation and task-execution willingness (A) and actual procrastination rates (B).**

ADE = averaged direct effect, ACME = averaged causal mediated effect, CI = confident interval.

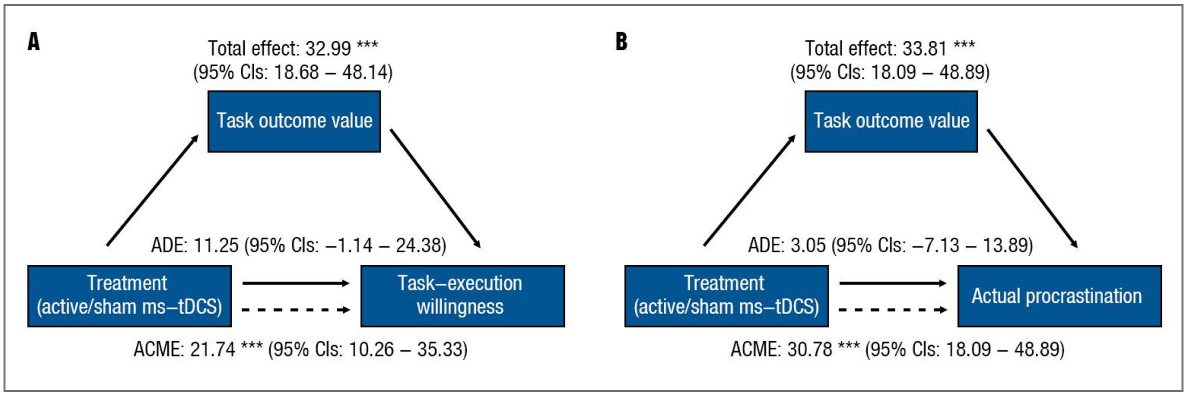
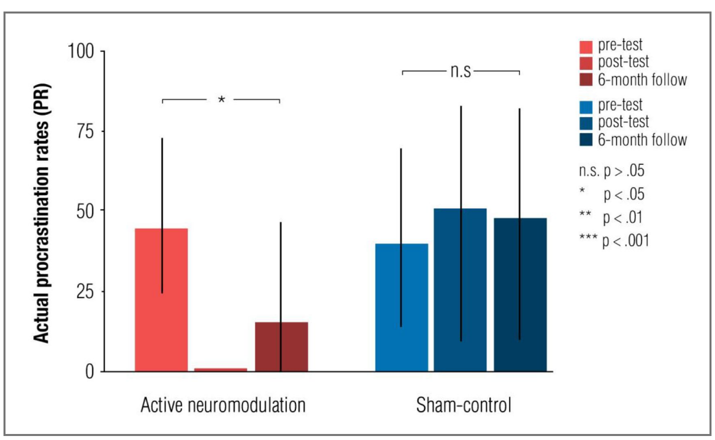


Figure 6. **Changes of actual procrastination rates among pre-test, post-test and 6-month follow-up for active neuromodulation group and sham-control group.**

Pre-test means to test the actual procrastination rates before first HD-tDCS neuromodulation. Post-test means to test the actual procrastination rates after last neuromodulation. The 6-month follow means to re-investigate the actual procrastination rates after last neuromodulation for 6 months.



procrastination. On balance, our findings clarified the neurocognitive mechanism of procrastination by showing that self-control could increase task-outcome value so as to reduce procrastination. In addition, this study provided an effective way to reduce actual procrastination by using ms-tDCS neuromodulation.

One major contribution this study has made is to disentangle the neurocognitive mechanism of procrastination by demonstrating that self-control could increase task-outcome value so as to reduce procrastination. Neurobiological substrates of procrastination have been investigated in recent years, and have demonstrated the crucial roles of the left DLPFC in predicting procrastination (Chen & Feng, 2022; Chen et al., 2021; Chen et al., 2022; Hu et al., 2018; Liu & Feng, 2017; Zhang et al., 2017; Zhang et al., 2016). Not only the brain functional anomalies of the left DLPFC but also the neuroanatomical disruptions of self-control brain network constituted by the left DLPFC were found to be linked with more procrastination behaviors (Chen & Feng, 2022; Zhang et al., 2016). Notwithstanding this, it still remains unclear to claim their causal brain-behavior relationship - that is - no known evidence existed to clarity whether changes of the left DLPFC lead to procrastination or vice versa. The current study demonstrated the causal role of the left DLPFC in procrastination by showing that the neuromodulation of the left DLPFC indeed manipulated procrastination, and thus provided straightforward and powerful evidence to fill this gap.

It has long been acknowledged that the left DLPFC is associated with many aspects of self-control communities, such as patience to wait long-term gratification for a delay, inhibition of impulsiveness, and control of game addiction (Cohen & Lieberman, 2010; Lin & Feng, 2024). Furthermore, the increased activation of the left DLPFC has been observed during the exertion of self-control which modulates value signals (Hare et al., 2009; Harris et al., 2013). Meanwhile, procrastination has been argued to be the consequence of self-control failures and self-regulation failure for a long time (Ariely & Wertenbroch, 2002; Rebetez et al., 2018; Rozental & Carlbring, 2014). Supporting this, both the brain morphological disruptions in the DLPFC and anomalies in the functional coupling of the DLPFC-based self-control network were interpreted as the phenotype of reduced self-control, making individuals more prone to procrastinate tasks, as reported in existing literature (Xu et al., 2021; Yang et al., 2021). Moreover, it was worth noting that the increased activation of the left DLPFC was found to be involved in outcome value evaluation through self-control regulation (Chen et al., 2018; Zha et al., 2019). There was more straightforward evidence to substantiate the role of manipulating the DLPFC in changing one's subjective value evaluation (Huang et al., 2017; Minati et al., 2012). On the other hand, the theoretical explanations and empirical evidence have increasingly converged into one line for claiming that the increased task outcome value would prompt more motivation to drive one to take action immediately and thus reduce procrastination (Zhang, Liu, et al., 2019). In this vein, this study advanced our understanding of the neurocognitive mechanism of procrastination by showing that the cortical excitability of the DLPFC produced by active neuromodulation could boost self-control to increase task outcome value so as to reduce procrastination behavior.

In addition, another contribution of the current study is to provide an effective way to reduce both procrastination willingness and actual procrastination in real-life tasks. As mentioned above, despite the fact that multifarious behavioral interventions and evidence have been massively studied for overcoming procrastination, they have shared a common aim - that is - reducing the intention-action gap (Miao et al., 2024; van Hooft et al., 2005). Eerde and Klingsieck (2018) put forward an insightful standpoint established by meta-analytic evidence: procrastination is characterized as an intention-action gap rather than an intention to postpone (van Eerde & Klingsieck, 2018). This notion has been partly supported by showing that cognitive behavior therapy (CBT) for goal-directed behaviors may outperform other interventions focusing on time management (Rozental et al., 2018). Moreover, the trans-theoretical model of procrastination has shown that the behavioral intervention may be effective in changing one's motivation to overcome procrastination but not in actual behaviors (Grunschel & Schopenhauer, 2015). Thus, the ms-tDCS neuromodulation the current study performed has a remarkable advantage in reducing procrastination - that is, the intention-action gap was attenuated so as to overcome procrastination behavior effectively. Furthermore, both 2-day-interval long-term effects and the 6-month long-term retention of the effects of ms-tDCS on reducing actual procrastination have been revealed as well. Thus far, the trends in adopting tDCS neuromodulation techniques in many aspects of behavioral therapies have emerged, but concern for a long-lasting effect of single session stimulation has continued (Brunoni et al., 2013; Brunoni et al., 2012). To tackle this concern well, instead of single-session tDCS, the current study adopted multiple-session stimulation to implement neuromodulation on the left DLPFC, which facilitates long-term effects (Au et al., 2017; Tedesco Triccas et al., 2016). Existing neurobiological theories and empirical evidence have demonstrated that multiple-session tDCS stimulation could boost cumulative effects of consolidation for activity-dependent LTP (long-term potentiation), which is crucial to neurobehavioral learning, and thus produce robust long-term after-effects (Agboada et al., 2020; Au et al., 2017). Intriguingly, the activity-dependent LTP process produced by multiple-session consolidation was found to contribute to long-term cortical plasticity, especially in the DLPFC (Jannati et al., 2023; Siebner & Rothwell, 2003). Thus, it led us to presume that the 6-month long-term retention of the ms-tDCS effect on reducing procrastination might be attributed to long-term neuroplastic changes in the DLPFC. On balance, this study provided an effective way to help procrastinators overcome actual procrastination in real-life.

Limitations

While the use of a multi-session design and the long-term assessment can be considered a strength of the present study, it also has several limitations. Even though various tDCS effects have been demonstrated so far, they also tend to be difficult to replicate and sensitive to not yet fully understood context conditions and interindividual differences, which also applies to transcranial magnetic stimulation (TMS) (Valle et al., 2009). To overcome this shortcoming, it will be necessary to establish an individually tailored tDCS protocol to improve the sensitivity of corresponding interventions (Chew et al., 2015). Thus, future research could further improve the effects of tDCS on reducing procrastination by adopting more individualized tDCS protocols. Another limitation is the lack of real-time functional neuroimaging measures to better monitor the impact of our intervention. In the absence of such measures, we had to rely on behavioral indicators to assess the success of the tDCS training. In addition to technical limitations, given the apparently limited size of the sample (total N = 46), it warrants caution in generalizing these findings elsewhere, and necessitates further validations in a large-scale cohort. Also, considering the lack of medical screening for psychiatric conditions (e.g., ADHD or depression) in this sample, it remains unclear whether these training effects are domain-specific for procrastination. Moreover, this study did not collect data for assessing participants' self-control at either baseline or post-neuromodulation, thereby limiting our ability to determine whether the effects on procrastination were uniquely attributable to neuromodulation-induced changes in self-control. In addition, despite instructing to report valid real-life tasks with high probabilities to procrastinate, we had not yet measured the task difficulty and consistency across sessions for each participant. Consequently, interpreting the effects of neuromodulation to mitigate procrastination as "unique contributions" should warrant cautions. Finally, given the absence of cathodal HD-tDCS stimulation as a contrast condition in causal inference, it warrants caution that the increased DLPFC excitability may not be the exclusively neural mechanism for procrastination.

Conclusions

In conclusion, this study potentially provides an effective way to reduce both procrastination willingness and actual procrastination behavior by using neuromodulation on the left DLPFC. Furthermore, such effects have been observed for 2-day-interval long-term after-effects, and were also found for 6-month long-term retention in part. More importantly, this study identified that the ms-tDCS neuromodulation could decrease task aversiveness and increase task outcome value, and further demonstrated that the increased task outcome value could predict decreased procrastination, a relationship conceptually driven by enhancing self-control. In this vein, the current study enriches our understanding of neurocognitive mechanism of procrastination by showing the prominent role of increased task outcome value in reducing procrastination. Also, it may provide an effective method for intervening in human procrastination.

Supplementary Information

SI Methods

Reconstructed preregistration statement

This study has been originally preregistered in the Open Science Framework (OSF, 10.17605/OSF.IO/Y3EDT) preregistration service on September, 2020. However, the creator's OSF account was suspended and further disabled due to an automated system flag, rendering the original HTML preregistration page inaccessible, including to the authors. To ensure the accessibility and transparency in full adherence with open science best practices, we have reconstructed the preregistration content herein, This reconstructed statement is not ***post hoc***, but reflects the exact hypotheses, sample size, and analysis plan as executed (Table. S1).

Randomised participants

To randomise participants into neuromodulation and sham-control group, the full randomised block design (FRBD) was conducted here. Furthermore, it could be beneficial from FRBD that the within-group variances can be minimized. In detail, the whole sample would be portioned into k blocks, which were manipulated for high homogeneity. For each block, the pairs of participants were then randomly designated to neuromodulation and sham-control group. Thus, adopting FRBD for randomised processes can reap huge fruits to keep within-group homogeneity for each group than do of that full randomised design (King & Eckersley, 2019). The randomised codes came from "*www.random.org*", which produced random labels by using atmospheric.

Estimation for statistical power

To determine adequate statistical power beforehand, we capitalized on the G*Power software to estimate the minimum sample size obtaining the medium effect size (α err prob = 0.05, 1-β err prob = 0.80, f = 0.25) by building a repeated measures, within-between, and interaction effect ANOVA model (Faul et al., 2007). In this vein, the medium effect size can be reached once total sample size n = 18, noncentrality λ = 15.75, critical F = 2.1945, numerator Df = 6, and denominator Df = 96. In addition, owing to the repeated measures for each participant, the 2-dimensional plot, so-called Power Contours estimation, was used to visualize and calculate the acceptable sample size by corresponding experimental design (Baker et al., 2020). Thus, according to the design this study made, the Power Contours estimation was done up front and indicated the total sample size of this study can attain the adequate statistical power (see Fig. S1). More detail for how to estimate and plot this map can be found elsewhere (Baker et al., 2020).

How to determine one's socioeconomic status (SES)

In line with Human Connectome Project (HCP) project proposed by National Institutes of Health (NIH), this study also acquired demographic information for each participant, including gender, age, nationality, educational level (years), family's economic status (poor, modest, middle and affluent class), family structure (FS), and status of birth (SB). In terms of criteria endorsed by the Food and Agriculture Organization (FAO) of the United Nation (UN) and the financial statement published by National Bureau of Statistics (NBS) of China in 2019 (*http://www.stats.gov.cn/tjsj/*), the economic status of the family was rated as poor, modest, middle and affluent class according to family incomes, with < ¥ 45 thousands per year for poor class, ¥ 45-65 thousands per year for modest class, ¥ 65-105 thousands per year for middle class, and ≥ ¥ 105 for affluent class.

To determine homogeneity between the HD-tDCS group and sham-controlled group, non- / parametric and Jeffreys-Zellner-Siow Bayesian examinations were adopted to identify significant differences between demographic variable.

Semi-structural interview questionnaire

To ensure the high ecological validity, we developed a semi-structural interview questionnaire to test whether participants were eligible for the current study. There were major four profiles to investigate them, including evaluation of how they perceived pain for procrastination, whether their social functions were disrupted by procrastination, whether their attitudes are to change procrastination and whether they accepted our protocol. The outlines of this questionnaire has been provided as below:

1. Please details your identity and investigation proposal; 2. Do you perceive you have procrastination symptoms, and how severe it is do you think; 3. Are you ever assumed you have “procrastination disorder”; 4. Do you feel pain due to procrastination and how it impacts your daily life; 5. What types of procrastination are do you think in yourself; 6. Do you think you would suffer from procrastination all the life; 7. Do you want to get rid of procrastination; 8. Have you try to stop procrastination; 9. Do you know neuromodulation technique, such as tDCS or TMS; 10. Do you feel panic or worrisome for medical technique, especially in electric medical technique; 11. Do you feel panic or worrisome for electric current; 12. Do you willing to receive electric medical technique for getting rid of procrastination despite limited skin pains.

High-definition neuronavigation system

To ensure the accuracy of targeting location (left DLPFC), this neuronavigation system was used to estimate the location from skull. This system reported the MNI coordinate of what we predetermined for the first, and would re-adjust automatically twice to self-verify the estimation accuracy. Subsequently, the brain labels for these coordinates were reported by using AAL atlas and Broadman atlas, respectively. Results indicated that the F3 node overlapped the left DLPFC with 94.33% probability, which was cross-checked automatically.

Temporal difference-to-difference model

In the current study, in addition to the estimation for the model including all the repeated measures, we still aimed to do a random-sham pre-post tests for clarifying whether this HD-tDCS by using multiple sessions protocol was effective. In this vein, the difference coefficient (Δ) was computed as difference between post-test after last session and pre-test before first session, one-by-one for participants. In this vein, the pre-post within-participant differences upon outcome variables can be estimated as the HD-tDCS training effect.

SI Results

Unexpected event effects

In the Session 1, a significant unexpected life event effect occurred by this fact that almost all the participants in both group do not procrastinate (Neuromodulation group, NM, Procrastination rate (PR): 4.34 % (1/23), Sham control group, SC, PR: 8.69 % (2/23)). In the follow-up investigation, all the participants reported a strong expectation for this neuromodulation as they received such treatment for the first time. In the Session 4, the PR was observed to be increased dramatically in both groups (Neuromodulation group, NM, Procrastination rate (PR): 86.95 % (20/23), Sham control group, SC, PR: 86.95 % (20/23)). In the follow-up investigation, all the participants reported that taking action immediately to complete task was hampered significantly due to weekend effect (Ryan et al., 2010, Stone et al., 2012). In this vein, data for these sessions were excluded in the analysis. Here, the follow-up investigation required participants to report whether their performance for completing task was influenced by additional effects. If in this case, they should report what unexpected events occur here. The x^2 test was used to examine whether those reported unexpected events confounding task execution posed significantly differences between groups across all the sessions (see Table. S2).

Robustness check for interaction effects

To examine whether Group*Neuromodulation_Session interactions are statistically robust, we reanalyzed interaction effects by removing data from session #6, #7 and both, respectively in which those sessions showed extraordinary high effectiveness of neuromodulation (i.e., outliers). The findings derived from those nested models showed that all the interaction effects are all retained, indicating a high statistical robustness (Table. S3-4).

Results of linear probability panel model

Given the panel data pattern (7 longitudinal sessions × task-execution willingness), this study has drawn upon the linear probability panel model (PLM) fitting the task aversiveness and outcome value to task-execution willingness. Specifically, the Fisher's Augmented Dickey-Fuller Test (ADF) tests were performed to examine whether these data are suitable for this model. Results indicated the stationary properties for all the variables (task aversiveness, DF = -5.78, p < .05; outcome value, DF = -5.83, p < .05; task-execution willingness, DF = -5.83, p < .01). Further, the findings derived from Breusch-Godfrey/Wooldridge test maintained the decision to reject the stability of pool model (x^2 = 22.75, p < .0001). Also, the Hausman test was done for determining what types of models would be accepted. Results indicated that the random effect model is unstability (x^2 = 12.92, p < .0015). Thus, the fixed effect model controlling both time and individual variants was adopted as final one.

Results of GLMM adjusted for baseline

To minimize false-positive risks, rather to take time and group as predictors meantime, we reanalyzed these data by remodeling post-neuromodulation procrastination as dependent and remodeling pre-neuromodulation procrastination, group and other covariates as predictors. Results showed the significantly predictive of pre-neuromodulation procrastination willingness (β = 24.48, SE = 6.24, p = .0018) and procrastination rate (PR, β = 30.66, SE = 8.48, p = .0015) to post-neuromodulation ones. Moreover, for those covariates of interests on cognitive mechanisms, these findings are validated as well, showing statistically significant predictions from pre-neuromodulation cognitive processes to post-neuromodulation ones (task aversiveness, β = 0.58, SE = 0.23, p= .018; outcome value, β= 22.86, SE = 5.11, p= .0005). This replicated effect has been observed in predicting post-neuromodulation PR by pre-neuromodulation one for 6 month (β = 34.79, SE = 11.1, p = .005). Taken together, using stringent statistical constrain to adjust baseline, we revealed the same findings compared to traditional GLMM.

Results of sensitivity analysis

To examine the robustness and specificity of this causal medication model, we conducted several sensitive analyses. Thus, the we attempted to re-do this mediation model by replacing the sampling method from bootstrap-based bias-corrected and accelerated (BCa) intervals to "bca" sampling at 5000 simulations. Results demonstrated the robustness of this model by showing same findings (see Table. S5-6).

Further, we inputted the age and gender as outcome variables into this model for testing whether this causal mediation model is specific to predict decreased procrastination. As hypothesized, no significant effects were found to predict task aversiveness by using this model, and thus supported the specificity of these findings (see Table. S7).

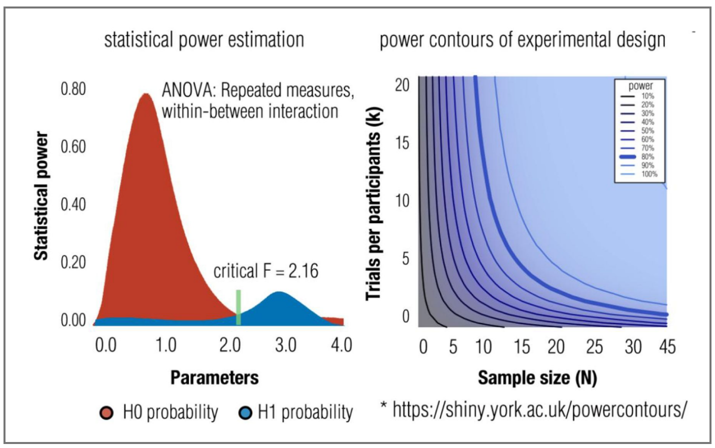


Figure S1. **Statistical power estimation by using ANOVA model and power contours according to experimental design**

Table S1. Reconstructed preregistration statement table.

Question	Hypothesis	Sampling plan (e.g. power analysis)	Analysis Plan	Interpretation given to different outcomes
Whether the multi-session HD-tDCS over the left DLPFC could reduce real-world procrastination?	This HD-tDCS neuromodulation could increasingly mitigate real-world procrastination	We capitalize on the G*Power software to estimate the minimum sample size obtaining the medium effect size (α err prob = 0.05, 1-β err prob = 0.80, f = 0.25) by building a repeated measures, within-between , and interaction effect ANOVA model (Faul et al., 2007). In this vein, the medium effect size can be reached once total sample size n = 18, noncentrality A = 15.75, critical F = 2.1945, numerator Df = 6, and denominator Df = 96. In addition, owing to the repeated measures for each participant, the 2-dimensional plot, so-called Power Contours estimation, would be used to visualize and calculate the acceptable sample size by corresponding experimental design (Baker et al., 2020)	(a) The generalized mixed-effect linear model (GLMM) would be constructed using 2 (active vs. sham) × 2 (before first neuromodulation vs. after last neuromodulation) full factorial design for procrastination willingness (i.e., self-reported scores) and actual procrastination rate (1 - self-reported task completion rate); (b) Markov Chain Monte Carlo Generalised linear mixed effects model (MCMCglmm) would be built to re-estimate results that probed above for validation; (c) Temporal difference-to-difference model would be used to obtain the difference coefficient (Δ) individually, and independent t-tests with Jeffreys-Zellner-Siow Bayesian examinations for between-group differences upon procrastination willingness (i.e., self-reported scores) and actual procrastination rate (1 - self-reported task completion rate) would be conducted; (d) Between-group comparison for the counts of reporting task procrastination across participants are conducted by x^2 test with ϕ correction or Fisher exact test would be carried out; (e) The joint model of longitudinal and survival data (JM-LAD), in conjunction of machine learning algorithm, was adopted to capture multi-session effects individually	-

Whether the multi-session HD-tDCS over the left DLPFC could reduce task aversiveness and increase outcome value?	Multi-session HD-tDCS could decrease task aversiveness and increase outcome values meanwhile	See above	The generalized mixed-effect linear model (GLMM) would be constructed using 2 (active vs. sham) × 2 (before first neuromodulation vs. after last neuromodulation) full factorial design for task aversiveness (i.e., AUC of five task time points) and outcome value (i.e., AUC of five task time points)	-
Why multi-session HD-tDCS could ameliorate procrastination willingness and real-world procrastination behavior?	(a) Multi-sessio n HD-tDCS could increase procrastination willingness and decrease real-world procrastination rate by undermining task aversiveness; (b) Multi-sessio n HD-tDCS could increase procrastination willingness and decrease real-world procrastination rate by increasing outcome value;	No suitable method to make this sample size estimation	(a) Generalized linear model to correlate $\Delta_{\text{Task aversiveness}}$ and $\Delta_{\text{Outcome value}}$ to $\Delta_{\text{Procrastination willingness}}$; (b) Generalized linear model to correlate $\Delta_{\text{Task aversiveness}}$ and $\Delta_{\text{Outcome value}}$ to $\Delta_{\text{Real-world Procrastination}}$; (c)Quasi-Bayesian causal mediation analysis to model the task aversiveness as the mediator for interpreting association of HD-tDCS intervention to changes of procrastination willingness and real-world procrastination; (d) Quasi-Bayesian causal mediation analysis to model the task aversiveness as the mediator for interpreting association of HD-tDCS intervention to changes of procrastination willingness and real-world procrastination; (e) Quasi-Bayesian causal mediation analysis to model the outcome value as the mediator for interpreting association of HD-tDCS intervention to changes of procrastination willingness and real-world procrastination;	-

Does this multi-session HD-tDCS neuromodulatio n has lasting-effect?	This effect can be tested in the 6-month follow-up		(a) The repeated-measure ANOVA model would be built to test real-world procrastination rates across three time points (Pre-, Post-, and 6-month follow-up test); (b) Jeffreys-Zellner-Sio w Bayesian factor model would be used to validate above results derived from repeated-measure ANOVA	-

Table S2. The number of reporting unexpected event effects in both group across all the session.

Here, we conducted a post-neuromodulation investigation to require participants to report whether their performance for completing task was influenced by additional impacts outside normal conditions, such as “get a flu” , “get a fever” , “ mandatory assignment for other tasks” and “unexpected emergency events”. If in this case, they should report what unexpected events occur to uncontrollably disrupt task execution. In the S1, all the 44 participants reported expected effects from the neuromodulation. In the S1, one participant reported to be in flu. In the S3, both participants in NM group reported a mandatory meeting assignment, whist one participant in the SC reported a bicycle accident and additional two reported mandatory meeting assignment. In the S4, all the 39 participants reported that their task performances are fully disrupted by the weekends. S5-7 reported the similar additional AE mentioned previously.

	S0	S1	S2	S3	S4	S5	S6	S7
NM	0/23	21/23	1/23	2/23	20/23	0/23	3/23	5/23
SC	0/23	23/23	0/23	3/23	19/23	1/23	0/23	3/23
x^2	-	.023	-	.200	.026	-	-	.500

Table S3. GLMM to robustness check with outcome as subjective procrastination willingness

Model	β (group*treatment_day)	Std. Error (SE)	*T* value	*P* value
Full model	-7.78	1.79	-4.35	< .001
Removing Session #7	-9.78	2.25	-4.34	< .001
Removing Session #6	-7.27	1.83	-3.98	< .001
Removing Session #6 and #7 both	-10.02	3.38	-2.96	.005

Table S4. GLMM to robustness check with outcome as real-world procrastination rates

Model	β (group*treatment_day)	Std. Error (SE)	*T* value	*P* value
Full model	-7.38	2.45	-3.02	.004
Removing Session #7	-10.34	3.16	-3.27	.002
Removing Session #6	-6.55	2.53	-2.59	.011
Removing Session #6 and #7 both	-11.07	4.36	-2.54	.013

Table S5. **Summary for causal mediation model in predicting task-execution willingness by using treatment (active ms-tDCS v.s. sham) from medicated effect of increased task outcome.**

	Estimate	95% Lower	95% Upper	P value
ACME	21.95 ***	10.67	34.90	.0001
ADE	11.14	-2.20	25.10	.10
Total Effect	33.10***	19.00	47.80	.0001

Table S6. **Summary for causal mediation model in predicting actual procrastination by using treatment (active ms-tDCS v.s. sham) from medicated effect of increased task outcome.**

	Estimate	95% Lower	95% Upper	P value
ACME	30.91 **	11.93	49.63	.002
ADE	2.77	-7.12	13.38	.61
Total Effect	33.68**	18.10	49.74	.002

Table S7. **Summary for causal mediation model in predicting task aversiveness by using treatment (active ms-tDCS v.s. sham) from medicated effect of increased task outcome.**

	Estimate	95% Lower	95% Upper	P value
ACME	0	0.00	0.00	1.000
ADE	25.09 **	8.29	42.00	0.0036
Total Effect	25.09 **	8.29	42.00	0.0036

Data availability

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study, and the study follows JARS (Appelbaum, et al., 2018). Data, analysis code, and research materials are available at Science Data Bank (ScienceDB, *https://doi.org/10.57760/sciencedb.35140*). Data were analyzed using R, version 4.4.1 (R Core Team, 2020) and the package ggplot, version 3.5.2, as well as MATLAB (2021, MathWork Inc.) and GraphPad Prisma.

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Author ORCID iDs

Zhiyi Chen: https://orcid.org/0000-0003-1744-4647
Chenyan Zhang: https://orcid.org/0000-0002-2945-6584
Tingyong Feng: https://orcid.org/0000-0001-9278-6474

Author notes

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Peer reviews

Reviewer #1 (Public review):

Summary:

The authors report the results of a tDCS brain stimulation study (verum vs sham stimulation of left DLPFC; between-subjects) in 46 participants, using an intense stimulation protocol over 2 weeks, combined with an experience-sampling approach, plus follow-up measures after 6 months.

Strengths:

The authors are studying a relevant and interesting research question using an intriguing design, following participants quite intensely over time and even at a follow-up time point. The use of an experience-sampling approach is another strength of the work.

Comments on revisions:

Overall, I think the authors made many improvements to their manuscript. There are, however, still a number of concerns that first need to be addressed, since it is still not currently possible to fully evaluate the analyses, results, and conclusions presented in the paper. I list these points below:

(1) The authors still use causal language where they must not use causal language. This is true for many places in the manuscript; I am highlighting here just a few places, but the authors nevertheless have to go carefully through the whole manuscript to change these instances.

Some examples:

(a) In response to my comment (1) in the previous round, where the authors adjusted their text, the authors still use causal language in their last sentence "... procrastination behavior has been observed to *impair* general health..." Unless the cited study truly allowed causal conclusions, the causal language should be removed here as well.

(b) The authors still make (causal) claims about the involvement of self-control in their observed results. To reiterate from the previous round of revisions: The authors cannot make any strong claims about the role of self-control processes because they do not directly measure self-control nor do they directly manipulate self-control or have a design that would rule out alternative mechanisms other than self-control. Therefore, their claims about self-control have to be toned down. It is laudable that the authors have added a statement towards the end of their discussion about not being able to make strong conclusions about the role of self-control. But the authors need to use similar careful wording not just at the end of the discussion but throughout the manuscript.

(i) In the abstract, the authors use the formulation "...conceptualized roles of self-control on procrastination..." -- this wording is still too strong, suggesting that you actually studied self-control.

(ii) In the introduction (page 4, lines162-169), the way the authors formulate these sentences suggests that they directly measured self-control. Again, the authors need to make it explicit that they are not directly measuring self-control but its hypothesized down-stream consequences on valuations/behavior.

(iii) In the discussion, for example, on page 11, lines 555 and following, the authors write:

"One major contribution this study has made is to disentangle the neurocognitive mechanism of procrastination by demonstrating that self-control could increase task-outcome value so as to reduce procrastination."

Again, please be aware that you are NOT demonstrating that self-control does anything, since you only measure procrastination rates, outcome values, and task aversiveness. It is possible that mechanisms other than self-control might be relevant for this. Perhaps neuromodulation directly increases outcome values, without involvement of self-control processes. You simply cannot know that and therefore you cannot make those claims in the form that you are making them. You can write that the observed results are consistent with the idea that neuromodulation might have had an effect on self-control and this in turn might have affected outcome values. But you also need to make it explicit that, to substantiate these claims, you would need more direct evidence that indeed self-control was involved. These more careful formulations would not at all reduce the value of your work, but indeed they would rather demonstrate your carefulness in interpreting the results you obtained.

(2) I am still puzzled by the power analysis. In the text, you write that a sample size of 18 participants (i.e., 9 per group) would be sufficient to achieve 80% power. I still feel this seems far too optimistic and hard to believe, but that is not my point here. While in the text, you write that you need 18 participants, the G*power output seems to suggest a sample size of 34, not 18. Why this contradiction? Or is it not contradictory? If it is not, then please explain it more fully.

(3) I have several comments about the mixed-effects analysis.

First of all, I want to thank the authors for adding more details, things have become much clearer now. However, I still have a few questions and comments related to these analyses:

(a) The variable Emotions was within-subjects, as far as I understood. Accordingly, Emotions should most likely be modelled with random slopes varying over participants (in addition to being modelled as a fixed effect).

(b) The analyses still cannot fully be evaluated as I cannot access the scripts and data. The authors mention that the scripts and data should be available via a link they provide (*https://doi.org/10.57760/sciencedb.35140*). However, when I try to access these materials via this link, no page opens; it seems the link is dead?

(c) What are the results and conclusions if you do not include the covariates of no interest? I.e., please re-run your main models without age, gender, SES, Emotions.

(d) The authors mention that they use GLMMs, which would suggest *generalized* mixed-effects models, but they do not describe what family/distribution they used. Since they mention lmerTest and seem to report F-tests, my guess is that they used Gaussian models. However, both their DVs (procrastination rates and their ratings) are bounded variables and at least procrastination rates hit the lower boundary. That can mean that their analyses suffer from inflated Type 1 and/or Type 2 rates. Therefore, please repeat the analyses with an appropriate generalized mixed-effects model (perhaps a beta regression type of model?).

(e) When reporting the results of the mixed-effects models, the authors report the regression coefficient, standard error, DFs and p value, but not the actual test statistic. Please add the information about the test statistic and report all degrees of freedom (in case of F tests that would be the degrees of freedom of the test and the residual degrees of freedom).

(f) Thank you for adding the analysis where you remove the last two sessions. But currently you present them in the manuscript without explaining/motivating why you do this. Please add this motivation, as otherwise it will be puzzling for the reader why you conduct these analyses.

(4) Mediation analysis

In your manuscript, you present some mediation analyses. Please be aware that such mediation analyses cannot establish causality and they suffer from extremely high Type 1 error rates (see, e.g., *https://datacolada.org/103*).

My suggestion would be to completely remove all mediation analyses. However, if you want to keep them, then you need to be extremely careful in how you present the results. You need to explicitly mention that you cannot derive any causal conclusions from them and that simulation studies have shown that such mediation analyses suffer from extremely high Type 1 errors.

As an example (but the mediation results are mentioned in several places, for example, also in the abstract):

On page 10, lines 501-503: What you can causally conclude is that neuromodulation affects your measured variables (outcome values, procrastination rates, task aversiveness), but you cannot conclude that the effect of neuromodulation on procrastination rates causally operates via outcome values. Thus, please adjust the formulation accordingly. The same applies to the mediation section that follows right afterwards (page 10, lines 505-522).

(5) In the introduction, the authors introduce several theoretical procrastination frameworks (TMT, mood repair, TDM). Do the results of the current paper help to decide which framework might be the most appropriate, at least for the authors data set? It might be of interest to address this explicitly.

(6) The language is sometimes hard to understand and seems in quite some places grammatically incorrect. Thus, I think the paper would profit very much from thorough English proofreading.

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Reviewer #2 (Public review):

Summary:

Chen and colleagues conducted a cross-sectional longitudinal study, administering high-definition transcranial direct stimulation (HD-tDCS) targeting the left DLPFC to examine the effect of HD-tDCS on real-world procrastination behavior. They find that seven sessions of active neuromodulation to the left DLPFC elicited greater modulation of procrastination measures (e.g., task-execution willingness, procrastination rates, task aversiveness, outcome value) relative to sham. They show that HD-tDCS reduces task aversiveness and increases task-execution willingness on real-world tasks as quantified by intensive experience sampling methods, providing causal evidence for the role of DLPFC in modulating contextual features to delaying or completing one's goals.

Strengths:

- This is a well-designed protocol with rigorous administration of high-definition transcranial direct current stimulation across multiple sessions. The intensive experience sampling approach which probes and assesses self-relevant task goals is innovative and aims to address an important question regarding the specific role of DLPFC in modulating specific features of chronic procrastination behavior (e.g., task-execution willingness, task aversiveness).
- The quantification of task aversiveness through AUC metrics is a clever approach to account for the temporal dynamics of task aversiveness, which is notoriously difficult to

quantify.

Weaknesses:

- While the findings that neurostimulation reduces procrastination behavior is compelling, there remain several alternative interpretations for these effects. For example, it could be that the task-execution willingness isn't increased per se, but rather that the goal completion becomes more valuable as participants learn from feedback or become more aware of their successful attainment of or failure to complete task goals. It is unclear whether the effects could be driven by improved working memory or attention to the reported tasks (and this limitation is addressed by the authors). In short, it is also difficult to examine the temporal dynamics of how these goals are selected across time.

- It is unclear whether the current evidence support long-retention of this neurostimulation intervention. The study includes one 6-month timepoint after the study to examine the long-term retention of the neural stimulation effect. Future studies that evaluate the long-term effects across multiple time points would strengthen the evidence for the robustness of this intervention.

https://doi.org/10.7554/eLife.108241.2.sa1

Author response:

The following is the authors' response to the original reviews.

> ***Public Reviews:***
>
> ***Reviewer #1 (Public review):***
>
> *Summary:*
>
> *The authors report the results of a tDCS brain stimulation study (verum vs sham stimulation of left DLPFC; between-subjects) in 46 participants, using an intense stimulation protocol over 2 weeks, combined with an experience-sampling approach, plus follow-up measures after 6 months.*
>
> *Strengths:*
>
> *The authors are studying a relevant and interesting research question using an intriguing design, following participants quite intensely over time and even at a follow-up time point. The use of an experience-sampling approach is another strength of the work.*
>
> *Weaknesses:*
>
> *There are quite a few weaknesses, some related to the actual study and some more strongly related to the reporting about the study in the manuscript. The concerns are listed roughly in the order in which they appear in the manuscript.*

We truly appreciate your dedicating time and efforts to review our manuscript. Yes, we do perceive that those weaknesses you raised all make sense. We agree with you on almost all the suggestions that you detailed below, particularly in clarifying statistics and sample size determination. Please see specific responses below.

> *Major Comments*
>
> *(1) In the introduction, the authors present procrastination nearly as if it were the most relevant and problematic issue there is in psychology. Surely, procrastination is a*

> *relevant and study-worthy topic, but that is also true if it is presented in more modest (and appropriate) terms. The manuscript mentions that procrastination is a main cause of psychopathology and bodily disease. These claims could possibly be described as 'sensationalized'. Also, the studies to support these claims seem to report associations, not causal mechanisms, as is implied in the manuscript.*

Thank you for this very practical suggestion. We agree that the current statements to underline the importance of procrastination are somewhat overreaching. Upon revision, we have overall toned down such claims by explicitly stating them as “associative evidence”, and rewritten a portion of terms in a more modest and balanced style. Please see specific revisions in the main text below:

Introduction Section (Page 5, Line 64-81)

“Procrastination is increasingly becoming a prevalent behavioral problem around the world, which reflects the irrational voluntary postponement of scheduled tasks albeit being worse off for such delays (Blake, 2019; Steel, 2007). In the epidemiological investigations, more than 15% of adults were identified as having chronic procrastination problems, and the situation for students was worse as 70-80% of undergraduates engaged in procrastination (American College Health Association, 2022; Ferrari et al., 2005). Moreover, the behavioral genetic evidence indicates a certain heritability of procrastination in human beings as well (Gustavson et al., 2017; Gustavson et al., 2014, 2015). In addition to its prevalence, the undesirable associations between procrastination behavior and health also warrant cautions. There is cumulative evidence to show the close associations between procrastination behavior and working performance, financial status, interpersonal relationships, and subjective well-being (Ferrari, 1994; Pychyl & Sirois, 2016; Steel et al., 2021). Further, as the prospective cohort studies indicated, many mental health problems emerge alongside procrastination, particularly in sleep problems, depression, and anxiety (Hairston & Shpitalni, 2016; Johansson et al., 2023). Even worse, chronic procrastination behavior has been observed to impair general health, as manifested by the intimate associations with close system disruption, gastrointestinal disturbance, as well as a high risk of hypertension and cardiovascular disease (Sirois, 2015; Sirois, 2016). ... ”

> *(2) It is laudable that the study was pre-registered; however, the cited OSF repository cannot be accessed and therefore, the OSF materials cannot be used to (a) check the preregistration or to (b) fill in the gaps and uncertainties about the exact analyses the authors conducted (this is important because the description of the analyses is insufficiently detailed and it is often unclear how they analyzed the data).*

We are sorry to encounter a serious technical barrier making our preregistration invisible and inaccessible. The OSF has disabled my OSF account, as it claimed to detect “suspicious user’s activities” in my account (please see the screenshot below). This results in no access to all materials already deposited in this OSF account, including this preregistration. We have contacted the OSF team, but received no valid technical solution to recover this preregistered report. We reckon that this may be triggered by my affiliation change to the Third Military Medical University of the People’s Liberation Army (PLA).

To address this unexpected circumstance and to ensure transparency, we have explicitly reported this case in the main text, and added the “Reconstructed Preregistration Statement” into the Supplemental Materials (SM). Also, as it has been out of best practices in preregistration, in addition to transparently reporting this case, we have removed this statement regarding preregistration elsewhere throughout the whole revised manuscript. Furthermore, we fully understand the gaps of comprehending the statistics of this study, resulting from inadequate methodological details in the reporting. Therefore, we have clearly reported extensive details in the Methods section to clarify how to conduct those analyses, favoring the smooth evaluations of our conclusions. Please see what we have added in the lines below (Comments #4-9).

Methods Section (Page 5, Line 186-191)

"This study fully adhered to CONSORT reporting guidelines, and was originally preregistered in the OSF repository (10.17605/OSF.IO/Y3EDT). However, due to the technical constraint related to OSF account service (see SM), this OSF page is no longer accessible. For transparency and best practices of open science, based on the original protocol documentations, a preregistration statement has been reconstructed to clarify aprior hypotheses, sample size determinations, and analysis plans for this study (Table S1)."

> *(3) Related to the previous point: I find it impossible to check the analyses with respect to their appropriateness because too little detail and/or explanation is given. Therefore, I find it impossible to evaluate whether the conclusions are valid and warranted.*

Again, we apologize for confusing you because of inadequate statistical and methodological details. As you may know, this manuscript has ever been reviewed by Nature Human Behaviour, which editorially constrained the paper length. Thus, a substantial number of details had to be omitted or removed. As you kindly suggested, we have diligently added extensive descriptions to clarify how we carried out statistical analyses in the present study. Please see specific instances underneath.

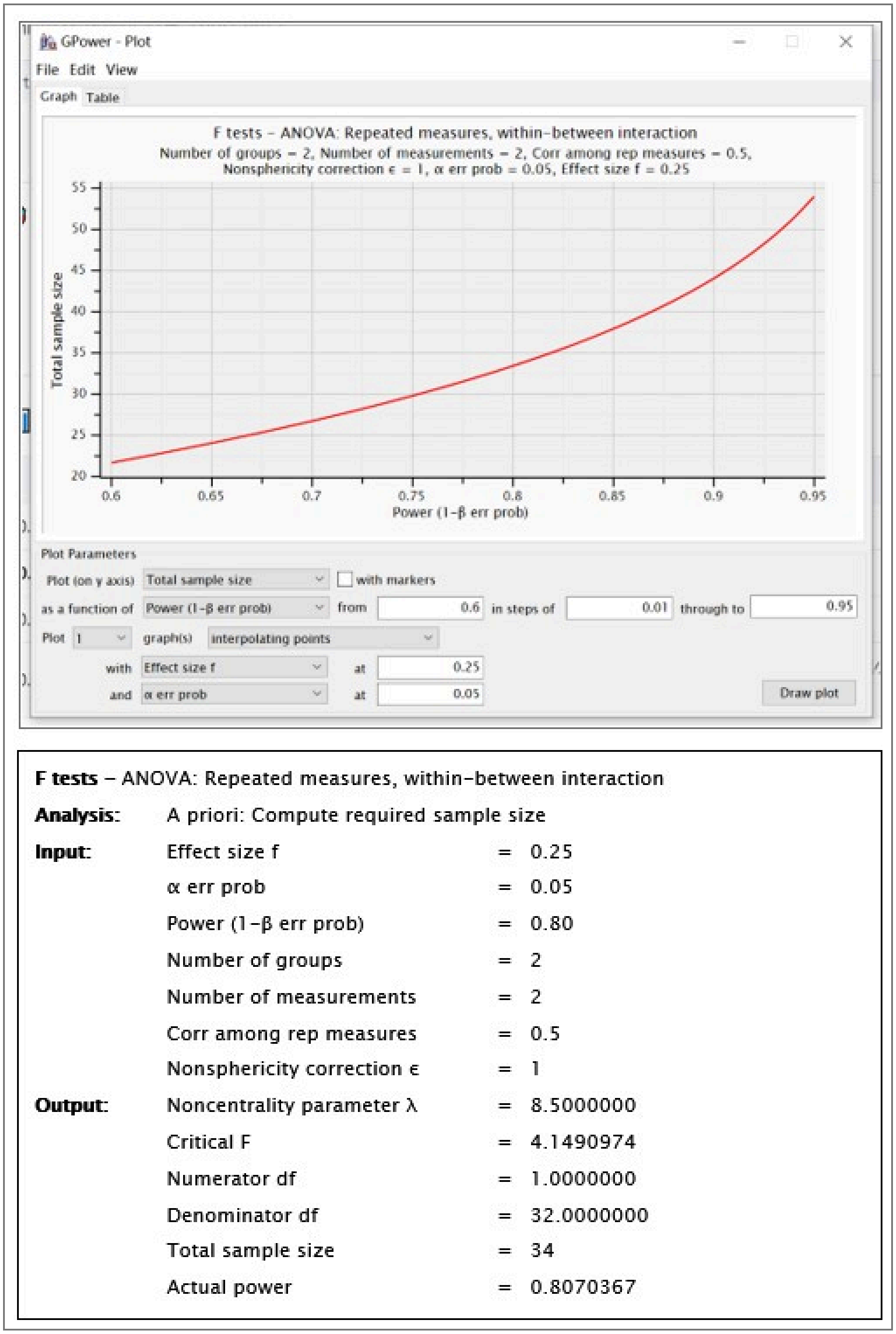
> *(4) Why is a medium effect size chosen for the a priori power analysis? Is it reasonable to assume a medium effect size? This should be discussed/motivated. Related: 18 participants for a medium effect size in a between-subjects design strikes me as implausibly low; even for a within-subjects design, it would appear low (but perhaps I am just not fully understanding the details of the power analysis).*

Thank you for raising this crucial question. We have determined this a priori effect size based on the existing work we published previously (Xu et al., 2023, J Exp Psychol Gen;152(4):1122-1133). In our pilot study (Xu et al., 2023), we identified a significant interaction effect between the single-session tDCS stimulation (active vs sham) and time (pre-test vs post-test) (t = 2.38, p = .02, n = 27; 95% CI [0.14, 1.49]) for changing procrastination willingness in the laboratory settings, indicating a medium effect size. Therefore, this pilot study provides supportive evidence to determine this effect size a priori. To clarify, we have explicitly justified the selection of this effect size in the Methods section.

Methods Section (Page 5, Line 206-215)

"A full randomized block design was used to assign participants to both groups (active neuromodulation group, NM; sham-control group, SC) (see Fig. 2C). As the pilot study probing into the effect of single-session tDCS stimulation to change procrastination willingness indicated (t = 2.38, p = .02, 95% CI [0.14, 1.49]; Xu et al., 2023), statistical power was predetermined by G*Power at a relatively medium effect size (1-β err prob = 0.80, f = 0.25), yielding the total sample size at 18 to reach acceptable power (see SM Methods and Fig. S1)...."

We fully understand that this sample size to reach a medium effect size is seemingly low, and that the18 participants for each group are apparently limited in any case. Upon double-checking these power analyses, we confirmed that this sample size requirement is indeed correct. Please see the G*Power outputs in Author response image 1.



Author response image 1.

Despite the absence of algorithmic errors in the power analysis here, we are aware that this limited sample size may hamper statistical robustness. To tackle this weakness, we have clearly warranted such cautions in the Limitation section:

Limitations Section (Page 12, Line 637-640)

"... In addition to technical limitations, given the apparently limited size of the sample (total *N* = 46), it warrants caution in generalizing these findings elsewhere, and necessitates further validations in a large-scale cohort."

> *(5) It remains somewhat ambiguous whether the sham group had the same number of stimulation sessions as the verum stimulation group; please clarify: Did both groups come in the same number of times into the lab? I.e., were all procedures identical except whether the stimulation was verum or sham?*

Yes, we fully followed the CONSORT pipeline to carry out this double-blind trial, and thus confirmed that all the participants in both groups had the same number of stimulation sessions in our lab. That is to say, except for the stimulation type (verum vs sham), all the procedures, equipment and even the room were identical for all the participants. For clarification, we have clearly stated this in the main text:

Results Section (Page 9, Line 419-423)

"In both groups, almost all participants (93.2%, 41/44) reported perceiving acceptable pain stemming from current stimulation, and believed they were receiving treatment (91.30% (21/23) for active neuromodulation group (NM), 86.95% (20/23) for sham control group (SC), x^2 = 0.224, p = .636). All the participants were engaged in the identical experimental procedures excepting to stimulation's type (active vs sham). ..."

> *(6) The TDM analysis and hyperbolic discounting approach were unclear to me; this needs to be described in more detail, otherwise it cannot be evaluated.*

We apologize for the inadequate details, which hindered a precise understanding of the TDM and the hyperbolic discounting model. The Temporal Decision Model (TDM) was originally proposed by our team (Xu et al., 2023; Zhang et al., 2019, 2020, 2021), which theoretically conceptualizes procrastination as the failure of trade-off between task outcome value (i.e., motivation to take actions now for pursuing task reward) and task aversiveness (i.e., motivations to take away from playing actions now for avoiding negative experiences). Once task aversiveness overrides the pursuit of task outcome values, the procrastination emerges. One overarching hypothesis in this theoretical model is that the task aversiveness is hyperbolically discounted when approaching the deadline: it would be discounted sharply when far from the deadline but discounted slowly when nearing the deadline (Zhang et al., 2019). Considering the nonlinear dynamics inherent in this hyperbolic discounting, we therefore employed a log-spaced temporal sampling scheme (Myerson et al., 2001) to strengthen curve-fitting performance (please see the schematic diagram (https://uen.pressbooks.pub/behavioraleconomics/chapter/the-reality-of-homo-sapiens, where each point indicates a sampling time)):

Specifically, based on the log-spaced temporal sampling rule, five time points were first selected to fulfill the statistical prerequisites for hyperbolic model fitting, with increasing sampling density toward the deadline (e.g., for a task due at 20:00: sampling occurred at 10:00, 16:00, 18:00, 19:30, 20:00). At each time point, participants reported task aversiveness (A) on a 0–100 Visual Analog Scale (VAS). Then, task aversiveness discounting was calculated as 1- (A_t / $A_{earliest}$), where $t_{earliest}$ was the earliest sampling point (e.g., 10:00), serving as the reference for immediate execution. Subsequently, using the GraphPad Prisma software (v9, 525), we estimated the AUC from these five data points based on the Myerson algorithm (Myerson et al., 2001), which was computed as the trapezoidal integration of task aversiveness discounting over time. By this modelling method, a higher AUC reflects stronger temporal discounting of task aversiveness, which means that participants experience a faster decline in subjective aversiveness as execution is delayed, yielding lower effective aversiveness and reduced avoidance behavior. That is to say, if a participant showcases a greater discounting of task aversiveness as reflected by a higher AUC, she/he experiences a more pronounced reduction in subjective aversiveness upon postponement, plausibly yielding less procrastination. As you kindly suggested, we have added these details to explicitly clarify how to use the hyperbolic discounting approach for determining sampling time points and for calculating AUC of task aversiveness discounting.

Methods Section (Page 6, Line 268-283)

"On the Task day, we developed a mobile app to implement experience sampling method (ESM) for tracking one's real-time evaluation of task aversiveness and task outcome value (see Fig. 1). The task aversiveness describes how disagreeable one perceives when performing a given real-life task to be, whereas outcome value refers to the subjective benefits of the task outcome brought about by completing the task before the deadline (Zhang & Feng, 2020). As theoretically conceptualized by the temporal decision model (TDM) of procrastination, the perceived task aversiveness is hyperbolically discounted when approaching deadline, showing sharply discounting when faring away from deadline but slowly discounting once nearing deadline (Zhang & Feng, 2020; Zhang et al., 2021). Thus, considering this nonlinear dynamics inherent in this hyperbolic discounting, the five recording moments of ESM were selected per task a priori by using a log-spaced temporal sampling scheme (Myerson et al., 2001), with increasing sampling density toward the deadline, such as moments of 10:00 (earliest), 16:00, 18:00, 19:30, 20:00 (deadline). The five sampling points could meet statistical prerequisite in the hyperbolic model fitting, requiring ≥ 4 points (Green & Myerson, 2004). To do so, recording moments of tasks were individually tailored for each task per participant in this ESM procedure."

Methods Section (Page 7, Line 318-334)

"... As articulated temporal decision theoretical model above, the task aversiveness evoked by executing a task was temporally dynamic in a hyperbolic discounting pattern, with sharply discounting in faring away from deadline but slowly discounting in nearing deadline (Zhang & Feng, 2020). To quantitatively characterize the task aversiveness with consideration for its dynamics, the model-free area under the curve (AUC) was calculated. Specifically, based on the log-spaced temporal sampling rule, task aversiveness was measured by 100-point visual analog scale at the five sampling moments. Then, the task aversiveness discounting (A) was calculated as 1- (A(t) / A(earliest)), where t(earliest) was the earliest sampling point, serving as the reference for immediate execution. Subsequently, using the GraphPad Prisma software (v9, 525), the AUC was computed as the trapezoidal integration between task aversiveness discounting and time across five data points, basing on the Myerson algorithm (Myerson et al., 2001). By doing so, a higher AUC reflects stronger temporal discounting of task aversiveness along with nearing deadline, which means that participants experience a faster decline in subjective aversiveness as execution is delayed, yielding lower effective aversiveness and reduced avoidance behavior. As for the task outcome value, it was theoretically posited as a relatively stable evaluation of the task (Zhang & Feng, 2020; Zhang et al., 2021)."

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> *(7) Coming back to the point about the statistical analyses not being described in enough detail: One important example of this is the inclusion of random slopes in their mixed-effects model which is unclear. This is highly relevant as omission of random slopes has been repeatedly shown that it can lead to extremely inflated Type 1 errors (e.g., inflating Type 1 errors by a factor of then, e.g., a significant p value of .05 might be obtained when the true p value is .5). Thus, if indeed random slopes have been omitted, then it is possible that significant effects are significant only due to inflated Type 1 error. Without more information about the models, this cannot be ruled out.*

Thank you for sharing this very timely and crucial comment. After careful scrutiny, we identified this statistical flaw you pointed out - each participant was not yet modeled as random slopes but as random intercepts merely. As you kindly suggested, we have reanalyzed all the statistics by adding random slopes (i.e., (1 + day|SubjectID)). Results showed a statistically significant interaction effect for both procrastination willingness (β = -7.8, SE = 1.8, DF = 45.6, p < .001) and actual procrastination rates (β = -7.4, SE = 2.4, DF = 46.6, p = .004), indicating the effectiveness of multi-session neuromodulation in mitigating procrastination. In the post-hoc simple effect analyses, participants who engaged in active neuromodulation (NM) showed a significant increase in task-execution willingness (i.e., decreased procrastination willingness; NM-before: 35.65 ± 30.20, NM-after: 80.43 ± 19.92, *t*.ratio = 5.4, *p* < .0001, Tukey correction) and a decrease in actual procrastination rates (NM-before: 43.26 ± 39.09, NM-after: 0.00 ± 0.00, *t*.ratio = 5.1, *p* < .0001, Tukey correction), while no such effects were identified for participants in the sham control group (for willingness, SC-before: 37.57 ± 26.46, SC-after: 47.35 ± 30.49, *t*.ratio =0.3, *p* = .77, Tukey correction; for actual procrastination, SC-before: 46.47 ± 40.75, SC-after: 33.34 ± 37.82, *t*.ratio = 0.7, *p* = .48, Tukey correction). Taken together, we do appreciate your pointing out this definitely crucial statistical weakness, and have confirmed that our findings remain reliable after adjusting for Type 1 error by adding random slopes. Moreover, as you kindly suggested, we have incorporated these statistical details, particularly those concerning the GLMM, into the main text to facilitate your evaluation. Please see specific revisions below:

Methods Section (Page 8, Line 381-401)

“To clarify whether multiple-session HD-tDCS neuromodulation can reduce procrastination, the generalized mixed-effects linear model (GLMM) was constructed with full factorial design for subjective procrastination willingness (i.e., self-reported visual analog scores) and actual procrastination behavior (i.e., real-world task-completion rate before deadline). Here, sex, age and socioeconomic status (SES) were modeled as covariates of no interest. As the National Bureau of Statistics (China) issued (*https://www.stats.gov.cn/sj/tjbz/gjtjbz/*), on the basis of per capita annual household income, the SES was divided into seven hierarchical tiers from 1 (poor) to 7 (rich). To obviate subjective rating bias stemming from individual daily mood, we separately measured participants’ daily emotional fluctuation at 10:00 and 16:00 using a self-rating visual analog item (i.e., “How do feel for your mood today?”, 0 for “completely uncomfortable” and 100 for “definitely happy”). By doing so, the averaged score of those self-rating emotions at the two time points was modeled into the GLMM as covariate of no interests, yielding the final expression of “outcome ~ Group*Treatment_Day + Age + Gender +

SES + Emotions + (1 + Treatment_Day | SubjectID)" in the statistical model". This analysis was implemented using the "lme4" and "lmerTest" packages. Employing "emmeans" package, simple effects were also tested at baseline and post-last-intervention using Tukey-adjusted pairwise comparisons of estimated marginal means from the full GLMM, controlling for covariates and random-effects structure. To validate statistical robustness, instead of continuous outcomes for parametric tests, we also conducted a between-group comparison for the number of tasks that procrastination emerges by using the nonparametric x^2 test with ϕ correction or Fisher exact test...."

Results Section (Page 9, Line 428-449)

"To identify whether ms-tDCS targeting the left DLPFC can alleviate subjective procrastination willingness and actual procrastination behavior, a generalized linear mixed-effects model with Scatterthwaite algorithm was built, with task-execution willingness and actual procrastination rates (PR) as primary outcomes, respectively. For procrastination willingness, results showed a statistically significant interaction effect between multi-session neuromodulations and groups (β = -7.8, SE = 1.8, DF = 45.6, p < .001; Fig. 3A). In the post-hoc simple effect analysis, it demonstrated a significantly increased task-execution willingness (i.e., decreased procrastination willingness) after neuromodulation in the active neuromodulation group (NM-before: 35.65 ± 30.20, NM-after: 80.43 ± 19.92, t.ratio = 5.4, p < .0001, Tukey correction), but no such effects were identified in the sham control group (SC-before: 37.57 ± 26.46, SC-after: 47.35 ± 30.49, t.ratio =0.3, p = .77, Tukey correction) (Fig. 3B-C). A linear uptrend for task-execution willingness was further observed across multiple sessions in the active NM group, indicating gradually increasing neuromodulation effects (Fig. 3D; p < .01, Mann-Kendall test). For actual procrastination behavior, changes to actual procrastination rates across all the sessions have been detailed in the Fig. 3E. Similarly, a statistically significant interaction effect was identified here (β = -7.4, SE = 2.4, DF = 46.6, p = .004), and the simple effect analysis further revealed decreased actual procrastination rates after ms-tDCS in the active neuromodulation group (NM-before: 43.26 ± 39.09, NM-after: 0.00 ± 0.00, t.ratio = 5.1, p < .0001, Tukey correction), but no such prominent changes found in the sham control group (SC-before: 46.47 ± 40.75, SC-after: 33.34 ± 37.82, t.ratio = 0.7, p = .48, Tukey correction) (Fig. 3F-G). Also, a significant downtrend for procrastination rates across all the sessions was identified in the active NM group (Fig. 3H; p < .01, Mann-Kendall test)."

> *(8) Related to the previous point: The authors report, for example, on the first results page, line 420, an F-test as F(1, 269). This means the test has 269 residual degrees of freedom despite a sample size of about 50 participants. This likely suggests that relevant random slopes for this test were omitted, meaning that this statistical test likely suffers from inflated Type 1 error, and the reported p-value < .001 might be severely inflated. If that is the case, each observation was treated as independent instead of accounting for the nestedness of data within participants. The authors should check this carefully for this and all other statistical tests using mixed-effects models.*

Thank you for underlining this very timely and helpful comment. As you correctly pointed out above, we did not include random slopes in the original GLMM, highly risking the inflation of the false-positive rate (i.e., Type-I error). By adding the random slopes, we reanalyzed all the statistics from the GLMM, and confirmed that all the findings are still reliable from those new GLMMs with random slopes. Again, thank you for this crucial statistical advice, and please see the above response for full details regarding what we have revised to address this comment you kindly raised.

> *(9) Many of the statistical procedures seem quite complex and hard to follow. If the results are indeed so robust as they are presented to be, would it make sense to use simpler analysis approaches (perhaps in addition to the complex ones) that are easier for the average reader to understand and comprehend?*

We do thank you for this practical and helpful comment. In the original manuscript, we incorporated a joint model of longitudinal and survival data (JM-LSD), in conjunction with machine learning algorithms, to strengthen the robustness of our statistical findings. Nevertheless, we all agree with you on this point: there is no need to complicate the analyses by repeatedly probing the same research question to increase methodological robustness, at the expense of compromising readability and intelligibility for a broader audience. As you suggested, we have removed these complicated statistical methods, and merely maintained the primary ones - GLMM and X^2 cross-tab test, as well as a complementary one - Mann-Kendall linear trend test. Thus, we have almost rewritten the whole Results section. Please see the specific instances below:

Results Section (Page 9, Line 468-485)

"Ms-tDCS changes task aversiveness and task-outcome value

Both task aversiveness and task outcome value serve as key pathways determining whether one would procrastinate. To this end, we further utilized a generalized linear mixed-effects model to examine the effects of ms-tDCS on changes in task aversiveness and task outcome value. Task aversiveness changes across all the sessions are shown in the Fig. 4A and 4C. We demonstrated a statistically significant decrease in task aversiveness and an increase in task outcome value via ms-tDCS in the neuromodulation group (Task aversiveness: interaction effect, β = -0.12, SE = 0.04, DF = 46.7, p = .002; simple effect, NM-before $_{(AUC)}$: 1.13 ± 0.53, NM-after $_{(AUC)}$: 1.95 ± 0.85, t.ratio = 4.5, p < .001, Tukey correction; Outcome value: β = -6.8, SE = 1.74, DF = 46.2, p < .001; simple effect, NM-before: 35.86 ± 27.82, NM-after: 73.08 ± 23.33, t.ratio = 5.0, p < .001, Tukey correction; see Fig. 4B), but not in the sham control group (Task aversiveness: SC-before $_{(AUC)}$: 1.07 ± 0.51, SC-after $_{(AUC)}$: 1.28 ± 0.46, t.ratio = 1.3, p = .20, Tukey correction; Outcome value: SC-before: 34.00 ± 25.17, SC-after: 40.13 ± 28.94, t.ratio = 0.8, p = .41, Tukey correction; see Fig. 4D). In the neuromodulation (NM) group, task aversiveness steadily decreased with the cumulative number of stimulation sessions, while perceived task outcome value increased significantly (see Fig. 4E-F, p < .05, Mann-Kendall test). Thus, it provides causal evidence clarifying that neuromodulation to left DLPFC reduces task aversiveness and enhances task-outcome value meanwhile."

Results Section (Page 10, Line 525-542)

"Long-term effects of ms-tDCS

We have also attempted to conduct a follow-up investigation to test the long-term retention of ms-tDCS in reducing actual procrastination. Almost all the participants had undergone follow-up except one in the neuromodulation group after last neuromodulation for 6 months (N_{NM} = 22, N_{SC} = 23). Thus, the GLMM was constructed, with the PR before first neuromodulation vs. PR after last neuromodulation for 6 months as covariates of interest. Results showed the statistically significant group*time interaction effects (β = 16.5, SE = 9.9, p = .049). Simple-effect model demonstrated a decrease in actual procrastination rates in the active neuromodulation group after last stimulation for 6 months compared to baseline (β = -22.05, SE = 10.0, p = .038, Tukey correction; NM-before: 40.68 ± 37.96, NM-after$_{6\text{-months}}$: 18.63 ± 29.80), and revealed null effects in the SC group (β = 1.26, SE = 9.78, p = .99, Tukey correction; SC-before: 46.47 ± 40.75, SC-after$_{6\text{-months}}$: 47.73 ± 39.18) (see Fig. 6).. Furthermore, using a nonparametric x^2 test to compare differences in the number of procrastinated tasks, we still found a statistically significant reduction in procrastination frequency in NM group after neuromodulation for 6 months compared to baseline (x^2 = 3.30, p = .035, NM-before: 68.19% (15/22), NM-after$_{6\text{-months}}$: 40.91% (9/22)), while no significant changes were observed in the SC group (x^2 = 0.11, p = .74, SC-before: 69.56% (16/23), SC-after$_{6\text{-months}}$: 73.91% (17/23)). Therefore, beyond to short-term effects, the benefits of ms-tDCS neuromodulation to reduce procrastination pose the long-term retention."

> *(10) As was noted by an earlier reviewer, the paper reports nearly exclusively about the role of the left DLPFC, while there is also work that demonstrates the role of the right DLPFC in self-control. A more balanced presentation of the relevant scientific literature would be desirable.*

We are grateful to you for noticing the unbalanced presentation of the literature on left DLPFC. As you kindly suggested, we have added literature to support the association between self-control and the right lateralization of the DLPFC. Please see below for what we have revised:

Introduction Section (Page 4, Line 137-143)

"...In addition to the left lateralization, there is solid evidence indicating significant associations between self-control and the right DLPFC indeed, particularly given that this region specifically functions in top-down regulation, future self-continuity representation and social decisions (Huang et al., 2025; Lin and Feng, 2024; Knoch & Fehr, 2007). Despite this case, Xu and colleagues demonstrated null effects of anodally stimulating the right DPFC to modulate either value evaluation or emotional regulation for changing procrastination willingness (Xu et al., 2023)."

> *(11) Active stimulation reduced procrastination, reduced task aversiveness, and increased the outcome value. If I am not mistaken, the authors claim based on these results that the brain stimulation effect operates via self-control, but - unless I missed it - the authors do not have any direct evidence (such as measures or specific task measures) that actually capture self-control. Thus, that self-control is involved seems speculation, but there is no empirical evidence for this; or am I mistaken about this? If that is indeed correct, I think it needs to be made explicit that it is an untested assumption (which might be very plausible, but it is still in the current study not empirically tested) that self-control plays any role in the reported results.*

We truly appreciate your pointing out this weakness with regard to conceptualization. Yes, you are correct in understanding this causal chain: we conceptually speculate that the HD-tDCS stimulation over the left DLPFC operates self-control to change procrastination, rather than empirically validating this component in the chain: brain stimulation → increased self-control → increased task outcome value → decreased procrastination. In this causal chain, we did not collect data to directly measure self-control at either baseline or post-neuromodulation times. Therefore, we all agree with your suggestion to explicitly claim this case in the main text. Following this advice, we have redrawn a portion of the Conclusion by clearly pointing out the hypothesis-generating role of self-control in mitigating procrastination, and have further claimed this case in the Limitation section:

Abstract Section (Page 2, Line 55-57)

"... This establishes a precise, value-driven neurocognitive pathway to account the conceptualized roles of self-control on procrastination, and offers a validated, theory-driven strategy for interventions."

Results Section (Page 10, Line 489-492 and 520-522)

"Given the dual neurocognitive pathways identified above—reduced task aversiveness and increased task-outcome value—we proposed that these changes, conceptually driven by enhanced self-control via ms-tDCS over left DLPFC, account for how neuromodulation reduces procrastination. ..."

"In summary, these findings demonstrated a mechanistic pathway underlying procrastination: the self-control that was conceptualized to be governed by left DLPFC mitigate procrastination by plausibly increasing task-outcome value."

Discussion Section (Page 13, Line 642-645)

"Moreover, this study did not collect data for assessing participants' self-control at either baseline or post-neuromodulation, thereby limiting our ability to determine whether the effects on procrastination were uniquely attributable to neuromodulation-induced changes in self-control. ..."

> *(12) Figures 3F and 3H show that procrastination rates in the active modulation group go to 0 in all participants by sessions 6 and 7. This seems surprising and, to be honest, rather unlikely that there is absolutely no individual variation in this group anymore. In any case, this is quite extraordinary and should be explicitly discussed, if this is indeed correct: What might be the reasons that this is such an extreme pattern? Just a random fluctuation? Are the results robust if these extreme cells are ignored? The authors remove other cells in their design due to unusual patterns, so perhaps the same should be done here, at least as a robustness check.*

Thank you for raising this highly important and helpful comment. Indeed, we fully understand that this result is somewhat extraordinary, a fact that was equally striking to us when unblinding the data. After carefully scrutinizing the data and statistics, we are thrilled to confirm that this pattern is true. In support of this observation, we were gratified to receive numerous thank-you letters from participants who engaged in active neuromodulation. They expressed gratitude to us, and reported that they have substantially ameliorated procrastination behavior in real-life activities after completing the trial. While this does not constitute formal scientific evidence, we are also glad to see the benefits of this neuromodulation for those procrastinators.

Two reasons could account for this pattern herein. One interpretation is to attribute this pattern to "scalar inflation". In the present study, the procrastination rate was calculated as 1 minus the task-completion rate (e.g., 80%, 60%, 40%) by the deadline. At sessions # 6 and #7, all the participants completed their real-life tasks before the deadline, yielding a 0% (1 minus 100% completion rate) procrastination rate, without any between-individual variation. Thus, rather than there being no individual variation in procrastination, this scalar – the procrastination rate - is too insensitive to capture subtle differences per se. For instance, although participants #1 and #2 both showed a 0% procrastination rate - meaning that both completed their tasks before the deadline - Participant #1 might have completed it 3 hours before the deadline, whereas Participant #2 might have completed it only 10 minutes before. In this case, the "scalar inflation" emerges to let us perceive that both participants have equivalent procrastination rates, although participant #2 may have a higher procrastination level than #1. As conceptually defined in the field, procrastination is contextualized as "not completing a task before the deadline". Thus, if this task is completed before the deadline, regardless of whether it was finished close to or far in advance of the deadline, this case is defined as "no procrastination". In the present study, the primary outcome is whether a participant procrastinated on a real-life task before the deadline in real-world settings, irrespective of when she/he completed this task. Thus, this scalar - procrastination rate - fits our conceptualization of procrastination.

Another reason is the potential accumulative effects from sequential multi-session tDCS stimulation. As shown in Mann-Kendall trend tests, the procrastination rates show a significant linear downtrend in the active neuromodulation group across sessions, even after removing sessions #6 and #7. This indicates that the improvements of going against procrastination may be sequentially accumulative along with the increase in sessions, implying a potential "dose-dependent effect". Despite a speculative interpretation, this "dose-dependent effect" in neuromodulation has been well-documented in previous studies, showing the robustly linear association between the number of sessions and effectiveness (c.f., Cole et al., 2020; Hutton et al., 2023; Sabé et al., 2024; Schulze et al., 2018). Therefore, although this extreme pattern is somewhat extraordinary compared to previous observations, it makes sense.

Yes, this is a definitely great idea to carry out a robustness check by removing sessions #6, #7, or both. We do believe that this analysis could support statistical robustness to go against potential biases from extreme cells. By doing so, we found that all the group*treatment_day interaction effects remained significant when removing either session #6 or session #7 (or even both, all p-values < .05), indicating high statistical robustness. Please see Supplementary table S3 and S4

Taken together, in spite of their being extraordinary, we confirm that those findings are statistically robust to extreme outliers. As you kindly suggested, we have added those findings of the robustness check into the revised Supplemental Materials section.

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> *(13) The supplemental materials, unfortunately, do not give more information, which would be needed to understand the analyses the authors actually conducted. I had hoped I would find the missing information there, but it's not there.*

Sorry to offer uninformative supplemental materials (SM) in the original submission. As you suggested, we have added a substantial number of details to clarify how we conducted data analyses in the main text, and also tightened the whole SM section to improve readability and comprehensibility. We do hope that this revised manuscript could offer clear and adequate information in understanding methods and statistics for broader readers.

> *In sum, the reported/cited/discussed literature gives the impression of being incomplete/selectively reported; the analyses are not reported sufficiently transparently/fully to evaluate whether they are appropriate and thus whether the results are trustworthy or not. At least some of the patterns in the results seem highly unlikely (0 procrastination in the verum group in the last 2 observation periods), and the sample size seems very small for a between-subjects design.*

Thank you for this very helpful summary. As you kindly suggested above, we have overhauled this manuscript to address those points that you listed here, particularly where we added relevant literature to balance our claims, added a huge amount of details to sufficiently/transparently report statistics, and conducted a robustness check to confirm the statistical robustness of our findings to those plausible extreme patterns (sessions #6 and #7), as well as justified how we determined this sample size fulfilling medium statistical power in a priori. Please see above for full details regarding how we addressed those comments, point-by-point.

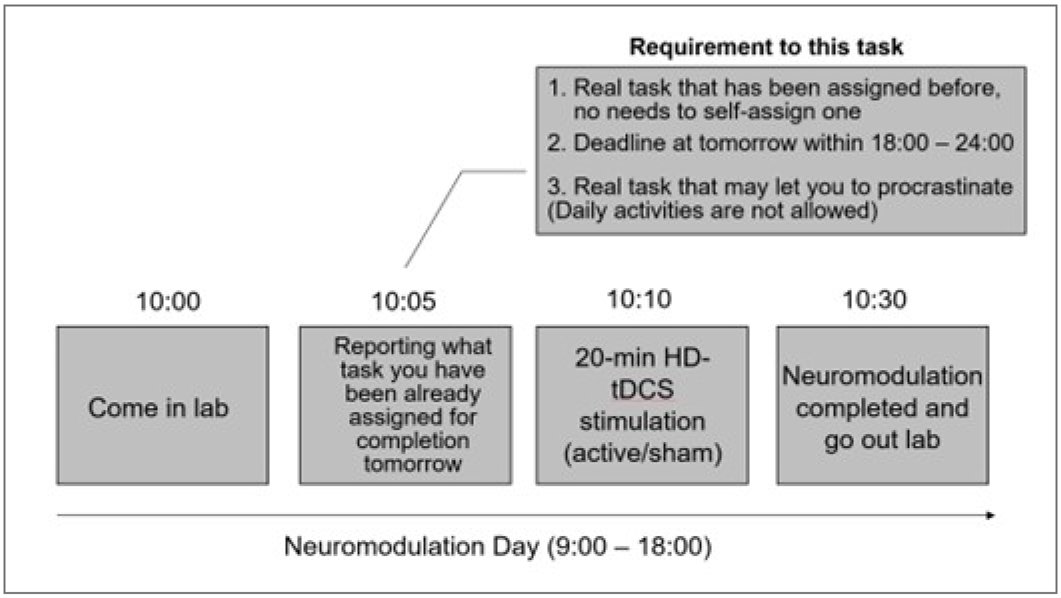
> ***Reviewer #2 (Public Review):***
>
> *Chen and colleagues conducted a cross-sectional longitudinal study, administering high-definition transcranial direct stimulation targeting the left DLPFC to examine the effect of HD-tDCS on real-world procrastination behavior. They find that seven sessions of active neuromodulation to the left DLPFC elicited greater modulation of procrastination measures (e.g., task-execution willingness, procrastination rates, task aversiveness, outcome value) relative to sham. They report that tDCS effects on task-execution willingness and procrastination are mediated by task outcome value and claim that this neuromodulatory intervention reduces procrastination rates quantified by their task. Although the study addresses an interesting question regarding the role of DLPFC on procrastination, concerns about the validity of the procrastination moderate enthusiasm for the study and limit the interpretability of the mechanism underlying the reported findings.*
>
> *Strengths:*
>
> *(1) This is a well-designed protocol with rigorous administration of high-definition transcranial direct current stimulation across multiple sessions. The approach is solid and aims to address an important question regarding the putative role of DLPFC in modulating chronic procrastination behavior.*
>
> *(2) The quantification of task aversiveness through AUC metrics is a clever approach to account for the temporal dynamics of task aversiveness, which is notoriously difficult to quantify.*

Thank you for taking your invaluable time to review our manuscript, warmly applauding the strength in research design and the conceptualization of scaling task aversiveness, as well as kindly sharing such helpful and insightful evaluations. As you correctly pointed out, we are aware of the absence of detailed, clear and understandable reporting of measures (e.g., real-world procrastination), statistics and methods, in the original manuscript. Following all your suggestions, we have thoroughly revised this manuscript to address those comments that you kindly made, point-by-point. Please see the full response underneath.

> *Weaknesses:*
>
> *(1) The lack of specificity surrounding the "real-world measures" of procrastination is problematic and undermines the strength of the evidence surrounding the DLPFC effects on procrastination behavior. It would be helpful to detail what "real-world tasks" individuals reported, which would inform the efficacy of the intervention on procrastination performance across the diversity of tasks. It is also unclear when and how tasks were reported using the ESM procedure. Providing greater detail of these measures overall would enhance the paper's impact.*

We genuinely appreciate your raising this very crucial comment. We are sorry for omitting a tremendous number of methodological details to comply with the editorial requirement on the manuscript's length, which hampered the comprehension of how we measure "real-life tasks" and "real-world procrastination".

As shown in the schematic diagram for experimental procedure (Fig. 1), the experimental protocol alternated between Neuromodulation Days (Days 2, 4, 6, 8, 10, 12, 14) and Task Days (Days 1, 3, 5, 7, 9, 11, 13, 15). On each Neuromodulation Day, participants received either active or sham HD-tDCS, and—critically—before stimulation—were instructed to specify a real-life task they were required to complete the following day, with a deadline between 18:00 and 24:00. This ensured ≥24 hours between neuromodulation and task execution, isolating offline after-effects. For instance, on Day #2 (Neuromodulation Day), before carrying out stimulation, participants were asked to report a real-life task that has a deadline within 18:00 - 24:00 for tomorrow's "task day" (Day #3) (please see the schematic diagram in Author response image 2).



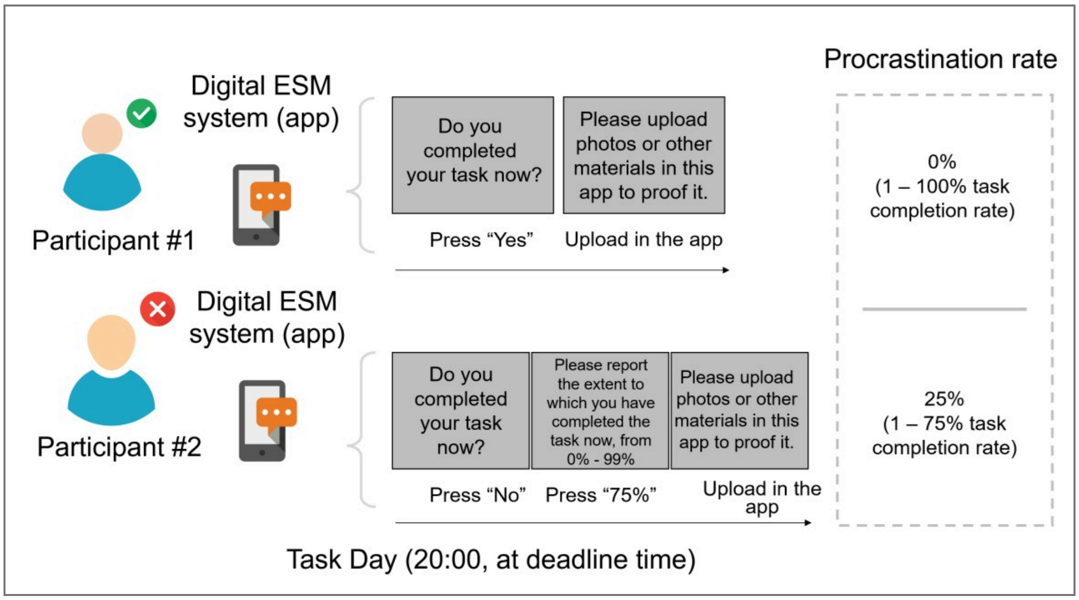
Author response image 2.

There are some real-life tasks that they reported in our experiment as examples: "Complete and submit a homework assignment", "Complete a standardized English proficiency test", "Complete an online course module required for applying a Class C driver's license", "Prepare slides for a seminar presentation", "Practice guitar", "Practice Chinese calligraphy", and "Do the laundry". Reported tasks spanned academic (e.g., submitting an assignment), occupational (e.g., preparing a presentation), administrative (e.g., applying for a license), self-improvement (e.g., practicing guitar for ≥30 min), domestic (e.g., laundry), and health-related domains (e.g., running ≥ 2,000m for exercise), indicating a plausible task diversity.

On each "task day", participants engaged in an intensive Experience Sampling Method (iESM) protocol via a custom-built mobile app. Using this app, participants were required to report a subjective task-execution willingness score (i.e., a one-item 100-point visual analog scale, "How willing are you to do this task?", 0 for "I will definitely procrastinate this task" and 100 for "I will take action to complete this task immediately"; procrastination willingness = 100 – the task-execution willingness score), the subjective task aversiveness (i.e., a one-item 100-point visual analog scale), the subjective task outcome value (i.e., a one-item 100-point visual analog scale), and the objective procrastination rate, respectively.

Rather than self-reported scores from those one-item visual analog scales, we asked participants to report real "task completion rate" for the objective quantification of the "real-world procrastination behavior". Specifically, at the deadline, each participant was asked to report whether she/he had completed this task. If she/he reported not having yet completed the task (i.e. procrastination behavior emerged), she/he was further required to report the percentage of the task completed (1% - 99%), which was defined as the task completion rate. By doing so, we could calculate the real-world procrastination rate for the real-life task as the "1 – the task completion rate". For instance, if a participant did not complete her/his real-life task before the deadline (i.e. she/he procrastinated this task) and reported completing 75% of this task at the deadline, her/his real-world procrastination rate was computed as the 25% (1 - 75%) (Please see the schematic diagram in Author response image 3).

Moreover, rather than merely a self-reported task completion rate, each participant was also asked to upload proof (e.g., screenshots of submitted assignments, photos of printed documents, system timestamps) to the ESM digital system for validation.



Author response image 3.

To determine the sampling time points for this mobile app in the ESM, we capitalized on both the conceptual temporal decision model and the statistical Myerson algorithm. Specifically, the Temporal Decision Model (TDM) was originally proposed by our team (Xu et al., 2023; Zhang et al., 2019, 2020, 2021), which theoretically conceptualizes procrastination as the failure of the trade-off between task outcome value (i.e., motivation to take actions now for pursuing task reward) and task aversiveness (i.e., motivations for avoiding taking action now for avoiding negative experiences). Once task aversiveness overrides the pursuits of task outcome values, procrastination emerges. One overarching hypothesis in this theoretical model is that the task aversiveness is hyperbolically discounted when approaching the deadline: it would be discounted sharply when far from the deadline but discounted slowly when nearing the deadline (Zhang et al., 2019). To maximize statistical power to fit dynamic motivational curves, we employed a log-spaced temporal sampling scheme (Myerson et al., 2001) (please see the schematic diagram in https://uen.pressbooks.pub/behavioraleconomics/chapter/the-reality-of-homo-sapiens, where each point indicates a sampling time):

By this fitting algorithm (Myerson et al., 2001), five time points were selected to fulfill the statistical prerequisites for hyperbolic model fitting, with increasing sampling density toward the deadline (e.g., for a task due at 20:00: sampled at 10:00, 16:00, 18:00, 19:30, 20:00). Once the task-specific five sampling time points were determined per participant, this mobile app sent a digital message to ask her/him to immediately report the task aversiveness and the task outcome value then. As the primary outcomes, the procrastination rate (i.e., 1 – the task completion rate) and the procrastination willingness were sampled at the deadline point.

Furthermore, yes, we fully concur with you on this great idea, that is, transparency about task diversity strengthens the generalizability of our findings. In response, we have tabulated these real-life tasks that were reported in this experiment in the independent Appendix 1, with automatic translations from Chinese to English via Qwen GPT. Please see below for what we have added to the main text:

Methods Section (Page 6-7, Line 238-308)

"Nested cross-sectional longitudinal design

This study used a nested cross-sectional longitudinal design to investigate whether the multiple-session anodal HD-tDCS targeting the left DLPFC could reduce actual procrastination behavior and to probe how this effect manifests. To assess procrastination in daily life, we implemented a 15-day protocol alternating between Neuromodulation Days (Days 2, 4, 6, 8, 10, 12, 14) and Task Days (Days 1, 3, 5, 7, 9, 11, 13, 15). On the Neuromodulation days, the 20-min anodal HD-tDCS neuromodulation targeting the left DLPFC was performed for HD-tDCS active group at intervals of 2 days, while the sham-control group received sham HD-tDCS training. This HD-tDCS training was repeated for a total of seven sessions, and lasted 15 days (see Fig. 1a). Crucially, to capture procrastination in ecologically valid contexts, prior to receiving either active or sham HD-tDCS (administered between 09:00–18:00), participants were instructed to specify a real-life task they were personally obligated to complete the following day, with a self-defined deadline strictly constrained to 18:00–24:00 to ensure ≥24 hours between stimulation offset and task deadline, thereby isolating offline after-effects. This task should meet the following three criteria: (a) it should be already assigned in the real-world settings; (b) deadline should be constrained to 18:00-24:00 (see above); (c) it should be more likely to induce procrastinate. By doing so, more than 300 real-life tasks were collected, spanning academic (e.g., "submit a statistics homework assignment"), occupational (e.g., "draft and email a project proposal"), administrative (e.g., "complete online application for Class C driver's license"), self-improvement (e.g., "practice guitar for ≥30 minutes"), domestic (e.g., "do laundry "), and health-related (e.g., "running 2,000m for exercise"). Full task list has been tabulated in the Appendix 1. As primary outcomes, all the participants were required to reported task-execution willingness (TEW) (Zhang & Feng, 2020; Zhang, Liu, et al., 2019), for a real-life task 24 hours post-neuromodulation. Thus, procrastination willingness was quantified as 100-TEW score (see underneath for details). Furthermore, we asked participants to report the actual task completion rate (CR) of the task at the deadline (e.g. participant A finished 90% homework at deadline and reported this situation to us at deadline). In this vein, the actual procrastination rate (PR) was quantified as 1-CR.

On the Task day, we developed a mobile app to implement experience sampling method (ESM) for tracking one's real-time evaluation of task aversiveness and task outcome value (see Fig. 1). The task aversiveness describes how disagreeable one perceives performing a given real-life task to be, whereas outcome value refers to the subjective benefits of the task outcome brought about by completing the task before the deadline (Zhang & Feng, 2020). As theoretically conceptualized by the temporal decision model (TDM) of procrastination, the perceived task aversiveness is hyperbolically discounted when approaching deadline, showing sharply discounting when faring away from deadline but slowly discounting once nearing deadline (Zhang & Feng, 2020; Zhang et al., 2021). Thus, considering this nonlinear dynamics inherent in this hyperbolic discounting, the five recording moments of ESM were selected per task a prior by using a log-spaced temporal sampling scheme (Myerson et al., 2001), with increasing sampling density toward the deadline, such as moments of 10:00 (earliest), 16:00, 18:00, 19:30, 20:00 (deadline). The five sampling points could meet statistical prerequisite in the hyperbolic model fitting (requiring ≥ 4 points; Green & Myerson, 2004). To do so, recording moments of tasks were individually tailored for each task per participant in this ESM procedure. To obviate the confounds of daily emotions in task aversiveness evaluation, we used the averaged scores of PANAS at 10:00 (noon) and 16:00 (afternoon) as anchoring points to quantify one's daily emotions by using this ESM app. Before each session of HD-tDCS training, each participant was required to report a real-life task whose deadline is tomorrow. To obtain the long-term effect of HD-tDCS (i.e., the interval between HD-tDCS and task completion is at least 24 hours), the task deadline that participants reported was required to be between 18:00 - 24:00. Once a sampling time reached, this app would send a digital message to require participants to fill online form for data collection.

Quantification of covariates of interests

Outcome variables of this study were twofold: one is task-execution willingness and another is procrastination rate (PR). Task-execution willingness is used to evaluate one's subjective inclination to avoid procrastination (Zhang & Feng, 2020). In this vein, we used a 100-point scale to require participants to report their task-execution willingness (0 for "I will definitely procrastinate this task" and 100 for "I will take action to complete this task immediately"). This metric was recorded 24 hours after neuromodulation to examine its long-term effects. PR is used to quantify the extent to which one task has been procrastinated, and was calculated as 1 - CR (task completion rate). Critically, at the precise deadline, the app prompted participants to (a) indicate task completion status (yes/no), and if incomplete, (b) report the percentage completed (1–99%), defined as the Task CR, while simultaneously uploading objective evidence (e.g., screenshots of submitted files, photos of physical outputs, system-generated logs, or app-exported records). If the task was actually completed before the deadline, the CR would be 100% and the PR would be calculated as 0% (1-CR). PR was recorded at the actual task deadline for each participant. We were also interested in re-investigating their actual procrastination by using PR 6 months after the last neuromodulation to test the long-term retention of this neuromodulation effect."

References

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Xu, T., Zhang, S., Zhou, F., & Feng, T. (2023). Stimulation of left dorsolateral prefrontal cortex enhances willingness for task completion by amplifying task outcome value. Journal of experimental psychology. General, 152(4), 1122–1133. *https://doi.org/10.1037/xge0001312*

Zhang, S., Verguts, T., Zhang, C., Feng, P., Chen, Q., & Feng, T. (2021). Outcome Value and Task Aversiveness Impact Task Procrastination through Separate Neural Pathways. Cerebral cortex (New York, N.Y. : 1991), 31(8), 3846–3855. *https://doi.org/10.1093/cercor/bhab053*

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Zhang, S., & Feng, T. (2020). Modeling procrastination: Asymmetric decisions to act between the present and the future. Journal of experimental psychology. General, 149(2), 311–322. *https://doi.org/10.1037/xge0000643*

> *(2) Additionally, it is unclear whether the reported effects could be due to differential reporting of tasks (e.g., it could be that participants learned across sessions to report more achievable or less aversive task goals, rather than stimulation of DLPFC reducing procrastination per se). It would be helpful to demonstrate whether these self-reported tasks are consistent across sessions and similar in difficulty within each participant, which would strengthen the claims regarding the intervention.*

Thank you for raising this very crucial comment. We indeed agree with you on this point that the reported effects may vary with task difficulties and task-execution proficiency, which potentially confound the effects of stimulation on mitigating procrastination. As you correctly comment, given no data collection on difficulties or other relevant characteristics of tasks, we cannot completely rule out this confounder in interpreting our findings on the one hand. As a result, we have explicitly claimed this limitation in the Discussion section.

On the other hand, despite no quantitative evidence, this risk of confounding main effects with disparities in task characteristics was controlled experimentally. As we reported above, all the reported tasks were mandated to meet three criteria: (a) they were already assigned in the real-world settings; (b) the deadline was constrained to 18:00-24:00; (3) they were likely to lead to procrastinate. To do so, each participant was clearly instructed to report a real-life task that was more likely to be procrastinated in real-world settings, and was not allowed to report easy, achievable and cost-less tasks. Supporting this case, those reported tasks were found spanning academic (e.g., submitting an assignment), occupational (e.g., preparing a presentation), administrative (e.g., applying for a license), self-improvement (e.g., practicing guitar for ≥30 min), domestic (e.g., laundry), and health-related domains (e.g., running ≥ 2,000m for exercise), indicating a plausible task diversity and difficulty. This was resonated by observing the high within-subject task homogeneity. For instance, for Participant #5, she/he reported the tasks that were almost all around academic activities across all the sessions. Therefore, as the task list reported (please see Appendix 1), these self-reported tasks were plausibly consistent across sessions and similar in difficulty within each participant.

In addition, as we tested, almost all the participants reported they were receiving treatment, with 91.30% (21/23) for the active neuromodulation group (NM) and with 86.95% (20/23) for the sham control group (SC) (x^2 = 0.224, p = .636), indicating the effectiveness of the double-blinding methods. If participants learned across sessions to report more achievable or less aversive task goals, their procrastination willingness and procrastination rates for their reported tasks would all increasingly decrease, irrespective of whether they were in the active neuromodulation-effect group or the sham group. However, no such effects - procrastination willingness and procrastination rates for their reported tasks increasingly decreasing across sessions - existed in the sham control group (Mann-Kendall test, for procrastination willingness, tau = 0.60, p = .13; for procrastination rate, tau = 0.61, p = .13), indicating no statistically significant learning effect or strategic effect on task performance. Again, thank you for this very crucial comment, and we do hope these clarifications could address it.

Limitations Section (Page 12, Line 637-640)

“In addition, despite instructing to report valid real-life tasks with high probabilities to procrastinate, we had not yet measured the task difficulty and consistency across sessions for each participant. Consequently, interpreting the effects of neuromodulation to mitigate procrastination as “unique contributions” should warrant cautions. ...”

> *(3) It would be helpful to show evidence that the procrastination measures are valid and consistent, and detail how each of these measures was quantified and differed across sessions and by intervention. For instance, while the AUC metric is an innovative way to quantify the temporal dynamics of task-aversiveness, it was unclear how the timepoints*

> *were collected relative to the task deadline. It would be helpful to include greater detail on how these self-reported tasks and deadlines were determined and collected, which would clarify how these procrastination measures were quantified and varied across time.*

We do appreciate your highlighting the importance of clarifying how to measure procrastination, substantially helping readers to interpret these findings. As reported above, the primary outcomes of this experiment included subjective procrastination willingness and objective actual procrastination rate. For the subjective procrastination willingness, using the purpose-built mobile app, participants were required to report subjective task-execution willingness score (i.e., one-item 100-point visual analog scale, “How willing are you to do this task?”, 0 for “I will definitely procrastinate this task” and 100 for “I will take action to complete this task immediately”). Thus, the procrastination willingness was computed as “100 – the task-execution willingness score”. For the objective procrastination rate, rather than self-reported scores from those one-item visual analog scales, we asked participants to report the real “task completion rate from 1% to 99%” for the objective quantification of the “real-world procrastination behavior”. Full details can be found in Response #1.

For determining sampling time points for the quantification of AUC, we capitalized on both the conceptual Temporal Decision Model and the statistical Myerson algorithm. Specifically, the Temporal Decision Model (TDM) was originally proposed by our team (Xu et al., 2023; Zhang et al., 2019, 2020, 2021), which theoretically conceptualizes procrastination as the failure of the trade-off between task outcome value (i.e., motivation to take actions now for pursuing task reward) and task aversiveness (i.e., motivations for avoiding taking action now for avoiding negative experiences). Once task aversiveness overrides the pursuits of task outcome values, the procrastination emerges. One overarching hypothesis in this theoretical model is that the task aversiveness is hyperbolically discounted when approaching the deadline: it would be discounted sharply when being far from the deadline but discounted slowly when nearing the deadline (Zhang et al., 2019). To maximize statistical power to fit dynamic motivational curves, we employed a log-spaced temporal sampling scheme (Myerson et al., 2001). By this fitting algorithm (Myerson et al., 2001), five time points were selected to fulfill the statistical prerequisites for hyperbolic model fitting, with increasing sampling density toward the deadline (e.g., for a task due at 20:00: sampled at 10:00, 16:00, 18:00, 19:30, 20:00).

Once the task-specific five sampling time points were determined per participant, this mobile app sent a digital message to ask her/him to immediately report the task aversiveness and the task outcome value then. After capturing the task aversiveness from those five time points, the task aversiveness discounting was calculated as 1- (A(t) / A(earliest)), where t(earliest) was the earliest sampling point (e.g., 10:00), serving as the reference for immediate execution. Subsequently, using the GraphPad Prisma software (v9, 525), we estimated the AUC from those five data points based on the Myerson algorithm (Myerson et al., 2001), which was computed via the trapezoidal integration between task aversiveness discounting and time. By this modelling method, a higher AUC reflects stronger temporal discounting of task aversiveness, which means that participants experience a faster decline in subjective aversiveness as execution is delayed, yielding lower effective aversiveness and reduced avoidance behavior. That is to say, if a participant showcases a greater discounting of task aversiveness as reflected by a higher AUC, she/he experiences a more pronounced reduction in subjective aversiveness upon postponement, plausibly yielding less procrastination.

Taken together, following your suggestion, we have added a substantial number of details to clarify how to measure procrastination, when to sample the data and how to estimate the AUC into the revised manuscript. Please see them in Response #1.

> *(4) There are strong claims about the multi-session neuromodulation alleviating chronic procrastination, which should be moderated, given the concerns regarding how*

> *procrastination was quantified. It would also be helpful to clarify whether DLPFC stimulation modulates subjective measures of procrastination, or alternatively, whether these effects could be driven by improved working memory or attention to the reported tasks. In general, more work is needed to clarify whether the targeted mechanisms are specific to procrastination and/or to rule out alternative explanations.*

Yes, we fully agree with you on this consideration: we should tone down the conclusions currently claimed in the main text, given the inherent shortcomings mentioned above. As you helpfully suggested, we have moderated our overall claims regarding the effects of multi-session neuromodulation in alleviating chronic procrastination. Please see specific instances below:

Abstract Section (Page 2, Line 55-57)

"… This establishes a precise, value-driven neurocognitive pathway to account the conceptualized roles of self-control on procrastination, and potentially offers a validated, theory-driven strategy for interventions."

Conclusion Section (Page 13, Line 657-664)

"In conclusion, this study potentially provides an effective way to reduce both procrastination willingness and actual procrastination behavior by using neuromodulation on the left DLPFC. Furthermore, such effects have been observed for 2-day-interval long-term after-effects, and were also found for 6-month long-term retention in part. More importantly, this study identified that the ms-tDCS neuromodulation could decrease task aversiveness and increase task outcome value while, and further demonstrated that the increased task outcome value could predict decreased procrastination, a relationship conceptually driven by enhancing self-control. In this vein, the current study enriches our understanding of neurocognitive mechanism of procrastination by showing the prominent role of increased task outcome value in reducing procrastination. Also, it may provide an effective method for intervening in human procrastination."

Moreover, yes, as we clarified above, in addition to the objective measure of procrastination behavior, we also leveraged a one-item visual analog scale (i.e. one-item 100-point visual analog scale, "How willing are you to do this task?", 0 for "I will definitely procrastinate this task" and 100 for "I will take action to complete this task immediately") to measure subjective procrastination willingness. Results demonstrated that the subjective procrastination willingness significantly decreased across neuromodulation sessions in the active group, but not in the sham control group, consistent with the observed reduction in the objective procrastination measure. In addition, we all perceive it as helpful and crucial to note that we cannot draw the conclusion that the effects of neuromodulation on mitigating procrastination are contributed by increasing task outcome value uniquely. Given no measures or evidence of other factors, such as working memory and attention, we cannot rule out other neurocognitive pathways. To address this point, we have removed or rephrased such statements throughout the whole revised manuscript, and explicitly constrained to interpret this neurocognitive mechanism (i.e., increased task outcome value) within the theory-driven framework of the temporal decision model.

> ***Reviewer #3 (Public review):***
>
> *This manuscript explores whether high-definition transcranial direct current stimulation (HD-tDCS) of the left DLPFC can reduce real-world procrastination, as predicted by the Temporal Decision Model (TDM). The research question is interesting, and the topic - neuromodulation of self-regulatory behavior - is timely.*

Many thanks for kindly dedicating time to review our manuscript, and for the helpful comments detailed below. Thank you for appreciating the novelty of this study.

> *However, the study also suffers from a limited sample size, and sometimes it was difficult to follow the statistics.*

Thank you for pointing out these crucial concerns. As you correctly raised, the sample size is somewhat small in any case, but we confirm that this sample size is adequate to obtain medium statistical power.

For estimating the sample size, we determined the a priori effect size based on the existing work we published (Xu et al., 2023, J Exp Psychol Gen;152(4):1122-1133). In this pilot study, we identified a significant interaction effect between single-session tDCS stimulation (active vs sham) and time (pre-test vs post-test) (t = 2.38, p = .02, n = 27; 95% CI [0.14, 1.49]) for changing procrastination willingness in laboratory settings, indicating a medium effect size. Therefore, this pilot study provides supportive evidence to determine this effect size a priori.

Using the G*Power software with an estimation of a medium effect size, we determined that a total sample size of* N_{total} *= 34 could reach adequate statistical power. Please see outputs of the G*Power in Author response image 1.

As for the statistics, we genuinely acknowledge that the vague methodological descriptions and complex algorithms indeed complicated the understanding of the methods and statistics. To address this, echoing the comment raised by Reviewer #1, we have removed the complicated statistics and methods, and further clarified how we used the generalized linear mixed-effect model (GLMM) for statistical analysis. Please see the specific revisions below:

Methods Section (Page 8, Line 378-403)

"Statistics

All the statistics were implemented by R (*https://www.rstudio.com/*) and R-dependent packages.

To clarify whether multiple-session HD-tDCS neuromodulation can reduce procrastination, the generalized mixed-effects linear model (GLMM) was constructed with full factorial design for subjective procrastination willingness (i.e., self-reported visual analog scores) and actual procrastination behavior (i.e., real-world task-completion rate before deadline). Here, sex, age and socioeconomic status (SES) were modeled as covariates of no interest. As the National Bureau of Statistics (China) issued (*https://www.stats.gov.cn/sj/tjbz/gjtjbz/*), on the basis of per capita annual household income, the SES was divided into seven hierarchical tiers from 1 (poor) to 7 (rich). To obviate subjective rating bias stemming from individual daily mood, we separately measured participants' daily emotional fluctuation at 10:00 and 16:00 using a self-rating visual analog item (i.e., "How do feel for your mood today?", 0 for "completely uncomfortable" and 100 for "definitely happy"). By doing so, the averaged score of those self-rating emotions at the two time points was modeled into the GLMM as covariate of no interests, yielding the final expression of "outcome ~ Group*Treatment_Day + Age + Gender + SES + Emotions + (1 + Treatment_Day | SubjectID)" in the statistical model". This analysis was implemented using the "lme4" and "lmerTest" packages. Employing "emmeans" package, simple effects were also tested at baseline and post-last-intervention using Tukey-adjusted pairwise comparisons of estimated marginal means from the full GLMM, controlling for covariates and random-effects structure. To validate statistical robustness, instead of continuous outcomes for parametric tests, we also conducted a between-group comparison for the number of tasks that procrastination emerges by using the nonparametric x^2 test with ϕ correction or Fisher exact test. Regarding the 6-month follow-up investigation, this GLMM was also built to examine the long-term retention of neuromodulation on reducing actual procrastination."

> *The preregistration and ecological design (ESM) are commendable, but I was not able the find the preregistration, as reported in the paper.*

We are sorry to encounter a serious technical barrier that has rendered our preregistration invisible and inaccessible. The OSF has disabled my OSF account, as it claimed to detect "suspicious user's activities" in my account. This has prevented access to all materials deposited in this OSF account, including this preregistration. We have contacted the OSF team, but received no valid technical solution to recover this preregistered report (please see the screenshot below). We reckon that this may be due to my affiliation change to the Third Military Medical University of People's Liberation Army (PLA).

To address this unexpected circumstance and to ensure transparency, we have explicitly reported this case in the main text, and added the "Reconstructed Preregistration Statement" to the Supplemental Materials (SM). Also, as it has been out of best practices in preregistration, in addition to transparently reporting this case, we have removed this statement regarding preregistration elsewhere throughout the revised manuscript.

> *Overall, the paper requires substantial clarification and tightening.*

We are grateful for your evaluation, and we fully agree with you. In response, we have added a tremendous number of details to clarify how to measure procrastination, how to conduct the statistical analyses, and how to collect real-life tasks, as well as other experimental materials. Please see the revisions in the Methods section of the revised manuscript. Again, thank you for those helpful suggestions.

> ***Recommendations for the authors:***
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> ***Reviewer #1 (Recommendations for the authors):***
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> *(1) In the Supplemental Materials, page 4, lines 163 to 167 seem to be from a different manuscript (as the section talks about neural markers, significant clusters, and brain networks).*

We are sorry for erroneously embedding this irrelevant section here. We have removed it, and have double-checked the document to avoid such mistakes.

> *(2) I'm no expert here, but some of the trace and density plots in the SOM look problematic (e.g., Figure S5 top panel). But it's not made clear to which model/analysis these plots belong, so they are not very helpful without that information.*

Thank you for bringing these potentially problematic plots to our attention. Following your great suggestion, these results have been removed from the SM to amplify readability and comprehensibility.

> *(3) Table S1 reports side effects "from the neurostimulation" (this is also the language used in the main manuscript), but having the flu is rather unlikely to be a side effect from the stimulation, isn't it? Thus, this language is highly confusing, and when reading the main text, it's not clear that these are just life events that are most likely unrelated to the stimulation, but have the potential to affect the measured variables (i.e., ultimately, they seem a source of noise).*

We apologize for this confusing wording. Here, the "side effects" are defined as confounding effects deriving from unexpected life events that uncontrollably disrupt task execution and task performance, such as "having the flu", or "an unexpected mandatory CCP (Communist Party of China) meeting assignment". To obviate misunderstanding, we have rephrased "side effects" as "unexpected life events disrupting task execution" in both the main text and the SM section both.

> *(4) The use of the English language could be improved.*

Thank you for your very practical suggestion. As you kindly suggested, we have invited a proofreading editor to edit and polish the English of the revised manuscript.

> ***Reviewer #2 (Recommendations for the authors):***
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> *(1) It would be helpful to include greater detail about the ESM procedure and details of the self-reported tasks. This would help rule out potential confounds of difficulty or learning (e.g., participants may have learned to identify more achievable and less difficult tasks across the sessions, which would mean they are learning to perform the task better rather than to procrastinate less). Further elaboration on the quantification of procrastination measures would help clarify the mechanism underlying this behavior, which is important for clarifying how these effects arise and what aspect of procrastination behavior is being targeted by the tDCS intervention (and rule of alternative explanations).*

We wholeheartedly appreciate your sharing this very crucial recommendation. As we mentioned above, we fully followed your helpful suggestions, particularly by adding massive details to fully report how to collect real-life tasks (with consistent and plausible difficulty across sessions), how to determine sampling time points, and how to quantify metrics (e.g., subjective procrastination willingness score, objective procrastination rate, AUC of task aversiveness, and task outcome value) to the revised manuscript. We do believe that these revisions and clarifications are imperative and necessary. By including these details, we do believe that the readability and clarity have been substantially improved in the current form. Please see the specific revisions and clarifications above.

> *(2) It would be helpful to proofread for grammatical and spelling typos (e.g., DLPFC is spelled incorrectly in line 140, Satterwaite is spelled incorrectly in Line 415).*

Thank you for your kind suggestion. Both spelling typos have been corrected, and we have double-checked the revised manuscript to ensure no such typos remain. As you kindly suggested, we have invited a proofreading editor to edit and polish the English of the revised manuscript.

> *(3) Please clarify in Figure 4 that a higher AUC is associated with lower task aversiveness (which is stated in the methods but not clearly in the figure).*

Many thanks to you for your helpful suggestion. As you kindly suggested, we have clarified this case in the figure legend.

> ***Reviewer #3 (Recommendations for the authors):***
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> *I want to see the preregistration.*

Thank you for your helpful recommendation. As we replied above, a serious technical issue on OSF occurred, making our preregistration invisible and inaccessible. OSF has disabled my account, claiming to detect "suspicious user's activities" in my account. As a result, there is no access to all materials that were already deposited in this OSF account, including this preregistration. We have reconstructed this preregistration based on archived documents, and reported it in the SM. As we reported above, although this partially addresses the problem, it no longer fulfills the best practices of preregistration. Consequently, in addition to transparently reporting this case, we have removed all the preregistration statements throughout the revised manuscript.

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