Acta Psychologica 260 (2025) 105710

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

The role of the medial prefrontal cortex in risk and time preferences: A tDCS study

Chao Liu [a], Hongzhen Lei [a], Yuzhen Li [b,*], Wanjun Zheng [b], Fan Li [c]

[a] School of International Business, Shaanxi Normal University, Shaanxi, 710019, China
[b] School of Economics, Center for Economic Behavior and Decision-Making (CEBD), Zhejiang University of Finance and Economics, Zhejiang, 310018, China
[c] School of Economics & Management, Xidian University, Shaanxi, 710126, China

ARTICLE INFO

Keywords:
Medial prefrontal cortex
Risk preference
Time preference
Transcranial direct current stimulation

ABSTRACT

Risk and time preferences are fundamental determinants of economic decision making. Although medial prefrontal cortex (mPFC) activity has been associated with valuation across these domains, causal evidence that focal mPFC perturbation alters both risky and intertemporal choices remains limited. In this research, we applied anodal, cathodal, or sham transcranial direct current stimulation (tDCS) to mPFC and administered a battery of risky lotteries and a Convex Time Budget task that jointly elicits risk and intertemporal trade-offs. Our results indicate that individuals who received cathodal stimulation were more likely to choose safe lotteries and to allocate their tokens to an earlier date rather than future dates; these effects were statistically reliable in nonparametric tests and remained evident after covariate adjustment. This co-modulation of both preferences following mPFC perturbation provides causal evidence that the mPFC supports a shared valuation component and can co-modulate both risky and delayed choices. Our findings clarify the mPFC's specific causal role within the broader neural circuitry governing economic preferences.

1. Introduction

Risk and time preferences are fundamental to decision-making, influencing outcomes across economic growth, health, and education (Dohmen et al., 2010; Epper et al., 2020; Golsteyn et al., 2014). Risk preference denotes an individual's attitude toward uncertain monetary outcomes — specifically, the extent to which the individual accepts or avoids variability in payoffs, potentially trading expected value for certainty. Time preference refers to an individual's systematic way of trading off payoffs at different points in time—that is, the degree to which a person values an amount of money received today versus the same amount received in the future (Andreoni et al., 2015). It captures how patient or impatient someone is when choosing between sooner and later rewards, and underlies the behavioral tendency to discount future benefits relative to immediate ones (Andreoni & Sprenger, 2012b). Given their critical role in shaping long-term goals—such as capital accumulation, technological progress, and economic development—these preferences have become a focal point of interdisciplinary research, bridging economics, psychology, and neuroscience.

The behavioral economics literature has suggested links between risk and time preferences, although empirical evidence is mixed (Clot et al., 2017; Dohmen et al., 2012). For instance, Clot et al. (2017) found that farmers exhibiting greater impatience (steeper discounting) also displayed stronger risk aversion, possibly due to a common aversion to uncertainty: impatient individuals overweight the uncertainty of future payoffs, avoiding both delayed and risky options. Other work finds that any association emerges only under particular task framings or samples (Spaniol et al., 2019) and several studies report little or no correlation between the two preferences (Ohmura et al., 2005; Peters & Buchel, 2009; Weber & Huettel, 2008). In addition, both preferences have been linked to cognitive ability in some datasets—people with lower cognitive ability tend to take fewer risks and show greater impatience (Dohmen et al., 2010; Falk et al., 2018) —though these findings are not consistently replicated (Benjamin et al., 2013). These inconsistent findings highlight the need for research linking these preferences to neural mechanisms.

The medial prefrontal cortex (mPFC) plays a central role in value computation across decision-making domains (Bartra et al., 2013; Kable & Glimcher, 2007). Neuroimaging studies consistently show that mPFC activity tracks subjective value across intertemporal and risky choices,

* Corresponding author at: School of Economics, Center for Economic Behavior and Decision-making (CEBD), Zhejiang University of Finance and Economics, Hangzhou, China.
E-mail address: yuzhenl@zufe.edu.cn (Y. Li).

https://doi.org/10.1016/j.actpsy.2025.105710
Received 9 May 2025; Received in revised form 15 August 2025; Accepted 1 October 2025
Available online 9 October 2025

supporting its domain-general role in valuation (Boorman et al., 2013; Clithero & Rangel, 2014; McClure et al., 2007; Peters & Buchel, 2011; Seaman et al., 2018). Meta-analyses confirm that the ventromedial prefrontal cortex (vmPFC) encodes subjective value in both domains, while the dorsolateral prefrontal cortex (dlPFC) contributes in a more lateralized manner: the left dlPFC supports self-control in delaying gratification (Hare et al., 2009; Hare et al., 2014), whereas the right dlPFC modulates risk evaluation and ambiguity tolerance (Fecteau et al., 2007; Knoch et al., 2006). These hemispheric distinctions reinforce the functional specificity within prefrontal circuits and contextualize our focus on the mPFC.

Lesion and fMRI studies offer converging but incomplete evidence. Patients with mPFC lesions exhibit steeper temporal discounting and increased impulsivity (Peters & D'Esposito, 2016; Sellitto et al., 2010), consistent with findings that reduced mPFC activation predicts greater impatience, whereas greater activation correlates with future-oriented behavior (Hare et al., 2014). However, when both preferences are examined simultaneously, results diverge: some studies report that mPFC lesions increase impatience but also risk tolerance (Mok et al., 2021; Peters & D'Esposito, 2020). These inconsistencies may stem from methodological limitations, such as not controlling for one preference when measuring the other. To address this, Andreoni and Sprenger (2012a) developed the Convex Time Budget (CTB) method, which jointly measures risk and time preferences within a single framework, reducing estimation bias (Augenblick et al., 2015; Giné et al., 2018).

To move beyond correlational evidence and establish causal links between prefrontal activity and preference expression (Cacioppo et al., 2003), we use transcranial direct current stimulation (tDCS) to modulate activity in mPFC prior to decision-making tasks. tDCS is a noninvasive brain stimulation method that provides a safe, low-cost, and long-lasting means of modulating brain activity (Coffman et al., 2014; Reinhart et al., 2016). This technology can regulate the activity of specific cortical areas, enabling causal manipulation of the target region (Reinhart et al., 2016; Reinhart & Woodman, 2014). Previous studies have demonstrated that anodal (cathodal) stimulation generally enhances (reduces) cortical excitability, thereby influencing participants' brain functions (Nitsche & Paulus, 2000). The tDCS technique is now widely used in the field of research on the neural mechanisms underlying individual decision-making behavior and has become one of the key research tools in cognitive science and neuroeconomics (Reinhart et al., 2016; Reinhart & Woodman, 2014; Wang & Li, 2022).

In this study we experimentally manipulated mPFC excitability using transcranial direct current stimulation (tDCS) prior to a sequence of decision-making tasks. Participants first completed two separate binary-choice batteries—one probing gain-domain risk attitudes (10 Holt–Laury items) and one probing loss-frame choices (7 items)—and then completed a 25-item Convex Time Budget (CTB) protocol in which they allocated tokens between sooner and later dates. The CTB provides joint, within-task elicitation of risk and intertemporal trade-offs. Our contribution is twofold. Methodologically, to our knowledge this is the first study to combine CTB-based joint elicitation with focal prefrontal neuromodulation, which reduces estimation bias associated with isolated paradigms and permits a direct, within-sample comparison of measures obtained separately and jointly. Substantively, we ask whether experimentally decreasing or increasing mPFC excitability causally alters observed risk and time preference measures and cognitive performance. Our primary objectives are therefore: (i) to determine whether mPFC stimulation causally affects individuals' risk preferences, time preferences, and task performance; (ii) to assess whether any observed pattern of effects is compatible with mPFC supporting a component process shared across the two preference domains.

2. Materials and methods

2.1. Participants

We recruited 137 participants, with 126 (65 females, age range 17–27, M = 20.39, SD = 1.97) included in the final analysis. Six individuals did not complete the experiment because of machine malfunction, and five individuals never altered their decision from a specific corner solution for all CTBs and thus provided insufficient variation for the calculation of utility parameters. Sample size was determined based on previous neurostimulation studies of risk and time preference (Xiong et al., 2019). A sensitivity analysis using G*Power (Faul et al., 2007) indicated that 96 participants would yield 80 % power to detect a medium effect at α = 0.05. No participant had prior knowledge of the experimental tasks or tDCS.

2.2. Experimental tasks

The study used behavioral experimental games to assess the subjects' behavioral tendencies in three dimensions: risk aversion, loss aversion, and time preferences. The time preference dimension can distinguish the degree of individual patience, for example, those with high patience tend to delay gratification while those with low patience focus more on immediate returns (Fig. 1).

2.2.1. Risk aversion

The experimental task is based on that of (Holt & Laury, 2002), which measures an individual's attitude toward risk within a gain framework. Each participant is asked to complete 10 binary-choice questions in Table 1. In question 1, lottery A is more profitable than lottery B. As one moves down the series, the relative returns of lottery B gradually rise. Among them, the expected return of lottery A in questions 1–4 is higher, and the expected return of lottery B in questions 5–9 is higher. Participants with higher risk aversion are expected to prefer lottery A more than those who are less risk averse.

Participants' risk aversion is determined using the number of lottery A options they choose. Following the methodology of (Holt & Laury, 2002), we assume the following form of the utility function:

$$U_{(x)} = \frac{x^{1-\rho}}{1-\rho} \tag{1}$$

The Holt & Laury risk aversion parameter ρ can be measured through the subject's decision-making behavior. This coefficient quantitatively represents the individual's degree of risk aversion — a higher ρ value indicates that the subject is more risk-averse (Holt & Laury, 2002).

2.2.2. Loss aversion

This task is used to measure individuals' attitudes toward risk in a loss framework. The participants were asked to make a binary choice, with the possibility of losing some money in both options (see Table 2). Each of the two options in each question has a 50 % chance of winning and a 50 % chance of losing money. In question 1, the expected return of lottery A is higher than that of lottery B. As one moves down the series, the relative gain of lottery B gradually increases. In questions 1–3, lottery A has a higher expected return. In question 4, lotteries A and B have the same expected return. In questions 5–7, Lottery B has a higher expected return. Since the amount of loss in lottery A is lower than that in lottery B, loss-averse people are more likely to prefer lottery A. Furthermore, the degree of individual loss aversion can be estimated according to the number of subjects choosing lottery A.

Following Liu (2013) and Tanaka et al. (2010), we assume that the utility functional form is:

$$U_{(x)} = \frac{x^{1-\rho}}{1-\rho} \text{ if } x \geq 0 \text{ and } U_{(x)} = -\lambda^* \frac{(-x)^{1-\rho}}{1-\rho} \text{ if } x < 0 \tag{2}$$

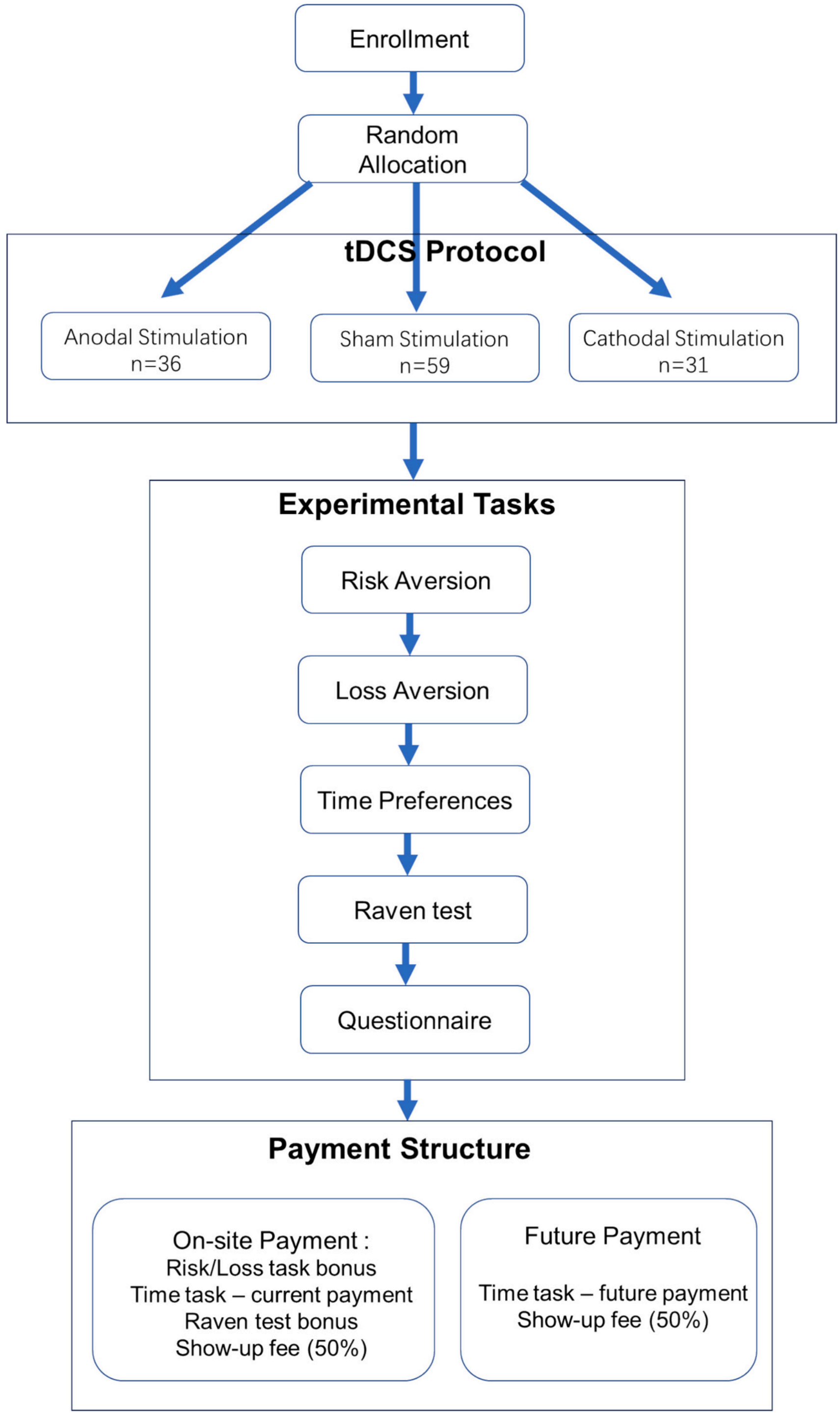

Fig. 1. Design of the experiment.

where choices in the risk-aversion and loss-aversion tasks permit joint estimation of the relative risk aversion parameter ρ and the loss aversion coefficient λ. Since standard expected utility is nested in eq. 2, failure to reject the null hypothesis $\lambda = 1$ implies no evidence of loss aversion.

2.2.3. *Time preferences*

It may seem straightforward to use an experimental approach to simultaneously elicit risk and time preferences, but there is no consensus on the best approach. One approach is to use a double multiplex price list (DMPL); subjects made trade-offs between a smaller sooner reward and a larger later reward (Andersen et al., 2006, 2008; Harrison et al., 2002; Reuben et al., 2010; Tanaka et al., 2010). However, the DMPL always requires the players to choose between a smaller, earlier payment, X, and a larger, later payment, Y; that is, subjects are effectively restricted to the corner solutions in (sooner, later) space, $(\mathrm{X}, 0)$ and $(0, \mathrm{Y})$, but when the utility function is not linear, the optimal choice does not always occur between the two corner solutions (Andreoni & Sprenger, 2015). The other is using the CTB method developed by Andreoni and Sprenger (2012a). This method adds some interior solution options (x_1, x_2) between the corner solutions $(\mathrm{X}, 0)$ and $(0, \mathrm{Y})$ of each row. The basic design of CTB is that subjects continuously allocate a certain amount of money between earlier and later dates based on a

Table 1
Risk aversion experiment.

	Lottery A	Lottery B	Differences in Expected Payoff (A-B)
1	10 %: Gain 200 tokens; 90 %: Gain 160 tokens;	10 %: Gain 385 tokens; 90 %: Gain 10 tokens;	116.5
2	20 %: Gain 200 tokens; 80 %: Gain 160 tokens;	20 %: Gain 385 tokens; 80 %: Gain 10 tokens;	83
3	30 %: Gain 200 tokens; 70 %: Gain 160 tokens;	30 %: Gain 385 tokens; 70 %: Gain 10 tokens;	49.5
4	40 %: Gain 200 tokens; 60 %: Gain 160 tokens;	40 %: Gain 385 tokens; 60 %: Gain 10 tokens;	16
5	50 %: Gain 200 tokens; 50 %: Gain 160 tokens;	50 %: Gain 385 tokens; 50 %: Gain 10 tokens;	−17.5
6	60 %: Gain 200 tokens; 40 %: Gain 160 tokens;	60 %: Gain 385 tokens; 40 %: Gain 10 tokens;	−51
7	70 %: Gain 200 tokens; 30 %: Gain 160 tokens;	70 %: Gain 385 tokens; 30 %: Gain 10 tokens;	−84.5
8	80 %: Gain 200 tokens; 20 %: Gain 160 tokens;	80 %: Gain 385 tokens; 20 %: Gain 10 tokens;	−118
9	90 %: Gain 200 tokens; 10 %: Gain 160 tokens;	90 %: Gain 385 tokens; 10 %: Gain 10 tokens;	−151.5
10	100 %: Gain 200 tokens;	100 %: Gain 385 tokens;	−185

Table 2
Loss aversion experiment.

	Lottery A	Lottery B	Differences in Expected Payoff (A-B)
11	50 %: Gain 60 tokens; 50 %: Lose 35 tokens;	50 %: Gain 75 tokens; 50 %: Lose 65 tokens;	7.5
12	50 %: Gain 55 tokens; 50 %: Lose 35 tokens;	50 %: Gain 75 tokens; 50 %: Lose 65 tokens;	5
13	50 %: Gain 50 tokens; 50 %: Lose 35 tokens;	50 %: Gain 75 tokens; 50 %: Lose 65 tokens;	2.5
14	50 %: Gain 45 tokens; 50 %: Lose 35 tokens;	50 %: Gain 75 tokens; 50 %: Lose 65 tokens;	0
15	50 %: Gain 40 tokens; 50 %: Lose 35 tokens;	50 %: Gain 75 tokens; 50 %: Lose 50 tokens;	−10
16	50 %: Gain 40 tokens; 50 %: Lose 35 tokens;	50 %: Gain 75 tokens; 50 %: Lose 45 tokens;	−12.5
17	50 %: Gain 35 tokens; 50 %: Lose 35 tokens;	50 %: Gain 75 tokens; 50 %: Lose 40 tokens;	−17.5

budget constraint line, and the extent of risk aversion and discount rate are measured by adjusting the distribution of the amount of money at different points in time. Andreoni and Sprenger (2015)compared the predictive validity of the two methods and found that they both perform equally well within samples, but the CTB significantly outperforms the DMPL on out-of-sample measures. The CTB method has been used in a series of papers and in various contexts (Augenblick et al., 2015; Giné et al., 2018). Given this premise, combined with the consideration of controlling for risk preferences, we applied CTB in this study.

Each subject is given 300 tokens (m), distributed between time C_t and C_{t+h} , with varying interest rates r over these h periods. Here t indicates the sooner dates, i.e., t = today, 4 weeks or 8 weeks later; h is the delay time (h = 4 weeks, 8 weeks or 12 weeks later). C_t and C_{t+h} represent the monetary allocations to the sooner and later date, respectively. The interest rate r is set at 5 % to 25 %, and C_{t+h} includes the rates of return (see Table 3). For example, allocating x tokens to time t means that the subject will receive x tokens at time t and receive $(300 - x)*(1+r)$ tokens at time $t+h$. For a given rate, more impatient participants (preferring the present to the future) generally allocated more tokens to earlier payment dates.

To facilitate comparison with the HL method, the CTB is assumed to follow the same utility function form (constant relative risk aversion, CRRA):

$$u = \frac{c_t^{1-\alpha} - 1}{1-\alpha} \tag{3}$$

Following Andreoni and Sprenger (2012a), the utility function and corresponding budget constraints can be written as follows:

$$U = u(c_t) + \beta\delta u(c_{t+k}) \tag{4}$$

$$\text{S.t.}(1+r)c_t + c_{t+k} = m \tag{5}$$

where α is the extent of risk aversion (based on the CTB model); the higher the value of α is, the more risk averse the participants are. β represents the present bias or future bias ($\beta > 0$); if $\beta < 1$, present bias exists; if $\beta > 1$, future bias exists; and if $\beta = 1$, there is no evidence of present bias. δ is the discount factor, and a higher δ indicates that a participant is more patient and better able to delay gratification.

The marginal condition of maximizing an individual's utility can be written as follows:

Table 3
Choices for convex time budget task.

	Game	Interest Rate	Sooner Date	Later Date
choice set 1	1	5 %	today	4 weeks
	2	10 %	today	4 weeks
	3	15 %	today	4 weeks
	4	20 %	today	4 weeks
	5	25 %	today	4 weeks
choice set 2	6	5 %	today	8 weeks
	7	10 %	today	8 weeks
	8	15 %	today	8 weeks
	9	20 %	today	8 weeks
	10	25 %	today	8 weeks
choice set 3	11	5 %	today	12 weeks
	12	10 %	today	12 weeks
	13	15 %	today	12 weeks
	14	20 %	today	12 weeks
	15	25 %	today	12 weeks
choice set 4	16	5 %	4 weeks	8 weeks
	17	10 %	4 weeks	8 weeks
	18	15 %	4 weeks	8 weeks
	19	20 %	4 weeks	8 weeks
	20	25 %	4 weeks	8 weeks
choice set 5	21	5 %	8 weeks	12 weeks
	22	10 %	8 weeks	12 weeks
	23	15 %	8 weeks	12 weeks
	24	20 %	8 weeks	12 weeks
	25	25 %	8 weeks	12 weeks

$$exp(-(\alpha-1)(c_t-c_{t+h})) = \begin{Bmatrix} \beta\delta^k(1+r) & t=0 \\ \delta^k(1+r) & t>0 \end{Bmatrix} \tag{6}$$

Eq. (6) can be rearranged as:

$$c_t - c_{t+h} = -\frac{ln\beta}{\alpha-1}P - \frac{ln\delta}{\alpha-1}h - \frac{1}{\alpha-1}ln(1+r) \tag{7}$$

where P is a dummy variable; when $t = 0$, it equals one. The model is reduced to:

$$(c_t - c_{t+h})_{ik} = -\frac{ln\beta}{\alpha-1}P - \frac{ln\delta}{\alpha-1}h - \frac{1}{\alpha-1}ln(1+r) + \varepsilon_{ik} \tag{8}$$

where k is the choice situation and ε_{ik} is an additive mean-zero error term. To empirically address the corner observations, following Yang and Carlsson (2021), we relied on a two-limit Tobit model for analysis. The model can be simplified as follows:

$$(c_t - c_{t+h})_{ik} = -\gamma_1 P - \gamma_2 h - \gamma_3 ln(1+r) + \varepsilon_{ik} \tag{9}$$

The parameters we care about can be obtained as follows:

$$\widehat{\alpha} = \frac{1}{\gamma_3} + 1 \quad \widehat{\beta} = exp\left(\frac{\widehat{\gamma_1}}{\widehat{\gamma_3}}\right) \quad \widehat{\delta} = exp\left(\frac{\widehat{\gamma_2}}{\widehat{\gamma_3}}\right) \tag{10}$$

Information we are interested in can be obtained from the allocation scheme. Variations in interest rates, $(1+r)$ and delay interval, h, allow for the identification of CTB risk preference (α) and time preference (δ), for example, game 1–5 or game 6–10. Variations in starting times, t, allow for the identification of present bias (β), for example, games 1–5 vs. games 16–20.

2.3. Procedure

Participants came to the laboratory, and each participant was assigned a seat in a partially enclosed cubicle to privately complete the experiment on a personal computer. Once seated, participants completed control questions to ensure that they understood the task, as illustrated in the Appendix A (control questions), and gave their informed consent before the experiment. Participants then received three different types of stimulation using tDCS separately: anodal (N = 36), sham (N = 59) and cathodal (N = 31) stimulation. As soon as the stimulation was completed, the participants performed three tasks sequentially. The sham stimulation group was presented with two versions of the survey, which differed only in the positioning of temporal questions to detect potential order effects in the time preference experiment (Holt & Laury, 2002; Liu et al., 2014; Tanaka et al., 2010).[1] Within the sham arm, 30 participants completed sequence A (choice sets 1–5) and 29 completed sequence B (choice sets 4,5,1,2,3); after confirming no order effects we pooled them.

Given that risk preference and time preference may be influenced by cognitive abilities (Dohmen et al., 2010; Falk et al., 2018), the participants completed a 60-item Raven's Progressive Matrices test. We selected this measure because it specifically assesses relational reasoning and abstract problem-solving – cognitive processes that share neural substrates (particularly prefrontal regions) with value-based decision making (Eslinger et al., 2009; Gray et al., 2003). The Raven test is also widely regarded as a robust measure of fluid intelligence, a core component of general cognitive ability (Carroll, 1993; Raven, 2000), minimizing verbal bias that could confound results in our educated sample. Thus, the experimental tasks (including the Raven test) consist of a total of 102 questions. Finally, the participants were asked to complete a questionnaire related to risk and time preferences as well as personal information. All the above experiments were performed via z-tree (Fischbacher, 2007) (version 3.5.1).

Participants were also told that their earnings would be comprised of four parts[2]: first, a 20 RMB yuan show-up fee; second, the system would randomly select one item from the risk-averse and loss-averse tasks to make a payment based on the generated random number and the outcome of the participants' decisions; third, the system would also randomly select one item from the time preference task to make a payment based on the allocation plan of the participants; and fourth, earnings from completing the Raven test (proceeding after the three experiments). Earnings are represented in the form of tokens in the experiment, and the experimenter announces the exchange rate between the tokens and the cash at the end of the experiment[3]. Since participants may prefer to receive all of their experimental gains on the day of their participation in the experiment to reduce transaction costs, to avoid this distortion of preferences, we announced at the beginning of the experiment that gains in risk aversion and loss aversion, the Raven test, and half of the show-up fee would be paid immediately after the experiment, while the other half of the show-up fee would be paid into the participants' bank accounts 4 weeks after the experiment. The gains from the time preference task would be remitted to the subjects' bank accounts according to the timing of their decisions. The average gain for the subjects was 77.02 RMB yuan (SD = 6.73).

3. tDCS

In our experiments, we applied tDCS via a battery-driven stimulator (NeuroConn, Ilmenau, Germany) using a double-blind, randomized, sham-controlled design. Participants were randomly assigned to one of three conditions (anodal, cathodal, or sham) through a lottery system drawing sealed envelopes upon arrival. Assignment was concealed from both participants and experimenters. To ensure experimenter blinding, stimulation protocols were prepared and activated by a study technician who did not interact with participants during task administration.

The target area of stimulation was the mPFC. For anodal tDCS, a 3 × 3 cm anode was placed at Fpz, and a 10 × 10 cm cathodal return was placed at Oz (Sellaro et al., 2015; van't Wout-Frank & Philip, 2021) (Fig. 2). For cathodal stimulation, the polarity was reversed. Stimulation was applied at 1.5 mA for 20 min with 30 s ramp-up and 30 s ramp-down. Sham stimulation consisted of the same 30 s ramp-up to 1.5 mA followed by 30 s ramp-down, after which no current was delivered while the participant remained fitted with the electrodes for the remainder of the 20-min period. Previous research has demonstrated the safety and efficacy of these tDCS protocols (Gandiga et al., 2006; Nitsche et al., 2003; Nitsche et al., 2008). After the stimulation was completed, the stimulation devices were removed from the participants' heads, and they proceeded to complete the experimental tasks. Participants were monitored for adverse sensations during and after stimulation, and no serious adverse events were reported. All procedures conformed to the Declaration of Helsinki, and participants provided written informed consent prior to participation; the experimental protocol and consent procedures were approved by the institutional ethics committee.

[1] We intentionally oversampled the sham group—approximately double the size of each active stimulation group—in order to test for potential order effects in our time preference task. The Risk Aversion and Loss Aversion tasks were designed to examine how participants make decisions across systematically varied probability-reward contingencies (Lottery A/B options). Following established protocols (Holt & Laury, 2002; Liu et al., 2014; Tanaka et al., 2010), these options were presented in a fixed sequence, a well-validated experimental control strategy to ensure comparability with foundational studies in reward valuation paradigms.

[2] The complete experimental payment rules can be found in Appendix A: Payment Instructions.

[3] The exchange rate is 0.067 (1 token = 0.067 RMB yuan) for risk aversion, loss aversion and time preference experiment, and 0.4 (1 token = 0.4 RMB yuan) for Raven test. Therefore, their maximum earnings can reach 94.92 RMB yuan.

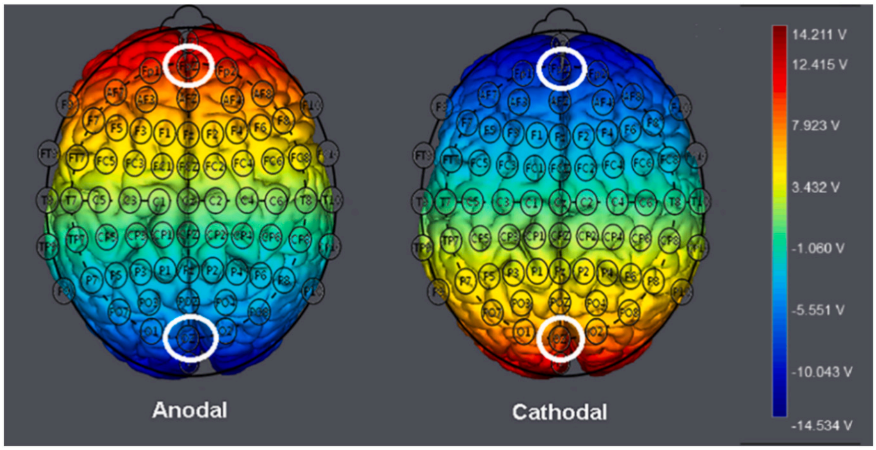

Fig. 2. Electrode placements and stimulation configurations for tDCS. Electrodes were positioned at Fpz and Oz according to the international 10–20 EEG system, and shading indicates input voltages ranging from −14.534 to 14.211 V.

4. Results

Table 4 reports the demographic characteristics and task performance of the participants. Given that no significant differences were observed in demographics or experimental data between the two presentation order subgroups, we report the subgroup results alongside the combined data.

Shapiro–Wilk tests indicated that several key outcome variables (risk and time preferences) departed from normality ($p < 0.05$); therefore, primary between-group comparisons were conducted with nonparametric methods (Kruskal–Wallis tests for $k > 2$ groups), reporting H-statistics, degrees of freedom, p-values and effect sizes ($\varepsilon^2 = (H - k + 1)/(n - k)$). Significant Kruskal–Wallis results were followed by Dunn's pairwise tests with Benjamini–Hochberg correction. To complement these nonparametric comparisons and to adjust for potential confounds, we also estimated multivariate OLS models with heteroskedasticity-robust standard errors; these regressions quantify conditional associations between stimulation condition and preference parameters while controlling for age, gender, education, response time, and an mPFC-insensitive composite score derived from baseline questionnaire items probing relatively stable trait-like attitudes. Analyses were performed in SPSS (v22) and Stata (v15.1).

Balance checks showed no statistically significant baseline differences across stimulation groups in age, gender, education or Raven score. Specifically, Kruskal–Wallis tests yielded: age: $H(2) = 4.201$, $p = 0.122$; gender: $H(2) = 0.424$, $p = 0.809$; education: $H(2) = 4.825$, $p = 0.090$; Cognitive ability (accuracy rate): $H(2) = 1.382$, $p = 0.501$. These results indicate no statistically significant pre-treatment differences between groups.

4.1. Behavioral performance

We first examined the differences among the three stimulation groups in the risk-aversion task. Fig. 3 depicts the cumulative distribution of Lottery A selections, stratified by stimulation type, in the risk aversion paradigm. The distribution of lottery choices of the sham group was distributed to the left of the anodal and cathodal stimulation groups. That is, the sham stimulation group chose fewer lotteries A than the anodal and cathodal stimulation groups. Specifically, for the sham stimulation group, the number of lottery A was 5.186, which was somewhat below the 6.290 found among the cathodal stimulation group (Benjamini-Hochberg adjusted $p = 0.02$), while no significant difference was found between the anodal stimulation group and the sham stimulation group. Thus, based on the number of lotteries A, the cathodal stimulation group was significantly more risk-averse than the sham stimulation group.

Table 4
Participant characteristics and task performance.

	Anodal	Sham	Cathodal
Demographic characteristics			
N	36	59	31
Age	20.417 (2.034)	20.508 (1.924)	19.806 (1.957)
Education[a]	2.694 (1.489)	2.966 (1.924)	2.387 (1.430)
Cognitive ability (accuracy rate)[b]	56.417 (2.719)	56.186 (3.730)	55.387 (4.333)
Cognitive ability (completion time)[c]	1435.580 (323.835)	1478.452 (353.044)	1507.278 (420.716)
Risk aversion task			
Number of lottery A in risk aversion task	5.806 (1.687)	5.186 (2.080)	6.290 (1.847)
Holt–Laury risk aversion (ρ)	0.507 (0.464)	0.326 (0.603)	0.622 (0.519)
Response time in risk aversion task (s)	109.238 (63.929)	79.556 (55.802)	110.683 (89.343)
Loss aversion task			
Number of lottery A in loss aversion task	3.972 (0.845)	3.627 (1.338)	3.839 (1.128)
Loss aversion (λ)	1.502 (0.621)	1.583 (1.358)	1.371 (0.706)
Response time in loss aversion task (s)	59.869 (39.137)	72.032 (44.036)	105.702 (79.843)
Time preference task			
CTB-derived risk aversion (α)	0.9989 (0.001)	0.9986 (0.001)	0.9992 (0.001)
Present bias (β)	1.0004 (0.085)	0.9617 (0.139)	0.9878 (0.058)
Discount factor (δ)	0.9992 (0.002)	1.0000 (0.003)	0.9986 (0.002)
Response time in CTB experiment (s)	257.339 (166.259)	217.471 (146.311)	320.443 (173.164)
Amount allocated to earlier payment	91.211 (79.559)	88.456 (86.249)	88.972 (66.944)
Risk preference[d] (rp)	44.944 (21.652)	49.881 (17.836)	38.387 (19.709)
Time preference[e] (tp)	117.750 (23.418)	122.186 (21.514)	109.645 (21.832)

Notes: a Coding: freshman = 1; sophomore = 2; junior = 3; senior = 4; graduate = 5. b, c The cognitive ability variable captures both the number of correctly solved Raven matrices and the time taken by the individual to complete them. d, e Risk preference and time preference are the sum of the positive responses to questions on the self-assessment of risk and time attitude. The figures presented in the table represent the average values, with standard deviations indicated in parentheses.

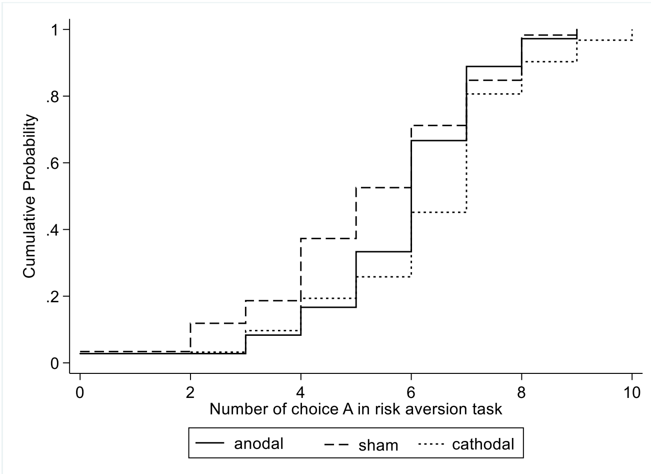

Fig. 3. Cumulative distribution of lottery a in the risk aversion task by three stimulation conditions.

Fig. 4 Depicts the distribution of lottery a (low-loss option) selections across the three stimulation groups in the loss aversion task.

Table 5 summarizes choices in the time preferences task across varying interest rates for five decision scenarios: immediate versus 4-week delay (row 1), immediate versus 8-week delay (row 2), immediate versus 12-week delay (row 3), 4-week versus 8-week delay (row 4), and 8-week versus 12-week delay (row 5). Notably, as interest rates rose, the proportion of tokens allocated to the earlier date declined.

The correlation coefficients between cognitive ability, measured by Raven's test accuracy, and risk preference (α) and time preference (δ) were 0.065 ($p > 0.05$) and 0.010 ($p > 0.05$), respectively. Similarly, the correlation coefficients between cognitive ability, assessed through Raven's test completion time, and risk preference (α) and time preference (δ) were 0.041 ($p > 0.05$) and − 0.055 ($p > 0.05$), respectively. These results indicate no significant association between individual cognitive ability and time/risk preferences.

4.2. Influence of stimulation

Figs. 5–7 display each participant's parameter estimate as jittered points overlaid on group boxplots; group means are marked by yellow diamonds.

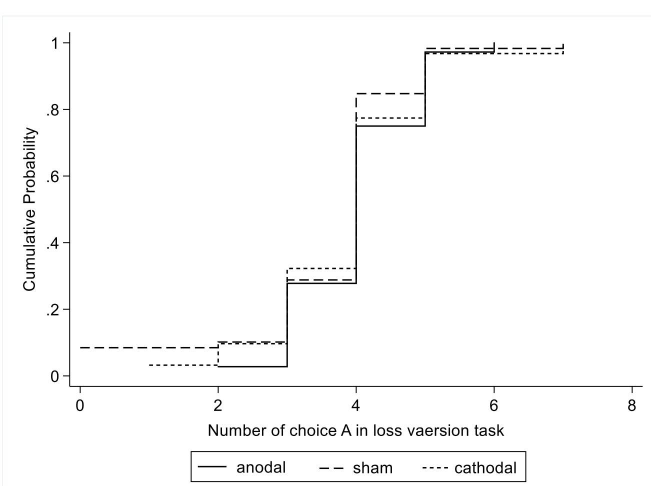

Fig. 4. Cumulative distribution of lottery a in the loss aversion task by three stimulation conditions.

Table 5
Tokens allocated to earlier payment stratified by interest rates.

	Amount allocated to earlier payment					p
	(1) 5 %	(2) 10 %	(3) 15 %	(4) 20 %	(5) 25 %	
(1) Today, vs. 4 weeks	131.683	103.103	70.952	34.397	18.556	$p < 0.001$
Today, vs. 8 weeks	160.294	129.095	100.151	64.016	43.214	$p < 0.001$
Today, vs. 12 weeks	169.937	147.357	108.778	74.444	61.421	$p < 0.001$
4 weeks vs. 8 weeks	132.048	106.167	76.992	50.556	37.056	$p < 0.001$
8 weeks vs. 12 weeks	128.627	106.286	81.119	58.016	39.992	$p < 0.001$

The p-value reflects the statistical significance of between-group differences as determined by the Kruskal-Wallis test.

4.2.1. *Time preference (discount factor δ)*

A Kruskal–Wallis test confirmed a significant group effect on the discount factor ($H(2) = 11.74$, $p = 0.003$, $\varepsilon^2 = 0.08$), indicating a moderate effect of stimulation on time preference. Post-hoc pairwise comparisons (Benjamini–Hochberg–adjusted) showed that the cathodal group ($N = 31$; mean $\delta = 0.9986$) had significantly lower δ than both the anodal group ($N = 36$; mean $\delta = 0.9992$; $p = 0.044$) and the sham group ($N = 59$; mean $\delta = 1.0000$; $p = 0.001$), whereas anodal and sham did not differ ($p > 0.05$). As for the individual datapoints, 25 of 31 participants in the cathodal arm (78 %) exhibited discount factors below the overall sham mean, indicating a robust shift toward impatience under cathodal stimulation.

4.2.2. *Risk preference (CTB α and HL ρ)*

For the CTB-derived risk parameter α, the Kruskal–Wallis test again revealed a significant effect ($H(2) = 7.013$, $p = 0.03$, $\varepsilon^2 = 0.04$), indicating a small effect. In post-hoc tests (Benjamini–Hochberg–adjusted), the cathodal group (mean $\alpha = 0.9992$) showed higher risk-aversion parameters than the sham group (mean $\alpha = 0.9986$; $p = 0.014$), while anodal vs. cathodal and anodal vs. sham were non-significant (both $p > 0.05$). At the individual level, 27 of 31 cathodal-stimulated participants (87 %) had α values exceeding the sham mean, demonstrating a majority effect. Consistent with this finding, the Holt–Laury risk-aversion coefficient ρ was highest in the cathodal group (cathodal = 0.622; anodal = 0.507; sham = 0.326). A Kruskal–Wallis test indicated a group effect ($p = 0.039$), and BH-adjusted pairwise comparisons found cathodal > sham ($p = 0.02$), while other contrasts were not significant.

4.2.3. *Loss aversion (λ)*

The loss-aversion parameter λ, estimated from the loss-frame lottery task. A Kruskal–Wallis test found no significant difference across stimulation groups ($H(2) = 1.399$, $p = 0.497$). Group means (SD) were 1.502 (0.621) for the anodal group, 1.583 (1.358) for the sham group, and 1.371 (0.706) for the cathodal group (see Table 4). Post-hoc pairwise comparisons with Benjamini–Hochberg correction did not reveal any significant contrasts between groups (all BH-adjusted $p > 0.05$). Thus, within the sensitivity of our loss-frame lottery, tDCS of mPFC did not produce measurable changes in loss aversion. Results were unchanged when controlling for age, gender and education in OLS regressions (all stimulation coefficients $p > 0.1$). Because loss aversion and risk aversion are often assessed jointly in many behavioral paradigms; we report this null result here for completeness and transparency.

The response times of the participants receiving cathodal stimulation were longer than those of the anodal and sham stimulation groups in the time preference tasks (cathodal vs. anodal: 320.443 s vs. 257.339 s, BH-adjusted $p = 0.05$; cathodal vs. sham: 320.443 s vs. 217.471 s, BH-adjusted $p = 0.003$; anodal vs. sham: 257.339 s vs. 217.471 s, $p >$

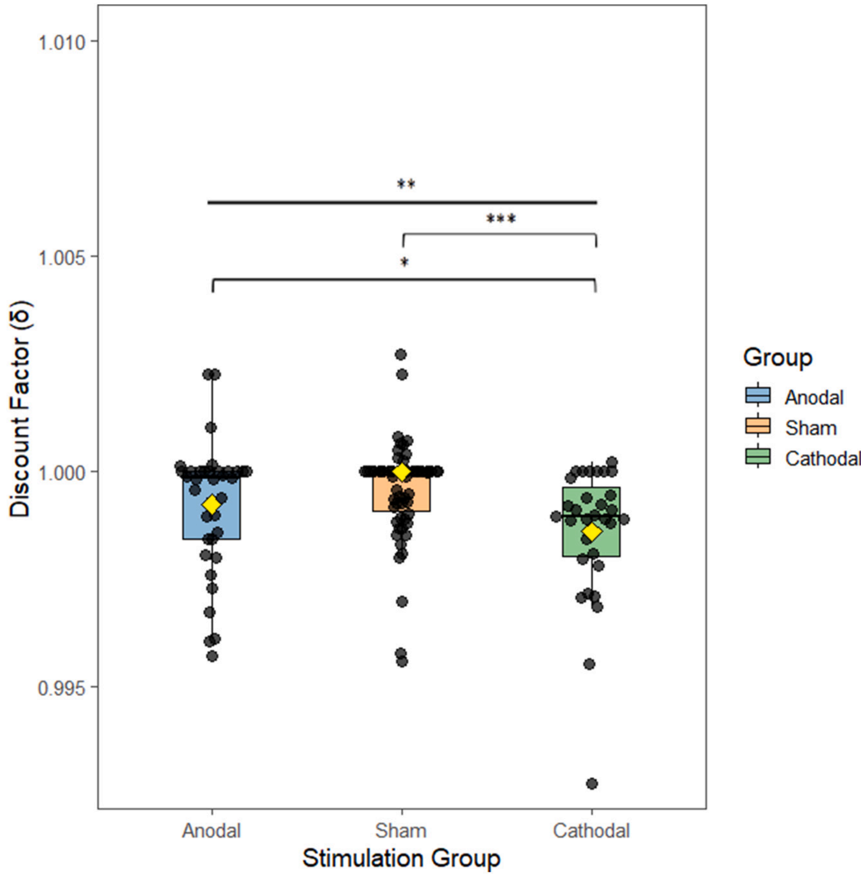

Fig. 5. tDCS on discount factor (δ) by three stimulation conditions. The jittered points in the figure display each participant's parameter estimate, overlaid on the group boxplots, with the group means marked by yellow diamonds. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

0.05; Fig. 8). The anodal stimulation group took 109.238 s (SD = 63.929) in the risk aversion task, which was significantly higher than that of the sham stimulation group (BH-adjusted $p = 0.016$; Fig. 9). Because response time differences can reflect changes in decision processing time, we tested whether response time differences could help account for the stimulation effects on choice parameters (in 4.2.4 Econometric regression).

4.2.4. *Econometric regression*

We estimated OLS regressions with robust standard errors to further quantify the stimulation effects while controlling for demographic covariates and response time. Tables 6–7 summarize the results of the preference parameter estimates derived from the tasks.

Table 6 summarizes the OLS regression estimates with the coefficient of risk preference (α) measured in the CTB experiment as the dependent variable, and stimulation types (reference: sham) were used as explanatory variables. The coefficient of cathodal stimulation is 0.593, which is significant at the 1 % level (column (1)). Various factors, including age, gender and education, were gradually added to the model, and the results remained robust (column (3)). Using the coefficient of risk aversion (ρ) measured in the risk aversion experiment as a proxy for risk preference, the above conclusions remain unchanged (column (5)). The regressions support our conjecture that the participants in the cathodal stimulation group were less risk tolerant than those in the sham stimulation group. Although education is known to significantly influence risk preferences (e.g., Liu, 2013; Tanaka et al., 2010), our sample of predominantly well-educated students may have hindered the examination of this variable.

Table 7 summarizes the OLS estimates with time preference, δ, as the dependent variable, and stimulation types (reference: sham) were used as explanatory variables. The results showed that cathodal stimulation increased impatience (−1.392, $p = 0.019$). The results remained robust after controlling for demographic variables (e.g., gender, age and, education column (3)). The regressions support our conjecture that the participants in the cathodal stimulation group were less patient than those in the sham stimulation group.

Some studies in psycho-economics and behavioral economics have argued that there are similarities and connections between risk and time preferences (Bartoš et al., 2021; Clot et al., 2017; Yang & Carlsson, 2021). To eliminate the possibility of a chain reaction in which mPFC stimulation leads to a change in one preference and subsequently to a change in another, we estimated risk preference (α) and time preference (δ) using only the CTB method. Specifically, we added the coefficient of risk preference (α) to the model as an explanatory variable (column (4)), and the coefficient of α is −374.4, significant at the 5 % level, indicating that individuals who are more risk tolerant are more impatient. The coefficient of cathodal stimulation varied slightly, but the direction remained the same; thus, the conclusion that cathodal stimulation leads to greater impatience remained robust after controlling for risk factors.

To assess whether these response time differences drive our main findings on risk and time preference, we re-estimated the OLS models including each participant's average response time as an additional predictor (see Tables 6 and 7). In the risk-aversion model (Table 6, column (4)), cathodal stimulation remained a significant positive predictor of α ($\beta = 0.566$, $t = 2.29$, $p = 0.024$), even after controlling for response time ($\beta\_RT = -0.0003$, $t = -0.22$, $p = 0.828$). Likewise, in the temporal-discounting model (Table 7, column (5)), cathodal tDCS still significantly increased impatience (i.e. reduced δ; $\beta = -1.230$, $t = -2.45$, $p = 0.016$), while response time per se did not reach significance ($\beta\_RT = -0.002$, $t = -1.96$, $p = 0.052$). Including response time

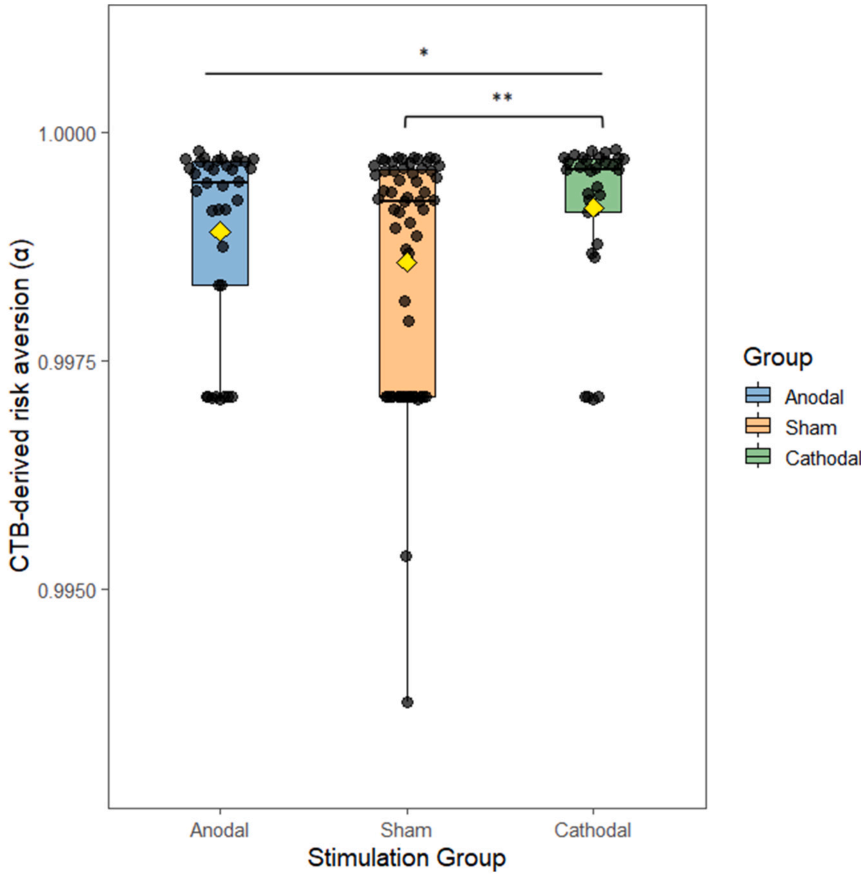

Fig. 6. tDCS on CTB-derived risk aversion (α) by three stimulation conditions. The jittered points in the figure display each participant's parameter estimate, overlaid on the group boxplots, with the group means marked by yellow diamonds. *$p < 0.05$, **$p < 0.01$.

improved model fit modestly (risk model R^2 from 0.059 → 0.059; time model R^2 from 0.076 → 0.089), indicating that although stimulation–RT effects are robust, response time differences do not statistically mediate the effect of tDCS on choice parameters. By expanding our analyses to include response time as both an outcome and covariate, we demonstrate that tDCS-induced shifts in α and δ are not mere artifacts of decision-slowing, but reflect genuine modulation of valuation processes in the mPFC.

4.3. Validation check

To validate our experimental design, participants completed a brief 5–10 min questionnaire on self-assessed risk and time preferences at the conclusion of the experiments (Appendix B: Questionnaire).

We employed the Global Preference Survey (GPS), which includes experimentally validated measures of time and risk preferences, positive and negative reciprocity, altruism, and trust from roughly 80,000 respondents in 76 countries. Prior work has demonstrated that GPS metrics reliably predict a range of economically relevant preferences (Falk et al., 2018; Falk et al., 2023). All items asking how well a statement describes the participant as a person were answered on a scale from 0 "least agree (not willing to do so)" to 10 "describes me very well (most agree)". The risk preference questionnaire includes 12 items, such as "Are you a person who is willing to take risks or do you try to avoid risks?" and "Do others see you as a person who is willing to take risks or as someone who tries to avoid risks?". The time preference questionnaire includes 21 items, such as "Are you a person who is willing to give up something today in order to benefit from that in the future, or are you not willing to do so?" and "Do others generally see you as a person who is willing to give up something today in order to benefit from that in the future?" The scores are computed by summation.

The Cronbach's alpha coefficients of the risk and time preferences were 0.902 (M = 45.643, SD = 19.844) and 0.816 (M = 117.833, SD = 22.545), respectively, and Spearman's rank correlation coefficient test showed that the coefficient between the score of attitude toward risk (rp) and risk preference (α) was −0.226 (p = 0.011), the coefficient between the score of attitude toward risk (rp) and coefficient of risk aversion (ρ) was −0.338 ($p < 0.001$), and the coefficient between the score of attitude toward time (tp) and discount factor (δ) was 0.371 ($p < 0.001$). The rp and tp of the cathodal stimuli were significantly lower than those of the sham stimuli (rp: 38.387 vs. 49.881, BH-adjusted p = 0.011; tp: 109.645 vs. 122.186, BH-adjusted $p = 0.019$). These results were consistent with the conclusions obtained from the neural experiments, which suggested that cathodal stimulation of the mPFC significantly decreased tolerance to risk and increased impatience.

To rule out the possibility that baseline trait differences drive our tDCS effects, we further classified items a priori based on construct content and prior literature, then partitioned the post-experiment questionnaire into those probing immediate decision-making processes (Questions 1–2, 4–14, 16–23, 28, 31–33) versus those reflecting relatively stable, domain-general traits less tied to acute value computation (Questions 3, 15, 24–27, 29–30) (Boggio et al., 2010; Peters & Buchel, 2011). A Kruskal–Wallis testing on the mPFC-insensitive composite score revealed no significant differences across anodal, cathodal, and sham groups (risk preference: H(2) = 4.535, $p = 0.104$; time preference: H(2) = 4.956, $p = 0.084$). We then re-ran our main regression on choice behavior, adding the mPFC-insensitive score (Risk preference attitude & Time preference attitude) as a covariate; stimulation condition remained a highly significant predictor (risk preference: β =0.482, $p = 0.038$; time preference: β = −1.173, p = 0.012). This pattern confirms that (a)

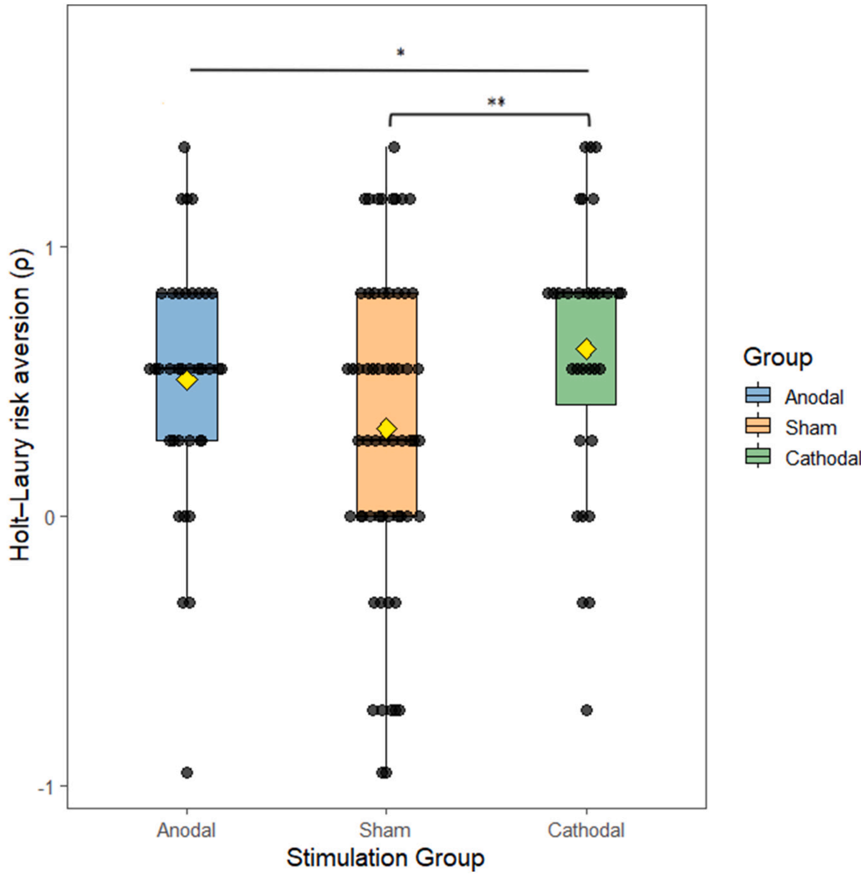

Fig. 7. tDCS on Holt–Laury risk aversion (ρ) by three stimulation conditions. The jittered points in the figure display each participant's parameter estimate, overlaid on the group boxplots, with the group means marked by yellow diamonds. $*p < 0.05$, $**p < 0.01$.

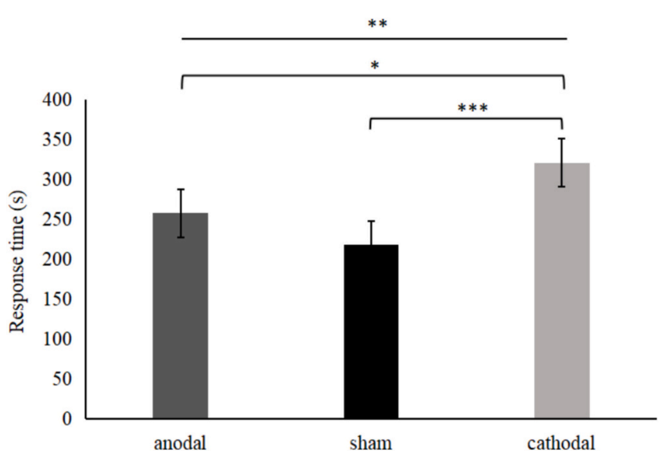

Fig. 8. Response time (s) in the time preference game by three stimulation conditions. Error bars indicate ±1 SEM. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

groups did not differ on baseline-type traits and (b) our tDCS effects cannot be explained by pre-existing differences in stable personality measures.

5. Discussion

In this study, we causally tested whether modulating medial prefrontal cortex (mPFC) excitability alters both risk and time preferences. We exposed participants to anodal, sham or cathodal stimulation (separately) to the mPFC before presenting a series of risky and temporal

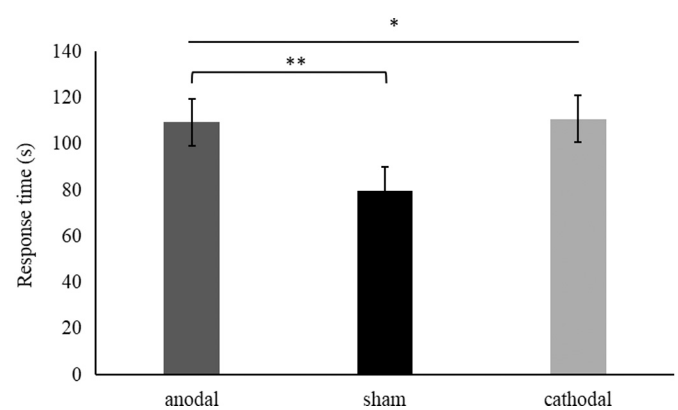

Fig. 9. Response time (s) in the risk aversion game by three stimulation conditions. Error bars indicate ±1 SEM. $*p < 0.05$, $**p < 0.01$.

tasks. The findings reveal that individuals who received cathodal stimulation were more likely to choose safe lotteries and allocate their tokens more to an early date than to the future. These results are consistent with the interpretation that decreasing mPFC excitability reduces tolerance for uncertainty and increases temporal discounting — and therefore with the hypothesis that risk and time preferences may share at least one component process supported by mPFC. We note, however, that the precise neural mechanisms remain to be established.

These behavioral findings are consistent with a broader literature implicating mPFC/vmPFC and ventral striatum in domain-general value computation (the "common neural currency") linking mPFC disruption to changes in impulsivity and risk preferences (Hare et al., 2014; Kable &

Table 6
OLS results (coefficient of risk aversion α).

	(1)	(2)	(3)	(4)	(5)
Anodal	0.332	0.266	0.345	0.354	0.182
	(0.244)	(0.234)	(0.251)	(0.246)	(0.11)
	[1.36]	[1.14]	[1.37]	[1.44]	[1.65]
Cathodal	0.593*	0.482*	0.555*	0.566*	0.262*
	(0.232)	(0.23)	(0.237)	(0.247)	(0.124)
	[2.56]	[2.09]	[2.34]	[2.29]	[2.11]
Risk preference attitude		−0.108*			
		(0.052)			
		[−2.08]			
Female			0.109	0.114	0.032
			(0.206)	(0.212)	(0.1)
			[0.53]	[0.54]	[0.31]
Age			−0.098	−0.095	−0.062
			(0.103)	(0.107)	(0.056)
			[−0.95]	[−0.89]	[−1.11]
Education			0.058	0.056	0.018
			(0.142)	(0.144)	(0.08)
			[0.41]	[0.39]	[0.23]
Response time				−0.0003	
				(0.001)	
				[−0.22]	
Constant	998.584***	999.082***	1000.366***	1000.323***	1.535
	(0.171)	(0.240)	(1.759)	(1.803)	(0.972)
	[5827.29]	[4166.6]	[568.62]	[554.68]	[1.58]
Observations	126	126	126	126	126
R-squared	0.045	0.092	0.059	0.059	0.083

To amplify the causal effect, the CTB-derived risk aversion α (columns (1)–(4)) is multiplied by 1000. The values in parentheses are robust standard errors, and the values in square brackets are t-values.
* $p < 0.05$.
*** $p < 0.001$.

Table 7
OLS results (temporal discounting δ).

	(1)	(2)	(3)	(4)	(5)
Anodal	−0.759	−0.608	−0.860	−0.731	−0.766
	(0.52)	(0.495)	(0.554)	(0.521)	(0.539)
	[−1.46]	[−1.23]	[−1.55]	[−1.40]	[−1.42]
Cathodal	−1.392*	−1.173*	−1.434**	−1.226*	−1.230*
	(0.534)	(0.463)	(0.514)	(0.477)	(0.502)
	[−2.61]	[−2.54]	[−2.79]	[−2.57]	[−2.45]
Time preference attitude		0.053**			
		(0.019)			
		[2.80]			
Female			−0.813	−0.772	−0.702
			(0.477)	(0.465)	(0.463)
			[−1.7]	[−1.66]	[−1.52]
Age			0.121	0.084	0.089
			(0.134)	(0.129)	(0.131) [0.68]
			[0.90]	[0.65]	
Education			−0.252	−0.23	−0.200
			(0.181)	(0.173)	(0.172)
			[−1.39]	[−1.33]	[−1.17]
α				−374.4**	
				(126.836)	
				[−2.95]	
Response time					−0.002
					(0.0001)
					[−1.96]
Constant	999.989***	997.935***	998.7***	1373.268***	999.557***
	(0.454)	(0.606)	(1.99)	(126.26)	(1.963) [509.09]
	[2204.70]	[1647.92]	[502.73]	[10.88]	
Observations	126	126	126	126	126
R-squared	0.046	0.076	0.076	0.101	0.089

To amplify the causal effect, δ (columns (1)–(5)) is multiplied by 1000. The values in parentheses are robust standard errors, and the values in square brackets are t-values.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Glimcher, 2007; Manuel et al., 2019; Seaman et al., 2018). Lesion and rTMS studies similarly show that mPFC disruption increases impulsivity (Peters & D'Esposito, 2016) and risk aversion (Pujara et al., 2015), although opposite patterns, such as greater risk tolerance, have been reported under different task demands (Mok et al., 2021; Peters & D'Esposito, 2020). Unlike studies estimating risk and time preferences in separate paradigms, our unified CTB-with-tDCS approach minimizes estimation bias and allows direct comparison across domains, thereby bridging neuropsychological and stimulation findings. Regression analyses using CTB-estimated time preference and HL-measured risk preference revealed that cathodal stimulation robustly increased risk aversion and impatience, with a significant negative correlation between CTB-derived risk aversion α and discount factor δ, in line with behavioral economics evidence (Andreoni & Sprenger, 2012b; Clot et al., 2017; Dohmen et al., 2012). By contrast, HL-measured ρ showed no significant correlation with δ, reinforcing the CTB method's advantage in disentangling risk from time preferences (Augenblick et al., 2015; Giné et al., 2018) and marking the first application of this approach in a neuromodulation context.

While cathodal effects were robust, anodal versus sham contrasts were not significant. Several factors may contribute to this asymmetry: ceiling or floor effects in a healthy young sample, inter-individual variability in baseline cortical excitability, or homeostatic mechanisms that constrain facilitatory effects of anodal stimulation (Horvath et al., 2014; Nitsche et al., 2007; Vergallito et al., 2022). Importantly, the regression results reported above include controls for demographic covariates, Raven cognitive score, response time (RT), and an mPFC-insensitive composite score derived from questionnaire items probing relatively stable trait-like attitudes. Inclusion of these covariates did not eliminate the cathodal effects, suggesting that the observed stimulation-induced behavioral shifts are unlikely to be driven by pre-existing differences in these trait-like measures.

Previous studies establish that the ventral striatum (VStr) and mPFC integrate domain-specific inputs into a domain-general "common neural currency," encoding subjective value across diverse reward types and decision stages (Bartra et al., 2013; Clithero & Rangel, 2014). This valuation involves a hierarchical process: the ventromedial PFC (vmPFC)-VStr circuit initially evaluates basic reward attributes, while the dlPFC subsequently adjusts vmPFC activity to incorporate abstract attributes (e.g., delay, probability), weighting them according to current goals to compute a net option value (Hare et al., 2014). Although we targeted the mPFC, prefrontal tDCS routinely produces distal effects via structural and functional connections: it modulates resting-state networks including the DMN and fronto-parietal systems (Keeser et al., 2011), alters cortico-striatal coupling (Polanía et al., 2012), and even changes subcortical neurotransmitter dynamics in ventral striatum (Fonteneau et al., 2018). HD-tDCS studies further demonstrate that anterior versus posterior DMN nodes (mPFC vs PCC) can be differentially affected (Huang et al., 2021) and that midline prefrontal montages can perturb bilateral prefrontal networks and oscillatory coupling with dlPFC and VStr (Gbadeyan et al., 2016; Polanía et al., 2011). These network-level perturbations plausibly explain our slowed decision times and the co-occurring shifts toward greater risk aversion and impatience. Reduced functional connectivity with dlPFC could compromise its complementary role in second-stage value integration (Boggio et al., 2010; Hare et al., 2014; McClure et al., 2004; Peters & Buchel, 2011; Tulviste & Bachmann, 2019), a mechanism that may contribute to the behavioral shifts we observed. These findings underscore the mPFC's integral role as a nexus within a broader prefrontal-striatal network during the multistage valuation of risk and time preferences, highlighting the need for future work combining tDCS with concurrent EEG or fMRI to directly probe these network dynamics.

Our study did not identify a direct correlation between individuals' cognitive abilities and their time and risk preferences. This lack of correlation may be attributed to our experimental sample primarily consisted of current university students. University students typically exhibit a high level of cognitive ability, and the variability in cognitive ability among individuals within this group may be limited. Insufficient variance in cognitive ability within the sample could lead to insignificant correlations between cognitive ability and time/risk preferences (Dohmen et al., 2010). Additionally, the fact that college students share similar educational backgrounds and cognitive training may further diminish the effect of cognitive ability on time and risk preferences (Benjamin et al., 2013). We evaluated the heterogeneity of time and risk preferences with respect to gender, age and education. Aligning with previous findings on gender differences in temporal discounting (Falk et al., 2018; Yang & Carlsson, 2021), our results revealed a non-significant trend suggesting that females may exhibit greater impatience than males ($p = 0.087$). Tanaka et al. (2010) noted that previous findings of a gender effect may be due to confounds with variables that often correlate with gender, such as education. We exclude this in our sample, which is mostly composed of students of similar age and education. Finally, our econometric regression analysis indicated that behavioral changes induced by cathodal stimulation of the mPFC are unlikely to be driven by differences in individual characteristics.

5.1. Limitations and Future Directions

While our between-subjects tDCS design minimized practice, carryover, and demand effects (Charness et al., 2012; Monte-Silva et al., 2013), it also introduces greater sensitivity to between-participant variability. Although we achieved adequate power ($N = 126$) and confirmed baseline balance across demographic and cognitive covariates, unmeasured individual differences could still influence group comparisons. Future work might adopt a hybrid crossover design with extended wash-out intervals and enhanced blinding procedures to further control inter-individual variability while mitigating residual stimulation effects. Complementary within-subject studies would help confirm the robustness of our findings and refine estimates of tDCS effect sizes in risk and time preference tasks.

Although we took standard precautions to minimize and monitor tDCS side effects—participants provided informed consent detailing potential discomfort and were instructed to report any adverse sensations during or after stimulation (no reports of discomfort were received), sham stimulation included a 30 s fade-in/fade-out and total wear time was identical (~25 min) across all groups, and the stimulator was fully shielded from view by a partition (Nitsche et al., 2008; Sellaro et al., 2015)—this study did not include formal side-effect questionnaires nor a post-session guess check for stimulation condition. Future studies should incorporate these measures to ensure rigorous assessment of participant blinding and tolerability.

6. Conclusion

This study used transcranial direct current stimulation (tDCS) to probe the causal contribution of the medial prefrontal cortex (mPFC) to risk and time preferences. Cathodal (inhibitory) stimulation of mPFC produced a reliable pattern of behavioral change—reduced tolerance for risk and greater temporal discounting—across both choice tasks and self-report measures, indicating a co-modulatory influence of mPFC on these fundamental decision dimensions. We interpret these effects cautiously within a hierarchical valuation framework: attenuating mPFC activity may impair integration of reward attributes, biasing choice toward more immediate or conservative valuations potentially supported by subcortical structures (e.g., ventral striatum), and may reduce effective coupling with dorsolateral prefrontal cortex (dlPFC), thereby limiting the dlPFC's role in incorporating abstract, future-oriented information. By combining a unified Convex Time Budget elicitation with focal neuromodulation, the study reduces methodological confounds that complicate separate-paradigm comparisons. Nonetheless, because other nodes in the prefrontal–striatal network were not directly manipulated or imaged, these findings support the view that mPFC is a key node in a shared valuation process but do not fully map the broader circuit. Multimodal, connectivity-focused studies are required to delineate network mechanisms.

CRediT authorship contribution statement

Chao Liu: Writing – original draft, Methodology, Conceptualization. **Hongzhen Lei:** Writing – original draft, Conceptualization. **Yuzhen Li:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Wanjun Zheng:** Writing – original draft, Conceptualization. **Fan Li:** Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (72203199).

Appendix

Supplementary material to this article can be found online at https://doi.org/10.1016/j.actpsy.2025.105710.

Data availability

Data will be made available on request.

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