

Prospect-Theoretic Instance-Based Learning: A Neuromodulated Model of Exploratory Behavior in Experience-Based Decisions

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Abstract

Stress typically shifts human decision-making away from exploratory and towards more routine, risk-averse patterns. In this study, we investigate whether tDCS applied to the DLPFC reverses the shift, inducing curiosity-driven exploration and risk-taking under cognitive load. Participants performed a repeated decision-making task with risky, safe, and "reveal" (information-sampling) choices, under and without trivia-based cognitive load and tDCS. Behavioral outcomes indicate that tDCS greatly promoted risky and reveal decisions, implying elevated exploratory behavior under stimulation. To mechanistically account for these effects, we contrasted three models: a Default Instance-Based Learning (IBL) model, an Optimized IBL model with parameter-tuned memory parameters, and a hybrid Prospect-Theoretic IBL (PT-IBL) model with nonlinear valuation from Prospect Theory. Under tDCS, PT-IBL had the lowest mean-squared deviation (MSD) in risky decisions and competitive performance in reveal sampling. Without stimulation, PT-IBL was a superior fit to risky choice behavior, and Optimized IBL was superior at modeling reveal behavior. Parameter estimates show that tDCS increased memory decay ($d = 1.66$) and retrieval noise ($s = 4.72$) in line with recent-memory dependence and retrieval noise—a computational marker of exploration. In contrast, without tDCS, PT-IBL exhibited less decay ($d = 0.12$), in line with long-term memory trace dependence. PT parameters ($\alpha \approx 0.86$ – 0.97 ; $\beta \approx 0.66$ – 0.88 ; $\lambda \approx 1.55$ – 2.41) were in normative ranges. These results show that tDCS enables exploratory cognition by modulating memory retrieval dynamics and subjective value weighting, and PT-IBL offers a psychologically grounded explanation of neuromodulated decision-making.

Keywords: tDCS, Instance-Based Learning (IBL), Prospect Theory, Cognitive Load, Exploratory Decision-Making, Neuromodulation, Memory Decay, Value-Based Modeling

1 Introduction

Despite being essential components of adaptive decision-making, curiosity and risk-taking both deteriorate under cognitive load because they increase dependence on habitual decisions and decrease working memory [1-2]. Such a cognitive shift may hinder performance in real-world domains like emergency response, aviation, education, and

healthcare—particularly when decision-makers are expected to evaluate novel or uncertain alternatives [3].

According to recent studies, neuromodulation of the dorsolateral prefrontal cortex (DLPFC) by anodal transcranial direct current stimulation (tDCS) may improve executive control and cognitive flexibility [4-6]. Although tDCS has been linked to better exploratory decision-making, its interaction with cognitive load—and how it supports curiosity-driven behavior under such stress—remains less understood.

This work is important because it offers an integrative cognitive framework that describes how neuromodulation can preserve curiosity and risk preferences in the face of cognitive stress. Previous research has either studied decision dynamics separately or looked at the brain regulation of risk-taking. Our contribution fills a critical modelling gap by bridging these perspectives through a unified computational approach. Our study is new because we have developed a hybrid Prospect-Theoretic Instance-Based Learning (PT-IBL) model that accounts for subjective valuation biases as well as memory retrieval dynamics.

A mechanical explanation of decision-making based on the recall of prior experiences from memory is provided by instance-based learning theory (IBLT) [7-8]. Human decision-making has been simulated in a variety of dynamic and unpredictable situations. However, IBLT's assumption of objective outcome encoding limits its ability to capture deviations from rationality observed in real-world decisions.

On the other hand, Prospect Theory (PT) explains how people routinely manipulate their gains and losses according to criteria [9,10,11,12]. It does not have a temporal or experience-based mechanism, but it does reflect important psychological tendencies like loss aversion and diminishing sensitivity. By incorporating PT's value function into the IBL retrieval process, our hybrid model makes it possible to describe both dynamic memory effects and subjective reward encoding.

Few research have looked at how tDCS and cognitive load interact to influence risk-taking and exploration during repeated decisions, despite increased interest in understanding their effects independently [13]. Furthermore, the synergy between valuation (PT) and memory retrieval (IBL) is often overlooked by current cognitive models. To our knowledge, no prior study has combined PT and IBL mechanisms to jointly characterize how curiosity and risk preferences shift under neuromodulation and cognitive load.

By applying PT's nonlinear value function to every recovered memory instance inside the IBL architecture, we present a hybrid Prospect-Theoretic Instance-Based Learning (PT-IBL) model that fills this gap. This enables us to simulate the dynamics of memory-driven choice as well as subjective valuation. We perform a within-subjects experiment in which participants, with or without anodal tDCS delivered over the right DLPFC, complete a repeated decision task with safe, risky, and "reveal" (exploratory) options under trivia-based cognitive load.

Our main hypothesis is that tDCS restores exploratory activity even when cognitive load is present by increasing reward salience, which is manifested in an elevated choice utility parameter. Additionally, we anticipate that stress inhibits retrieval and accelerates memory degradation (modelled as). Specifically, we predict that PT-IBL will best capture human choices by jointly accounting for subjective reward valuation and memory decay under different tDCS-load conditions. We compare the suggested PT-IBL agent, an optimized IBL model, and a default IBL model to see which model best predicts risk-seeking and exploratory behavior in humans in each scenario.

In the following, we provide computational and empirical evidence that tDCS affects risky decision behavior and reveal behavior under cognitive strain. We assess how well these behavioral patterns are explained by the default IBL, optimized IBL, and the suggested PT-IBL models. We show that PT-IBL offers a more complete account of behavior by capturing the dual role of subjective valuation and retrieval noise in shaping decisions. This approach aids in our comprehension of how neuromodulation and cognitive processes combine to support risk-taking and exploration in stressful situations.

2 Methodology

2.1 Theoretical Framework

We formalize three agents in successive subsections: first the standard memory-based IBL model, then the standalone PT valuation, and finally their hybrid integration (PT-IBL).

Instance-Based Learning Architecture

IBLT represents each past experience as an instance i with outcome x_i . At decision time t , activation is given by [9]:

$$A_i = \ln(\sum_{j=1}^{n_i} (t - t_{ij})^{-d}) + \varepsilon_i \quad (1)$$

where d is the decay rate, $t_{i,p}$ indexes past occurrences, and $\varepsilon_i \sim \mathcal{N}(0, s^2)$ is retrieval noise. Retrieval probabilities follow a Luce rule:

$$P_{i,t} = \frac{\exp(A_{i,t})}{\sum_j \exp(A_{j,t})} \quad (2)$$

The Blended Value for each action j is

$$V_j = \sum_{i \in I_j} P_{i,t} x_i \quad (3)$$

with I_j the set of instances tied to action j . In IBLT, the model repeats its prior decision with an inertia probability (p_{inertia}) [14] or decides based upon the blended values in equation 3.

Prospect-Theoretic Valuation

Prospect Theory's value function transforms objective outcomes nonlinearly [12]:

$$v(x) = \begin{cases} x^\alpha, & \text{if } x \geq 0, \\ -\lambda(-x)^\beta, & \text{if } x < 0 \end{cases} \quad (4)$$

where α and β capture gain/loss sensitivity and λ captures loss aversion. Standalone PT predicts choice by comparing $u(x)$ across options.

Prospect-Theoretic Instance-Based Learning (PT-IBL) PT-IBL embeds PT's valuation directly into the IBL blending process. Each instance's outcome x_i is first mapped through $u(x_i)$, and then blended via memory activations:

$$V_j = \sum_{i \in I_j} P_i u(x_i) \quad (5)$$

To capture load and tDCS-induced shifts in memory dynamics, PT-IBL parameterizes:

$$s = s_0 - \delta_s \cdot \text{load} \quad (6)$$

$$d = d_0 + \gamma_d \cdot (\text{tDCS}) \quad (7)$$

where $\text{load} = 1$ under trivia demand, $\text{tDCS} = 1$ under stimulation, δ_s quantifies load-driven increases in retrieval noise, and γ_d quantifies sham-driven increases in memory decay. Under constant load, $s = s_0 + \delta_s$ always, while d toggles between d_0 (tDCS) and $d_0 + \gamma_d$ (sham). This unified architecture allows us to test how subjective valuation (PT) and memory retrieval (IBL) interact and are modulated by neuromodulation and cognitive load.

2.2 Experimental Design

This study employed a mixed factorial design with a between-subjects factor of tDCS (anodal vs. sham) and a within-subjects factor of cognitive load (low vs. High difficulty trivia) [15]. Thirty healthy volunteers (19 M, 11 F; mean age = 25.66 yrs, SD = 2.84) were randomly assigned to either the tDCS + Trivia group ($n = 15$) or the No-tDCS + Trivia group ($n = 15$).

The stimuli used in this study were specifically created to examine the effects of transcranial direct current stimulation (tDCS) and cognitive load on curiosity, decision-making, and the trade-off between exploration and exploitation. A binary-choice decision-making task and cognitive load tasks in the form of trivia questions were used as stimuli to accomplish this (see Figure ‘1’). These components were carefully designed to produce different degrees of cognitive load while maintaining experimental control, resulting in an environment that closely mimics real-world decision-making situations. Participants in the binary-choice task had to make choices in 50 trials, each of which included three different possibilities. A lesser but assured reward was provided by Option A (Safe Option), where participants received 2.5–3.5 points. This choice was intended to represent exploitation behavior, in which participants took advantage of a low-variability, predictable result. A probabilistic reward was added with Option B (Risky Option), giving players the possibility to receive 0 points or earn 16–18 points with a 20% likelihood (jittered between 18% and 22%).

Cognitive load was manipulated trial-by-trial via trivia questions preceding each choice. Low-load items required simple factual recall; high-load items required multi-step reasoning or assertion evaluation. Trivia questions were randomized across trials to simulate varying mental effort.

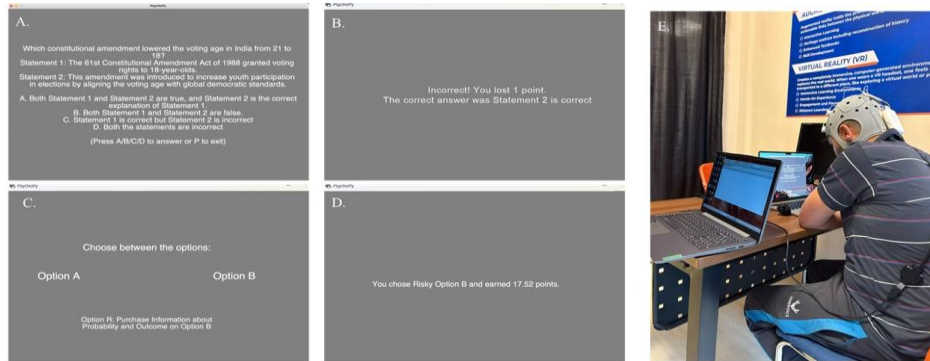


Fig.1. A trial of decision-making tasks in an experiment. (A) Trivial task before decision-making task. (B) Feedback on decision-making response. (C) Decision-making task where participant choose between option A, B or R. (D) Participant get to know the outcome of their choice in the prior trial and the trial ends.

Data Collection

We recruited 30 healthy adult volunteers with no history of neurological or psychiatric disorders. All participants provided informed consent, and the study received ethical approval from the Institutional Ethics Committee at the Indian Institute of Technology Mandi (IIT Mandi). Participants received a briefing before the experiment explaining the purpose of the study, which was to examine curiosity and decision-making under various cognitive loads, as well as their right to discontinue participation at any time. The study was carried out in the Applied Cognitive Science Laboratory, IKSMHA Centre, IIT Mandi, in a sound-attenuated, distraction-free environment. Performance-based financial incentives were given to participants as a thank you.

Upon arrival, participants underwent consent procedures and received a task briefing. Impedance checks were conducted to ensure safety and reliable current delivery. A quick pretest made sure that participants understood the contents and format of the assignment by acquainting them with the trivia questions used to manipulate cognitive load. There were two stages to the experimental session. Before each decision-making experiment in the first phase, trivia questions were used to modify cognitive load. In order to guarantee that the manipulation remained unaffected by incentives, responses were recorded but not linked to financial rewards. In the second stage, participants had to make judgments based on 50 randomized trials in a binary-choice problem. They had to choose between three options: choice A, which was safe and guaranteed to have a low reward; Option B, which was risky and had probabilistic big rewards or zero points; and Option R (see Figure 1), which was exploratory and allowed for more information about the probabilities involved in the risky choice. Participants in the tDCS + Trivia group received anodal stimulation targeting the left frontal and frontopolar area, with the reference electrode placed over the contralateral supraorbital area, using the Neuroelectronics Starstim 32 [16]. Stimulation was applied concurrently during the full experimental task, which included both the trivia-based cognitive load phase and the subsequent 50-trial decision-making task. Stimulation included a ramp-up time of 30 seconds and a ramp-down time of 45 seconds and was aimed at enhancing cognitive

flexibility during the stimulation. To maintain uniformity in the experimental Conditions between groups, participants in the control group experienced the identical setup and procedures but were not actively stimulated.

2.3 Computational Modeling

All agents were implemented in Python using the PyIBL framework. We compared three models:

Default IBL Uses standard ACT-R settings (decay $d_0 = 0.5$, noise $s_0 = 0.45$),

Optimized IBL Fits the five IBL parameters (d_0 , s_0 , δ_s , γ_d , $p_{inertia}$) and utility parameters to each condition’s data.

PT-IBL In addition to the eight IBL parameters, fits Prospect Theory parameters (α , β , λ) for nonlinear gain/loss valuation.

Model Fitting Procedure for each stimulation condition (tDCS vs. sham), we pooled all 50 trials per participant and ran SciPy’s *differential_evolution* optimizer [17] on a population of 40 candidate parameter sets for 40 generations, minimizing the mean-squared deviation (MSD) between simulated and empirical risky-choice rates (R-rate) on the training split.

At each generation the objective is computed as:

$$MSD = \frac{1}{N} \sum_{p=1}^N (\hat{R}_p - R_p)^2 \quad (8)$$

where $\hat{R}_p$ and R_p are the simulated and human R-rates for participant p .

The best-fitting parameter vector from generation 40 was then used to simulate all trials—including held-out test data—for final model comparisons.

This genetic-algorithm approach (40 agents over 40 generations) ensures thorough exploration of the high-dimensional parameter space, balancing exploration and exploitation in calibration, and provides robust, reproducible fits across participants and conditions.

3 Results

Under sham condition (tDCS = 0), the subjects exhibited low exploration behavior, as indicated by an R-rate of 0.3026 and a reveal rate of 0.2146. Under anodal tDCS (tDCS = 1), significantly greater behaviors were exhibited: the R-rate was raised to 0.5613 (85% increase) and the reveal rate to 0.3613 (68% increase). The findings indicate that prefrontal neuromodulation enhances risk-taking and exploration due to curiosity even under cognitive load.

Table 1 summarizes human decision rates and simulated output and mean squared deviations (MSDs) for all models. Default IBL model with ACT-R default parameters ($d_0 = 0.5$, $s_0 = 0.45$, $p_{inertia} = 0.0$) underpredicted R-rate and reveal behavior invariably when stimulated and when sham, with enormous MSDs (e.g., 0.293 and 0.201 under tDCS).

Table 1. Human vs. Model Risky-Choice and Reveal-Sampling with Mean-Squared Deviations under Anodal tDCS and Sham Conditions

Condition	Model	Parameters	Model Risky	Model Safe	Model Reveal	Human Risky	Human Safe	Human Reveal	MSD Risky	MSD Reveal
tDCS, trivia	Default IBL	$d_0=0.5$, $s_0=0.45$ pinertia=0.0	0.081	0.584	0.335	0.561	0.077	0.361	0.293	0.201
tDCS, trivia	Optimized IBL	$d_0=0.995$, $s_0=3.72$, $\delta_s=0.8923$, $\gamma_d=0.2762$, pinertia=0.3	0.624	0.000	0.376	0.561	0.077	0.361	0.020	0.019
tDCS, trivia	PT-IBL	$d_0=1.10$, $s_0=4.72$, $\delta_s=0.44$, $\gamma_d=0.56$, pinertia=0.0, $\alpha=0.972$, $\beta=0.660$, $\lambda=2.409$	0.612	0.072	0.316	0.561	0.077	0.361	0.015	0.037
No tDCS, trivia	Default IBL	$d_0=0.5$, $s_0=0.45$ pinertia=0.0	0.098	0.403	0.498	0.303	0.483	0.215	0.099	0.295
No tDCS, trivia	Optimized IBL	$d_0=0.6726$, $s_0=0.6025$, $\delta_s=0.5461$, pinertia=0.3	0.227	0.528	0.245	0.303	0.483	0.215	0.001	0.009
No tDCS, trivia	PT-IBL	$d_0=0.1238$, $s_0=4.2883$, $\delta_s=0.3368$, pinertia=0., $\alpha=0.8593$, $\beta=0.8766$, $\lambda=1.5482$	0.320	0.312	0.368	0.303	0.483	0.215	0.007	0.033

The Optimized IBL model, whose memory parameters were computed, modeled human behavior well. Upon tDCS-stimulation, its modeled R-rate (0.6240) and reveal rate

(0.3760) were very similar to observed ones (0.5613 and 0.3613) with minimal MSDs (0.020, 0.019). Its γ_d parameter (0.2762) only affected behavior when stimulated, demonstrating that neuromodulation affects decay-based retrieval modulation. The PT-IBL model that incorporated Prospect Theory's value transformation nonlinearity and IBL's memory structure also yielded similar good fits. Under tDCS, the model R-rate (0.6120) and reveal rate (0.3160) approximated human behavior closely, with very low MSD for risky decisions (0.015). Its fitted reward-sensitivity parameters— $\alpha = 0.972$, $\beta = 0.660$, and $\lambda = 2.409$ —emphasized elevated subjective value weighting under stimulation. Under sham condition, PT-IBL also captured R-rate better than Optimized IBL (MSD = 0.0074 vs. 0.0099) and had a higher reveal rate MSD (0.0331 vs. 0.0086), which is a compromise. Interestingly, without applying tDCS, PT-IBL exhibited low decay ($d_0 = 0.1238$), high noise ($s_0 = 4.2883$), and high sensitivity ($\alpha = 0.8593$, $\beta = 0.8766$), which would suggest deeper use of memory but greater variability in decision consistency.

Collectively, these results show that tDCS increases exploration and risk-taking and that PT-IBL models these effects by simulating both memory and subjective value. In addition, modulation of memory decay (γ_d) is functionally significant only after stimulation application.

4 Discussion and Conclusions

The effect of transcranial direct current stimulation (tDCS) on decision-making under cognitive load was investigated in this study with a focus on risk-taking and curiosity-driven exploration. We sought to test the impact of neuromodulation on subjective valuation and memory retrieval dynamics in risky and cognitively demanding contexts by providing anodal tDCS to the right dorsolateral prefrontal cortex (DLPFC). The behavioral statistics indicate tDCS produced a significant increase in the frequency of use of the reveal option and risky choice. Stimulation subjects produced a 68% increase in reveal rate and an 85% increase in risky-choice rate relative to sham. This is in line with previous work that connects prefrontal activation with increased cognitive control and reduced choice inertia [4,5] and implies anodal tDCS to the DLPFC facilitates cognitive flexibility and adaptive exploratory action. The behavioral effects were accounted for mechanistically by the computer modeling.

In both states, the Default IBL model consistently underestimated exploration with ACT-R base parameters. Optimized IBL, however, reached nearly human alignment by adding tDCS-related decay modulation (γ_d), load-dependent noise modulation (δ_s), retrieval noise (s_0), fitted decay rate (d_0), and decision inertia ($p_{inertia}$). Adding the Prospect Theory features of gain sensitivity (α), loss sensitivity (β), and loss aversion (λ) resulted in the PT-IBL model that surpassed this. The PT-IBL model was capable of modeling sophisticated behavior by adding subjective value—especially under tDCS, where exploration and reward salience were increased.

This model was based on the decay parameter modulated by γ_d , which accounts for how tDCS speeds up memory decay, thus enhancing dependence on recent experience. Instead of making it easier to recall long-term memory, this mechanism proposes that tDCS evokes a short-term, feedback-sensitive mode of decision. Similarly, the retrieval noise parameter s_0 , modulated by δ_s , scales up with load and stimulation, accounting

for choice behavior variability and malleability. These modulations account for how neuromodulation enhances exploratory variability, even for cognitively loaded conditions. Interestingly, γ_d had minimal functional impact in no-stimulation conditions, highlighting its specific significance under conditions of neuromodulation.

These results are in line with dual-process models of decision-making, in which memory retrieval (System 1) and valuation (System 2) dynamically interact [10,18]. PT-IBL unifies both by integrating memory-based sampling (IBL) with nonlinear valuation (PT) to yield a computationally grounded account of exploratory cognition under neuromodulation.

This is consistent with previous research that tested IBL models on tasks [7,8,14] and demonstrates how these models can be made adaptable by incorporating psychological constructs. Most importantly, being able to replicate risky and reveal behavior under tDCS demonstrates the activation of executive regions like the DLPFC in regulating retrieval processes and subjective value. [6] cite that such a result is consistent with brain research that indicates that tDCS is able to entrain oscillatory patterns in memory regions to enable task-relevant recall and episodic accessibility.

PT-IBL's ability to model at the grain of behavior, such as retrieval quality change and decision strategy, offers an exciting platform for studying the impact of neuromodulatory interventions on cognitive processes. The present research has two implications. At the theoretical level, it enhances our comprehension of how neuromodulation alters the interaction between valuation and retrieval, and it offers a cognitive model that generates predictions about behavior as well as accounts for it. The results have practical implications for high-stakes or cognitively demanding contexts, such as emergency response, military strategy, or clinical diagnosis, where selective brain stimulation can trigger curiosity and adaptive decision-making. Subsequent studies should look at how differences in control or valuation bias between individuals influence tDCS response and whether or not these influence generalize to tasks involving social uncertainty, delayed outcome, or dynamic feedback. Application of brain measures such as fMRI or EEG would offer convergent data on how stimulation impacts cognitive dynamics and further illuminate the putative mechanisms. This experiment concludes by showing how tDCS influences reward valuation and memory decay to facilitate exploration and risk-taking under cognitive load. In both cognitive modeling and applied neuroscience, the PT-IBL model provides a theoretically derived and empirically validated tool to account for the cognitive impact of neuromodulation.

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