The motor system optimizes decision-making by dynamically adjusting its sensitivity to environmental and internal uncertainties

Tianhe Wang*
Department of Psychology and Neuroscience
University of California Berkeley
Berkeley, USA
tianhewang@berkeley.edu

Maoxin Xia
Department of Psychology
Wuhan University
Wuhan, China
maoxin.xia@berkeley.edu

Ijin Yu
Department of Electrical Engineering and Computer Sciences
University of California Berkeley
Berkeley, USA
ijinyu1113@berkeley.edu

Ti-Fen Pan
Department of Psychology and Neuroscience
University of California Berkeley
Berkeley, USA
tfpan@berkeley.edu

Richard B. Ivry
Department of Psychology and Neuroscience
University of California Berkeley
Berkeley, USA
ivry@berkeley.edu

Abstract

Humans exhibit remarkable flexibility in adapting their motor behavior to a changing environment, while this remains a major challenge for robotic systems. In this study, we investigated: 1) how action selection is influenced by uncertainties arising from environmental volatility, stochasticity, and internal motor noise; and 2) whether the motor system responds to those uncertainties differently compared to other decision-making systems. Participants performed an air hockey task in which they controlled a virtual paddle by moving a trackpad to shoot a puck toward a goal. To manipulate environmental uncertainties, we varied the strength and direction of a wind that affected the puck's movement trajectory. Interestingly, the learning rate decreased as stochasticity increased and increased with higher volatility, consistent with predictions from a Bayesian optimal model. As a non-motor version of the task, participants completed a similar task but reported their desired speed and direction instead of physically moving the paddle, with all sources of uncertainties carefully matched between tasks. While participants also adjusted to stochasticity and volatility in the non-motor task, their overall error significantly increased compared to the motor task. Interestingly, participants showed less sensitivity to the change in the signal-to-noise ratio and sometimes adopted a learning rate beyond the optimal level in the non-motor task, leading to an overestimation of stochasticity. These findings demonstrate that humans respond more optimally to environmental uncertainty when the task requires motor system engagement compared to when decisions are made without physical movement.

Keywords: Environmental uncertainty, Action selection, Motor control, Volatility, Stochasticity, Motor noise

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*Corresponding author

1 Introduction

Living organisms including humans are remarkably adept at adjusting their movements to operate in an uncertain environment, flexibility that remains a major challenge for artificial agents and robots [1]. In the current study, we examined how action selection is modulated by uncertainty arising from the environment and internal noise (Fig 1A). In terms of the environment, two distinct sources of uncertainty have been shown to influence learning – volatility and stochasticity [2, 3]. Volatility refers to how rapidly properties of the environment change. In response to high volatility, an agent should increase the learning rate so as to be able to rapidly adjust to these changes. Stochasticity refers to random fluctuations in the environment (e.g., noise), where the resultant changes do not convey meaningful information about underlying structural changes. In the face of high stochasticity, the agent should reduce its learning rate. Internal uncertainty arises from the inherent noise within the motor system [4]. The agent should not respond to the error caused by motor noise. A fundamental challenge for the agent is to determine the source of an observed error and determine how and if the system should be altered in response to the error [5]. In the current study, we manipulated environmental volatility and stochasticity, comparing their effects when choices were instantiated by movements or in a symbolic manner.

2 Method

2.1 Air-Hockey Game with Motor Control

We designed a virtual air hockey game in which participants controlled a virtual paddle by moving their finger across a trackpad, aiming to launch a puck toward a target (Fig. 1C). This task was designed to capture key features of real-life skill learning, including: (1) delayed feedback about the outcome relative to the participant's movement (similar to most ball games); (2) dynamics governed by physical rules; (3) multidimensional control with redundant solution spaces; and (4) the absence of visuo-proprioceptive discrepancies caused by feedback perturbations.

At the start of each trial, the screen displayed the puck and paddle at a starting position and a target, along with obstacles between the start position and the target. Using the trackpad, participants moved the paddle to strike the puck. The puck's trajectory was determined by two factors: the speed and angle of collision, and a wind blowing at a constant speed for a given trial. We assumed the puck's movement was unaffected by friction. If the puck encounters an obstacle, its trajectory is modified based on reflection principles. The puck continues moving until it hits the target or exits the screen.

We employed a 2×2 between-subject design (n = 15 per condition), manipulating stochasticity and volatility (Fig. 1B). For stochasticity, Gaussian noise was introduced with a standard deviation equal to 0% (low) or 30% (high) of the average wind strength. For volatility, the direction (leftward or rightward) and strength of the wind condition were altered either every 8–15 trials (high volatility) or every 20–40 trials (low volatility). Participants inferred changes in wind conditions based on the observed trajectory of the puck. The positions of the target, puck, paddle, and obstacles remained fixed across all trials within each condition.

2.2 Bayesian Observer Model

Following a simple Bayesian observer model, state estimation is determined by the environmental stochasticity and volatility:

$$m_{t+1} = m_t + \alpha_t \delta_t \tag{1}$$

$$\alpha_t = \frac{w_t + v}{w_t + v + s} \tag{2}$$

$$w_{t+1} = (1 - \alpha_t)(w_t + v) \tag{3}$$

where m_t and w_t are the estimates of the mean and variance at time point t; v and s are volatility and stochasticity; and n is motor noise. We used this model to predict the ideal learning rate α (see Fig 1D).

2.3 Non-motor version of the air-hockey game

To investigate whether the motor system exhibits unique properties in response to uncertainty, we modified the task in a second experiment. Here, the participants did not move across the trackpad to control how the paddle struck the puck (Fig 1C bottom). Rather, they selected a position on a polar grid and clicked to confirm their choice to release the paddle. They observed an animation in which the paddle moved straight toward the puck, with the initial angle of the puck's trajectory defined by a line from the paddle to the puck and the speed defined by the distance from the paddle to the puck. As in Experiment 1, the trajectory of the puck was impacted by the wind and obstacles.

One key difference between the non-motor and motor tasks is that, in the former, the puck trajectory was not dependent on the participant's movement; as such, we assume motor noise is essentially eliminated. We introduced an additional source of noise in the non-motor version to make the tasks more similar in terms of noise structure. Participants were informed that the weight of the puck could vary in a random manner across trials. This information was not specified in advance; rather, the color of the puck changed after the collision to reveal its weight. In this way, the participant could account for this "weight noise" when interpreting the subsequent puck trajectory.

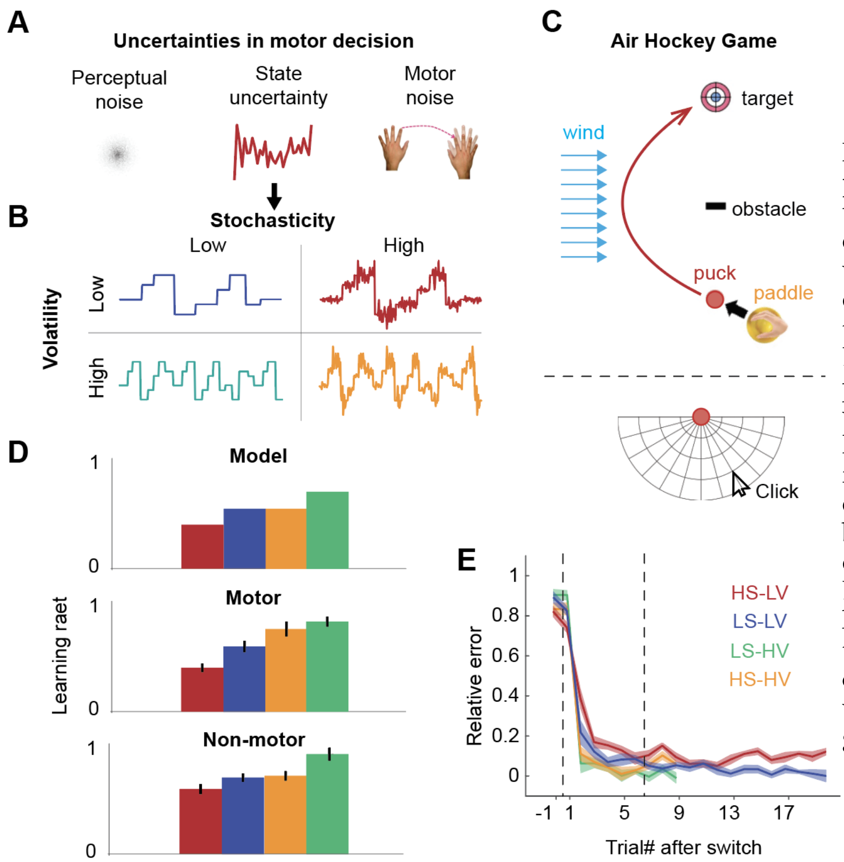

Figure 1: **Volatility and stochasticity have opposite effects on motor learning.** A) Sources of uncertainty in tasks where the decision depends on a movement. B) State uncertainty arises from volatility and stochasticity. We employed a 2×2 design to manipulate these two forms of uncertainty. C) Illustration of the air hockey game. Bottom: In the non-motor version of the game, participants clicked on a polar grid to decide where to release the puck. D) Top: Predicted learning rates of a Bayesian observer under different uncertainty conditions, color-coded based on panel B. Bottom: Observed learning rates in both motor and non-motor tasks align with predictions from the Bayesian observer model. E) Learning curves for the motor version of the air hockey game. We measured learning rates from the first five trials after a change in the wind, controlling the stimuli such that the experienced wind conditions were identical across all four groups.

2.4 Analysis

Participants controlled the direction and speed of the paddle at the moment of collision with the puck. Since the target and the initial position of the puck are vertically aligned, hitting the target requires that the collision speed (V) and the wind acceleration (W) satisfy the following equation:

$$V_x \cdot V_y = C \cdot W, \tag{4}$$

where V_x and V_y are the speed components in the x- and y-directions, respectively, and C is a constant scaled by the distance between the target and the initial position of the puck. We refer to the left side of the equation ($V_x \cdot V_y$) as the measurement of behavior and the right side ($C \cdot W$) as the solution. When the wind changes, the participants' behavior should gradually converge to the new solution.

To quantify this learning process, we define the relative error as:

$$\text{Error} = \frac{C \cdot W_n - V_x \cdot V_y}{C \cdot (W_n - W_o)}, \tag{5}$$

where W_n is the new wind acceleration and W_o is the old wind acceleration. We fit an exponential function to the relative error data at the group to estimate the learning rate. 95% confidence intervals were estimated by bootstrap.

3 Results

3.1 Motor task

Error increased following a change in the wind, and participants adjusted their movements to discover a new solution (Fig. 1E). Across all conditions, they rapidly adapted their motor strategy, as indicated by the sharp decrease in relative error. Behavior reached an asymptotic level by around the fifth trial.

The learning rate was modulated by both volatility and stochasticity. Consistent with the optimal Bayesian model, these variables had opposing effects (Fig. 1D). Participants in high-volatility conditions exhibited a higher learning rate compared to their low-volatility counterparts (bootstrap, $ps < 0.001$), while those in high-stochasticity conditions showed a lower learning rate (bootstrap, $ps < 0.005$).

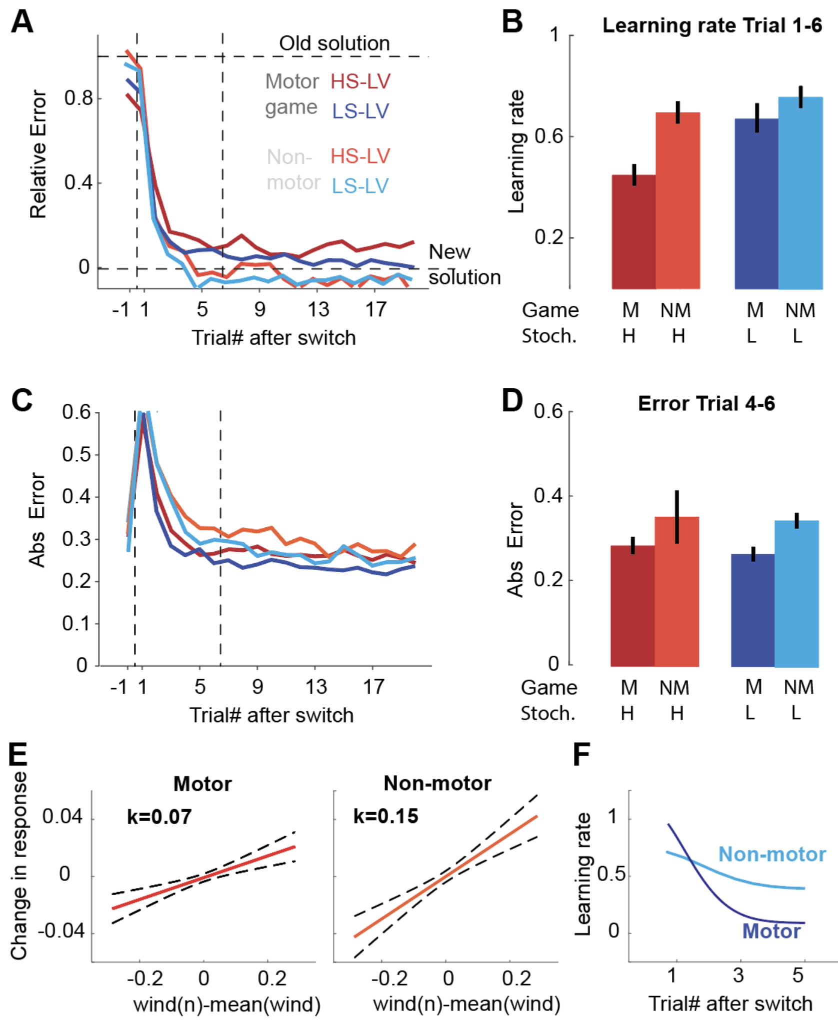

Figure 2: **Participants overcompensate for noise when the decision does not tax the motor system.** A) Learning curve measured in terms of relative error in the non-motor task (light blue and orange), with the data from Exp 1 replotted for comparison (motor task: dark blue and dark red). B) For the high-stochasticity condition, participants showed a higher learning rate in the non-motor task. For the low-stochasticity condition, the learning rate was similar across the two tasks. C) Learning curve measured in terms of absolute error. D) Participants consistently showed a larger error in the non-motor version, regardless of the difference in learning rate. E) Trial-by-trial changes in hand angle as a function of error induced by wind stochasticity. An optimal response would show no systematic adjustment to noise (zero slope). The stronger correlation in the non-motor task indicates overcompensation for stochastic noise. Error bars represent 95% confidence intervals. F) Hypothesized learning rate dynamics: Participants in the motor task may rapidly increase and then decrease their learning rate following environmental changes, leading to a lower time-averaged learning rate but higher overall accuracy compared to the non-motor task.

3.2 Comparing to a Non-Motor Decision-Making Task

To assess whether sensitivity to uncertainty differs between movement-dependent decisions and non-motor decisions, we tested another group of participants using a modified version of the air hockey game. In this version, participants selected a release position for the paddle that determined the contact angle and speed (Fig. 1C, bottom).

Similar to the motor task, we observed that high volatility increased the learning rate while high stochasticity decreased it (Fig. 1D). However, when directly comparing performance between the two tasks, we found notable differences. For example, in low-volatility conditions, participants exhibited a faster learning rate in the non-motor version (Fig. 2B; bootstrap, $ps < 0.001$) yet had larger overall errors (Fig. 2D; bootstrap, $ps < 0.001$). This suggests that participants may apply a learning rate larger than the optimal value in the non-motor task.

Consistent with this interpretation, we also observed differential sensitivity to errors caused by wind noise. Specifically, participants in the non-motor task showed stronger trial-by-trial responses to the noise signal (Fig. 2E; Spearman correlation, $ps < .001$). They appeared to attribute some stochastic variation to volatility changes in the high-stochasticity condition, inflating the learning rate and increasing response variability.

Based on these observations, we propose a possible explanation for the interaction between learning rate and error in motor versus non-motor tasks (Fig. 2F). We posit that participants were more sensitive to changes in the signal-to-noise ratio. When the wind state changed, they observed a large error and rapidly increased their learning rate. Critically, they should then quickly reduce the learning rate to avoid overfitting to noise. However, non-motor task participants decreased their learning rate more slowly, resulting in an overall inflated learning rate and greater error. This hypothesis should be tested in future work on model fitting.

3.3 Discussion

Our results indicate that, within a motor task, the nervous system correctly attributes three types of uncertainty: (1) volatility and (2) stochasticity of environmental states, and (3) internal motor noise. Participants adapted their learning rates to different environmental contexts in a manner consistent with Bayesian optimal models. Surprisingly, when the task retained a similar structure but removed the requirement for continuous motor control, participants appeared to attribute some degree of environmental stochasticity to volatility and thus adopted suboptimal strategies. Specifically, instead of adjusting minimally to the random noise sources, they tended to overcorrect on each trial, leading to inflated response variance and overall errors.

One interpretation is that the motor system, honed by extensive experience with bodily movements and sensory feedback, has specialized neurocomputational routines for accurately parsing different sources of uncertainty. In contrast, when internal cues associated with movement are absent (e.g., efference copies, proprioceptive feedback), participants overreact to random fluctuations [6]. These findings suggest that the ability of nervous system to handle multiple uncertainties relies on specialized motor processes, offering insights for training paradigms, adaptive robotics, and broader principles of human learning.

References

[1] Kai Yuan et al. "Hierarchical generative modelling for autonomous robots". en. In: *Nat. Mach. Intell.* 5.12 (Nov. 2023), pp. 1402–1414.

[2] Payam Piray and Nathaniel D Daw. "Computational processes of simultaneous learning of stochasticity and volatility in humans". en. In: *Nat. Commun.* 15.1 (Oct. 2024), p. 9073.

[3] Payam Piray and Nathaniel D Daw. "A model for learning based on the joint estimation of stochasticity and volatility". en. In: *Nat. Commun.* 12.1 (Nov. 2021), p. 6587.

[4] Howard G Wu et al. "Temporal structure of motor variability is dynamically regulated and predicts motor learning ability". en. In: *Nat. Neurosci.* 17.2 (2014), pp. 312–321.

[5] Samuel D McDougle et al. "Credit assignment in movement-dependent reinforcement learning". en. In: *Proceedings of the National Academy of Sciences* 113.24 (June 2016), pp. 6797–6802.

[6] B Bridgeman. "A review of the role of efference copy in sensory and oculomotor control systems". en. In: *Ann. Biomed. Eng.* 23.4 (July 1995), pp. 409–422.