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# Decomposing Executive Function into Distinct Processes Underlying Human Decision Making

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***Abstract*— Executive function (EF) consists of higher level cognitive processes including working memory, cognitive flexibility, and inhibition which together enable goal-directed behaviors. Many neurological disorders are associated with EF dysfunctions which can lead to suboptimal behavior. To assess the roles of these processes, we introduce a novel behavioral task and modeling approach. The gamble-like task, with sub-tasks targeting different EF capabilities, allows for quantitative assessment of the main components of EF. We demonstrate that human participants exhibit dissociable variability in the component processes of EF. These results will allow us to map behavioral outcomes to EEG recordings in future work in order to map brain networks associated with EF deficits.**

***Clinical relevance*— This work will allow us to quantify EF deficits and corresponding brain activity in patient populations in future work.**

## I. INTRODUCTION

*Executive function* (EF) encompasses several higher-level cognitive processes including working memory, cognitive flexibility, and inhibition. Together they enable and control goal-directed behaviors [1]. These processes depend on brain networks thought to be predominantly localized in prefrontal cortex [2]. Many developmental, neurological and neuropsychiatric disorders are associated with deficits in EF, including neurodegenerative conditions such as Alzheimer's disease, as well as stroke, autism spectrum disorders, attention deficit and hyperactivity disorder, obsessive-compulsive disorder, schizophrenia, bipolar disorder, major depression disorder, and Tourette's syndrome [3], [4], [5], [6], [7], [8], [9], [10]. Further, individuals in sub-clinical or non-clinical populations exhibit individual differences and longitudinal changes in executive function that impact well-being [11].

Executive function impairments associated with these disorders may stem from interacting deficits in working memory, cognitive flexibility, and inhibition. In order to target treatment for these disorders and restore EF, it is critical to understand the neural networks governing each component of EF. However, it is unclear if individuals exhibit differences in these EF components independently and in combination, and which brain networks generate these differences. Understanding how brain networks govern these EF processes in healthy individuals and how they change in disease may guide new diagnostic tools and neuromodulation therapies to restore brain networks in patients that suffer disorders.

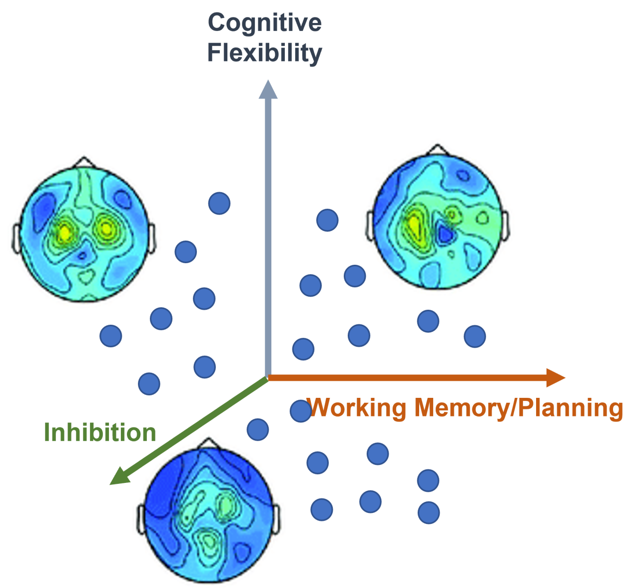


Fig. 1. Three component dimensions of Executive Function

We have developed a novel experiment to dissociate and quantify the EF processes of working memory, cognitive flexibility, and inhibition (**Figure 1**). We build on our previous work that used a card-game based gambling task and intracranial EEG to identify risk-taking bias and its neural basis in human decision-making [12], [13], [14], [15]. Here we propose a modified task that effectively decomposes EF into these processes and quantifies participant EF along each dimension. This novel task further allows us to dissociate participants into groups based on process-specific EF performance (*e.g.*, a group may entail participants who are stronger in cognitive flexibility than working memory). We quantify participant working memory, cognitive flexibility, and inhibition, and we show that participants exhibit individual differences in three distinct component dimensions of executive function. These results will guide future work to identify brain networks that govern each behavioral metric in healthy and patient populations.

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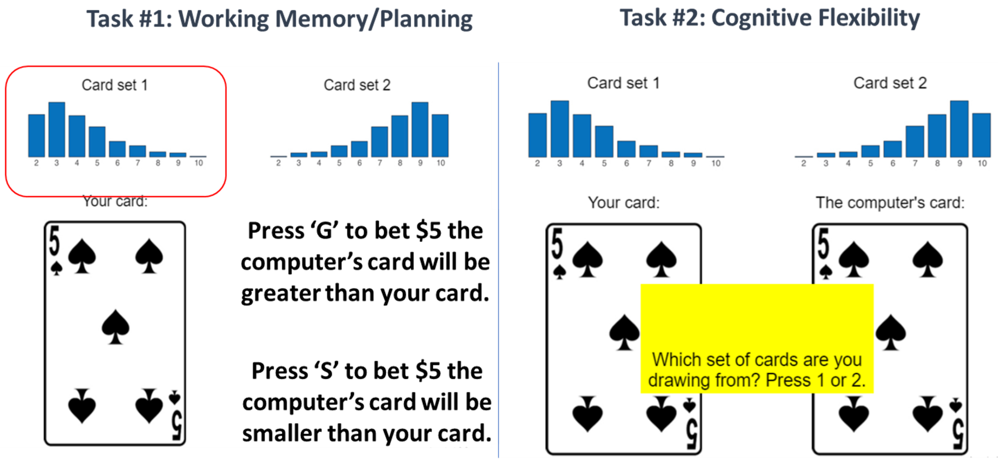


Fig. 2. Illustration of the two tasks. Task 1 tests both working memory/planning and inhibition, while task 2 tests cognitive flexibility. The red frame in task 1 (not present in display) indicates that participants are told which is the current deck in this task.

## II. METHODS

### A. Behavioral Task

We developed a novel two-stage behavioral experiment (**Figure 2**) to dissociate each component of EF:

1) Task 1 tests working memory and inhibition. The task is a modified version of the card game "War". In each gambling round, the participant is dealt one card. It is drawn from a deck of cards which consists of Spades 2-10 only. Cards are drawn from one of two possible distributions which are shown as histograms in the display, Figure 2. Critically, the probability of drawing each card is not uniform, but can be skewed toward either high cards or low cards. The participant knows that a second card (the "computer's card") will subsequently be drawn from the same distribution and has to bet whether the second card will be greater or smaller than their own card. In this task, the participant is informed which of the two distribution is being used in a given trial by being shown an image of the histogram of the card probabilities for only the correct, current deck. After pressing a button to indicate their response, the computer's card is revealed. In this task, optimal performance only depends on participants representing task conditions correctly to implement the optimal decision, (the decision that maximizes expected reward given the card). For the example shown in Figure 2 (left), the optimal decision is to press 'S' since the current deck is skewed to cards lower than 5. However, participants must also inhibit behavior based on biases such as rewarding outcomes on prior trials or repetition of the same choice as on prior trials. Thus, this task also enables us to quantify inhibition using a modeling approach.
2) Task 2 tests cognitive flexibility. Participants are shown two possible deck distributions (histograms) and informed that the deck occasionally switches randomly from one to the other, but not which desk is currently in use. They are shown two cards and asked to guess which of the two distributions the cards are currently being drawn from. This stage quantifies optimal performance in cognitive flexibility by assessing ability to detect when the environment changes. Optimal here is defined as the most likely deck given current and previous cards drawn. In the example shown in Figure 2 (middle), the optimal choice is deck 1 if previous trials also suggest deck 1.

### B. Behavioral Data

Tasks 1 and 2 were performed by 95 high-functioning participants, undergraduate students at a major North American research university who were compensated for their time by course credit. The study was approved by the Johns Hopkins University Institutional Review Board. The task was implemented online using PsyToolkit, a platform for custom-built cognitive tasks to be run in browser and accessed using a unique link for each participant [16], [17]. PsyToolkit allows the recording of precise response times for specified keyboard inputs in response to on-screen visual stimuli. Participants completed 100 trials of all tasks. The 95 participants that took part in the study were divided into four groups, differing in the specific sequence of cards on each part of the task.

### C. Data Analysis

We developed metrics to quantify optimal performance for each task and to quantify the distance between each participant's behavior and the optimal behavior. Optimal behavior in the first dimension, *working memory*, was defined as the choice that maximized expected reward given the known card distributions shown to the participants. Accordingly, when the deck was skewed low, optimal behavior would be to bet that the computer card would be higher only when the player card is 2 or 3; otherwise, the optimal behavior would be to bet that the computer card would be lower. Similarly, when the deck is skewed high, the optimal behavior would be to bet that the computer card would be lower only when the

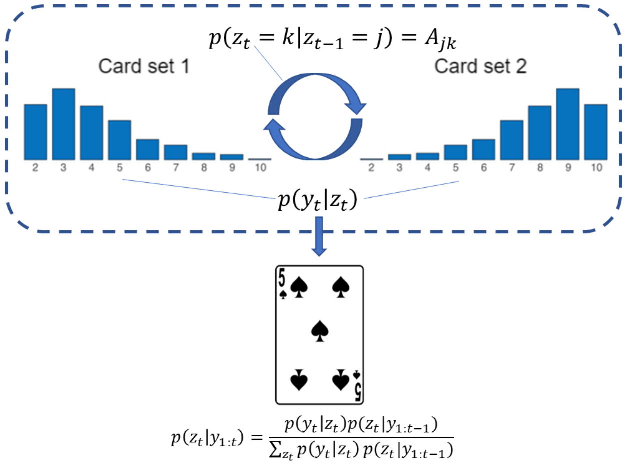


Fig. 3. Hidden Markov Model for task 2. Optimal player would compute the forward probability of the HMM to determine the most likely state of the deck on trial t, $p(z_t = k)$, based on the observation of card $y_t$. Dashed lines indicate the hidden state—the player is unaware of the true state of the deck and must compute the most likely state given the observation probabilities $p(y_t|z_t)$ and transition probabilities $A_{jk}$.

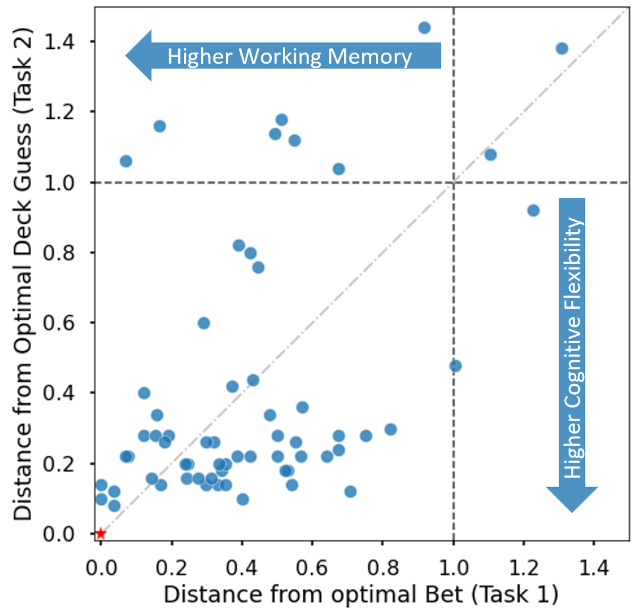


Fig. 4. Participants exhibit differences in executive function separable into distinct dimensions between task 1 and task 2. The origin (red star) indicates optimal performance, and horizontal/vertical dashed lines at 1.0 indicate chance performance in each dimension. The $x$-axis quantifies working memory/planning and inhibition performance as distance from optimal bet decision on task 1, and the $y$-axis quantifies cognitive flexibility as distance from optimal guess of current card distribution in switching task (task 2). Each scatter point represents an individual participant. Dashed diagonal line with slope of unity distinguishes performance in each behavioral dimension.

player card is 9 or 10; otherwise the optimal behavior would be to bet that the computer card would be higher.

Distance from optimal behavior in the first task was quantified as the normalized root mean square error between participant bets and the optimal bet. We computed the fraction of times the participant bet high for each participant card value and then computed the root mean square error (RMSE) with what the optimal fraction of betting high would be, then normalized the RMSE to chance performance. Optimal betting was defined as the bet on each card value that maximized expected reward given the card distribution. The distance from optimal was computed as:

$$d = \sqrt{\frac{\sum_{i=2}^{10} (f_i - po_i)^2}{n}} \tag{1}$$

Where $f_i$ is the fraction of high bets on card $i$, $po_i$ is the optimal probability of betting high on card $i$ (0 or 1 depending on which bet maximized reward), and $n$ is the number of cards.

For the second task, testing *cognitive flexibility*, optimal behavior was defined as the most likely choice given past and current card observations in task 2. This was computed by modeling the task as a hidden Markov model (HMM), with observation probabilities corresponding to the probability of observing each card value and transition probabilities corresponding to the true transition probability of switching between the two decks in the task (**Figure 3**). We quantified distance from optimal behavior by computing normalized RMSE between the optimal guess and the participant's actual guess on each trial, again normalizing to chance performance, similar to equation (1).

We developed a model to dissociate inhibition from working memory/planning in task 1. Participant bets were modeled using a logistic regression that considered card value and intercept terms as reflecting working memory/planning and prior outcome and prior choice terms as reflecting inhibition:

$$\ln \frac{p_t}{1 - p_t} = \beta_0 + \beta_1 \times c_t + \beta_2 \times po_t + \beta_3 \times pc_t \tag{2}$$

Here, $p_t$ is the probability of betting the computer card will be greater than the participant's card on trial $t$, $c_t$ represents the participant's card value (z-scored) on trial $t$, $po_t$ represents the effect of prior outcomes on trial $t$, and $pc_t$ represents the effect of prior choices on trial $t$. The model allows us to dissociate whether participant choices are driven by card values alone or also by biases due to reward history or choice history.

We quantified distance from optimal working memory/planning using the model by computing the 2-norm of $\beta_0 + \beta_1 \times c_t$ for each participant compared to the optimal model. Similarly, we quantified the distance from optimal inhibition by computing the 2-norm of $\beta_2 \times po_t + \beta_3 \times pc_t$ for each participant compared to the optimal model. We normalized these distance values to the maximum distance in each dimension.

## III. RESULTS

Executive function consists of distinct processes, but it is not clear to what extent these processes are separable and whether individuals vary in their ability independently for each component process. We designed a two-stage card game task (**Figure 2**) to separate the EF components of working memory/planning, cognitive flexibility, and inhibition, and we quantified individual participant variability along multiple dimensions of EF.

We found that participants exhibit individual differences in EF that are separable between distinct tasks. We independently quantified distance from optimal behavior for task 1 (working memory/planning and inhibition) and task 2 (cognitive flexibility) for each participant on each task (see methods). When we perform a scatter plot of individual participants showing distance from optimal behavior for each task (**Figure 4**), our results demonstrate that healthy individuals exhibit variability in their performance, and that individual performance is separable into distinct dimensions. Specifically, some participants perform better on the working memory/planning and inhbition task (above the dashed line with slope of unity) while others perform better on the cognitive flexibility task (below the line).

Deviations from optimal behavior in task 1 may be due to either deficits in working memory/planning or deficits in inhibition. Specifically, behavior that depends on reward history or choice history is suboptimal and reflects a lack of inhibitory control to suppress suboptimal choices. However, suboptimal behavior may also be free of any effect due to trial history and simply reflect that a participant is implementing a suboptimal betting strategy based on inaccurate beliefs about card values that is not consistent with the true expected reward of each card. Thus, to separately quantify working memory/planning and inhibition, we dissociated participant behavior in task 1 into these component dimensions using a modeling approach. We found that participants exhibited individual variability in working memory/planning and inhibition in task 1 (**Figure 5**). This result suggests healthy participants exhibit a range of inhibitory control and working memory/planning abilities with independent deficits in each of these EF processes.

Altogether, our results indicate that individual differences are observable in healthy participants that distinguish performance by the EF components of working memory/planning, inhibition, and cognitive flexibility.

## IV. DISCUSSION

The behavioral results from this study demonstrate that our novel task decomposes executive function into its component processes and identifies individual variability between participant in the dimensions of working memory/planning, inhibition, and cognitive flexibility. We demonstrate a range of individual behavior from a healthy, non-clinical population, suggesting that the task is sensitive enough to detect a wide range of individual differences. This sensitivity to individual differences may enable detection of cognitive impairments in clinical patients with early, mild symptoms. Specifically, this task may help identify patients with gradual onset of mild cognitive impairment, which is currently difficult to diagnose in its earliest stages—the time when pharmacological intervention would be likely to be the most effective.

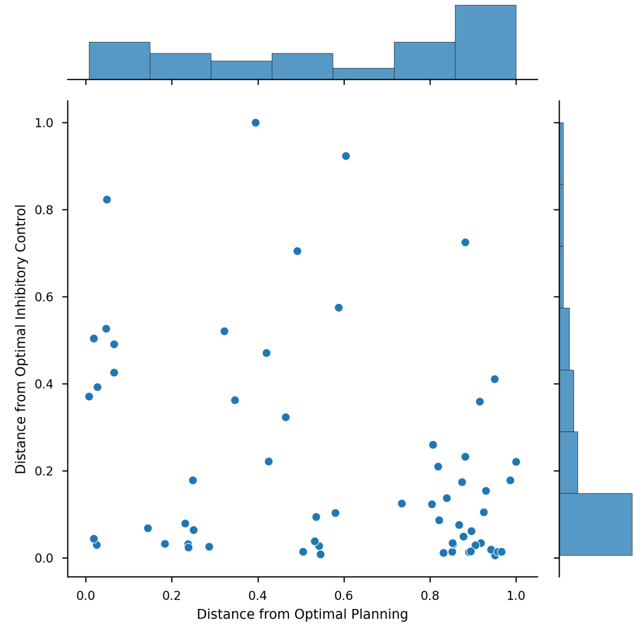


Fig. 5. Model dissociates behavior in task 1 into two dimensions—working memory/planning and inhibitory control. The origin indicates optimal performance. The $x$-axis quantifies working memory/planning deficits and the $y$-axis quantifies inhibition deficits. Each scatter point represents an individual participant. See Methods for model details.

These behavioral results will enable future work to identify brain networks that govern these EF processes in both healthy and clinical populations by performing EEG recordings during the experiment. In future work we intend to apply decoding methods to EEG spectrotemporal data and network connectivity analyses to EEG signals from distinct areas to predict each metric of executive function from EEG signals and identify network activity patterns that underlie differences in executive function. Furthermore, the EEG brain networks identified in each aspect of EF in future work may inform targeted neurostimulation therapies for different disorders that exhibit EF deficits.

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