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Behavioral/Cognitive

Online Movements Reflect Ongoing Deliberation

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From navigating a crowded hallway to skiing down a treacherous hill, humans are constantly making decisions while moving. Insightful past work has provided a glimpse of decision deliberation at the moment of movement onset. Yet it is unknown whether ongoing deliberation can be expressed during movement, following movement onset and prior to any decision. Here we tested the idea that an ongoing deliberation continually influences motor processes—prior to a decision—directing online movements. The deliberation process was manipulated by having humans of either sex observe tokens that moved into a left or right target. Supporting our hypothesis, we found that lateral hand movements reflected deliberation, prior to a decision. We also found that a deliberation urgency signal, which more heavily weighs later evidence, was fundamental to predicting decisions and explains past movement behavior in a new light. Our paradigm promotes the expression of ongoing deliberation through movement, providing a powerful new window to understand the interplay between decision and action.

Significance Statement

Simultaneously deciding and acting have been critical to our survival and undoubtedly shaped our evolution. Classic decision-making and sensorimotor paradigms do not permit or have obscured the expression of ongoing deliberation via online movement. Here we found that deliberation could be expressed via movement when the motor system was already actively engaged. By considering both urgency and evidence accumulation, often cast as competing theories, we were able to consolidate current and past decision-making and movement behavior.

Introduction

When presented with the option of a sweet candy or chocolate, our hand may move back and forth over the two tempting options before we finally make a decision. In this example, our online hand movement seems to provide a readout of our ongoing deliberation before a decision. Over the past two decades, both behavioral (Chapman et al., 2010a; Gallivan and Chapman, 2014; Wong and Haith, 2017; Alhussein and Smith, 2021) and neural (Cisek and Kalaska, 2005; Dekleva et al., 2018) findings support the idea that deliberation and motor planning are intertwined. Yet it has not been shown that the *ongoing* deliberation—prior to a decision—is expressed throughout online movement execution.

Past work has helped to illuminate the interplay between motor planning and decision-making. During the “go-before-you-know” paradigm, participants are required to initiate a reaching movement toward multiple potentially correct targets (Spivey et al., 2005; Hudson et al., 2007; Chapman et al., 2010a; Gallivan and Chapman, 2014; Wong and Haith, 2017; Alhussein and Smith, 2021). At movement onset, participants launched their reaches between or directly at the potentially correct targets. These initial movements reflect priors of the deliberation process, such as representations of the probability of each potential target and movement speed constraints, known during motor planning before movement onset. The correct target is then indicated during the reach via an abrupt and discrete change of evidence (e.g., target color, phonological input, etc.), where participants would often immediately select and rapidly redirect their movement toward one of the targets. In a different paradigm, humans have been similarly shown to make a “change-of-mind” by rapidly redirecting their movement toward one target (Resulaj et al., 2009) following an initial reach to the other target. These rapid movement redirections were based on evidence provided prior to reaching, demonstrate delayed processing times, and have been interpreted to

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reflect a second decision. Rapid movement redirections would reflect a final decision, but would obscure a short deliberation and its potential influence on movement. These studies have collectively provided important insights into how priors of deliberation influence motor planning and the timing of midreach decisions, but have not shown that a continuous and ongoing deliberation process directly influences the online movement.

Perceptual decision-making studies manipulate uncertain and continuous evidence, such as the movement of dots (Britten et al., 1992; Shadlen and Newsome, 2001; Ratcliff and McKoon, 2008; Winkel et al., 2014) or tokens (Cisek et al., 2009; Thura et al., 2012; Thura and Cisek, 2014), toward or into potential targets over time, to influence a more prolonged deliberation and subsequent decision. A plethora of work suggests that during deliberation, humans and animals accumulate (integrate) evidence over time to make a decision (Ratcliff, 1978; Shadlen and Newsome, 2001; Usher and McClelland, 2001; Roitman and Shadlen, 2002; Mazurek et al., 2003; Bogacz et al., 2006; Lokesh et al., 2022). Another competing theory is that an urgency signal increasing over time is multiplied by evidence to cause a decision (Cisek et al., 2009; Thura et al., 2012; Thura and Cisek, 2014; Lokesh et al., 2022; Fievez et al., 2023). A feature of perceptual decision-making tasks is that there is no movement during the deliberation period, a decision is made, and subsequently there is a movement to indicate choice. Thus, even though there is a prolonged deliberation, it does not have the opportunity to be expressed with movement.

Previous studies have collectively provided important insights, but not on how a continuous and ongoing deliberation process directly influences online movement. The goal of this work was to elucidate whether the deliberation process influences online movements, prior to a decision. To investigate, we developed a novel paradigm that allows an expression of the ongoing deliberation via movement, prior to a decision. Across three experiments, we permitted movement while concurrently providing uncertain and continuous evidence in the form of 15 tokens that jumped into a left or right target (Cisek et al., 2009). In Experiment 1, we provided participants evidence during posture to test whether the ongoing deliberation can elicit movement onset and subsequently influence online movements, prior to a decision. In Experiment 2, we provided participants evidence after movement onset, when the motor system was already actively engaged, to determine whether the ongoing deliberation can influence the online movements prior to a decision. In Experiment 3, we replicated the results from Experiment 2 while additionally testing the role of urgency on deliberation. For all experiments, we predicted that lateral hand movements would reflect the deliberation process, following movement onset and prior to a decision. Using a decision-making and movement model that considers urgency, we were able to replicate previous work on motor planning with multiple potential targets (Wong and Haith, 2017). These authors interpreted their results to reflect a single flexible motor plan as opposed to the averaging of parallel motor plans. By considering urgency, we provide an alternative perspective that is compatible with either a single flexible motor plan or averaging of parallel motor plans. Collectively, our findings show that the ongoing deliberation, which includes urgency, directly influences online movements.

Methods

Participants

In total, we collected 51 human participants of either sex across three experiments. Seventeen individuals (24.8 ± 2.37 years old) participated in Experiment 1, 17 individuals (21.4 ± 1.76 years old) participated in Experiment 2, and 17 individuals (23.2 ± 2.93 years old) participated in Experiment 3. Participants reported they were free of musculoskeletal or neuromuscular disorders. All participants provided informed consent to participate in the experiment and the procedures were approved by the University of Delaware's institutional review board. Participants were provided $10 USD compensation.

Apparatus

For all three experiments, participants grasped the handle of a robotic manipulandum with their dominant hand (Fig. 1*A*; KINARM, BKIN Technologies) to perform reaching movements in the horizontal plane. Participants held a hand trigger in their nondominant hand. A semi-silvered mirror projected images (start position, left and right targets, tokens) from an LCD screen onto the horizontal plane of motion. To assess muscle activity, we recorded electromyography (EMG) signals with bipolar surface electrodes (single differential electrode, Trigno System, Delsys) from the flexor policis brevis of the nondominant hand. To obtain an estimated decision time, a voltage signal indicated when the thumb pushed the hand trigger. Kinematic, EMG, and hand trigger data were recorded at 1,000 Hz and stored offline for data analysis.

Protocol

General task protocol. For each trial, participants were visually presented with a white start position (2 cm diameter) and two targets (5 cm diameter). The left and right targets were respectively 20 cm to the left and right of the start position (Fig. 1*A*). A yellow cursor (1 cm diameter) provided real-time feedback of their hand position. The participants were instructed to move their cursor into the start position. After holding the cursor with the start position for 400 ms, participants heard a beeping sound and 15 yellow tokens appeared between the left and right targets. At trial onset (0 ms), the tokens jumped from the center into the left target or right target in 160 ms time intervals (Cisek et al., 2009; Fig. 1*C*). Participants had to make their decision prior to 2,400 ms, corresponding to the final token moving into one of the targets. Once they felt confident which target would end up with the most tokens, they were instructed to simultaneously (i) press a trigger with their nondominant hand and (ii) move toward and hit the selected target. As soon as participants pressed the hand trigger, the remaining token movements were not visible to the participant to prevent them from changing their decision with later evidence. The hand trigger was crucial in dissociating movements caused by deliberation or a decision. If participants selected the correct target, they would hear a pleasant ding and their selected target would turn blue. If participants selected the incorrect target, they would hear an unpleasant buzzer and their selected target would turn red. When participants did not press the hand trigger and/or enter a target within 2,400 ms of the beginning of the trial, both targets would turn red. Furthermore, unknown to participants, the trial would be repeated later on during the experiment.

Experiment 1 task protocol. The goal of Experiment 1 was to determine if ongoing deliberation can elicit and subsequently influence movements, prior to a final decision, when evidence was initiated during posture. The targets were directly to the left and right of the start position (Fig. 1*A*). Participants were given no instructions with regard to their movement prior to a decision and were free to move after beginning the trial.

The participant waited in the start position for 400 ms. After this wait period, trial onset (0 ms) was indicated with a beep. The tokens moved into the left or right target one at a time in 160 ms intervals. In total, participants experienced 216 trials in the main experiment. We used bias, pseudorandom, late, and null token patterns (Fig. S1).

We were primarily interested in the bias token patterns, since we tightly controlled the token movement and consequently the experienced uncertain and continuous evidence. During the bias token patterns, the first three tokens moved individually into the left or right target (i.e., left bias or right bias), the next three tokens moved individually into the opposite target, and the remaining tokens moved with an 80% probability into the left or right target (i.e., left target or right target; Fig. 2*A–D*). In these bias token patterns, we had each of the four combinations of left

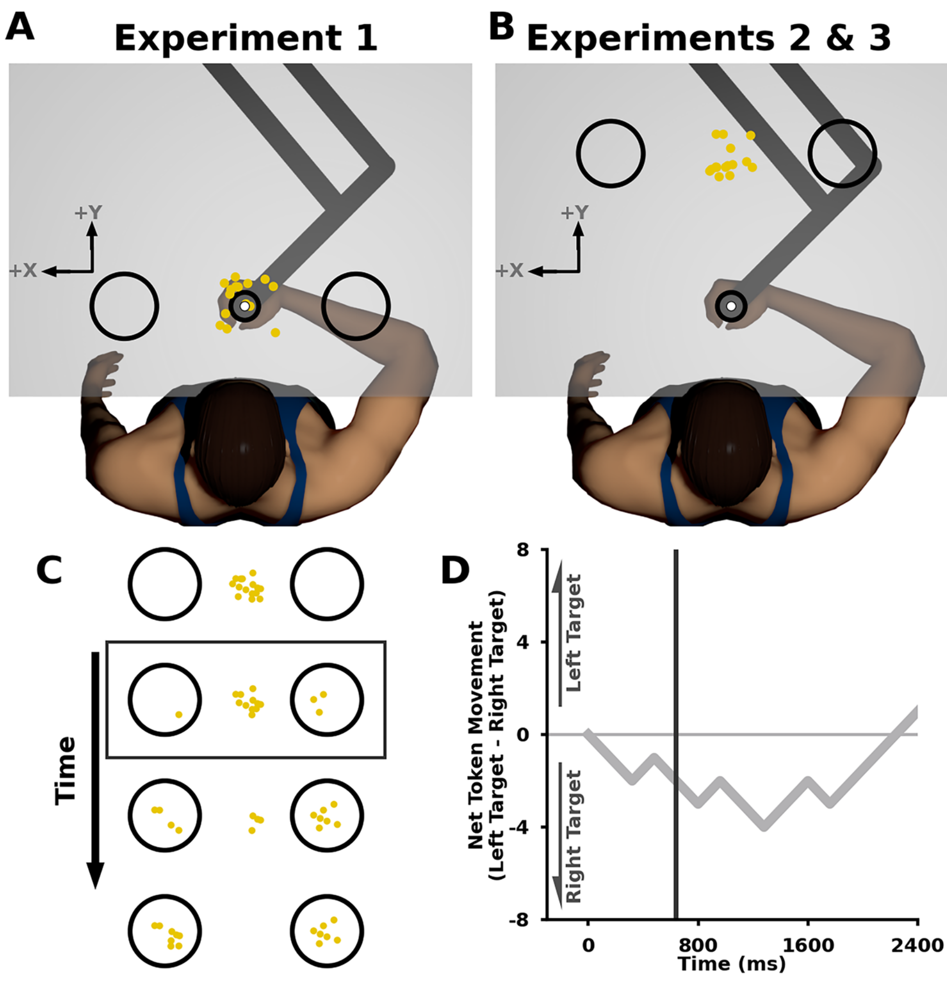

Figure 1. Experimental design. ***A***, ***B***, Participants grasped a robotic manipulandum (Kinarm) using their dominant hand and a hand trigger in their nondominant hand. A semi-silvered mirror projected images from an LCD screen above. A cursor (white circle) represented their hand position. ***A***, In Experiment 1, participants began with the cursor within a start position (small black circle) between two targets (large black circles) that were 20 cm to the left and right of the start position. After 400 ms in the start position, the trial would begin and 15 tokens would appear (yellow circles) between the two targets. The tokens moved individually into the left or right target over time. Participants were instructed to select the target which would finish with the most tokens as soon as they were confident. They indicated their decision by simultaneously pressing the hand trigger in their nondominant hand and moving the cursor into the corresponding target. ***B***, In Experiments 2 and 3, the targets were placed 30 cm forward of the start position as well as 20 cm to the left and right. Tokens began moving once participants left the start position. Participants were also instructed not to stop or move backwards. ***C***, An example of the participant display while the tokens moved into the left or right target over time (*y*-axis). ***D***, Net token movement (left target–right target tokens, *y*-axis) over time (*x*-axis) of an example token pattern. The dark gray box in (***C***) and the dark gray vertical line (***D***) correspond to the same time point.

bias or right bias and left target or right target. Each bias token pattern was presented 12 times, which resulted in 48 bias token patterns. The bias token patterns allowed us to probe how controlled patterns of evidence influenced deliberation and consequently movement.

We also had pseudorandom token patterns where each token had the same probability of going to the left target. We had 20%, 35%, 50%, 65%, or 80% probability pseudorandom token patterns. Each pseudorandom token pattern was presented 12 times except for the 50% condition which was presented 24 times, which resulted in 72 pseudorandom token patterns. Additionally, we had null token patterns (24 trials), late token patterns (48 trials), and late null token patterns (24 trials). Similar to the ambiguous token patterns used by Cisek et al. (2009), the null bias token patterns had a net token movement that was close to zero throughout the beginning portion of a trial.

Experiment 2 task protocol. The goal of Experiment 2 was to determine if ongoing deliberation was reflected in movements, prior to a final decision, after movement onset when the motor system was already actively engaged. In Experiment 2, the targets were 30 cm forward and 20 cm to the left and right of the start position (Fig. 1*B*). The participant waited in the start position for 400 ms, after which they heard a beep. The beep indicated that the participant may leave the start position. Trial onset (0 ms) occurred once the participant left the start position. Tokens did not begin to move until trial onset. Similar to others (Wong and Haith, 2017; Alhussein and Smith, 2021), participants were instructed to not stop moving forward after leaving the start position. Experiment 2 used the same token patterns as Experiment 1.

Experiment 3 task protocol. The goal of Experiment 3 was to replicate the results found in Experiment 2, while also elucidating the roles of evidence accumulation or urgency on deliberation and consequent movement. The experimental setup was the same as Experiment 2, except for the specific token patterns (Fig. S1). Participants experienced 336 total trials. Trials included slow rate bias (Fig. 2*E–H*), fast rate bias (Fig. 2*I–L*), pseudorandom, late, and null token patterns.

In this experiment, we were primarily interested in the slow rate and fast rate bias token patterns because we tightly controlled their movement and experienced uncertain and continuous evidence. Furthermore, the slow rate and fast rate token patterns lead to unique decision times depending on how humans accumulate evidence and/or rely on urgency during deliberation. During the slow rate bias token patterns, the first four tokens moved individually into the left or right target (i.e., left bias or right bias), the next four tokens moved individually into the opposite target, and the remaining tokens moved with an 80%

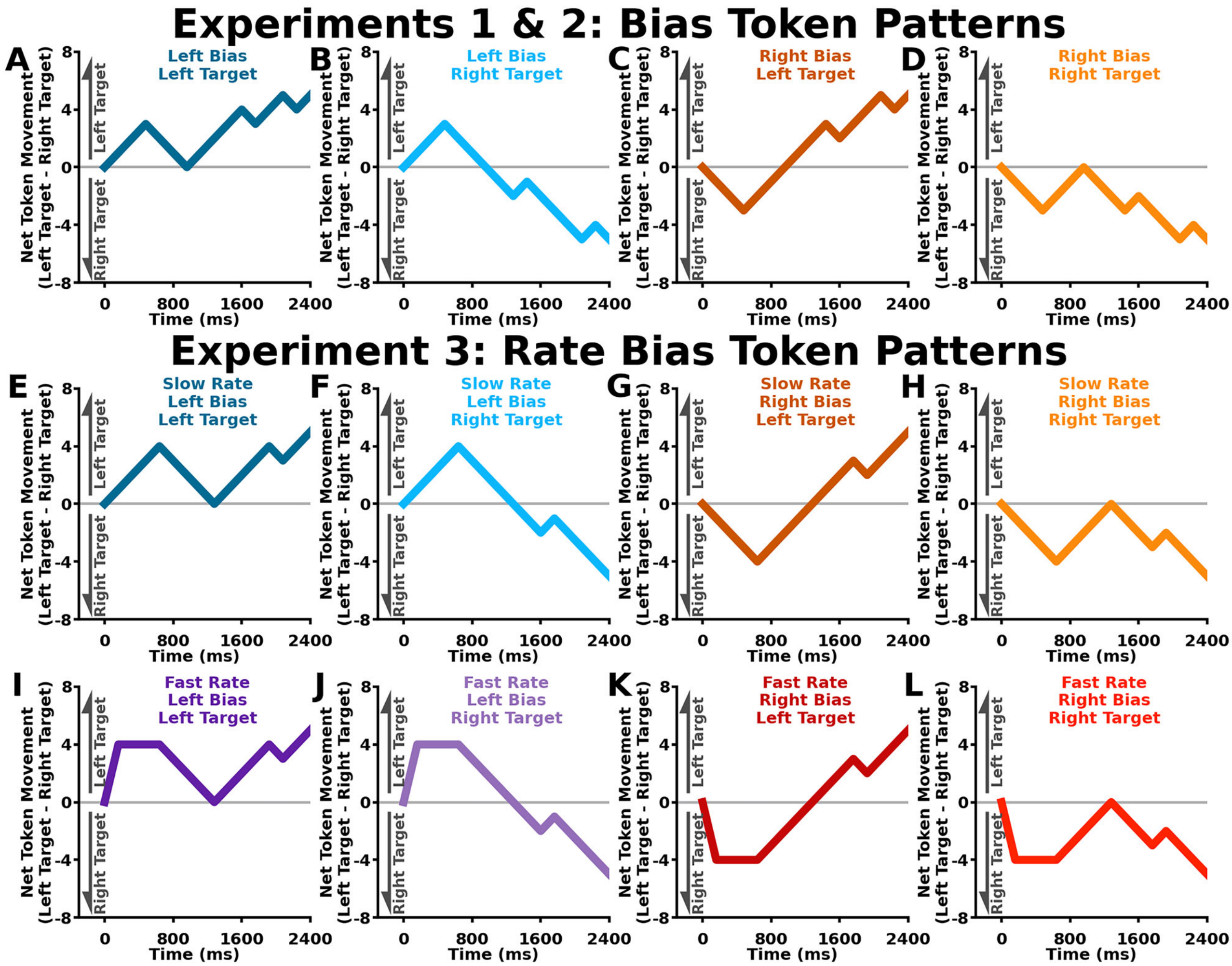

Figure 2. Bias token patterns. ***A–L***, Net token movement (left target–right target tokens, *y*-axis) over time (*x*-axis) for sample bias token patterns. ***A–D***, Bias token patterns in Experiments 1 and 2. ***A–D***, Bias token patterns: the first three tokens moved individually into the left or right "bias" target, the next three tokens moved individually into the opposite target, and then the remaining tokens moved with an 80% probability into the left or right target. ***E–L***, Rate bias token patterns in Experiment 3. ***E–H***, Slow rate bias token patterns: the first four tokens moved individually into the left or right "bias" target, the next four tokens moved individually into the opposite target, and then the remaining tokens moved with an 80% probability into the left or right target. ***I–L***, For the fast rate bias token patterns: the first four tokens moved together into the left or right "bias" target at 160 ms after the beginning of the trial. No other tokens moved until 800 ms after the beginning of the trial. The slow rate and fast bias token patterns were identical past 800 ms after the beginning of the trial. For each experiment, the bias token patterns were interleaved with pseudorandom token patterns.

probability into the left or right target (i.e., left target or right target; Fig. 2*E–H*). In the fast rate bias token patterns, the first four tokens moved at the same time into the left or right target (i.e., left bias or right bias), the next four tokens moved individually into the opposite target, and the remaining tokens moved with an 80% probability into the left or right target (i.e., left target or right target; Fig. 2*I–L*). For these bias token patterns, we had each of the eight combinations of fast rate or slow rate, left bias or right bias, and left target or right target. Each bias token pattern was presented 12 times, which resulted in 96 bias token patterns.

The pseudorandom token patterns were the same as Experiments 1 and 2 (Fig. S1). Similar to Experiments 1 and 2, we also had late and null token patterns.

Reaction time task. Prior to any of the experiments described above, participants performed a reaction time task to determine the sensory and motor delays involved in making and indicating a decision. In the reaction time task, the targets were in the same location as the corresponding main experiment (as described in Experiment task protocols above). The reaction time task used the same trial onset as the corresponding experiment. At trial onset (0 ms), all 15 tokens jumped into either the left or right target. Participants were instructed to select the target that all of the tokens jumped into as fast as they could. Again, participants indicated their decision by pressing the hand trigger and moving the cursor into their selected target. Participants performed minimum 20 familiarization trials in the reaction time paradigm to become accustomed to the experimental setup. After the familiarization trials, participants performed 24 reaction time trials. There were 12 left reaction time trials and 12 right reaction time trials that were presented in a randomly interleaved order.

Data analysis

Estimated decision time. Trigger time was determined when the voltage of the hand trigger crossed 3 V for each trial. We found an estimated decision time on each trial to determine when decisions were made independent of reaching movements. We estimated a neural + mechanical delay for each participant using their reaction time trials. For each muscle per trial, we subtracted the global mean muscle activity across all the reaction time trials. Flexor policis brevis muscle activity was full wave rectified and then dual-pass, sixth order, low-pass (20 Hz), and Butterworth filtered. We determined EMG onset time with a dual-threshold method given a critical amplitude threshold and a 10 ms temporal threshold (Walter, 1984). We defined a critical amplitude threshold of mean + three standard deviations of the flexor policis brevis muscle activity in the 400 ms before the trial onset across all trials. EMG onset time was determined when the EMG activity rose and stayed above the critical amplitude threshold for 10 ms. The onset time was calculated using the dual-threshold method and verified by human inspection per reaction time trial (Fig. S2*A*, *B*). We found the average difference between trigger time and EMG onset time for the reaction time trials per subject (Fig. S2*C*). The neural + mechanical delay for each participant was defined as the average difference between trigger time and EMG onset time plus a nerve propagation delay of 20 ms (Jo and Perez, 2019). We calculated the estimated decision time on each trial during the main experiments as the trigger time minus the neural + mechanical delay (Fig. S2*D*).

Movement analysis. Hand position data were digitally dual-pass, second order, low-pass (20 Hz cutoff), and Butterworth filtered. Our primary focus was to determine whether the deliberation process influences movements, prior to a final decision. We were interested in the movement prior to the influence of the final decision and subsequent actions. To this end, we looked at the lateral hand position at estimated decision time (Fig. 2).

Statistical analysis

All statistical tests were performed in Python 3.8.5. We used repeated measures analysis of variance (rmANOVA) as the omnibus tests for each dependent variable. We were primarily interested in estimated decision time, lateral hand position at estimated decision time, and selection rate metrics for the bias token patterns. In Experiments 1 and 2, we used a 2 (bias: left or right) × 2 (target: left or right) rmANOVA for decision time, lateral hand position at estimated decision time, and selection rate. In Experiment 3, we used a 2 (rate: fast or slow) × 2 (bias: left or right) × 2 (target: left or right) rmANOVA for decision time and selection rate. For lateral hand position at estimated decision time, we performed separate 2 (bias: left or right) × 2 (target: left or right) rmANOVAs for fast bias patterns and slow bias patterns. Here we used separate rmANOVAs, since we found significantly different decision times between slow rate and fast rate bias token patterns. For Experiments 1, 2, and 3, we were also interested in the pseudorandom token patterns and used a 1-way rmANOVA (probability of left target: 20%, 35%, 50%, 65%, and 80%) for estimated decision time, lateral hand position at estimated decision time, and selection rate. For all experiments, we performed nonparametric bootstrap hypothesis testing for mean comparisons ($n = 1{,}000{,}000$; Gribble and Scott, 2002; Cashaback et al., 2015, 2017a,b, 2019; Coltman et al., 2019; Calalo et al., 2023; Roth et al., 2023). Holm–Bonferroni corrections were used to control for type 1 error. We computed common language effect size ($\hat{\theta}$) for all mean comparisons (McGraw and Wong, 1992; Calalo et al., 2023). Statistical significance was set to $p < 0.05$.

Results

Individual movement behavior

We were primarily interested in the lateral hand position at the estimated decision time. Lateral hand position at estimated decision time provided a measure of the influence of ongoing deliberation on the movement. In other words, the lateral hand position at estimated decision time precludes movement that is a result of a final decision and subsequent action. Estimated decision time was calculated by subtracting a neural plus mechanical delay from the trigger time on each trial (Fig. 3*A*, *B*).

The mean (±1 SD) participant neural + mechanical delay was 184.2 (±17.6) ms, 186.4 (±23.5) ms, and 196.7 (±18.0) ms in Experiments 1, 2, and 3, respectively. We found that the estimated decision times were strongly correlated with peak tangential acceleration times in the bias token patterns for Experiments 1, 2, and 3 (Fig. S2*E–G*). We examined lateral hand position at estimated decision times to compare between conditions (Fig. 3*C*).

Figure 4 presents results by representative individuals in each experiment. In Experiment 1, this participant did not initiate lateral movements prior to their estimated decision time (Fig. 4*A–D*). In Experiment 2, the participant displayed lateral movements aligned with token bias direction prior to the estimated decision time (Fig. 4*E–H*), which reflects movement that occurred before their final decision. Moreover, their lateral hand position aligned with the token bias direction (Fig. 4*H*). In Experiment 3, the representative participant displayed lateral movements that aligned with the direction of the bias in both slow rate bias (Fig. 4*I–L*) and fast rate bias (Fig. 4*M–P*) token patterns. That is, the displayed participants in Experiments 2 and 3 moved with the evidence prior to a final decision, suggesting that their movements were influenced by the ongoing deliberation.

Group movement behavior

We predicted that the lateral hand movements would be influenced by the ongoing deliberation, prior to a decision. For example, a participant that is considering the left target will

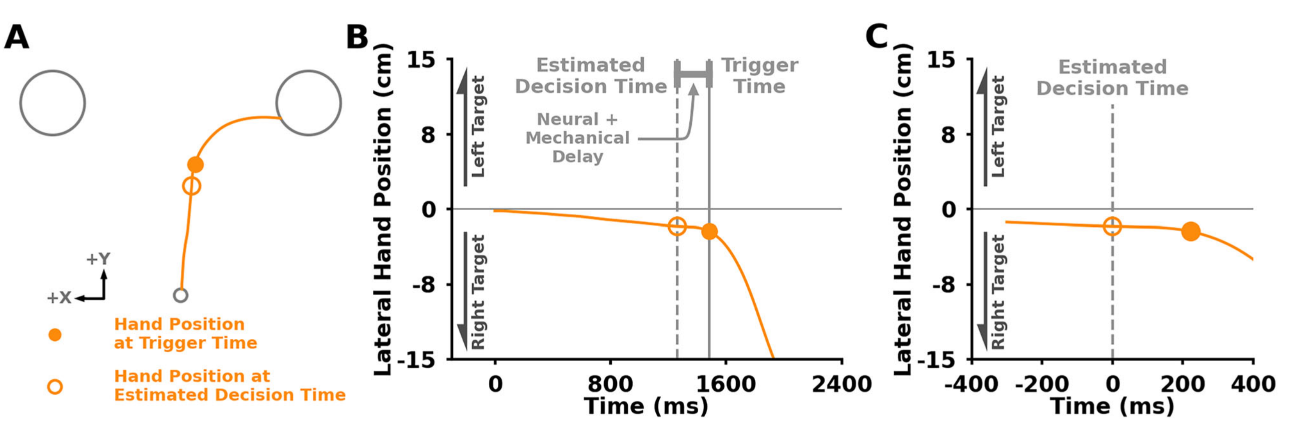

Figure 3. Analysis description. ***A***, Hand path for a single example trial in Experiment 2. Solid circles represent the hand position when the participant pressed the hand trigger (trigger time). Empty circle represents the hand position at estimated decision time. Estimated decision time was calculated by subtracting a neural and mechanical delay from the trigger time on a trial-by-trial basis. Neural + mechanical delay was estimated for each participant using a reaction time task (Fig. S2). ***B***, Lateral hand movement (*y*-axis) over time (*x*-axis). Solid gray line represents when the hand trigger was pressed. Dashed gray lane represents estimated decision time. ***C***, Lateral hand position (*y*-axis) over time (*x*-axis) aligned to estimated decision time. The lateral hand position at the estimated decision time allows us to look at the influence of deliberation on movement, prior to a final decision.

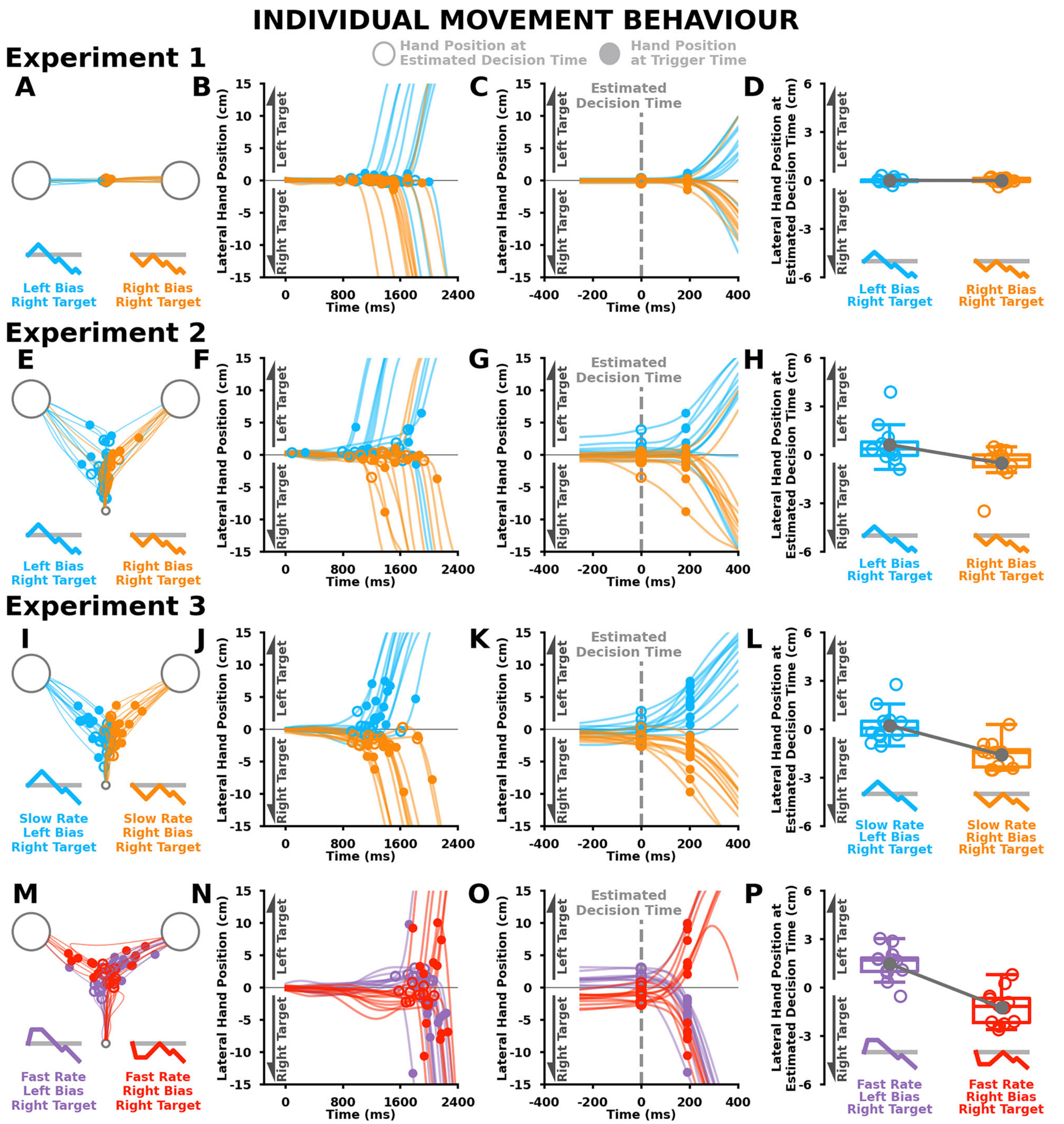

Figure 4. Individual movement behavior. ***A–H***, Individual participant movement behavior for left bias, right target (light blue) and right bias, right target (light orange) token patterns in Experiment 1 (***A–D***) and Experiment 2 (***E–H***). ***I–P***, Individual participant movement behavior in Experiment 3 for ***I–L***, slow rate, left bias, right target (light blue) and slow rate, right bias, right target (light orange) token patterns. ***M–P***, Fast rate, left bias, right target (light purple) and fast rate, right bias, right target (light red) token patterns. Solid circles represent hand position at trigger time. Empty circles represent hand position at estimated decision time. ***A***,***E***,***I***,***M***, Individual participant reaching trajectories. ***B***,***F***,***J***,***N***, Individual participant lateral hand positions (*y*-axis) over time (*x*-axis). ***C***,***G***,***K***,***O***, Individual participant lateral hand positions (*y*-axis) over time (*x*-axis) aligned to estimated decision time. Vertical gray dashed line at 0 ms represents estimated decision time. ***D***,***H***,***L***,***P***, Individual participant lateral hand positions at estimated decision time (*y*-axis) between bias token patterns (*x*-axis). In Experiment 1, this participant did not display differences in lateral hand position at estimated decision time between conditions. Participants in Experiments 2 and 3 show differences in lateral hand positions at estimated decision time between left and right bias conditions.

move toward the left target, prior to their final decision. Figure 5 displays the average group movement behavior for the three experiments. We show the average lateral hand trajectories over time for Experiments 1, 2, and 3 (Fig. 5*A*, *D*, *G*, *J*). However, it is important to examine lateral hand positions at the estimated decision time (Fig. 5*B*, *E*, *H*, *K*), which reflects movement caused by deliberation prior to a final decision.

Hand movements are influenced by deliberation when the motor system is actively engaged

In Experiment 1, lateral hand position at the estimated decision time was not impacted by the token patterns (Fig. 5*B*). We did not find a significant main effect of bias [$F(1, 16) = 3.681$, $p = 0.073$], main effect of target [$F(1, 16) = 1.016$, $p = 0.328$], or an interaction between bias and target [$F(1, 16) = 0.067$,

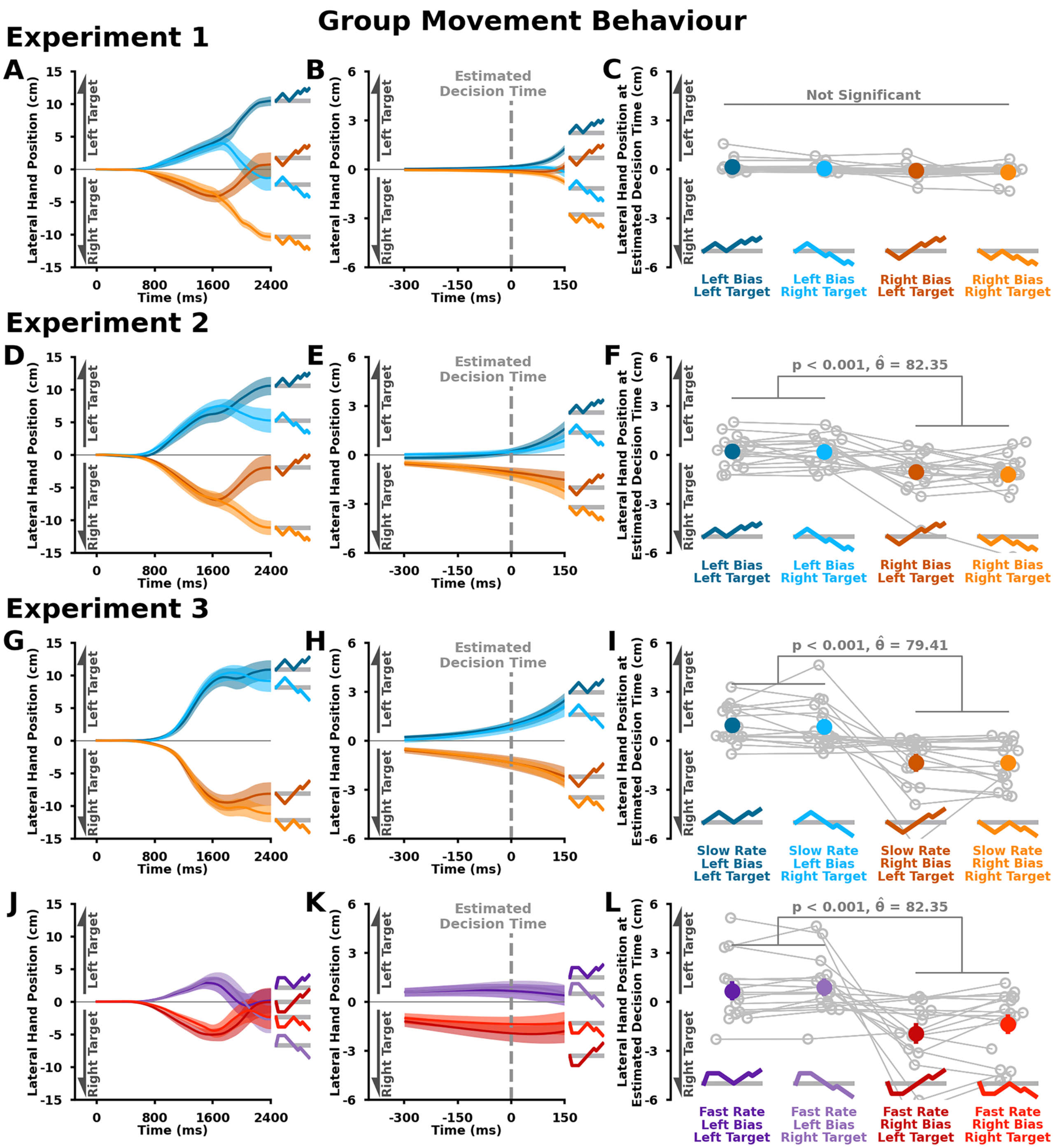

Figure 5. Group movement behavior. ***A–F***, Average participant movement behavior for bias token patterns in Experiment 1 (***A–C***) and Experiment 2 (***D–F***). ***G–L***, Average participant movement behavior in Experiment 3 for ***G–I***, slow rate bias token patterns and ***J–L***, fast rate bias token patterns. Solid lines represent group mean trajectories for each condition. Shaded regions represent ±1 standard error. ***A***,***D***,***G***,***J***, Average participant lateral hand positions (*y*-axis) over time (*x*-axis). ***B***,***E***,***H***,***K***, Average participant lateral hand positions (*y*-axis) over time (*x*-axis) time aligned to estimated decision time. Vertical gray dashed line at 0 ms represents estimated decision time. ***C***,***F***,***I***,***L***, Average participant lateral hand positions at estimated decision time (*y*-axis) across bias token patterns (*x*-axis). In Experiment 1, there were no significant differences in lateral hand positions at estimated decision time between bias token patterns. Participants in Experiments 2 and 3 were significantly more toward the left target in left bias token patterns compared to right bias token patterns at the estimated decision time ($p < 0.001$ for all comparisons). Taken together, these results suggest that lateral hand movements reflect the ongoing deliberation during movement prior to a decision.

$p = 0.799$] on lateral hand position at estimated decision time (Fig. 5C). The results in Experiment 1 do not support the idea that the deliberation process continuously interacts with the motor control processes to influence online movements, specifically when evidence is initially presented while in posture. In Experiment 2, we examined the influence of ongoing deliberation on the motor control system when the motor system was actively engaged. Here participants displayed lateral hand positions at estimated decision time that was aligned with the direction of the token bias (Fig. 5E). Specifically, we found a significant main effect of bias [$F(1, 16) = 11.533$, $p = 0.004$] on lateral hand position at estimated decision time. We did not find an interaction between bias and target [$F(1, 16) = 0.300$, $p = 0.591$] nor a main effect of target [$F(1, 16) = 0.255$, $p = 0.620$]. When collapsing across target, as expected we found significantly different lateral hand positions at estimated decision time between left bias and right bias token patterns (Fig. 5F; $p < 0.001, \hat{\theta} = 82.35$). Moreover, our findings and interpretation were consistent when we very conservatively looked further back in time (Fig. S3), along with pseudorandom token patterns (e.g., 20%, 35%, 50%, 75%, and 80% left target probability; Fig. S4). The findings in Experiment 2 support the hypothesis that the ongoing deliberation process influences online movements, prior to a decision, when the motor system is actively engaged.

In Experiment 3, we replicated the movement behavior findings of Experiment 2. We analyzed lateral hand position at estimated decision times separately for slow rate and fast rate token patterns, since they had different decision times (see Group decision-making behavior below). For the slow rate token patterns, we found a significant main effect of bias [$F(1, 16) = 14.663$, $p = 0.001$] on lateral hand position at estimated decision time, but no main effect of target [$F(1, 16) = 0.0875$, $p = 0.771$] or bias and target interaction [$F(1, 16) = 0.040$, $p = 0.844$]. For the fast rate token patterns, we found a significant main effect of bias [$F(1, 16) = 9.114$, $p = 0.008$] and a significant main effect of target [$F(1, 16) = 4.834$, $p = 0.043$] on lateral hand position at estimated decision time, and not a bias and target interaction [$F(1, 16) = 1.297$, $p = 0.272$]. We found significantly different lateral hand positions at estimated decision time between left bias and right bias conditions for both slow rate bias token patterns ($p < 0.001, \hat{\theta} = 79.41$; Fig. 5I) and the fast rate bias token patterns ($p < 0.001, \hat{\theta} = 82.35$; Fig. 5L). Again, differences in lateral hand position support the hypothesis that ongoing deliberation influences movement, prior to a decision, when the motor system is actively engaged.

We also analyzed the tangential hand velocity at the estimated decision. For the bias token patterns in Experiments 1 and 2, we did not find any significant main effects or interaction effects of bias and target on tangential hand velocity at the estimated decision time ($p > 0.164$). In Experiment 3, we found a significant main effect of target in the slow rate [$F(1, 16) = 4.667$, $p = 0.046$] and fast rate [$F(1, 16) = 6.762$, $p = 0.019$] token patterns. We did not find a significant main effect or interaction effect including bias in the slow rate and fast rate token patterns ($p > 0.120$). When collapsing across bias in the slow rate condition, we did not find significantly different tangential hand velocities at estimated decision time ($p = 0.093$, $\theta = 67.65$) between left and right target. When collapsing across bias in the fast rate token patterns, we found significantly different tangential hand velocities at estimated decision time ($p = 0.006$, $\theta = 67.65$) between left and right target. Thus, we did not observe any consistent results across experiments when examining tangential velocity.

Taken together, our results from Experiments 1, 2, and 3 support the idea that the ongoing deliberation process influences hand movement—prior to a decision—when the motor system is actively engaged but not during posture.

Group decision-making behavior

Humans relied less on early evidence when making decisions

We were also interested in the processes that underscore the deliberation. Figure 6 shows the estimated decision times for each bias token pattern and experiment. In Experiment 1, we found a significant main effect of bias [$F(1, 16) = 7.222$, $p = 0.016$] on estimated decision time, but there were no significant differences in followup mean comparisons ($p = 0.053, \hat{\theta} = 61.76$; Fig. 6A). We did not find a significant main effect of target [$F(1, 16) = 0.606$, $p = 0.447$] or an interaction between bias and target [$F(1, 16) = 0.930$, $p = 0.349$] on estimated decision time. In Experiment 2, we did not find a significant main effect of bias [$F(1, 16) = 0.989$, $p = 0.335$], significant main effect of target [$F(1, 16) < 0.001$, $p = 0.993$], or an interaction between bias and target [$F(1, 16) = 0.154$, $p = 0.700$] on estimated decision time (Fig. 6B). Interestingly, participants made faster decisions during Experiment 2 compared to Experiment 1 ($p = 0.003, \hat{\theta} = 67.76$). One possibility for our result is that decisions are made faster when the motor system is actively engaged, supporting bidirectional interactions between decision and motor processes. Complementing this notion, it is possible that moving closer to one of the targets during deliberation would lead to a lower energetic cost to reach that target, which in turn may promote a faster decision time.

In Experiment 3, we found a significant main effect of rate [$F(1, 16) = 27.18$, $p < 0.01$] on estimated decision time (Fig. 6C). Counterintuitively, we found that participants made earlier decisions in slow rate compared to fast rate token patterns ($p < 0.001, \hat{\theta} = 89.71$; Figs. 6C, 7A). We did not find main effects of target [$F(1, 16) = 0.689$, $p = 0.419$], main effect of bias [$F(1, 16) = 0.588$, $p = 0.454$], nor any significant interactions ($p > 0.105$). The selection rates for each token pattern are shown in Figures S5 and S6.

Above we did not find a significant bias and target interaction on estimated decision time. This pattern is consistent with past work by Cisek (2009) that proposed that urgency is involved with deliberation. As a reminder, urgency represents less reliance on early evidence compared to later evidence when making a decision. Interestingly and counterintuitively, we found that participants made earlier decisions with a slow rate token pattern compared to the fast rate token pattern. This finding strongly align with the idea that decision-making processes more heavily value information that is presented later in time (i.e., second, third, and fourth tokens in the slow rate token pattern) compared to the same information presented earlier in time (i.e., second, third, and fourth tokens presented earlier in time during the fast rate token pattern). However, as shown below in Decision-making models, the presence of both urgency and evidence integration best explain the reported estimated decision times.

Computational modeling

Our central focus was to investigate the interaction between the decision-making and motor control processes. To this end, we used a computational framework that combines a decision-making model and an optimal feedback control model.

Decision-making models

Before combining decision and motor models, we first sought to determine the decision-making model that would best explain estimated decision times and selection rate proportions. Below, we define current evidence or novel evidence that was used as input into the decision-making models. Next we describe four different classes of decision-making models we used, while highlighting the Trueblood model that did well to capture our data (Trueblood et al., 2021).

Evidence was a function of the current correct probability (p) for the left target given the number (N_i) of tokens within the left (L), right (R), and center (C) locations (Eq. 1).

$$p(L \mid N_L, N_R, N_C) = \frac{N_C!}{2^{N_C}} \sum_{k=0}^{\min(N_C, 7-N_R)} \frac{1}{k!(N_C - k)!}. \tag{1}$$

We separately used either current evidence (E_{curr}, Eq. 2) or novel evidence (E_{novel}, Eq. 3) as inputs into the decision-making models. $N(t)$ represents Gaussian noise.

$$E_{\text{curr}}(t) = p(t) + N(t) - 0.5, \tag{2}$$

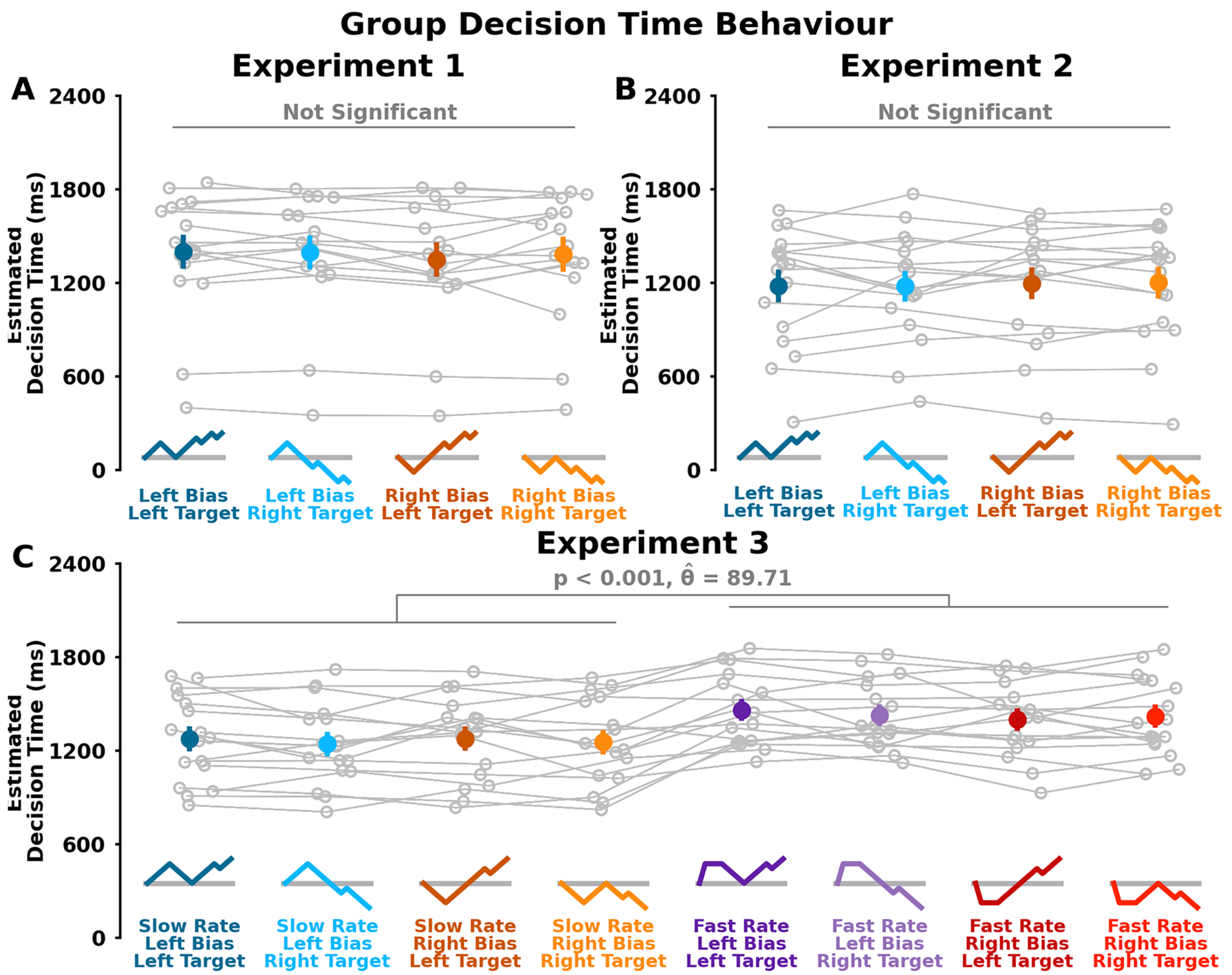

Figure 6. Group decision time behavior. Estimated decision time (ms; *y*-axis) in ***A***, Experiment 1, ***B***, Experiment 2, and ***C***, Experiment 3 across bias token patterns (*x*-axis). Open gray circles and connected gray lines represent individual participants. Closed colored circles (and error bars) represent mean (and standard error of the mean) for each token pattern. Estimated decision time did not change between bias token patterns in ***A***, Experiment 1 ($p > 0.05$) and ***B***, Experiment 2 ($p > 0.05$). ***C***, Participants had earlier estimated decision times in Experiment 3 for slow rate token patterns (blue and orange colors) compared to fast rate token patterns (purple and red colors; $p < 0.001$), suggesting a greater temporal weighing of later evidence in the decision-making process.

$$E_{\text{novel}}(t) = \frac{dp(t)}{dt} + N(t). \tag{3}$$

We tested four decision-making models (drift-diffusion model, drift-diffusion model with leak, Trueblood, urgency-gating model with a low-pass filter) to model decision behavior (Text S1 and Table S1 for complete model descriptions; Cisek et al., 2009; Trueblood et al., 2021). Here we highlight the Trueblood model that utilizes urgency (k) and leak (L) to simulate a decision variable (DV) over time (t) as follows:

$$\frac{dDV}{dt} = \left(\frac{k}{1+kt} - L\right) DV(t) + E(t)(1+kt). \tag{4}$$

As shown by Trueblood and colleagues, the Trueblood model can be used to describe a two parameter space defined by urgency (k) and leak (L) which contains the drift-diffusion model ($k = 0$, $L = 0$) and the drift-diffusion model with leak ($k = 0$, $L > 0$). The Trueblood model also reduces to the standard urgency-gating model with a low-pass filter ($k \to \inf, L > 0$), but note that urgency can be found with a sufficiently high k (i.e., $k >> 0$). Here we showed the drift-diffusion model, drift-diffusion model with leak, and the urgency-gating model with a low-pass filter to highlight the typically used models within the field. Here we focus on Experiment 3 (Fig. 7) since there was a significantly earlier estimated decision time in the slow rate token patterns compared to the fast rate token patterns.

We found the Trueblood model with novel evidence and the urgency-gating model with a low-pass filter with novel evidence were the only two models that could capture the earlier decision times in the slow rate token patterns relative to the fast rate patterns (Fig. 7*A*). The other best-fit models found decision times that were similar between the two different sets of rate token patterns.

To give insight into the mechanisms of the models, we show representative model behavior in Figure 7*C*, *D*. In Figure 7*B*, we show examples of fast rate right bias left target and slow rate right bias left target token patterns. These two token patterns were similar except for the different rates of token movement for the initial bias. For both the Trueblood model with novel evidence (Fig. 7*C*) and the urgency-gating model with a low-pass filter on novel evidence (Fig. 7*D*), we see similar decision variable

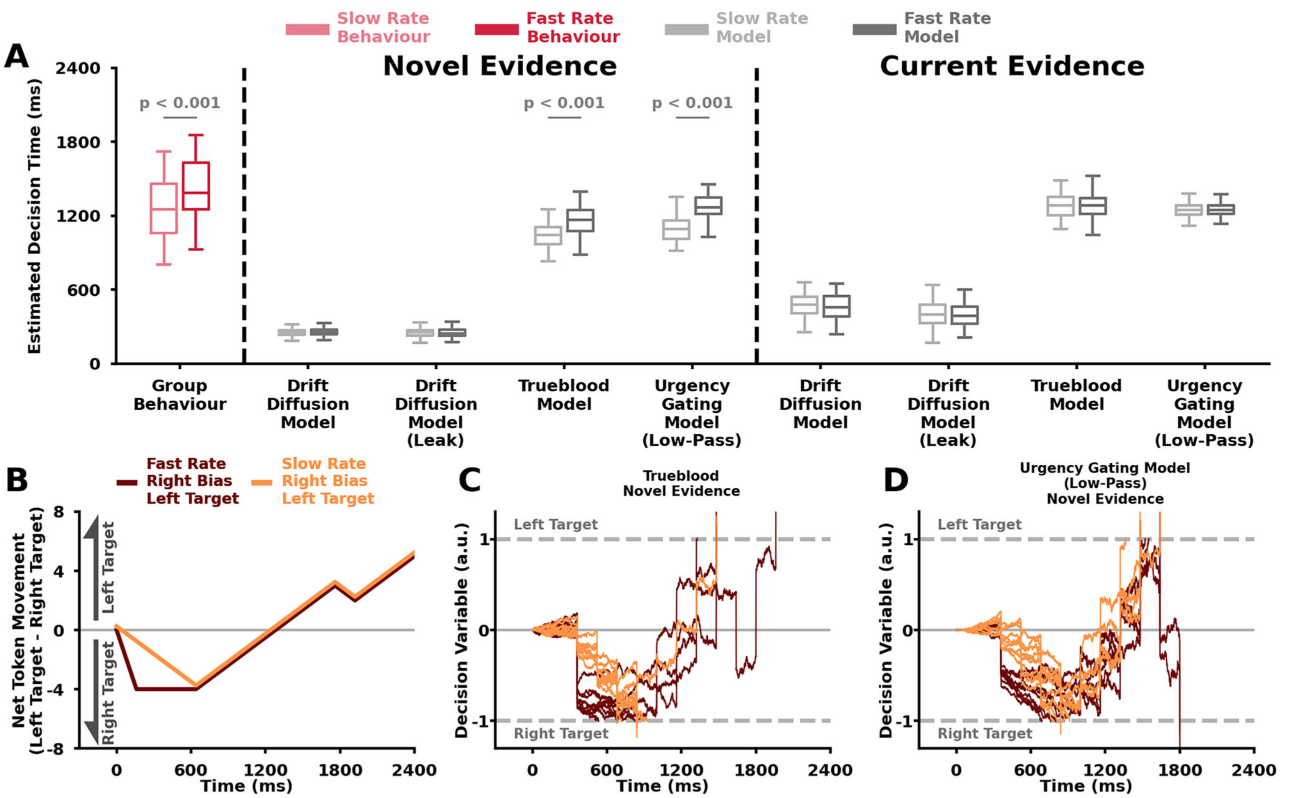

Figure 7. Best-fit decision-making model simulations. ***A***, Experiment 3 estimated decision time (*y*-axis) for group behavior (pink) and decision-making models (gray; *x*-axis). Group participant estimated decision times are shown for slow rate token patterns (light pink) and fast rate token patterns (dark pink). Best-fit model simulations of decision times are shown for slow rate token patterns (light gray) and fast rate token patterns (dark gray). Box and whisker plots show 25%, 50%, and 75% quartiles. Decision-making models simulated decisions using novel sensory evidence or current sensory evidence. As described above in Figure 6, participants made earlier decisions with slow rate token patterns compared to fast rate token patterns. Only the Trueblood model using novel sensory evidence and the urgency-gating model with a low-pass filter on novel sensory evidence were able to capture the behavioral difference in decision time between slow rate token patterns and fast rate token patterns. The Trueblood model and urgency-gating model with a low-pass filter both contain a temporally increasing (urgency) component and an integration of evidence. ***B***, Net token movement (*y*-axis) over time (*x*-axis) for slow rate, right bias, right target (orange) and fast rate, right bias, right target (dark red) token patterns. ***C***–***D***, Example simulations of decision-making models showing decision variables (*y*-axis) over time (*x*-axis). Each trace represents a single decision-making trial for either slow rate, right bias, right target (orange) and fast rate, right bias, right target (dark red) token patterns. The dashed gray lines represent decision thresholds for a left target decision or right target decision. ***C***, Trueblood model using novel evidence. ***D***, Urgency-gating model with a low-pass filter using novel evidence. Our model results suggest that the deliberation process likely includes an urgency signal, or temporal scaling, component as well as the integration of novel evidence.

trends. Both the Trueblood model and the urgency-gating model with a low-pass filter utilize urgency and integrate evidence leading to similar behavior. For the fast rate token pattern, there is some initial integration of evidence, either through evidence accumulation or the low-pass filter. However, urgency is low early when the first four tokens move, so that the decision variable does not immediately cross the decision threshold. Conversely for the slow rate token pattern, each individual token movement leads to some integration of evidence. Crucially, individual token movements later in time are more heavily weighted by urgency, which compounded over time leads to an earlier crossing of the decision variable over the decision threshold. Note for the drift-diffusion models, the best solution to capture the trend was achieved by having high noise parameters since they would be unable to produce the observed faster decision time with the slow rate token pattern. We chose to use the Trueblood model as an input into the decision-making and movement model, described directly below, because it explicitly defines both urgency and evidence accumulation.

Decision-making and movement model

We found that ongoing deliberation influenced online movement. To capture this movement behavior, we developed an optimal feedback control model (Todorov and Jordan, 2002; Scott, 2004; Liu and Todorov, 2007; Nashed et al., 2012; Kasuga et al., 2022; Lokesh et al., 2023) that used the evolving decision variable to influence the ongoing movements. The decision variable was simulated using the Trueblood model with novel evidence.

Optimal feedback control has been able to capture a large range of human reaching movements, selects feedback gains in an emergent way to handle various task demands by considering biologically plausible objectives such as accuracy and energy, has allowed us to address competing theories in the field within this paper, and has been one of the most influential theory of movement in sensorimotor neuroscience in the past couple of decades. While we view optimal feedback control as a useful framework to study and predict human behavior, we do not suggest that these exact computations are performed by the brain.

In short, we used an optimal feedback controller that directed the hand toward an evolving and weighted averaged target that was a function of deliberation. This model is able to capture individual movement behavior (Fig. 8*A*–*C*) and group movement behavior (compare Fig. 8*D*–*F* to Fig. 8*G*–*I*). Here we provide a brief description of the model, but refer the reader to Text S1 for further details.

Here, we model the movement as a linear dynamic system (Eq. 5) where **x** represents the states of the system (e.g., position,

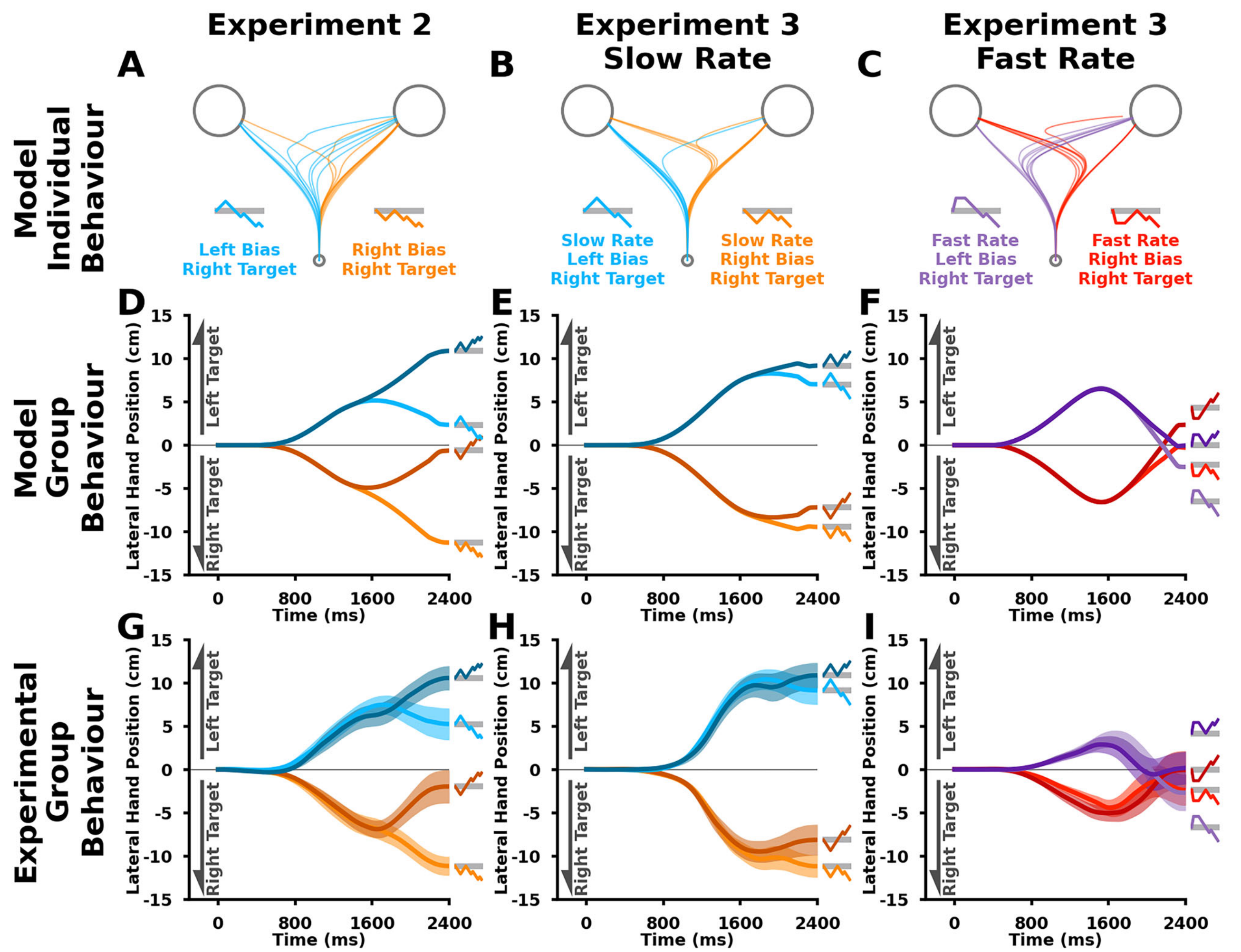

Figure 8. Best-fit movement model simulations. We fit a decision and movement model across the movement trajectories in biased token patterns in Experiments 2 and 3. The models utilized a weighted average of the targets to control the feedback responses. For each trial and time step, the weighting for each target was calculated from a decision variable generated by the Trueblood model using novel sensory information. ***A–C***, Model individual behavior. ***D–F***, Model group behavior lateral hand position (*y*-axis) over time (*x*-axis). ***G–I***, Experimental group behavior lateral hand position (*y*-axis) over time (*x*-axis; repeated from Fig. 4). The model was able to capture the trends found in the experimental group behavior. This model supports the idea that online movements reflect the ongoing deliberation process.

velocity, and goal location), $\mathbf{u}$ represents the control inputs to the system, and $\mathbf{A}$, $\mathbf{B}$ represent the dynamics of the system.

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \boldsymbol{\xi}_k. \tag{5}$$

The goal location (p_{goal}) is an average of the two targets weighed by a term (α) that is a function of the decision variable. The controller finds the control signal that minimizes the quadratic cost function (J; Eq. 6) where $\mathbf{Q}$ represents the weighting on the state cost and $\mathbf{R}$ represents the weighting on the control costs.

$$J = \mathbf{x}_N^T\mathbf{Q_N}\mathbf{x}_N + \sum_{k=0}^{N-1}(\mathbf{u}_k^T\mathbf{R}\mathbf{u}_k + \mathbf{x}_k\mathbf{Q}\mathbf{x}_k). \tag{6}$$

The optimal feedback control policy ($\mathbf{L}$) is found by solving the algebraic Ricatti equation. The control policy is used at each time step to find the optimal control signal ($\mathbf{u}^*$) as a function of the current state (x_k).

$$\mathbf{u}_k^* = -L_k(\mathbf{x}_k). \tag{7}$$

Re-interpreting previous work with the movement model

Using our decision-making and movement model, we were also able to propose an alternative explanation for a go-before-you-know task by Wong and Haith (2017). The researchers defined reaches that were not directly at one of the two targets as intermediate movements. They found that slow reaching movements resulted in more intermediate movements compared to fast reaches (Fig. 9). The authors interpreted these findings to indicate a single flexible plan that maximized task performance, since an averaging of static motor plans would always launch as an intermediate movement regardless of movement speed (Chapman et al., 2010a). As noted above, we used a single flexible motor plan to model the influence of deliberation on movement. However, we found that a single flexible motor plan is mathematically equivalent to averaging two parallel control policies (Text S1). Here we provide an alternative explanation for their results when considering urgency. That is, urgency may explain why participants made less intermediate movements in the fast reach condition. Thus, urgency can be used to explain behavior and is compatible with proposed theories of a single flexible motor plan or averaging of parallel control policies.

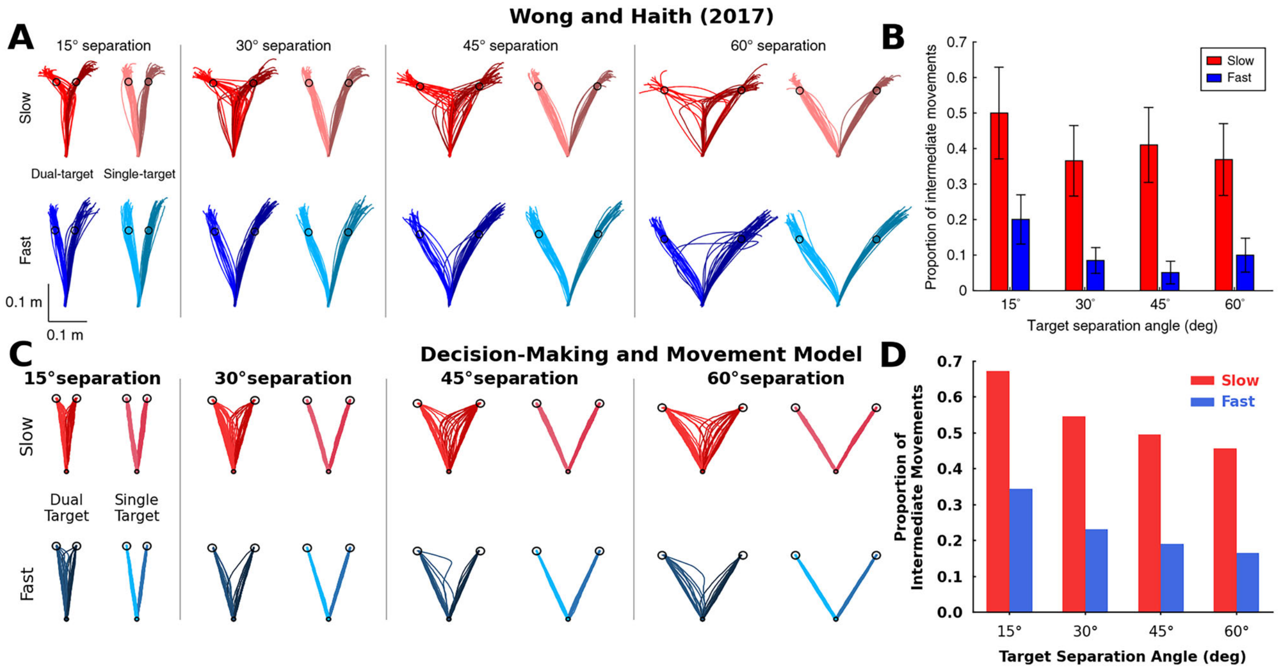

Figure 9. Replicating previous work ***A***, ***B***, Behavioral data from Wong and Haith (2017; reprinted with permission) showing that required movement speed and target separation affect the proportion of intermediate movements. ***A***, Individual single trajectories for dual-target and single target reaches with different target separation angles. Red and blue represent movements in the slow and fast conditions respectively. ***B***, Group proportion of intermediate movements (*y*-axis) between target separation angles (*x*-axis). In ***C***, ***D***, our model predicts that differences in urgency between conditions can lead to differences in the proportion of intermediate movements. Here, we modulated urgency as a function of the relative cost of an intermediate movement and the time to get to the target. ***C***, Model single trajectories for dual-target and single target reaches with different target separation angles. Red and blue represent movements in the slow and fast conditions, respectively. ***D***, Model average proportion of intermediate movements (*y*-axis) between target separation angles (*x*-axis). Our model was able to replicate the influence of required movement and target separation angle on the proportion of intermediate movements by manipulating the urgency in the deliberation process.

We replicated their findings (Fig. 9*C*, *D*) using an urgency signal (k) that was inversely proportional to allowable reach time (T), as well as reward (r) and the relative energetic cost of an direct movement compared to an intermediate movement (c) (Eq. 8). This equation follows the suggestion of Carland et al. (2019), where urgency is a function of reward, energy, and time.

$$k = \frac{(m_r * r) - (m_c * c)}{m_T * T}, \quad \text{where } c = \frac{z}{z\sin(\theta/2) + z\cos(\theta/2)}, \tag{8}$$

where m_i are scalars, z is the distance of a direct movement, and θ is the angle between the two targets. To capture target selections prior to the reveal of the correct option, we allowed the deliberation process to begin prior to movement onset in line with the experimental paradigm seen in Wong and Haith (2017; Text S1 for further details). In particular, when comparing slow and fast movement speeds, our decision-making and movement model suggests that the proportion of intermediate movements arises due to the urgency to make a decision. For example, urgency is higher in the fast movement condition since there is less time to reach the target. As a consequence during these fast movements, a target is more quickly selected even without evidence, since the deliberation noise is multiplied by a high urgency signal and crosses a decision threshold (i.e., guessing). Conversely in the slow movement condition, the lower urgency does not push the noise over a decision threshold and the participant can wait for evidence of the correct target.

Collectively, our empirical and computational results suggest that deliberation, which involves urgency, directly influences online movements.

Discussion

We show that ongoing deliberation is reflected in movements—prior to a decision—when the motor system is actively engaged. We also find that urgency was necessary to explain decision times in the third experiment, as well as predicting movement behavior in the literature.

In Experiment 2, Experiment 3, and the Control Experiment in Figure S7, we were able to elucidate the influence of the ongoing deliberation of uncertain and continuous evidence on movements. Prior literature has utilized a "go-before-you-know" paradigm where participants were presented multiple potential targets and initiated their movements without complete knowledge of the correct target (Spivey et al., 2005; Chapman et al., 2010a,b; Wood et al., 2011; Gallivan and Chapman, 2014; Wong and Haith, 2017; Alhussein and Smith, 2021). In these studies, the correct target was indicated partway through the reach via a sudden and discrete change of evidence (e.g., target color or location, phonological input, etc.) that resulted in participants making rapid movement redirections. These rapid movement redirections reflect a rapid decision in response to a sudden and discrete change of evidence. Similar rapid movement redirections have been seen following uncertain and continuous evidence (i.e., random dot motion task) that is presented prior to movement initiation (Resulaj et al., 2009; Moher and Song, 2014; Visser et al., 2023). In a small subset of trials, participants displayed "changes of mind" where they rapidly redirected toward the other target. It has been suggested that these changes of mind reflect a second decision based on delayed sensory information. Due to the sudden decisions and rapid movement redirections in the above works, it would be difficult to dissociate whether movement was caused either from deliberation or acting solely on a second decision.

There has also been increased interest in midreach decisions, such as when using the target-split paradigm by Kurtzer et al. (2020). In this task, participants would move their hand to one target and this would occasionally change to two target options during the movements. Participants showed a preference toward the options nearest the original target. Others have shown that midreach decisions are sensitive to other factors such as relative target frequency (Ulbrich and Gail, 2023), reward magnitude (Marti-Marca et al., 2020), and biomechanics (Michalski et al., 2020; Cos et al., 2021; Canaveral et al., 2024). In these midreach decision tasks, participants indicate their choice with a rapid movement redirection. Again however, it would be difficult to dissociate whether movement was caused either from deliberation or the final decision.

Unlike the above works and others (Song et al., 2008; Dotan et al., 2018), a key aspect of our design was using the hand trigger to estimate the decision time, allowing us to separate whether movement was caused either from deliberation or action selection following a final decision. Future work could adapt this paradigm during reaching or gait to study the influence of energetics, reward (e.g., hasty decisions Derosiere et al., 2022), and other factors that may impact decision-making to gain an understanding of the ongoing deliberation via movement.

In Experiment 1, we found that the ongoing deliberation did not induce movements prior to a decision, at least to a significant level, when initially in posture. Conversely, in both Experiments 2 and 3, we found that when the motor system was already actively engaged, there was an expression of the deliberation process via movement. Being able to express deliberation in movement but not in posture aligns with previous results showing differential configuration and engagement of motor circuits for movement and posture (Kurtzer et al., 2005; Cluff and Scott, 2016; Shadmehr, 2017). One possibility is that the deliberation processes may not have had enough influence on postural circuits to elicit movement initiation. While our paradigm allows for a continuous expression of deliberation during movement execution, past work has shown that it is possible to elicit an instantaneous expression of deliberation from a postural state. Selen and colleagues were able to gain a momentary expression of deliberation at the moment of movement onset (Selen et al., 2012; Visser et al., 2023). Specifically, they perturbed the upper limb while in posture and measured the resulting long-latency stretch reflex. They found that the long-latency stretch reflex reflected deliberation at the time of perturbation while in posture. One potential avenue would be to use a forced response time task (Haith et al., 2015) where participants must initiate a reach from posture while deliberating, allowing a readout of the instantaneous influence of deliberation on movement vigor (i.e., via hand velocity).

We also found that participants made faster decisions when already moving in Experiment 2 compared to when in posture for Experiment 1. This finding may reflect "embodied decisions," where the current and future states of the motor system can influence decision-making (Cos et al., 2011, 2021; Nashed et al., 2014; Lepora and Pezzulo, 2015; Marcos et al., 2015; Morel et al., 2017; Reynaud et al., 2020; Grießbach et al., 2021; Korbisch et al., 2022; Carsten et al., 2023; Daniels and Burn, 2023; Canaveral et al., 2024). Korbisch et al. (2022) had participants select between short or long walking durations or shallow and steep walking inclines (Korbisch et al., 2022). When participants looked at depictions of the various options, the researchers found higher saccade vigor (i.e., velocity) toward the depictions associated with less effort. These results suggest that potential energy costs are embodied and can be reflected during deliberation with eye movement. In their study, evidence of potential effortful options was discrete and did not change during the course of the eye movement. Here, saccade vigor provides a glimpse of deliberation reflecting past evidence acquired from previous eye movements. Building on this work, we show that the online movement itself is influenced by an ongoing deliberation. It would be interesting for future work to manipulate both potential energetic costs over time and evidence during movement to further understand embodied decisions.

In Experiments 1 and 2, we found no difference in decision times between the bias token patterns, which replicates previous findings and is consistent with the urgency-gating hypothesis (Cisek et al., 2009). For Experiment 3, we used slow rate and fast rate token patterns to manipulate the rate of evidence and further understand deliberation. The standard evidence accumulation (with or without leak) would predict that the fast rate token patterns would respectively cause earlier or similar decision times compared to the slow rate token patterns. Counterintuitively, we found that the slow rate token patterns made faster decisions compared to the faster rate token patterns. We were able to capture faster decisions with the slow rate token patterns with both the Trueblood model and urgency-gating model with a low-pass filter. Both these models are similar mathematically and have terms that relate to urgency and an integration of evidence. Conceptually, the Trueblood model integrates to accumulate evidence toward a decision, whereas the integration from the low-pass filter of the urgency-gating model is intended to reflect an estimate of evidence from sensory processes. Neural activity during perceptual decision-making in monkeys has been attributed to either evidence accumulation toward a decision (Ratcliff, 1978; Shadlen and Newsome, 2001; Roitman and Shadlen, 2002) or the scaling of low-pass filtered estimate of evidence with an urgency signal that arises from the basal ganglia (Cisek et al., 2009; Thura and Cisek, 2014). An important future direction, such as through neural recordings in animals, is to determine where and why there is an integration of evidence. Irrespective of evidence integration, urgency was needed to predict decision times and replicate reaching trajectories from past work (Wong and Haith, 2017).

Here we developed a movement model that reflected deliberation, by combining the Trueblood decision-making model and optimal feedback control. This differs from past work that has used dynamic programing (Haith et al., 2015), Bayesian methods (Priorelli et al., 2024), only optimal feedback control (Nashed et al., 2014), and relative desirability of multiple options (Christopoulos and Schrater, 2015). While these other modeling approaches have been insightful and motivated the current work, they do not have a deliberation process that includes urgency. Urgency was a critical component to capture decision-making time and reaching movements from the past literature. However, it would be possible to include an urgency term in these previous modeling approaches. A limitation of our model as currently formulated is that it only allows for the deliberation process to influence the movement. That is, it does not allow the motor states to directly influence the deliberation process. This model design reflects our experiments where we manipulate the deliberation process to test its influence on movement. However, several of the aforementioned models would be able to capture some of the bidirectional relationships between cognitive and motor processes during embodied decisions reported in the literature (Cos et al., 2011; Morel et al., 2017; Reynaud et al., 2020; Grießbach et al., 2021; Korbisch et al., 2022; Canaveral et al., 2024). One particular embodied model is by Lepora and Pezzulo, which moved a point as a function of a drift-diffusion model that considered sensory evidence and the current distance to the potential targets. In this model, the controller moved the point toward an aim at a constant velocity, which we did not find in our study (Lepora and Pezzulo, 2015). Moving forward, it will be important to have a computational model of embodied decisions that captures several important features of both motor behavior (e.g., bell-shaped velocity profiles and vigor) and decision-making behavior (e.g., skewed reaction time, speed accuracy tradeoff, Hicks law, and urgency).

Prior literature has examined how the decision-making and motor systems interpret and act on multiple potential options (Cisek, 2007; Wong and Haith, 2017; Dekleva et al., 2018; Alhussein and Smith, 2021). In the go-before-you-know task, intermediate movements between two targets have been suggested to be an outcome of parallel averaged motor plans (Chapman et al., 2010a; Gallivan and Chapman, 2014; Christopoulos and Schrater, 2015) or a single flexible motor plan that optimizes task performance (Nashed et al., 2017; Wong and Haith, 2017; Alhussein and Smith, 2021). Wong and Haith (2017) interpreted more intermediate movements with slow hand speeds compared to fast hand speeds to reflect a single flexible motor plan (Wong and Haith, 2017). Here we provide an alternative perspective by considering urgency. When one also considers urgency, it is possible to explain different proportions of intermediate movements between slow or fast hand speeds with either a single flexible motor plan or parallel averaged motor plans.

It is important to consider that a single flexible motor plan or parallel averaged motor plans are a combination of two factors: (i) single versus parallel average and (ii) static versus flexible. Obviously a single static motor plan is not a viable option to handle multiple potential goals. Alhussein and Smith (2021) rule out a parallel average of static motor plans, since their prediction was based on the initial reach angle to each target. Yet their finding does not rule out the possibility of a parallel average of flexible motor plans, where each motor plan (more specifically, control policy) could contain a safety margin. As shown above, we were able to replicate the results of Wong and Haith (2017) by considering urgency (Wong and Haith, 2017). It is mathematically equivalent to have a single flexible motor plan that reflects a weighted average of two targets based on evidence compared to flexible parallel plans (control policies) that are weighted based on evidence (Text S1). At the moment it is unclear to us how to behaviorally dissociate between a single flexible motor plan or parallel average of flexible motor plans through movement execution, which would be a fruitful and important finding. Another potential approach is to consider the neural space. There has been conflicting neural support with regard to parallel motor plans or a single flexible motor plan (Cisek and Kalaska, 2005; Dekleva et al., 2018). It would be useful for future work involving neural recordings to determine where, when, and how multiple target representations and deliberation processes finally converge to produce a single executed movement.

Humans often must make decisions while moving. We found that deliberation was reflected in ongoing movements—prior to a decision—when the motor system was actively engaged. We found that an urgency signal, which more heavily weighted evidence later in time, was fundamental to predicting decision times and explaining previous reaching behavior. Our results support the hypothesis that the decision-making process influences movements prior to a decision. Understanding the integration of decision and motor processes may allow us to better understand neurological disorders where cognitive and motor processes and deficits may be entangled.

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