Reward accelerates the preparation of goal-directed actions under conflict

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Abstract

Our goals sometimes conflict with our habits, leading to impaired performance. People are better at exerting cognitive control to overcome prepotent and automatic responses when they are motivated by the prospect of reward. The standard experimental paradigms used to study this phenomenon examine free response times that allow participants to delay the initiation of their responses to avoid committing errors. However, this approach makes it difficult to determine which control processes are affected by reward. Does reward lead to improved performance via the inhibition of prepotent responses or the facilitation of goal-directed processing? Here we use a forced-response paradigm to fix response initiation and systematically vary the time available for response preparation. Using a probabilistic model that dissociates the preparation of habitual and goal-directed responses, we obtain evidence across multiple experiments ($N = 87$ people) that reward accelerates the preparation of goal-directed actions.

Introduction

Human actions are simultaneously controlled and automatic. When our goals align with our prepotent dispositions, we can achieve our goals with relative ease. But often our habits conflict with our goals, leading to impaired performance and the need to use of cognitive control to override prepotent responses (consider pressing the control key instead of command key after switching from Windows to Mac). Research shows that people perform better under conflict when they are motivated by the prospect of reward (Krebs et al., 2010; Locke & Braver, 2008; Padmala & Pessoa, 2011), but the mechanism by which this occurs remains unclear. One possibility is that reward improves our capacity to ignore distracting stimuli or inhibit inappropriate prepotent automatic responses (Boehler et al., 2012, 2014). Another possibility is

that reward improves our capacity to focus on goal-relevant information or disinhibit goal-directed responses (Hickey et al., 2011; Padmala & Pessoa, 2011). The aim of the present study is to test whether reward enhances goal-relevant processing or impairs goal-irrelevant processing (or both).

Research on cognitive control has historically focused on tasks that allow free response times (RT), in the sense that participants decide when to respond. A robust finding from such tasks is that free responses are slower when there is response conflict (Eriksen & Schultz, 1979; Simon, 1969; Stroop, 1935). It is commonly assumed that slower free response times reflect the increased processing time required to prepare the appropriate response by resolving conflict and overcoming the prepotent response (M. M. Botvinick et al., 2001). Alternatively, slower response times could reflect delays in response initiation, rather than slower preparation. Indeed, recent work in motor control shows that in free RT tasks people initiate movement quite some time after the movement is prepared (Haith et al., 2016). This finding makes it especially difficult to determine how to interpret prior studies examining the effect of reward in mitigating conflict as virtually all experiments have employed free RT tasks.

Figure 1. *Forced response conflict task.* Participants performed a modified Simon task with forced responding. Participants were trained to respond when a white dot appeared (at 2500 ms) and the target stimulus appeared at a random time between 1500 and 2500 ms. Participants were instructed to press the ‘w’ key with their left index finger if they saw a blue target circle and press ‘p’ with their right index finger if they saw an orange target circle. However, targets could appear to the left or right of center, so participants’ goals were on some trials congruent, and on other trials incongruent, with their prepotent dispositions to react towards the source of stimulation (Simon, 1969).

One way to glean more insight into how reward affects the underlying cognitive processing under conflict is to examine performance when response initiation is experimentally controlled. Response initiation can be experimentally controlled using a forced-response methodology in which participants are trained and cued to respond at the same predetermined time on each trial, rather than allowing them to decide when to respond (Haith et al., 2015, 2016; Hardwick et al., 2019). The time available for response preparation (PT) is manipulated by fixing the RT and varying the onset of the target stimulus. Recently this forced-response technique was used to disentangle habitual and goal-directed response preparation in a visuomotor stimulus-response task (Hardwick et al., 2019).

In the experiments reported below, we use a forced-response incentivized conflict task and a response preparation model to investigate whether reward mitigates conflict by inhibiting the preparation of prepotent responses or enhancing the preparation of goal-directed responses. Using a probabilistic response preparation model, we dissociate the preparation of automatic and goal-directed responses and quantify the separate effects of reward on these underlying processes. Across three experiments, we find evidence that reward accelerates the preparation of goal-directed actions.

Methods

Sample

Convenience samples of 27 people (10F, 17M, mean age of 25.3 years) participated in the first study, 30 people (9F, 21M, mean age of 24.2) participated in the replication study, and 30 people (10F, 19M, mean age of 25) participated in the control study. All participants were recruited using Prolific. Participants were compensated at a base rate of approximately \$10 per hour and

with opportunities for cash bonuses of \$1 or \$5. The experiments took about 45 minutes to complete. All materials and methods were approved by the Institutional Review Board at the [UNIVERSITY NAME REMOVED FOR MASKED REVIEW].

Experiment

The experiments started with training in the Simon task (40 trials). The stimulus appeared at a random time between 0 and 1000 ms after the start of each trial and participants were free to respond with no time limit. In the first study, participants were instructed to press ‘w’ with the left index finger if they saw a blue circle and to press ‘p’ with their right index finger if they saw an orange circle; in the replication study, the blue circle was replaced with a leftward pointing arrow and the orange circle was replaced with a rightward pointing arrow. We gave participants feedback about whether their responses were correct or incorrect. Next, participants in all studies were trained in the forced-response paradigm (60 trials). For this training session, participants were instructed to respond exactly when a centrally presented dot flashed for a fourth time within the trial. We gave participants feedback about whether they were too slow ($t > 100$ ms late) or too fast ($t < 100$ ms early). The final part of each study was the test session (10 blocks of 60 trials). For the first study and the replication study, the session was a Simon task with forced-responding; for the control study, the session was split into two stimulus-response tasks (color, then location). Participants were offered cash bonuses of \$1 or \$5 for making the correct response at the correct time (± 100 ms) on a randomly selected trial. The reward value varied randomly between blocks.

At the start of each trial in the test session, the value of the reward prospect was displayed for 600 ms in green text just above a central fixation cross, followed by a blank screen for 400

ms. Next, a series of response time cues were presented at the center of the screen. The response time cue was a small dot that appeared for 100ms then disappeared for 400 ms. The cue disappeared then reappeared three times. The cue changed color from black to white when it appeared for the fourth and final time. Participants were instructed and trained to respond exactly when this white cue appeared (see details above). The onset of the target stimulus was sampled from a uniform distribution between 0 and 1000 ms prior to the forced-RT signal. In the control study, participants were instructed to respond based on color in the first five blocks (color phase) and to respond based on the target's location in the last five blocks (location phase).

Analysis

We performed a sliding window analysis to visualize trajectories of accuracy over time for congruent and incongruent trials in \$1 and \$5 blocks. This analysis consisted of repeatedly computing means and standard errors of binary accuracies in a 100 ms window sliding from 0 to 1000 ms with a step size of 1 ms. This visualization helped to localize time periods of interest, such as between 200 and 400 ms after stimulus onset where large overt conflict effects emerge. To test for the existence of effects of reward and congruency on accuracy in the sliding window, we fit multilevel logistic regression models using the R package *brms* (Bürkner, 2017). These models included an intercept and one zero-centered binary covariate (congruency or reward). The slope and intercept were allowed to (co-)vary across participants. We report the probability of direction, *pd*, for each effect, which is the posterior probability that the effect goes in the direction indicated by the posterior median (i.e., positive or negative). We assigned normal(0, 1) priors to the slopes used software default priors elsewhere (*brms* version 2.14.4). The models of the reward effect were estimated separately for congruent and incongruent trials.

We also implemented a mathematical model of participants responses (i.e., binary accuracies) over time (Hardwick et al., 2019). The purpose of this model is to disentangle the underlying preparation of habits and goals and measure how (if at all) reward separately influences these two types of responses. This approach allows us to formalize the separate hypotheses of how reward affects performance under conflict: reward either (1) inhibits the preparation of the prepotent, habitual response, (2) facilitates the preparation of the goal-directed response, or (3) both (see Figure 2).

The model assumes that response accuracies ($y \in \{0,1\}$) are sampled from a Bernoulli distribution with probability θ . This probability (θ) of expressing the correct response at time t was defined as the product of a matrix specifying the participant's preparatory state at t (ϕ) and the conditional mappings from preparatory states to responses (ψ):

$$\theta(t) = \psi \cdot \phi(t) \quad (1)$$

The matrix $\phi(t)$ in Eq. 1 gives the probabilities of whether the automatic response (hereafter, habit) and goal-directed response (hereafter, goal) are prepared at time t . These probabilities depend on the time of movement initiation (t) and the preparation parameters (μ and σ):

$$\phi(t) = \begin{bmatrix} \text{Pr. not habit and not goal} \\ \text{Pr. habit and not goal} \\ \text{Pr. goal and not habit} \\ \text{Pr. habit and goal} \end{bmatrix} = \begin{bmatrix} (1 - \Phi(t, \mu_h, \sigma_h))(1 - \Phi(t, \mu_g, \sigma_g)) \\ \Phi(t, \mu_h, \sigma_h)(1 - \Phi(t, \mu_g, \sigma_g)) \\ (1 - \Phi(t, \mu_h, \sigma_h))\Phi(t, \mu_g, \sigma_g) \\ \Phi(t, \mu_h, \sigma_h)\Phi(t, \mu_g, \sigma_g) \end{bmatrix} \quad (2)$$

The expression $\Phi(t, \mu, \sigma)$ in Eq. 2 is the cumulative distribution function at t for a normal distribution with mean μ and standard deviation σ . We assume that responses are prepared at normally distributed times, $T_k \sim N(\mu_k, \sigma_k)$. So, $\Phi(t, \mu_k, \sigma_k)$ represents the probability that the response k is prepared by time t , $1 - \Phi(t, \mu_k, \sigma_k)$ represents the probability that k is *not* prepared by t , $\Phi(t, \mu_k, \sigma_k)\Phi(t, \mu_j, \sigma_j)$ represents the probability that both response k and response j are prepared by t , and so on. Thus μ_g and μ_h correspond with the mean time at which the goal-directed response and the habitual response are prepared respectively and σ_g and σ_h correspond with the variability in the latency of this response preparation.

The matrix ψ in Eq. 1 specifies the probabilities of expressing a habit or goal depending on the preparatory state:

$$\psi = [\alpha \quad 1 - \beta_h \quad \beta_g \quad \gamma] \quad (3)$$

In Eq. 3, α is the probability of expressing the goal, if neither the goal nor the habit is prepared. The parameter β_h is the probability of expressing the habit, if the habit is prepared but the goal is not (since we are modeling accuracy and the habitual response is correct on congruent trials, we subtract β_h from 1 on incongruent trials). The parameter β_g is the probability of expressing the goal, if the goal is prepared but the habit is not and the parameter γ is the probability of expressing the goal, if both the goal and the habit are prepared (for simplicity, we let $\gamma = \beta_g$).

To quantify the effects of increasing reward value on the preparation speed of habits and goals, we allow the μ parameters to vary linearly with reward:

$$\mu = \Delta_0 + \Delta * r \quad (4)$$

The reward covariate in Eq. 4 was centered and scaled, so that \$1 = -0.5 and \$5 = 0.5. The intercept Δ_0 therefore represents the average preparation time (across reward values) and the slope Δ represents (half) the difference in μ between \$1 and \$5 blocks.

The probability model described above was programmed using Stan(Carpenter et al., 2017). The likelihood function was $y \sim \text{Bernoulli}(\theta)$. We assigned weakly informative priors to parameters to increase identifiability and the prior for the reward effect Δ was zero-centered. We first sample the parameters in unconstrained space and later transform them to have a lower bound of 0 and upper bound of 1 using the inverse logit function. We estimate posterior probability distributions over model parameters using Markov Chain Monte Carlo sampling(Hoffman & Gelman, 2011). The sampler had four chains and ran 3000 iterations per chain (1000 warmup).

Prior to analyzing the data, we filtered the dataset to consider only those trials where participants responded at the correct time (+/- 100 ms), since these are the only trials that were valid for the participants. We ignored preparation times prior to 50ms, because there were very few data points and our model tended to overfit to them. We also ignored preparation times after 700 ms because there were very many data points which greatly increased computation time, despite adding little useful information (since accuracy was near ceiling by this time for all conditions). The initial number of trials was 15401 for Experiment 1, 18000 for Experiment 2, and 14400 for Experiment 3. After filtering out mis-timed trials, the number of trials remaining was 8017 for Experiment 1, 10525 for Experiment 2, and 8977 for Experiment 3. The final number of trials remaining, after ignoring very early and very late PTs, was 5402 for Experiment

1, 7314 for Experiment 2, and 6034 for Experiment 3. In total, 9999 trials were excluded from Experiment 1, 10686 trials were excluded from Experiment 2, and 8366 Trials were excluded from Experiment 3.

Figure 2. Two hypothetical effects of reward on response preparation. Column 1 illustrates the hypothesis that reward inhibits the preparation of automatic actions in conflict tasks and column 2 illustrates the hypothesis that reward facilitates the preparation of goal-directed actions. Row 1 depicts these hypotheses in terms of the preparation distributions for habit and goal posited by the model used in the present study (See Methods for modeling details). Row 2 depicts the hypotheses in terms of model-predicted behavioral performance over time (i.e., time available to prepare a response).

Results

We first examined whether the effect of congruency on performance depends on the amount of time available for response preparation. We used a sliding window analysis to visualize the trajectory of response accuracy over time (i.e., forced response time – stimulus onset). This visualization revealed a complex but systematic interaction between the effects of congruency and preparation time on response accuracy (Fig. 2). We performed follow-up regression analyses to test for congruency effects in time periods of interest. Before 150 ms, there was no effect of congruency (probability of direction, $pd = .616$) and response accuracy was near chance on both congruent trials (mean of participant means, $M = .545$, standard deviation of participant means,

$SD = .250$) and incongruent trials ($M = .521$, $SD = .239$). Similarly, after 600 ms, there was minimal evidence for a congruency effect ($pd = .825$) and response accuracy was approximately at ceiling for both congruent ($M = .910$, $SD = .126$) and incongruent trials ($M = .932$, $SD = .113$). However, between 200 and 400ms, there was an effect of conflict ($pd = 1$) such that accuracy was lower on incongruent trials ($M = .503$, $SD = .170$) compared to congruent trials ($M = .792$, $SD = .128$).

Figure 3. Results from the Color Simon task. **a** Trajectories of accuracy over preparation time by trial congruency and reward block. Solid lines are means and ribbons are standard errors of accuracies. The lines above the plot denote the time periods in which there were effects of reward on accuracy, as determined by a Bayesian multilevel regression model (see Methods). These statistics were computed within a sliding window from 50 to 700 ms (see Methods). **b** Posterior estimates of the effect of reward on the mean preparation time for habits and goals (arbitrary units). The shaded density represents the full posterior, the point represents the median, the thick line represents the 50% CI and thin line represents the 95% CI. **c** Posterior predicted response preparation distributions for habits and goals in \$1 and \$5 blocks. These densities were computed using posterior median estimates of μ and σ . **d** Posterior predicted trajectories of response accuracy over time for congruent and incongruent trials and \$1 and \$5 blocks. See the Methods section for modeling details.

Next, we examined the possibility that motivation due to reward protects performance against the effects of conflict. For incongruent trials, reward had a beneficial effect on performance between 300 and 400 ms ($pd = .973$), with lower accuracy in \$1 blocks ($M = .535$,

$SD = .246$) compared to \$5 blocks ($M = .605$, $SD = .275$). However, for congruent trials, reward had a detrimental effect on performance between 150 and 250 ms ($pd = .921$), with higher accuracy in \$1 blocks ($M = .670$, $SD = .220$) compared to \$5 blocks ($M = .517$, $SD = .252$).

The time required to prepare an automatic response to location (posterior median, $\mu_h = 214$ ms, 95% credible interval, $CI = [185, 239]$) was much lower than the time required to prepare a goal-directed response to color ($\mu_g = 339$ ms, $CI = [326, 351]$) (Fig. 3b). The variability in the preparation of habits ($\sigma_h = 70$ ms, $CI = [50, 99]$) was slightly lower than variability in the preparation of goals ($\sigma_g = 97$ ms, $CI = [82, 115]$). And the probability of expressing a prepared habit ($\beta_h = .774$, $CI = [.728, .818]$) was lower than the probability of expressing a prepared goal ($\beta_g = .924$, $CI = [.911, .935]$).

There was strong evidence (probability of direction, $pd = .95$) that goal-directed responses were prepared more quickly in \$5 blocks ($\mu_g = 330$, $CI = [314, 346]$) compared to \$1 blocks ($\mu_g = 349$, $CI = [331, 365]$) (Fig. 3b). There was little evidence ($pd = .72$) that automatic responses were prepared more slowly in \$5 blocks ($\mu_h = 221$, $CI = [184, 254]$) compared to \$1 blocks ($\mu_h = 208$, $CI = [171, 240]$). And overall, there was some evidence ($pd = .91$) that the difference in preparation time between habits and goals was smaller in \$5 blocks ($\mu_g - \mu_h = 109$ ms, $CI = [80, 142]$) compared to \$1 blocks ($\mu_g - \mu_h = 140$ ms, $CI = [110, 172]$).

Replication Study

We conducted a replication study using an arrow version of the Simon task to assess the robustness and generalizability of the findings above. We expected that the associations between left/right arrow and left/right response would be stronger than the color-response associations from the first experiment, leading to faster goal-directed response preparation. However, since

the target and distractor dimensions both contain spatial information, it may be more difficult for participants to inhibit automatic slips-of-action when preparation time is restricted.

Figure 4. Results from the Arrow Simon task. **a** Trajectories of accuracy over preparation time by trial congruency and reward block. **b** Posterior estimates of the effect of reward on the mean preparation time for habits and goals (arbitrary units). **c** Posterior predicted response preparation distributions for habits and goals in \$1 and \$5 blocks. **d** Posterior predicted trajectories of response accuracy over time for congruent and incongruent trials and \$1 and \$5 blocks.

The sliding-window visualization and regression analyses revealed a similar time-varying effect of congruency on response accuracy (Fig. 4a). Before 150 ms, there was no effect of congruency ($pd = .673$) and response accuracy was near chance for both congruent trials ($M = .483$, $SD = .219$) and incongruent trials ($M = .454$, $SD = .205$). Similarly, after 600 ms, there was no effect of congruency ($pd = .601$), with response accuracy near ceiling for both congruent trials ($M = .958$, $SD = .122$) and incongruent trials ($M = .957$, $SD = .108$). However, between 200 and 400ms there was an effect of congruency ($pd = 1$), such that accuracy was lower on incongruent trials ($M = .454$, $SD = .137$) compared to congruent trials ($M = .827$, $SD = .106$).

We also find evidence that between 250 and 350 ms, accuracy on incongruent trials was lower ($pd = .964$) in \$1 blocks ($M = .347$, $SD = .199$) compared to \$5 blocks ($M = .420$, $SD = .176$).

We use the same model as before to explain this pattern of results (Fig. 4b,c,d). This model-based analysis revealed that the time required to prepare an automatic response to location ($\mu_h = 213$ ms, $CI = [196, 229]$) was much lower than the time required to prepare a goal-directed response to the arrow ($\mu_g = 348$ ms, $CI = [341, 356]$) (Fig. 4b). The variability in the preparation of habits ($\sigma_h = 61$ ms, $CI = [46, 80]$) was slightly lower than variability in the preparation of goals ($\sigma_g = 73$ ms, $CI = [63, 83]$). And the probability of expressing a prepared habit ($\beta_h = .811$, $CI = [.779, .844]$) was lower than the probability of expressing a prepared goal ($\beta_g = .955$, $CI = [.947, .963]$).

There was evidence ($pd = .95$) that goal-directed responses were prepared more quickly in \$5 blocks ($\mu_g = 342$ ms, $CI = [332, 353]$) compared to \$1 blocks ($\mu_g = 354$ ms, $CI = [344, 364]$) (Fig. 4b). There was no evidence ($pd = .51$) that automatic responses were prepared at different latencies in \$5 blocks ($\mu_h = 213$ ms, $CI = [192, 233]$) compared to \$1 blocks ($\mu_h = 214$ ms, $CI = [190, 235]$). Overall, there was some evidence ($pd = .81$) that the difference in preparation time between habits and goals was smaller in \$5 blocks ($\mu_g - \mu_h = 129$ ms, $CI = [111, 148]$) compared to \$1 blocks ($\mu_g - \mu_h = 140$ ms, $[121, 162]$).

Control Study

The results above suggest that reward enhances the preparation of goal-directed but not automatic actions. In this control study we test whether, in the absence of conflict, reward globally enhances the preparation of all responses, including automatic ones.

Figure 5. Results from the Control task without conflict. **a** Trajectories of accuracy over preparation time by test phase (L: location, C: color) and reward block. **b** Posterior estimates of the effect of reward on the mean preparation time for habits and goals (arbitrary units). **c** Posterior predicted response preparation distributions for habits and goals in \$1 and \$5 blocks. **d** Posterior predicted trajectories of response accuracy over time for color and location phases and \$1 and \$5 blocks.

We used the same forced-response technique and response preparation model for the present study (Fig. 5). Our modeling analysis revealed that automatic responses to location ($\mu_h = 209$, $CI = [184, 228]$) were prepared more quickly than goal-directed responses to color ($\mu_g = 285$, $CI = [256, 309]$) (Fig. 5b). There was some evidence ($pd = .89$) that goals were prepared more quickly in \$5 blocks ($\mu_g = 275$, $CI = [240, 305]$) compared to \$1 blocks ($\mu_g = 295$, $CI = [263, 321]$) (Fig. 5b). Similarly, there was some evidence ($pd = .90$) that habits were prepared more quickly in \$5 blocks ($\mu_h = 202$, $CI = [175, 224]$) compared to \$1 blocks ($\mu_h = 216$, $CI = [189, 237]$) (Fig. 5b). So, in isolation, reward seems to accelerate the preparation of both automatic and goal-directed actions.

Discussion

While prior work has shown that the prospect of reward can reduce the effect of interference in conflict tasks, it has remained unclear whether this reduction is due to the enhancement of goal-directed processing or the inhibition of task-irrelevant processing. Using a paradigm with fixed response time (RT) and variable preparation time (PT), we were able to examine a fine-grained time course of response preparation. A model of these data indicated that reward differentially affects the preparation of automatic and goal-directed actions in the presence of conflict. We find that reward accelerates the preparation of goal-directed actions, but not automatic actions. These results are not due to changes in response *initiation*, and instead reflect changes in the speed of cognitive processing underlying the *preparation* of goal-directed responses to stimuli.

Converging evidence suggests that motivation enhances performance under conflict by increasing proactive cognitive control (Fröber & Dreisbach, 2016). However, this increased proactive control could be realized by inhibiting automatic responses or by facilitating goal-directed responses. We obtained strong evidence that reward enhanced the preparation of goal-directed responses. There was comparatively less evidence for an effect of reward on automatic response preparation. However, when participants performed the same responses in a context without potential conflict, reward globally enhanced the preparation of both habits and goals. This suggests that reward increases the *intensity* of control, while the *direction* of control (e.g., attend color, ignore location) may be determined by other contextual factors, such as the possibility of conflict (M. Botvinick & Braver, 2015). This is supported by prior work showing that reward can modulate both interference and facilitation in conflict tasks, but only under

conditions in which reward and *conflict* cues were presented before the stimulus appeared (Chiew & Braver, 2016).

Prior work has examined the relationship between response accuracy and response time in conflict tasks. For example, response accuracy falls below chance on incongruent trials for response times around 200 ms (Gratton et al., 1988) and this flux of habitual errors has been linked to homologous variations in lateralized readiness potentials over motor cortex at similar post-stimulus latencies (Jong et al., 1994; Vallesi et al., 2005). However, free response times confound movement initiation and movement preparation, which have recently been shown to be independent (Haith et al., 2016). So, free response times alone cannot be used to infer the time required to prepare a response. Prior work has also used response deadlines to examine the time-course of conflict effects (Miles & Proctor, 2015; Simon et al., 1976; Toth et al., 1995).

Response deadlines are useful because they impose an upper bound on the duration of time available for response preparation. A limitation of this approach is that it does not place response initiation under experimental control—i.e., participants can still initiate their response any time before the deadline. For this reason, variation in free RTs under response deadlines may still reflect delays in response initiation rather than changes the speed of response preparation.

In the present study, we use a mathematical model of response preparation to explain participants behavior in the forced-response conflict task (Haith et al., 2017; Hardwick et al., 2019). A variety of alternative models have been proposed to explain human behavior in free-response conflict tasks, including artificial neural network models (Cohen et al., 1992), biological neural circuit models (Wiecki & Frank, 2013), and evidence accumulation models (Ulrich et al., 2015; White et al., 2011). The response preparation model used here is largely consistent with these alternatives since it is agnostic about the algorithms and architectures that

may underly behavior. However, the response preparation model does make some substantive assumptions about the latent processes. First, the response preparation model diverges philosophically from prior models in its interpretation of response times. Traditionally, response time is treated as an *effect* of the cognitive processes involved in response preparation. However, in this model, response time is treated as an intervening *cause* which imposes a deadline on preparation (Haith et al., 2017). Second, the model assumes that automatic and goal-directed responses are prepared independently and in parallel. This aligns closely with race models such as the linear ballistic accumulator model (Brown & Heathcote, 2008), but diverges from models which explicitly posit interactions between competing processes, such as some connectionist and evidence-accumulation models (Cohen et al., 1992; Usher & McClelland, 2001). Prior models have been successful at accounting for free RT data across a wide variety of tasks and have provided insights about the role of dopamine in cognitive control (Servan-Schreiber et al., 1998). The response preparation model used here could accommodate prior models by replacing normal distributions for preparation times with distributions generated by an underlying dynamical system such as the Wiener diffusion process.

In summary, we provide evidence across multiple experiments that reward enhances performance under conflict, and we infer from a model of these data that this improvement was driven by an increase in the speed with which goal-directed responses were prepared.

Open Practices Statement

All materials and data used in this manuscript can be accessed at

[GITHUB_LINK_REMOVED_FOR_MASKED_REVIEW]. The studies were not preregistered.

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