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Behavioral strategies and pupillary response in a rewarded stop-signal task

Valentina Giuffrida [a,b,*], Isabel Beatrice Marc [a], Stefano Ferraina [a], Emiliano Brunamonti [a], Pierpaolo Pani [a,*]

[a] *Department of Physiology and Pharmacology, Sapienza University, Rome, Italy*
[b] *PhD Program in Behavioral Neuroscience, Sapienza University, Rome, Italy*

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ABSTRACT

Cognitive control, specifically inhibition, is essential for behavior adaptation to environmental changes. While reward expectation influences cognitive strategies, it is still underexplored how reward may influence inhibitory control and how and whether this may be reflected in autonomic physiological responses. In this study, we explore whether trial-by-trial reward cues modulate both behavioral performance and pupil size, an autonomic correlate of cognitive effort. Twenty-five participants performed a rewarded Stop-Signal Task under three reward conditions: Go Plus (greater reward for correctly performed movements Go trials), Stop Plus (greater reward for correctly inhibited movements Stop trials), and Neutral (equal reward for both trial types). Although inhibitory ability remained unchanged across reward conditions, Go trials' accuracy was higher in Go Plus and Neutral conditions. Reaction times were longer in Go trials in the Stop Plus condition, where inhibition was most rewarded. When task strategies required balancing focus to achieve high rewards in both trial types, pupil size increased, suggesting increased cognitive effort. These findings support the hypothesis that reward expectancy shapes cognitive control and its autonomic correlates.

1. Introduction

In everyday life, we constantly adjust our actions in response to environmental demands while anticipating their consequences. This adaptive ability is defined as cognitive control (Logan, 1985; Baddeley, 1996), which includes, as a key aspect, the ability to inhibit reactive or planned actions when required. Over the years, this aspect of cognitive control has been studied using the Stop-Signal Task (SST), a widely used paradigm that measures both movement execution and inhibition (Fiori et al., 2024; Hannah et al., 2022; Verbruggen and McLaren, 2018). In the classic SST, participants are instructed to respond as quickly as possible to a Go signal (Go trials), usually by pressing a button. On a subset of trials, a Stop signal appears after a variable Stop signal delay (SSD), following the Go signal, instructing participants to inhibit their response (Stop trials). The performance in the SST is usually modeled by the Race Model, based on two independent processes, the Go and the Stop processes, which are triggered by the Go and the Stop signal, respectively. Whether a response is executed or inhibited depends on which process reaches the threshold first (Logan, 1985; Matzke et al., 2018; Verbruggen et al., 2019). A variable we can estimate from this model is the Stop-Signal Reaction Time (SSRT), which represents the latency of the Stop process, and is an indicator of inhibitory control (Logan, 1985; Matzke et al., 2018; Verbruggen et al., 2019).

While this model has provided a valuable framework to investigate inhibition, recent theoretical models have expanded this framework to take into account other phenomena that influence control mechanisms in this task, such as trial history (Oldenburg et al., 2012a; Verbruggen et al., 2008; Emeric et al., 2007; Rieger and Gauggel, 1999), attentional bias (Haque et al., 2024; Verbruggen et al., 2014; Hilt and Cardellicchio, 2020), task difficulty (Middlebrooks et al., 2020; Andujar et al., 2022; Marc et al., 2025; Marc et al., 2023), and motivational influences such as reward (Verbruggen and McLaren, 2018; Schevernels et al., 2015; Boehler et al., 2012; Giuffrida et al., 2023; Salomoni et al., 2023). Among the models, the Dual Mechanisms of Control framework (Braver, 2012) distinguishes between two complementary strategies to influence cognitive control: proactive and reactive control (Aron, 2011). In the SST, reactive control represents stimulus-driven behavior after a Stop signal is detected (Boehler et al., 2012; Boehler et al., 2014), whereas proactive control describes the anticipatory regulation of behavior based on goals or cues, by intentionally slowing Go responses in anticipation of a potential Stop signal (Schevernels et al., 2015; Giuffrida et al., 2023; Verbruggen and Logan, 2009; Leotti and Wager, 2010;

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* Corresponding authors at: Department of Physiology and Pharmacology, CU027, 00165, Rome, Italy.
E-mail addresses: valentina.giuffrida@uniroma1.it (V. Giuffrida), pierpaolo.pani@uniroma1.it (P. Pani).

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Greenhouse and Wessel, 2013). According to the literature, reward expectation strongly influences the dynamics of cognitive control. Some studies suggest that when rewards depend on successful stopping, it promotes reactive inhibitory processes (Boehler et al., 2012; Boehler et al., 2014), while proactive adjustments are preferred when cues indicate reward contingencies at the trial onset (Schevernels et al., 2015; Giuffrida et al., 2023; Verbruggen and Logan, 2009; Leotti and Wager, 2010; Greenhouse and Wessel, 2013). For instance, rewarding Stop trials has been shown to shorten SSRTs (Boehler et al., 2012; Boehler et al., 2014), whereas rewarding only Go trials can impair inhibition (Padmala and Pessoa, 2011). Moreover, when rewards were stable within the task and known a priori, participants strategically slowed their reaction times to improve stopping ability (Giuffrida et al., 2023; Leotti and Wager, 2010; Greenhouse and Wessel, 2013). However, the findings are contrasting, and the mechanisms through which motivational context influences inhibitory control remain unclear. To better understand these mixed findings, one promising direction involves reconsidering how inhibitory control is evaluated when external variables, such as reward, influence SST performance. Traditional SSRT estimates with the Race model assume that the Stop process is always engaged. Yet, newer models introduce the possibility of trigger failures, trials where the Stop process fails to start the race. This conceptualization highlights that inhibitory control depends on both SSRT and the reliability of triggering the stop process (i.e., trigger failures) (Matzke, 2013; Matzke et al., 2017). Ignoring trigger failures may lead to overestimating SSRT, missing potential differences, especially in contexts where rewards incentivize greater inhibitory control (Doekemeijer et al., 2021). For example, participants may disengage from the task and use a proactive strategy that deliberately ignores the possibility of a Stop signal in low-reward conditions. High rates of trigger failure may indicate a deliberate shift in control strategy, rather than just a simple failure to inhibit the action (Skippen et al., 2020), making trigger failure a behavioral marker of engagement and strategic cognitive control adjustment (Skippen et al., 2019).

To further understand how reward influences strategic adjustment in cognitive control, recent studies have begun using physiological correlates of cognitive control related to the autonomic nervous system, such as pupillometry (McDougal and Gamlin, 2015; Loewenfeld, 1958), which provides a sensitive, non-invasive method to detect internal states and covert processes such as arousal, attention, and cognitive control (Clewett et al., 2020; de Gee et al., 2020; Cole et al., 2022; Walsh et al., 2019; Fröber et al., 2020; Doekemeijer et al., 2025; Colizoli et al., 2018; Wainstein et al., 2017; Joshi and Gold, 2020) and (van der Wel and van Steenbergen, 2018 for a review on cognitive control). Pupil size reflects changes in both the parasympathetic and sympathetic branches of the autonomic nervous system and is modulated by neural activity of the locus coeruleus (LC) (Cole et al., 2022; Sara and Bouret, 2012; Bouret and Richmond, 2015). In particular, LC-norepinephrine (LC-NE) activity has been associated with task-evoked pupil size during performance, and this latter one is considered an expression of cognitive effort allocation to meet these task demands (van der Wel and van Steenbergen, 2018; Murphy et al., 2011; Aston-Jones and Cohen, 2005; Joshi et al., 2015). Importantly, when cues informing about a specific condition of the task is presented before each trial, two separable processes are engaged: cue evaluation, i.e., the assessment of the motivational significance of the cue and the updating of expectations (Murphy et al., 2011; Eayrs et al., 2025; Chiew and Braver, 2013; Gilzenrat et al., 2010), and task preparation, i.e., the proactive adjustment of the upcoming response and the anticipatory effort allocation to perform adequately (van den Brink et al., 2016; Jepma and Nieuwenhuis, 2011). While the underlying processes have been delineated, how trial-specific reward conditions shape pupil dilation and cognitive-control effort in inhibition tasks remains unclear. Furthermore, some scholars have shown that together with changes in pupil size, other measures, such as the first temporal derivative of pupil size (pupil slope), can help in revealing the dynamics of the preparatory effort (Eayrs et al., 2025; Reimer et al., 2016; de Gee et al., 2014). Converging evidence indicates that pupil slope is a sensitive index of phasic LC-NE activity in the cortex (Reimer et al., 2016). Transient "phasic" bursts of NE (linked to focused exploitation of task-relevant cues) cause rapid pupil enlargement, according to early computational (Aston-Jones and Cohen, 2005) and neurophysiological models (Sara and Bouret, 2012; Bouret and Richmond, 2015; de Gee et al., 2014; de Gee et al., 2017). For instance, Reimer et al. (2016) showed that cortical noradrenergic axons become active just before and during rapid pupil dilations, with NE activity correlating strongly with the pupil slope, suggesting that moment-to-moment pupil dilations are largely driven by phasic LC-NE release. Human studies similarly found that slope dynamics are modulated by anticipatory effort in association with reward and other task conditions (Eayrs et al., 2025; Reimer et al., 2016; de Gee et al., 2014). As a result, cortical NE activity (i.e., a phasic arousal response triggered by salient or effortful events) can be represented by a rapid increase in pupil size (high pupil slope). Taking into account this perspective is important in cognitive control tasks because, rather than being a gradual increase in general arousal, a rapid pupil dilation frequently indicates an LC-mediated "alerting" or resource-mobilization signal activated by task cues.

In the present study, we investigated how reward modulates both behavior and pupil size in a rewarded SST. During the task, a reward Cue signaled one of three reward conditions, i.e., Go Plus, Neutral, or Stop Plus, each defining the reward size for the correct trials. In the Go Plus condition, the reward Cue informed that a higher amount of reward would be provided in case of a Go trial successfully executed; in the Stop Plus condition, Stop trials received higher rewards; in the Neutral condition, both trial types were equally rewarded. Importantly, the reward Cue anticipated the reward conditions but not the trial type, and Go trials were more frequent (75 %) than Stop trials (25 %). We examined how reward influences, at the behavioral level, SSRT, the probability of trigger failure, and the reaction time adjustment, and, at the physiological level, pupil dilation. In addition to the traditional focus on absolute pupil size, we also considered pupil slope, hypothesizing that it would be particularly sensitive to reward-predictive cues and preparatory control demands.

Our findings show that participants adopted a proactive strategy to maximize the reward and to modulate the engagement in Go or Stop trials, depending on the condition. Moreover, pupil responses reflected the cognitive effort associated with the different reward conditions, with pupil slope emerging as a potential marker of strategic motor preparation.

2. Methods

2.1. Participants

A total of 25 healthy participants (mean age = 29.4, range 24–37 years, 6 males and 19 females) took part in the study. The sample size was determined based on comparable recent studies on pupillometry (Doekemeijer et al., 2025; Manohar et al., 2017; Oliva and Anikin, 2018) and was sufficient to detect medium effect sizes (d ≈ 0.6), with a statistical power of 0.8, ensuring robust analysis (Brysbaert, 2019; Erdfelder et al., 2009; Faul et al., 2007). All participants had normal or corrected-to-normal vision, normal hearing ability, and no history of known neurological or psychiatric conditions. None was under the influence of pharmacological substances affecting the central nervous system. The study adhered to the Declaration of Helsinki and received ethical approval from the Sapienza University of Rome Ethics Committee, and written informed consent was obtained from each participant.

2.2. Behavioral Task

Participants were comfortably seated ~55 cm away from a 26-inch LCD monitor (1920 × 1080 resolution, 60 Hz) in a dark, sound-attenuated room. Ambient brightness was maintained at 34 lx (±5 lx).

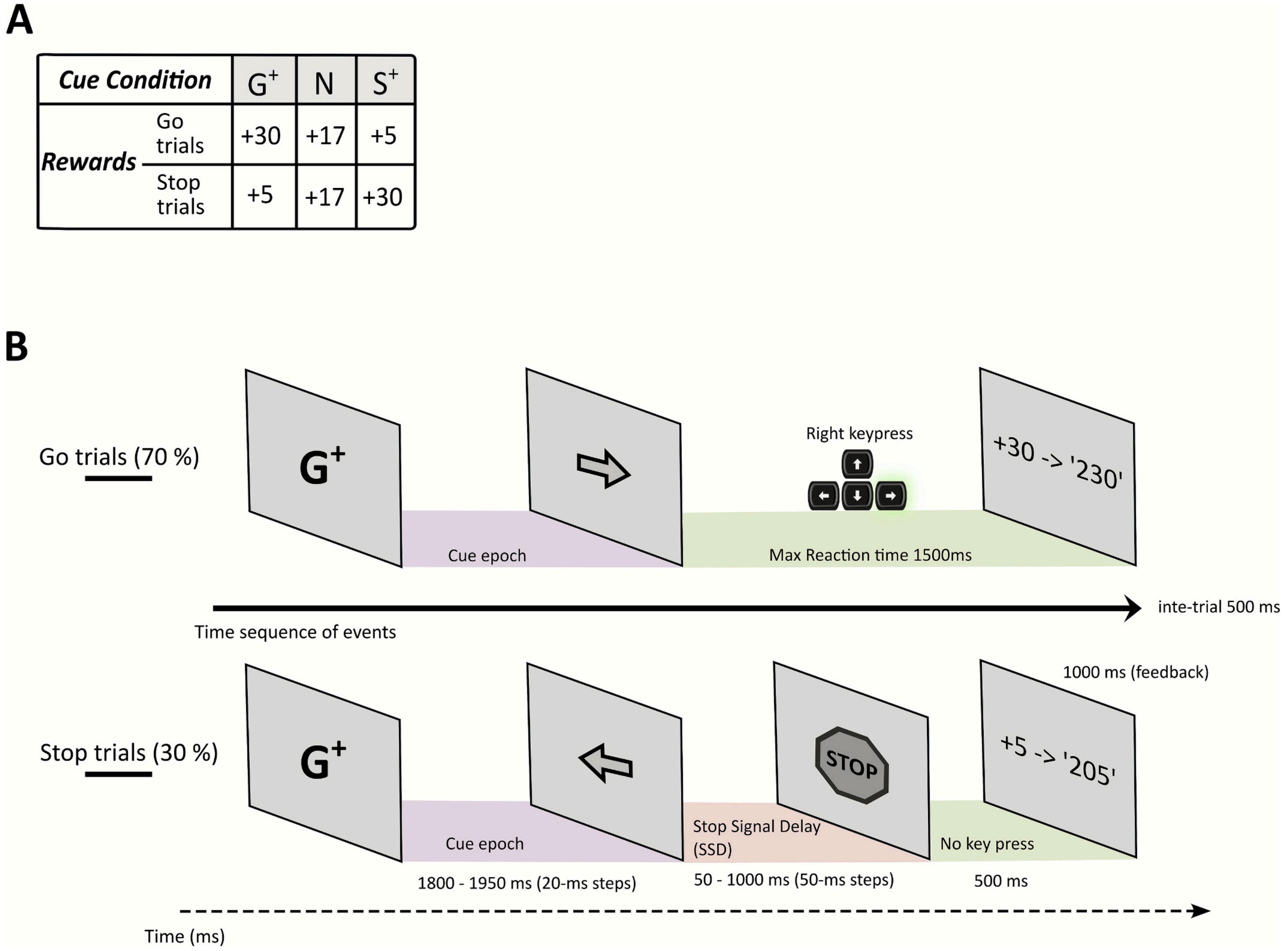
Stimulus presentation and behavioral event collection were managed using MATLAB with the Psychophysics Toolbox Version 3 (PTB-3). Pupil diameter was recorded binocularly using a mobile eye-tracker at a sampling rate of 120 Hz (Pupil Labs glasses; Pupil Labs, Berlin, Germany (Kassner et al., 2014)). The eye-tracker was connected to a host PC via customized MATLAB scripts and ZeroMQ packages. Trigger signals for experimental events were transmitted via Ethernet, with a measured average offset of 0.0007 s across 1000 send-received tests. Stimuli were presented in black against a gray background (RGB = [128, 128, 128]). Participants completed the rewarded SST, in which Go trials and Stop trials were presented under three reward conditions, indicated by the reward Cue (i.e., G+, S+, or N; Fig. 1A). The reward, i.e., the amount of points, varied across conditions (Go Plus, Stop Plus, and Neutral), to influence strategic adjustment. In the Go Plus condition (G+), correct Go trials gave +30 points and correct Stop trials gave +5 points, while in the Stop Plus condition (S+), correct Stop trials gave +30 points and correct Go trials gave +5 points. In the Neutral condition (N), participants received +17 points for correct responses in both types of trials.

At the start of each trial, the reward Cue indicated the reward structure (Fig. 1A), followed by the Go Signal, which appeared after a relatively fixed interval (random range 1800–1950 ms, in 20-ms steps). The Go Signal, a left or right-pointing arrow, prompted participants to respond as quickly as possible by pressing the corresponding key on the keyboard within 1500 ms (Fig. 1B, upper panel). In 30 % of the total trials, a Stop Signal appeared after a variable SSD, requiring participants to inhibit the response triggered by the Go Signal (Fig. 1B, lower panel).

A staircase procedure was employed to change the SSD duration based on the participant's performance. The SSD started from 50 ms and was increased by 50 ms after Correct Stop trials or decreased after Wrong Stop trials in the next Stop trial, with limits set between 50 and 1000 ms. This approach aimed to maintain the probability of responding to the Stop Signal around 50%, discouraging participants from adopting wait-and-see strategies (Verbruggen et al., 2019).

Feedback (1000 ms) showed the points earned if the participants responded correctly, i.e., pressing the correct key (Correct Go trial) or withholding their response (Correct Stop trial). Otherwise, the feedback showed "Score 0" or "Score 0, too late!" for incorrect responses, including pressing the wrong key (Wrong Go or Stop trial) or failing to respond within the maximum allowed time (omission Go trial). An intertrial interval (ITI) of 500 ms followed each trial.

Participants completed a learning phase (100 trials per reward condition) before the test phase (600 randomized trials, 1/3 per reward condition). SSDs were independently adjusted for each reward condition using separate staircases. To minimize fatigue effects on pupillary size measurements, trials were split into two 300-trial blocks with a 10-minute break. Before each acquisition, participants were introduced to the staircase procedure to prevent the use of wait-and-see strategies (see (Verbruggen et al., 2019)). To enhance motivation, participants were informed that their performance would be ranked against that of previous participants, and the task instructions emphasized the importance



Cue Condition		G+	N	S+
Rewards	Go trials	+30	+17	+5
	Stop trials	+5	+17	+30

Fig. 1. Behavioral paradigm. A) Overview of the Cue Signals associated with the respective rewards for each Cue and trial type. B) Rewarded Stop-Signal Task (sequence of events for the Go Plus condition) for the two trial types: Go trials and Stop trials.

of beating the current record as a form of social competition. No additional monetary or other type of reward was provided. Before the task, they viewed a ranking of previous participants' scores, aiming to beat the current record, except for the first participant, who saw the highest possible score.

2.3. Data analysis

2.3.1. Behavior

In this task, response inhibition is modeled as a race between two independent processes: the Go and the Stop processes. The independence assumption suggests that the Go process in Stop trials should be the same as in Go trials, since the Stop signal should not influence the Go process. To test this assumption, we compared RTs between wrong Stop trials and correct Go trials, where the former should be shorter than the latter. This assumption could be compromised if reward manipulations differed between Go and Stop trials, as shown in previous studies (Verbruggen and McLaren, 2018; Leotti and Wager, 2010; Matzke et al., 2017). For comparability with previous work, SSRT was first estimated using the integration method (SSRT-IN), which follows the traditional independent race model by subtracting the mean SSD from the nth percentile of the Go RT distribution, where n corresponds to the observed inhibition probability, and replacing omitted Go trials with the maximum RTs (Verbruggen et al., 2019). This method, although widely used, assumes that all Stop signals are successfully detected and therefore cannot account for potential trigger failures. To address these limitations, we additionally applied the BEESTS-WTF (Hannah et al., 2022; Matzke et al., 2017), which allows estimation of both SSRT and the probability of trigger failures, thus providing a more valid account of inhibitory control (SSRT-BTS).

To evaluate how the reward Cue affects participant's performance, we analyzed the following variables: a) Go RTs, as the time between the presentation of the Go signal and response in Go trials; b) Wrong Stop RTs, the time between the presentation of the Go signal and unsuccessful inhibited response in Stop trials; c) Accuracy in Go trials as percentage (%), calculated as the number of condition-specific correctly performed trials divided by the total number of Go trials for each reward condition; d) probability of responding to the Stop signal (p(Respond)), that is of failing to inhibit, determined as the number of condition-specific wrong Stop trials divided by the total number of Stop trials for each reward condition; e) mean SSD derived from the staircase procedure and f) SSRT-IN, an estimate of the covert response inhibition for each reward condition.

We analyzed the data using one-way repeated measures ANOVAs with a within-subjects design for each key variable described. Post hoc comparisons were conducted using Bonferroni tests to examine differences across reward conditions. We then evaluated internal reliability of individual-difference variables by computing split-half correlations for Go RT, Stop RT, and SSD within each reward condition (Go Plus, Neutral, Stop Plus). For each participant and measure, trials were randomly divided into two halves 500 times, and mean values across halves were correlated. The resulting coefficients were then Spearman–Brown corrected to estimate full-length reliability (Clayson et al., 2021; Clayson, 2024).

We furthermore quantified participants' behavioral adjustments across reward Cues by computing a normalized index of strategic RT shifting that captured the overall magnitude of behavioral adaptation. For each subject, mean RTs were computed from correct Go trials in each condition, and the normalized RT shift index was derived as:

$$RTshift_{index} = \left| \frac{RT_{Go+} - RT_{nt}}{RT_{nt}} \right| + \left| \frac{RT_{ST+} - RT_{nt}}{RT_{nt}} \right|$$

This measure reflects the total magnitude of RT deviation relative to the Neutral (RT_{nt}) baseline, irrespective of direction (i.e., speeding or slowing).

We then assessed whether larger strategic shifts were associated with better task performances by correlating the indices with participants' *task efficiency*, computed as the ratio between the total reward earned and the theoretical maximum reward attainable for each condition:

$$Task\ Efficiency\ (c) = \frac{Reward_{Earned(c)}}{Reward_{max\ (c)}}$$

The *Reward_Earned*(c) was obtained by summing the points gained across all correct trials in each reward Cue condition c, and the *Reward_max*(c) was estimated the sum of all Go and Stop trials multiplied by their respective reward values (30 or 5 points in biased conditions; 17 points in Neutral), weighted by the expected 50 % success rate enforced by the staircase procedure formalize as:

$$Reward_{Max}(c) = nGo_{trials} \times R_{go} + nStop \times 0.5\ x\ R_{stop}$$

where *nGo* and *nStop* are the total numbers of Go and Stop trials presented, R_{Go} and R_{Stop} are the reward values per correct response, and the 0.5 factor reflects the expected 50 % stopping success enforced by the staircase tracking procedure. To test whether task efficiency differed systematically across reward conditions, we first conducted a one-way repeated-measures ANOVA with Condition (Go Plus, Neutral, Stop Plus) as a within-subject factor and post hoc pairwise comparisons (Bonferroni-corrected). Individual Task efficiency indexes were then normalized to a 0–1 scale across subjects to facilitate comparisons.

Finally, Pearson's correlations were computed between RTShift_index and the overall mean Task_Efficiency (averaged across conditions) to assess whether larger strategic adjustments were associated with higher reward efficiency.

We also examined how correct Go trials RTs were influenced by the temporal sequence of trial types within each condition. Prior research has shown that task performance can be modulated by trial history, where the type or outcome of a preceding trial may influence response speed in subsequent trials (Verbruggen et al., 2008; Emeric et al., 2007; Rieger and Gauggel, 1999; Damaso et al., 2020). To investigate whether this effect persists in this rewarded version of the SST, we categorized trials based on whether they were preceded by a Go trial (Prior Go) or a Correct Stop trial (Prior Stop) within each reward condition and we computed a single-difference score comparing RTs in Go trials based on the type of preceding trial (Correct Stop vs Correct Go). This approach demonstrates that response slowing after successful inhibition can serve as an index of strategic adaptation in cognitive control, as proposed by Nelson et al. (2010) and Bissett and Logan (2012). Although more refined indices are present in the literature, such as triplet-based or double-difference scores (Nelson et al., 2010; Bissett and Logan, 2012), we could not estimate them because of limitations in the number of trials and in the task structure. Additionally, we investigated whether the reward condition of the previous trial influenced RTs in the current Go trial, i.e., whether responses were slower after the Stop Plus condition or faster after the Go Plus condition. To assess these effects, we conducted a 3 × 3 repeated-measures ANOVA on RTs across all possible Cue sequences (e.g., Go Plus → Stop Plus, Go Plus →Neutral, Go Plus →Go Plus, etc.). This approach allowed us to assess both direct reward-related slowing or speeding and possible sequential dependencies between consecutive reward conditions.

2.3.1.1. BEESTS model. To assess trigger failure in our reward SST and potential SSRT-IN overestimation, we estimated both the probability of trigger failure (p(TF)) and SSRT-BTS using the BEESTS-WTF model (Matzke, 2013), implemented via the Dynamic Models of Choice (DMC) toolbox (Oliva and Anikin, 2018), written in R (1.1.463). We applied the two-runner model, which conceptualizes response inhibition as a race between the Go and Stop processes (Hannah et al., 2022; Skippen et al., 2019). As previously noted, BEESTS estimates SSRT-BTS under the assumption that RTs follow an ex-Gaussian distribution, allowing for the estimation of three key parameters for each estimated variable: μ (mean), σ (standard deviation), and τ (mean of the exponential component). Consequently, the mean SSRT-BTS was computed as = μ_stop + τ_stop.

The model also allowed for the estimation of how reward modulation influenced the likelihood of trigger failure. A probit transformation was applied to project the data from probability space onto the real line. We adapted scripts from Hannah et al. (2022) within the DMC framework, using Bayesian parametric estimation to improve parameter accuracy given limited trials per reward condition (Matzke, 2013; Matzke et al., 2017). Individual participant behavior was first modeled separately with weakly informative priors, and these fits were then used to define population-level priors for hierarchical modeling. For the probability of trigger failure, the prior distribution was bounded between −6 and 6, capturing the full expected range. Because the model estimates the p(TF) for each participant, on this latent scale, they were later converted back to the 0–1 probability range using an inverse-probit (cumulative normal) transformation. In the hierarchical modeling framework, normal hyper-priors were applied to population-level mean parameters, maintaining the same truncation limits as in the uniform prior case. Convergence of the Markov Chain Monte Carlo chains was verified via the Gelman-Rubin diagnostic ($\hat{R} < 1.1$), and model fit was assessed through posterior predictive checks ($n = 200$). We focused our analyses on p(TF) and SSRT-BTS across reward conditions using the Friedman test and repeated-measures ANOVAs, and compared SSRT estimates from BEESTS-WTF (SSRT-BTS) and the integration method (SSRT-IN) using paired t-tests.

Bayes Factor (BF10) was calculated to quantify the strength of the evidence supporting differences between estimation methods, following conventional interpretation guidelines: BF10 < 1/3: Substantial evidence for the null hypothesis (no significant difference); 1/3 < BF10 < 3: Anecdotal evidence for either hypothesis; or BF10 > 3: Substantial evidence for the alternative hypothesis (a significant difference between SSRT estimates). Because SSRT-BTS and p(TF) were estimated via hierarchical BEESTS-WTF, internal reliability is reflected in the precision of the posterior distributions. The narrow 95 % Bayesian credible intervals across conditions indicate high estimation stability at both group and individual levels.

Finally, we assessed whether the mean SSRT-IN values fell within the 95 % Bayesian credible interval (i.e., an interval from the 2.5th to 97.5th percentiles of the distribution) of SSRT-BTS. If SSRT-IN estimates fell outside this interval, systematic deviations between the two methods would be indicated. This combined frequentist and Bayesian approach evaluated the comparability of SSRT estimates and quantified any systematic discrepancies.

2.3.2. *Pupil data*

The pupil diameter was processed offline using the Pupil Player software provided by Pupil Labs. The data were initially smoothed using a Butterworth filter with a low-pass cutoff of 10 Hz. Blinks, automatically detected by Pupil Player's blink classification algorithm (which utilizes a mathematical 3D eye model capturing ocular kinematics and optics; see (Swirski and Dodgson, 2013; Dierkes et al., 2019)), were linearly interpolated. Data were extracted in millimeters (mm) based on a model fit greater than 75 % for both eyes. For the analysis, we used data from the right eye and applied the left eye data for blink interpolation when applicable; otherwise, we used linear interpolation.

To enhance computational efficiency, second-order Savitzky-Golay filtering was applied to the data, with a frame length of 11 samples, followed by downsampling from 120 Hz to 50 Hz. Pupil data were then baseline-corrected by subtracting the mean of the pupil size, trial by trial, during the intertrial interval preceding the Cue onset of the subsequent trial. Then the signal was segmented into trials time-locked to the Cue onset, including 300 ms before and 1800 ms after the Cue onset. The mean pupil size across the Cue epoch was calculated for each participant and condition for all the trials. Grand-mean waveforms were computed from the individual mean pupil size across the Cue epoch for each reward condition. To examine reward condition-related modulations in pupil sizes, we applied a cluster-based one-way repeated-measures ANOVA across the three task conditions (Go Plus, Stop Plus, Neutral), for each time point. This resulted in a time series of F-values representing the main effect of Condition at each time point. To control for multiple comparisons across time, we employed a non-parametric cluster-based permutation test. Clusters of contiguous timepoints exceeding a critical F-threshold ($p < 0.05$) were identified, and a cluster-level statistic was computed as the sum of F-values within each cluster. A null distribution was generated by randomly permuting condition labels within subjects ($n = 1000$ permutations). Clusters in the observed data were considered significant if their cluster-level statistic exceeded the 95th percentile of the null distribution. Finally, we also identify which condition pairs contributed to the observed effects by applying a post-hoc paired t-test on subject-averaged responses within each significant cluster, with Bonferroni correction for multiple comparisons. For completeness, we also checked only Correct Go trials, aligned to the Go signal.

To complement the analysis on absolute pupil size, we also examined the first temporal derivative of pupil size ("pupil slope"), which has been suggested to more closely track phasic cortical noradrenergic activity (Reimer et al., 2016). Pupil slope was computed using a sliding-window linear regression across the Cue epoch (within a window of 150 ms with an overlap of 50-ms). This procedure yielded a time series of slope values for each trial, which were then averaged within each reward condition and participant. We applied the same statistical pipeline as for the absolute pupil size (see above). This approach allowed us to identify temporally specific modulations in the rate of pupil dilation as a function of reward expectation, complementing the analyses of absolute pupil size.

To further explore whether changes in pupil size could reflect preparatory motor output (i.e., RTs), we focused on Correct Go trials and calculated the Pearson correlation coefficient in the epoch of interest around Cue onset based on one-way repeated-measures ANOVA results (1700 ms to 2300 ms after Cue onset). To this aim, we extracted the mean pupil size in the epoch from −600 ms to +200 ms aligned to the Go Onset in the Correct Go trials and fit a linear function to extract the pupil slope, an index of pupil size growth rate. The choice of this epoch is justified because the pupil response peaks at about 1000 ms from event perception, decaying in a gradual mode (de Gee et al., 2014; Wierda et al., 2012; Murphy et al., 2016).

We sorted all RT distributions and divided them into tertiles. We took the mean RT and the mean pupil size and extracted the slope by fitting a linear model for each tertile, during the previously defined epochs. This provided us with three distributions ("fast," "medium", and "slow" RTs) for each reward condition. To assess the stability of the observed correlations, we used a nonparametric bootstrap procedure (1000 iterations). In each iteration, participants were resampled with replacement, and the correlation between pupil and RT values was recomputed; the 2.5th and 97.5th percentiles of the resulting distribution were taken as the 95 % confidence interval (CI). This approach provides a robust estimate of correlation reliability without assuming normality, and allows interpretation of non-significant effects in terms of their precision (Clayson et al., 2021; Clayson, 2024).

All data processing and analysis were performed using functions developed in MATLAB and R. Specifically, all preprocessing of pupil size data and subsequent analyses were conducted using custom functions developed in MATLAB (The MathWorks, MA). Behavioral analyses were conducted in R and MATLAB. Pupil data were originally exported and preprocessed from Pupil Labs' Pupil Player software (Python-based).

3. Results

We first verified that each participant's performance adhered to the independence assumption of the race model. To do so, we tested whether Go RTs for correctly executed Go trials were longer than wrong

Stop RTs in the Neutral condition and found that all participants satisfied this criterion (Wilcoxon rank-sum tests; all ps < 0.05).

3.1. *Reward conditions influence behavioral adjustments in the task*

To test whether the reward conditions influenced participants' RTs, we conducted one-way repeated measures ANOVAs to analyze Go RTs and wrong Stop RTs (Fig. 2 A-B). Reward condition had a significant effect on Go RTs ($F(2, 48) = 17.49$, $p < 0.001$, $\eta_p^2 = 0.42$), with longer Go RTs in the Stop Plus condition (mean = 871 ± 52 ms SEM) compared to the other conditions (Go Plus: mean = 789 ± 46 ms SEM; Neutral: mean = 826 ± 49 ms SEM; all post hoc comparisons $p < 0.001$). Similar effects were observed for wrong Stop RTs ($F(2, 48) = 11.41$, $p < 0.001$, $\eta_p^2 = 0.32$), with Stop Plus condition exhibiting longer RTs (mean = 736 ± 48 ms SEM) compared to the other conditions (Go Plus: mean = 651 ± 42 ms SEM; Neutral: mean = 695 ± 46 ms SEM, all post hoc comparisons $p < 0.05$). These findings suggest that participants adapted their RTs according to the reward conditions, particularly slowing down their responses in the Stop Plus condition, where successful movement inhibition was rewarded with the highest reward.

We next assessed whether this adaptation could also be reflected in participants' error rates in Go and Stop trials using one-way repeated-measures ANOVAs (Fig. 2C–D). Accuracy in Go trials was modulated significantly across reward conditions ($F(2,48) = 3.51$, $p < 0.05$, $\eta_p^2 = 0.12$).

In the Stop Plus condition, accuracy was lower (mean = 96.68 ± 0.67 % SEM) than in the other conditions, and no difference was found between Go Plus and Neutral conditions (Go Plus: mean = 97.52 ± 0.45 % SEM; Neutral: mean = 97.96 ± 0.37 % SEM). In contrast, the p (Respond) to the Stop signal did not significantly differ between reward conditions ($F(2,48) = 1.72$, $p = 0.19$, $\eta_p^2 = 0.06$), although a similar trend was observed (Go Plus: mean = 0.44 ± 0.012 SEM; Neutral: mean = 0.43 ± 0.015 SEM; Stop plus: mean = 0.42 ± 0.015 SEM). Together, these results suggest that reward conditions influenced movement initiation (as reflected in the accuracy), while inhibitory performance remained relatively stable, despite a slight trend.

Similar to the results for RTs, we found that SSD values significantly differed across reward conditions (one-way repeated measure ANOVA: $F(2,48) = 9.51$, $p < 0.001$, $\eta_p^2 = 0.28$; Fig. 2E), with shorter SSDs in the Go Plus condition (mean = 496 ± 43 ms) in which Go trials were most rewarded (Neutral: mean = 524 ± 44 ms; Stop Plus: mean = 560 ± 43 ms; all post hoc comparisons $p < 0.01$). We then assessed whether reward conditions influenced SSRT-IN (Fig. 2F), but no significant differences were found (one-way repeated measure ANOVA: $F(2,48) = 1.19$ $p = 0.31$, $\eta_p^2 = 0.04$), with mean values of 240 ± 12 ms (Go Plus), 252 ± 14 ms (Stop Plus), and 255 ± 12 ms (Neutral). Overall, for all behavioral measures where trial-by-trial values could be extracted, internal consistency was excellent (split-half, Spearman–Brown corrected; all $r > 0.98$ across reward conditions).

These results suggest that reward expectation modulated participants' movement initiation: participants selectively slowed their responses to optimize performance and maximize reward.

3.2. *Reward rate reflects strategic adjustments across conditions*

To determine whether participants' strategic adjustments translated into higher overall success (i.e, total amount of points earned as a reward), we first checked the total points earned. On average, they collected 8923 ± 38.6 SEM points (out of 10,400 possible). Specifically, participants earned 4242 ± 27.52 points in the Go Plus condition (out of

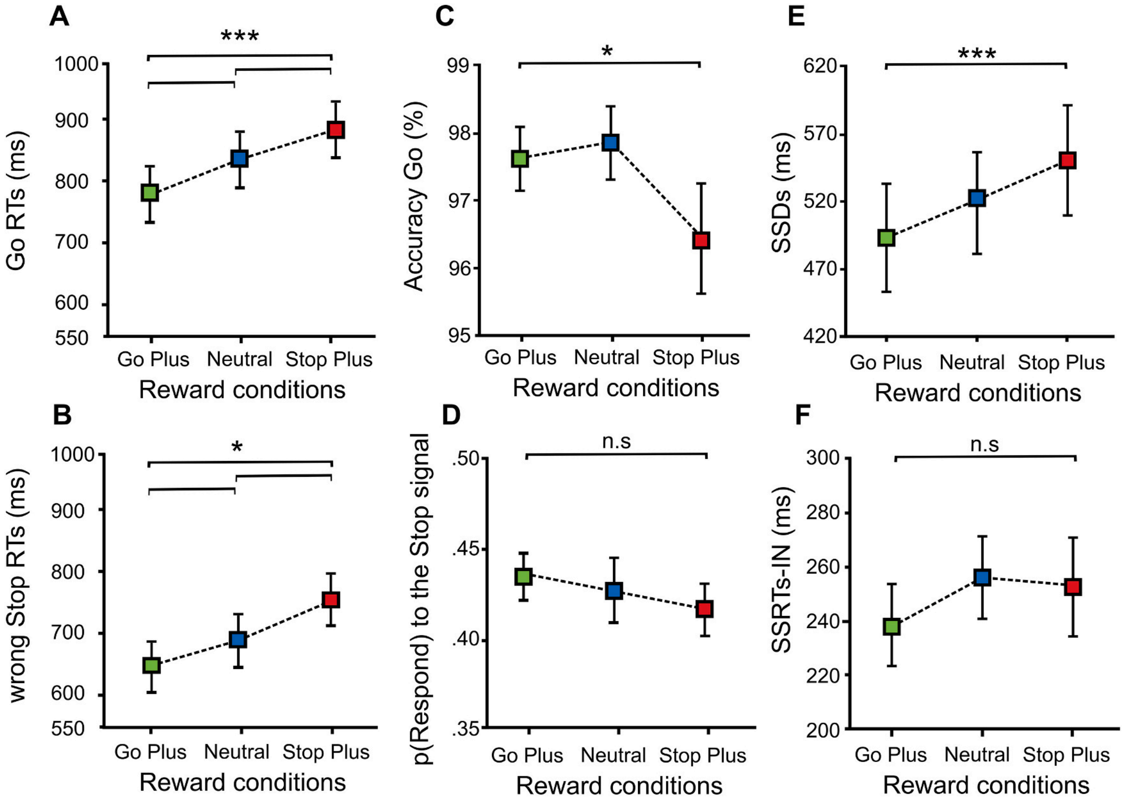


Fig. 2. Effect of reward conditions on movement initiation and inhibition variables. A) Go RTs of correctly performed Go trials; B) Wrong Stop RTs in unsuccessful inhibited Stop trials; C) Accuracy in Go trials expressed as a percentage (%); D) *p*(Respond) to the Stop signal; E) SSDs and F) SSRTs-IN for each reward condition. Error bars for the Go Plus (green squares), Neutral (blue squares), and Stop Plus (red squares) conditions are presented as means ±1 SEM. Asterisks indicate statistical significance, with $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, n.s. indicates non-significant results. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4500), 2953 ± 25.88 points in the Neutral condition (out of 3400), and 1728 ± 25.34 points in the Stop Plus condition (out of 2500) (Fig. 3A, colored bar).

The gray bars in Fig. 3A indicate the maximum attainable reward based on the adaptive task structure (SSD converging to $p(\text{Respond}) \approx 0.5$). As participants cannot earn a reward for all Stop trials by design, this value reflects the achievable performance. Notably, in the Stop Plus condition, participants slightly exceeded this bound by achieving fewer than 50 % failed stops—consistent with proactive slowing to maximize reward under high-stop incentive. We then calculated a Task Efficiency index, defined as the proportion of points earned relative to the maximum possible in each condition (see Methods). A one-way repeated-measures ANOVA on the Task Efficiency index revealed a significant effect of reward condition ($F(2,48) = 27.59$, $p < 0.001$), indicating that participants' efficiency varied systematically as a function of reward context. Post hoc Bonferroni-corrected comparisons confirmed that task efficiency was lowest in the Go Plus condition and highest in the Stop Plus condition (all $p < 0.001$), with intermediate values in the Neutral condition (Fig. 3B). Although participants earned nearly the maximum possible points in all conditions (Fig. 3A), the Task efficiency index revealed that the strategy was optimal in Stop Plus, where the reward for successful inhibition was higher. Conversely, in the Go Plus condition, participants tended to favor speed over control, showing fast but less accurate responding, which likely increased the probability of omission and commission errors.

These patterns indicate that participants strategically adjusted their behavior consistent with the idea that reward prospect modulates choices of strategic control. To move beyond these descriptive differences, which could be the result of the task structure itself, we tested whether the implemented strategy translated into greater overall task success. Specifically, we correlated the RT Shift index with the Task Efficiency index (see Methods) to assess whether larger across-condition changes in RTs were associated with improved efficiency. Overall, no clear relationship emerged between the RT Shift index and task efficiency (Fig. 3C). This finding suggests that moderate RT adjustments were sufficient to maintain optimal performance under the adaptive staircase procedure, which kept stopping accuracy close to 50 %. Consequently, participants could perform efficiently as long as their responses remained within a broad optimal RT range, without needing large shifts in response speed across reward conditions. This suggests that optimal performance did not require exaggerated flexibility, but rather consistent, well-calibrated proactive control tuned to the task's payoff structure.

3.3. Trial and Reward history do not affect behavioral adjustment to the Reward condition

To determine if Go RT of the current Go trial was influenced by either the Trial or Reward History, we analyzed average Go RTs as a function of the preceding trial type (Prior Go or Stop trial) and Prior Cue (G+, N, and S+) across the different reward conditions (Fig. 4A–B).

Analysis revealed no significant effect of Trial History (two-way repeated measure ANOVA: $F(1,24) = 0.02$, $p = 0.86$, $\eta_p^2 < 0$) (Fig. 4A). In contrast, we found a significant main effect of the reward condition ($F(2,48) = 10.26$, $p < 0.001$, $\eta_p^2 = 0.29$), but, no significant interaction was found ($F(2,48) = 0.50$, $p = 0.60$, $\eta_p^2 = 0.02$), indicating that while the reward condition modulated participants' responses these were not influenced by the Prior trial type (Go or Stop). We next explored whether Reward History, specifically the Cue presented in the previous Go trial, affected performance in the current Go trial (Fig. 4B). We categorized Go trials based on whether they were preceded by the same or by a different Cue (e.g., Go Plus → Go Plus or Go Plus → Neutral or Stop Plus). We performed a 3 (target reward Cue: Go Plus, Neutral, Stop Plus) × 3 (previous reward Cue: Go Plus, Neutral, Stop Plus) repeated-measures ANOVA. This analysis revealed a significant main effect of the target reward Cue ($F(2,48) = 20.72$, $p < 0.001$), consistent with the overall slowing observed in the Stop Plus condition. In contrast, neither the previous reward Cue ($F(2,48) = 1.35$, $p = 0.27$) nor the interaction between current and previous reward Cues ($F(4,96) = 1.53$, $p = 0.20$) reached significance. These results confirm that performance adjustments were driven by the current reward condition, with no evidence of systematic influence from reward history.

Our results suggest that the reward conditions modulate participants' behavior on a trial-by-trial basis. Once the Cue is displayed, participants engage in the current trial based solely on the information provided, without influence from prior trial contexts.

3.4. Reward conditions modulate the probability of trigger failure

We estimated the SSRT by two approaches: by the integration method (SSRT-IN) (Verbruggen et al., 2019) (shown in Fig. 2F) and by BEESTS-WTF (SSRT-BST) (Matzke, 2013; Matzke et al., 2017), to check whether the estimation of this variable had been overestimated due to the presence of trigger failure. We found that the BEESTS model produced substantially shorter SSRT estimates (Fig. 5A) compared to the integration method across reward conditions. Specifically, the posterior mean SSRT-BST was 134 ms (95 % CI [121–159]) for Go Plus, 132 ms

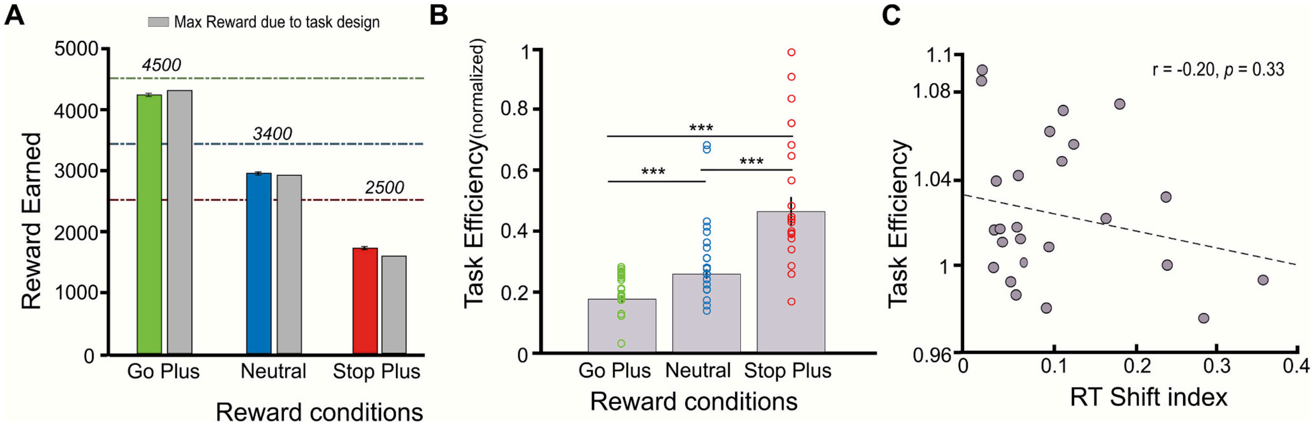


Fig. 3. Reward context modulates behavioral efficiency but not strategic RT shifting. A) Mean total reward earned (colored bars) and maximum attainable reward (gray bars) across reward conditions. For illustration purposes, the dashed color line represents the maximum attainable reward assuming 100 % successful stops (p(Respond) at 0 %), highlighting how the observed pattern reflects adaptive behavior within the task's performance constraints. B) Task Efficiency Index across reward conditions. Each dot represents the Task Efficiency for each participant across reward conditions; C) Correlation between the magnitude of strategic RT shifting (RT Shift Index) and mean task efficiency across participants. Asterisks indicate statistical significance, with $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, n.s. indicates non-significant results. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

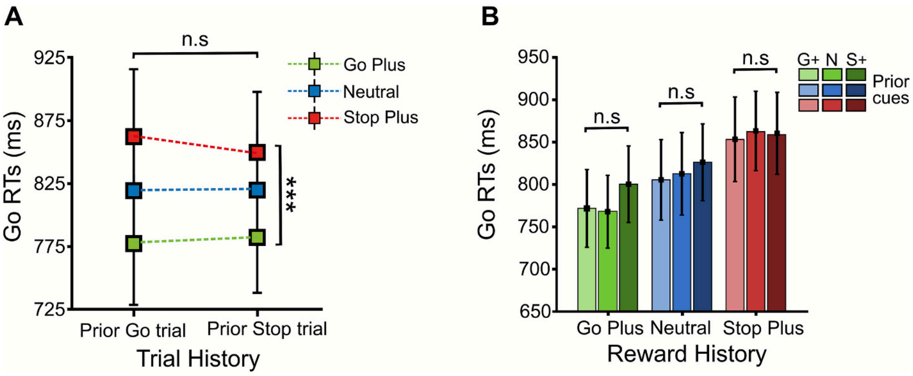


Fig. 4. Effects of Trial and Reward History on average Go RTs in Go trials. A) Trial History effects on Go RTs, showing how average Go RTs vary within each reward condition when the current Go trial was preceded by either a Prior Go or a Stop trial. The y-axis displays average Go RTs across reward conditions, color-coded as follows: green for Go Plus, blue for Neutral, and red for Stop Plus. B) Reward History effects on Go RTs, showing how average Go RTs are influenced by the reward Cues presented in the preceding Go trial. Each group of bars on the x-axis corresponds to the current Go trial's Reward condition, and within each group, each bar reflects a prior Cue (brighter to darker shades indicating G+, N, and S+ of the corresponding color). Error bars are presented as means ±1 SEM. Asterisks indicate statistical significance, with $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, n.s. indicates non-significant results. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

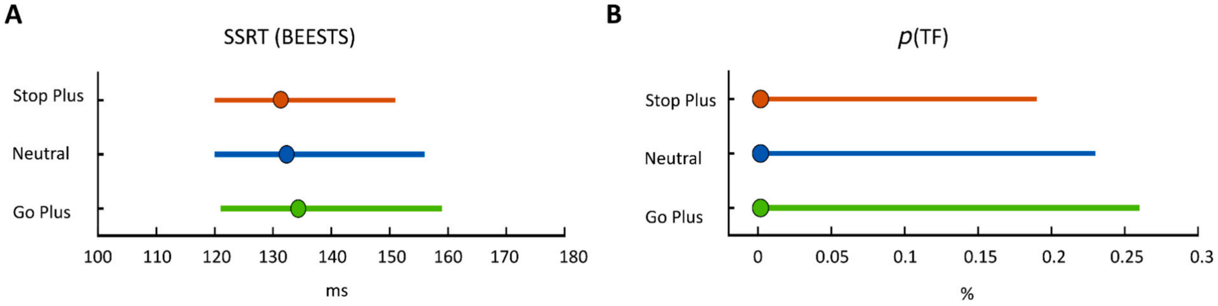


Fig. 5. Posterior estimates of stopping latency and probability of trigger failures across reward conditions. A. Posterior means and 95 % credible intervals (CIs) for the estimated SSRT derived from the BEESTS-WTF model (SSRT_BST) across reward conditions (Go Plus, Neutral, Stop Plus). B. Posterior means and 95 % CIs for the probability of trigger failure (p(TF)) across reward conditions.

(95 % CI [120–156]) for Neutral, and 131 ms (95 % CI [120–151]) for Stop Plus.

The sample fell outside the 95 % credible interval of the Bayesian estimates for all reward conditions, suggesting a significant deviation from Bayesian predictions. A paired t-test confirmed a significant difference between the observed data and the Bayesian estimates (Go Plus: $t = 5.96$, $p < 0.01$; Stop Plus: $t = 6.77$, $p < 0.01$; Neutral: $t = 7.60$, $p < 0.01$), with mean differences of 80 ms for Go Plus, 99 ms for Stop Plus, and 95 ms for the Neutral condition. The Bayes Factor was extremely large (BF > 100 for all conditions), providing strong evidence for a difference between the two estimation methods. Two-way RM-ANOVA detected only a difference in the estimation factor ($F(1,24) = 56.74$ $p < 0.01$, $\eta_p^2 = 0.70$), without any difference between condition ($F(1,24) = 0.71$ $p > 0.05$, $\eta_p^2 = 0.02$) or interaction between the estimation methods and condition ($F(2,48) = 1.83$ $p > 0.05$, $\eta_p^2 = 0.07$). The probability of trigger failure p(TF) was low overall, with posterior means of 0.00 [0–0.26] for Go Plus, 0.00 [0–0.23] for Neutral, and 0.00 [0–0.19] for Stop Plus. To compare the p(TF) across the three reward conditions, we transformed the group-level p(TF) estimates using an inverse probit transformation (Fig. 5B), and to check the statistical difference, we applied the Friedman test on the data mapped on a real scale, and we found a significant difference between reward conditions $X^2 = 27.92$ $p < .01$.

The presence of different reward conditions in our task modulated p (TF): it was reduced in the Stop Plus condition but increased in the Go Plus condition (Kruskal-Wallis $X^2 = 14.98$ $p < .01$). The increased trigger failure rate most likely reflects early motor preparation guided by the reward prospect, which may have led participants to respond before the Stop signal had appeared. Such anticipatory motor preparation could reduce the probability of successful inhibition according to a proactive strategy aimed at maximizing reward.

3.5. Pupil size is modulated in the Cue epochs by Reward conditions

We analyzed both absolute pupil size and pupil slope during the Cue epoch, using cluster-based permutation ANOVAs across conditions. This approach allowed us to identify condition effects on both the overall magnitude of dilation and on the rate of change in dilation over time. The analysis of pupil sizes showed a modulation according to the reward expectation in time. As shown in Fig. 6A, we observed two changes in the pupil size following the Cue onset: an early phasic response of the pupil around 300 ms and a later second response approximately 700 ms from the Cue onset. Cluster-based permutation ANOVA showed reward condition-related differences in the Pupil size over time. Two significant clusters exceeded the 95th percentile of a null distribution generated from 1000 permutations ($p < 0.05$, corrected; Fig. 6B). The first significant cluster is from around 680 to 1200 ms, and the second from approximately 1700 to 1950 ms post-Cue. Both clusters showed medium to large effect size generalized η^2 values (Fig. 6C), suggesting robust and temporally specific modulation of pupil size by the reward condition. We examined pupil responses time-locked to the Go signal (correct Go trials only). No significant differences emerged between reward conditions (all $ps > 0.05$). This null result likely reflects that, in this paradigm, the Go signal served only as an execution trigger, with motivational and control processes already engaged during Cue processing.

To further characterize the effects, we computed the mean pupil size

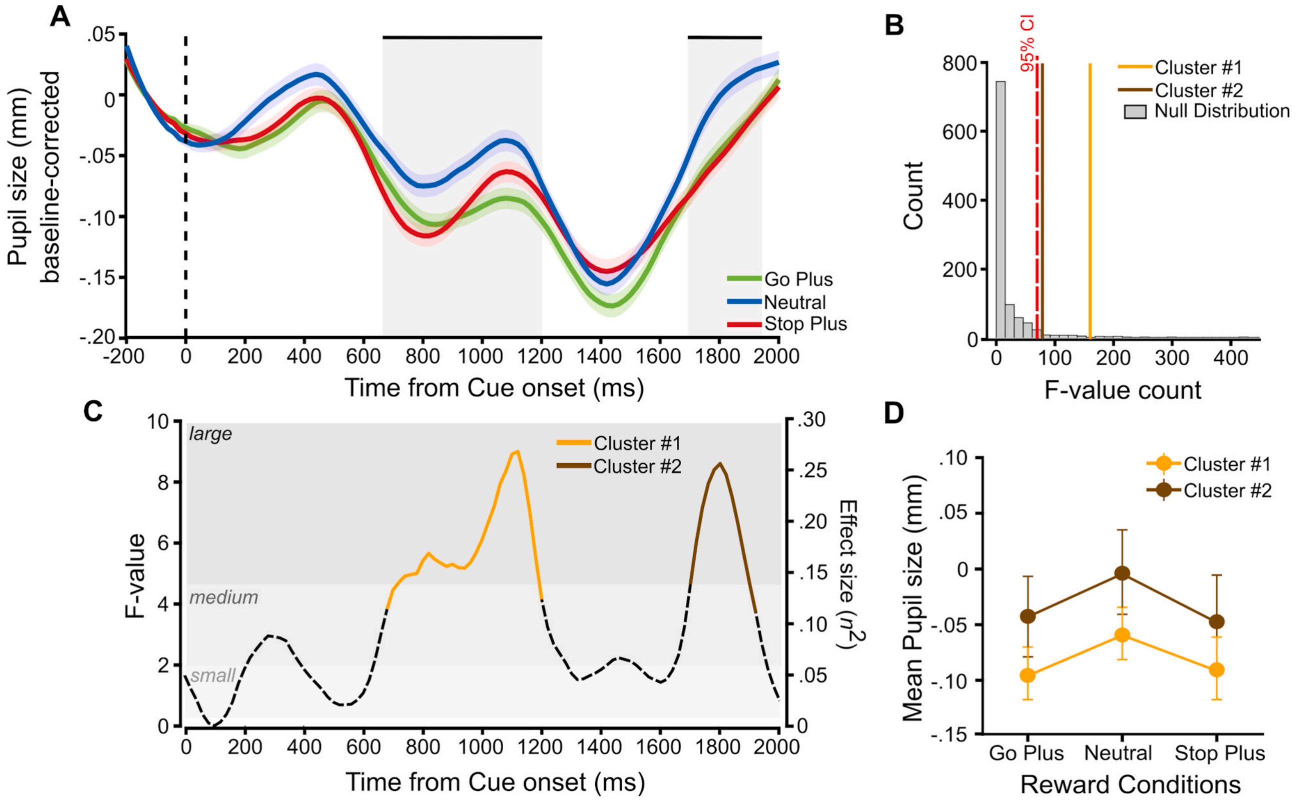


Fig. 6. A. Grand-mean pupil size (in mm, baseline-corrected) across participants for each reward condition from −200 to +2000 ms (0 ms dashed black line represents the Cue onset). Colored shaded areas represent ±1 SEM. The gray shaded background indicates significant time windows where clusters emerged from the cluster-based permutation test (all $p < 0.05$). B. Histogram of Null distribution of maximum cluster statistics obtained from 1000 permutations (histogram) with the two colored lines (color-coded: Cluster #1 in orange and Cluster #2 in brown) representing the F-values of the two clusters that exceeded the 95 % CI (dashed red line) of F-value count(x-axis) for a null distribution. C. Time series of F-values from repeated-measures ANOVA testing for significant difference in the pupil size across reward conditions at each time point. Colored segments denote statistically significant clusters (color-coded: Cluster #1 in orange and Cluster #2 in brown). Shaded gray areas correspond to the range of the effect sizes (small: $\eta^2 > 0.01$; medium = $\eta^2 > 0.06$; and large: $\eta^2 > 0.14$). D. Mean pupil size from each significant Cluster across reward conditions. Error bars are presented as means ±1 SEM, color-coded for each Cluster. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

within each cluster time window and performed pairwise *t*-tests between conditions (Fig. 6D). In both clusters, pupil size was significantly larger in the Neutral condition compared to both Stop Plus (Cluster #1: $p < 0.05$; Cluster #2: $p < 0.01$) and Go Plus ($p < 0.01$ for both clusters), which did not differ from each other (Cluster #1: $p = 0.70$; Cluster #2: $p = 0.81$). These results suggest that cognitive effort, as indexed by pupil size, is dynamically modulated by reward expectation and task demands, with stronger responses associated with the Neutral condition.

Complementing these results, the pupil slope analysis revealed three significant clusters: an early effect at 535–745 ms, and two later effects at 1435–1825 ms and 1795–2005 ms after Cue onset (all *ps* < 0.05, corrected, see Fig. 7A). Post-hoc comparisons showed that in the first (535–745 ms) and second (1435–1825 ms) clusters, slopes were significantly steeper in the Neutral condition compared with the Stop Plus condition, while no differences were detected between Neutral and Go Plus, and between Go Plus and Stop Plus (Fig. 7B). During the second cluster, together with differences between the Neutral condition and Stop Plus condition, slopes in the Go Plus condition were significantly steeper than in the Stop Plus condition (Fig. 7B). Finally, in the third cluster (1795–2005 ms), Neutral slopes were lower than both Go Plus and Stop Plus conditions (Fig. 7B). These findings also show that the temporal dynamics of dilation are modulated by reward context (see Fig. 7A).

After verifying that pupil size and slope showed differences among reward conditions, we tested whether the magnitude or the growth rate of the pupil slope could reflect the proactive strategy used by the participants. For this purpose, we used average Go RTs divided into fast, medium, and slow responses (see Methods for details) and performed a correlation between pupil size and slope and each average Go RTs group. Our data revealed no significant correlations between Go RTs and pupil size in any condition (all *ps* > 0.05, (Go Plus: $r = -0.07$, 95 % CI [−0.31, 0.15], $p = 0.527$; Neutral: $r = 0.09$, 95 % CI [−0.17, 0.29], $p = 0.468$; Stop Plus: $r = -0.01$, 95 % CI [−0.21, 0.20], $p = 0.938$), suggesting that absolute pupil dilation may not directly reflect preparatory control in this task (Fig. 8A). However, a different pattern emerged when considering the pupil slope. Indeed, we found a negative correlation between Go RTs and Slope values in the Stop Plus condition ($r = -0.29$, 95 % CI [−0.45, −0.11], $p < 0.05$), as well as a trend in the Neutral condition ($r = -0.22$, 95 % CI [−0.45, 0.00], $p = 0.059$) and no correlation in the Go Plus conditions (r = −0.01, 95 % CI [−0.29, 0.11], $p = 0.30$) (Fig. 8B).

These results suggest that in conditions requiring strategic inhibition (such as Stop Plus), faster pupil dilation was associated with slower, more controlled responses.

3.6. Power and sensitivity analysis

We performed a sensitivity analysis in G*Power (Erdfelder et al., 2009; Faul et al., 2007) (*F* tests, repeated-measures ANOVA, 3 levels; $\alpha = 0.05$; $1 - \beta = 0.80$) for the primary behavioral outcome (Go RTs), using the correlation among repeated measures (r ≈ 0.96) and Greenhouse–Geisser ε (≈0.52) estimated from our data, indicated that with $N = 25$ the design was sensitive to within-subject effects as small as f ≈ 0.09. The reward condition effect on Go RTs (f ≈ 0.85, η^2p ≈ 0.42) was

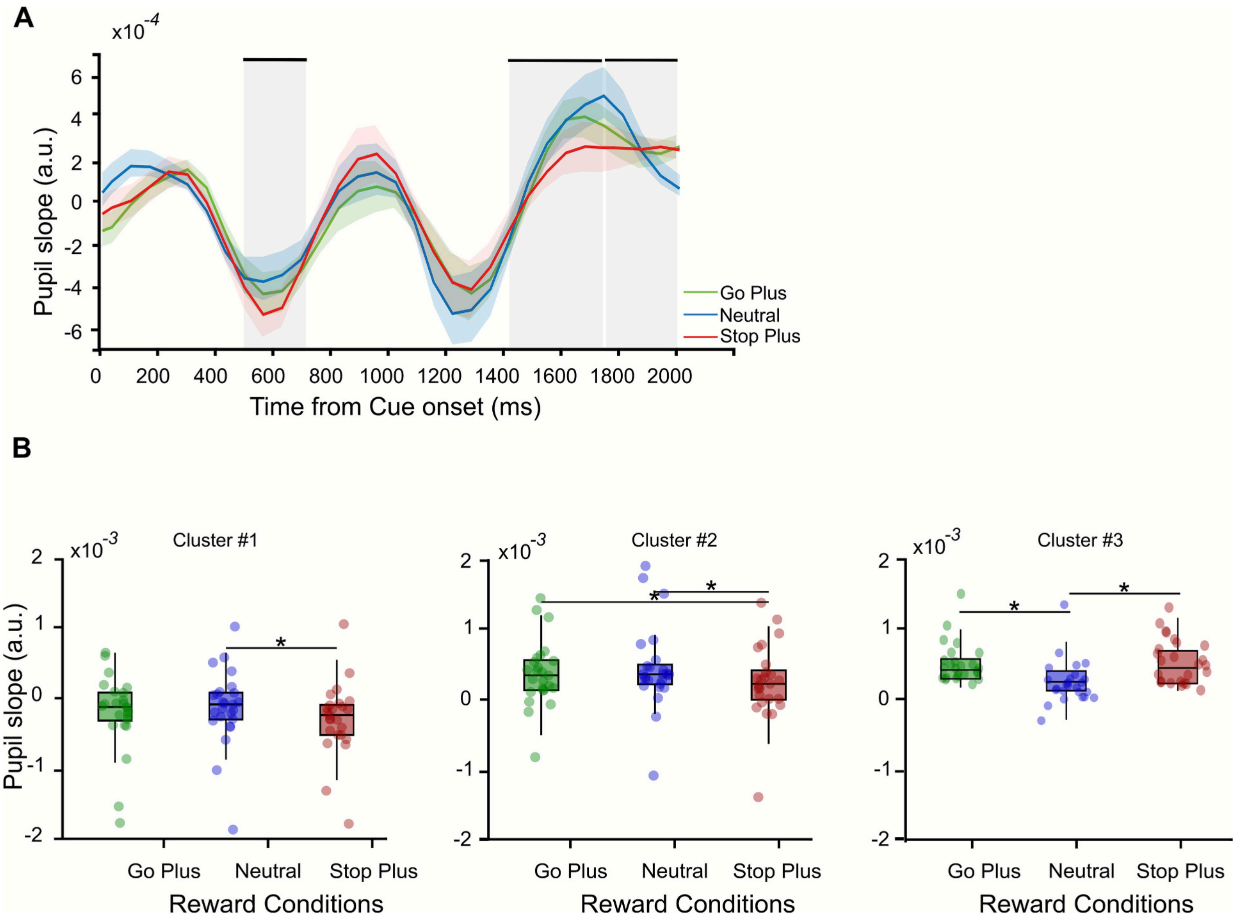


Fig. 7. A. Time course of pupil slope (first derivative of pupil size) aligned to Cue onset, averaged across reward conditions. Shaded areas = SEM; colored lines = reward condition means (green: Go Plus, blue: Neutral, red: Stop Plus). Black horizontal bars mark significant clusters identified by the cluster-based permutation test B. Mean pupil slope values extracted from each significant cluster. Each dot = participant; boxplots show median ± IQR; whiskers = range; error bars = SEM. Asterisks denote significance (*$p < 0.05$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

above this threshold, confirming adequate sensitivity to detect the primary effect of interest. Similarly, for the pupillometry post-hoc comparisons (paired-samples *t*-tests), a sensitivity analysis in G*Power ($\alpha = 0.05$, two-tailed, $N = 25$) showed that the design was sensitive to effects of $dz \approx 0.58$ with a power of 0.80. The observed differences in pupil size between Neutral and the other reward conditions in significant clusters exceeded these thresholds, further supporting the adequacy of our sample size for detecting both behavioral and pupillary effects.

4. Discussion

This study investigated how explicit reward prospects influence behavior in a rewarded Stop Signal Task (SST) and whether this modulation is reflected in pupillary response. Specifically, we adapted the classic SST by introducing a trial-by-trial reward Cue, which instructed participants on the upcoming reward contingency. The task included three reward conditions: Go Plus (higher reward for correctly executed Go trials), Stop Plus (higher reward for correctly inhibited Stop trials), and Neutral (equal reward for both trial types).

Behavioral results showed that participants adopted a trial-based proactive strategy, adjusting their RTs based on the reward Cue. Specifically, participants slowed down in anticipation of a Stop signal in the Stop Plus condition, where inhibiting a response maximized the reward. Conversely, they sped up in the Go Plus condition. These adjustments reflect a reward-modulated proactive control mechanism, as observed in previous studies on cognitive control (Schevernels et al., 2015; Giuffrida et al., 2023; Eayrs et al., 2025; Chiew and Braver, 2013; Fröber and Dreisbach, 2014). The SSD values and error rates further support this interpretation: slowing down in the Stop Plus condition led to longer SSDs and increased omission errors in Go trials.

Interestingly, we found no evidence of trial history effects, which contrasts with previous studies using the classic SST (Emeric et al., 2007; Rieger and Gauggel, 1999; Oldenburg et al., 2012b). Typically, in the absence of reward Cues, participants slow down on Go trials following a Stop trial due to sequential effects. However, in our task, the presence of reward Cues likely reduced dependence on trial history, providing participants with a more immediate source of information to guide their behavioral strategy. This suggests that reward expectation can override trial history-based adjustments, promoting a more future- and goal-oriented strategy. In line with recent cognitive theories, this shift probably occurs because reward expectation directs cognitive resources toward reward maximization (Rowe et al., 2008; Chen et al., 2022), and its observation supports the role of motivation in cognitive control (Parro et al., 2018; Dixon and Christoff, 2012).

Beyond these RT-based adaptations, we found that participants' task efficiency, defined as the ratio of earned to theoretically attainable reward, differed significantly across reward conditions, being highest in the Stop Plus and lowest in the Go Plus condition. This pattern confirms that participants adapted their strategy to the incentive structure. On the other hand, we found that the magnitude of RT shifting between reward conditions did not correlate with overall task efficiency. The absence of a strong correlation between RT shifting and task efficiency likely reflects intrinsic features of the task design. Specifically, the use of an adaptive staircase and a relatively long upper RT limit created a wide

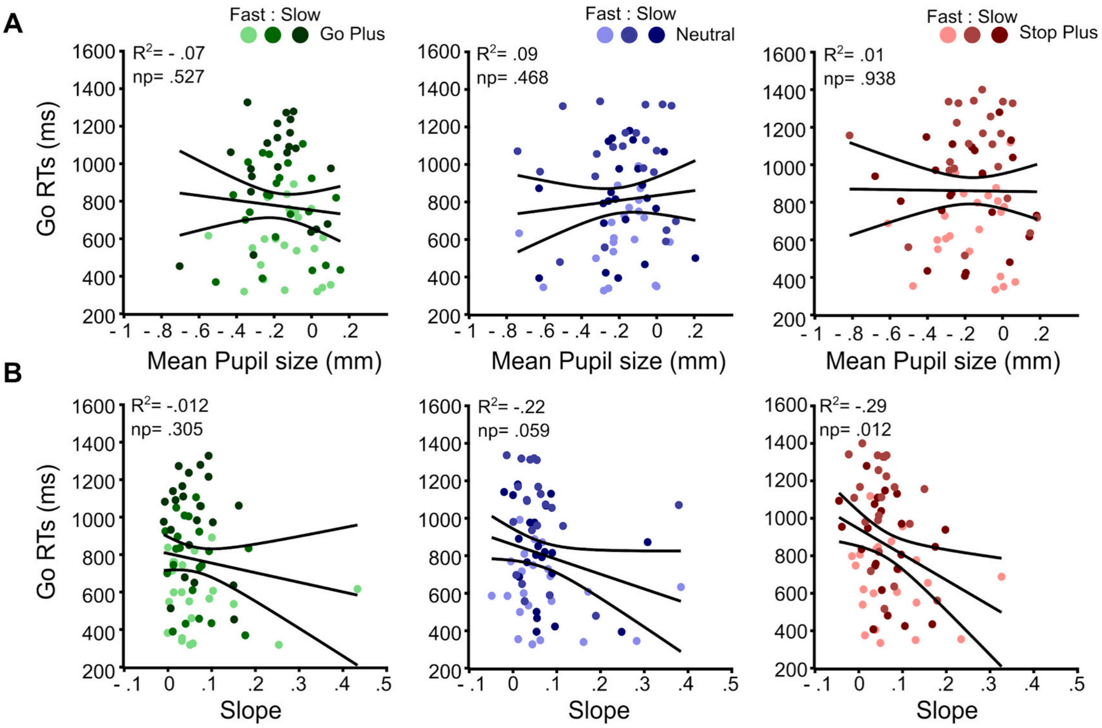


Fig. 8. Relationship between pupil variables and Go RTs across reward conditions. A. Scatterplots of average Go RT (y-axis) and Mean pupil size (x-axis) showing the relationship between the two variables. B. Scatterplots between average Go RT and pupil Slopes. In each panel, dots represent for each participant the mean of Go RTs trials divided into fast, medium, and slow responses (respectively color-coded from brighter to darker colors congruently for each reward condition). Black lines show the fitted linear regression lines, with 95 % confidence bounds of the fit. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

"performance window" in which typical variations in RT related to the conditions had limited impact on accuracy or total reward. Within this regime, participants who slightly slowed down and those who slightly sped up could achieve comparable success rates and point totals. The adaptive control mechanism thus purportedly relied on keeping responses within an optimal timing range, rather than executing large speed–accuracy shifts across Cues.

Finally, to analyze the effects of reward on inhibitory control, we applied the BEESTS-WTF model. Unlike traditional SSRT-IN estimation, which assumes that the stop process is always engaged, BEESTS-WTF allows for the possibility that the stop process is not triggered on some trials, enabling estimation of another variable that strongly influences inhibition: the probability of trigger failure (*p*(TF)) (Matzke, 2013; Matzke et al., 2017). We found that SSRT-IN was longer than SSRT-BTS, as previously observed, underscoring the importance of accounting for trigger failures in studies of inhibitory control. We report the effects of reward on SSRT-IN to insert our findings within the specific literature on the SST, and to provide continuity with prior work; however, our interpretations are based on the BEESTS-WTF results.

Our data show that when higher rewards are provided for correct inhibition (i.e., the Stop Plus condition), trigger failures are reduced. However, no differences were observed in SSRT-BTS, suggesting that increased reward for correct inhibition enhances proactive control primarily by improving engagement of the stopping process rather than by shortening its latency. This dissociation between SSRT-BTS and *p*(TF) is consistent with prior studies, which also found that *p*(TF) was more sensitive to reward context than SSRT-BTS (Matzke, 2013; Matzke et al., 2017; Skippen et al., 2019; McDougal and Gamlin, 2015). However, contrary to expectations, trigger failures were lower than predicted, especially in the Go Plus condition, based on previous studies (i.e., about 2 % for rewarded tasks, (Matzke et al., 2017)). A possible explanation for our findings is that a lower percentage of *p*(TF) may have been minimized at the group level due to the hierarchical fit of the model. By employing group-level distributions to estimate individual parameters, our results suggest that only a small subset of participants exhibited a failure to trigger the Stop process. We opted for this approach instead of individual-level model fitting because the limited trial count per participant would have led to unreliable estimates, as previously discussed in Matzke (2013) and Matzke et al. (2017).

Nevertheless, our SSRT-BTS and *p*(TF) estimates align with existing literature on rewarded Stop-signal tasks (Doekemeijer et al., 2021). In summary, reward prospect influenced the likelihood of initiating the stop process, while leaving its duration unchanged (Matzke et al., 2017).

To complement our behavioral analyses, we examined pupillary responses during the Cue epoch to evaluate the autonomic correlates. We observed a change in pupillary response across different reward conditions approximately 600 ms after the Cue onset, consistent with prior studies showing that pupil size modulation is related to cognitive effort with a delay of several hundred milliseconds (Murphy et al., 2016; Denison et al., 2020; Kostandyan et al., 2019; Naber and Murphy, 2019). In particular, we observed this increase in the Neutral condition, where both going and stopping were equally rewarded. In line with the dual-task requirement hypothesis framework (Verbruggen et al., 2014), this pattern suggests that the Neutral condition may require higher cognitive effort due to dual task demands, i.e., correctly perform all trial types to get a constant amount of reward. This balanced requirement and persistent demand for flexibility could have driven sustained effort compared to the Stop Plus and Go Plus conditions, for which the favored reward is higher either for stopping or moving. Indeed, although the reward in the Neutral condition was lower (+17) than in the other conditions (+30), it was likely still perceived as sufficiently valuable to motivate greater cognitive effort to perform properly. This interpretation is consistent with prior work linking pupil size to activity in the locus coeruleus–norepinephrine (LC–NE) system (de Gee et al., 2020; Joshi and Gold, 2020; Murphy et al., 2011; Joshi et al., 2015; Chiew and Braver, 2013; Mathôt et al., 2015; Schneider et al., 2018; Boehler et al., 2011; Costa and Rudebeck, 2016). Indeed, increased effort allocation is associated with phasic LC responses that manifest as transient pupil dilations. Consistent with this account, our results showed condition-related differences not only in absolute pupil diameter but also in its temporal derivative, the slope, capturing condition-dependent dynamics across distinct time windows. Specifically, the slope analysis identified three significant clusters: an early effect at ~535–745 ms and two later effects at ~1435–1825 ms and 1795–2005 ms after Cue onset. We interpreted the early cluster (535–745 ms) as reflecting cue-evaluation processes, possibly related to the behavioral strategy to adopt and the amount of effort to allocate. Trials in the Neutral condition were characterized by steeper slopes than Stop Plus trials, suggesting that, as for the pupil size, participants may have allocated greater effort to remain flexible, consistent with the "dual-task requirement" hypothesis (Verbruggen and Logan, 2009). This time window is consistent with previous evidence that pupil responses can track the motivational significance of Cues within several hundred milliseconds (Murphy et al., 2011; Chiew and Braver, 2013; Gilzenrat et al., 2010), and steeper slopes are consistent with a phasic burst of LC-NE activity (Reimer et al., 2016). Furthermore, there is an overlap between this cluster and the cluster observed for pupil size, confirming their close relationship (Eayrs et al., 2025).

We interpreted the second cluster (1435–1825 ms) as likely indexing effort associated to reward condition-specific motor preparation. Pupil-slope values were higher in Neutral than in Stop Plus, and higher in Go Plus than in Stop Plus. The same pattern, within a partially overlapping time window, was observed for pupil size. Neutral trials may have demanded greater anticipatory effort due to conflict between the Go and Stop options, both of which provided reward only when performed correctly. In addition, the steeper response in the Go Plus condition compared with Stop Plus may reflect anticipatory preparation of a potentially more rewarding motor plan or, not mutually exclusively, faster responses, whereas Stop Plus favored a more cautious premotor engagement (Eayrs et al., 2025). In line with this interpretation, we found a negative correlation between reaction time and pupil slope in the Stop Plus condition, a similar trend in the Neutral condition, and no significant relationship in the Go Plus condition. Stop Plus reward condition probably allowed participants to prepare for the response in a wait-and-see context, holding the responses to the Go signal while waiting for a more rewarding Stop signal, as reflected in the lengthening of the RTs. In this view, the increased pupil slope accompanying shorter RTs may reflect greater preparatory effort associated with more prolonged, conflict-laden options. As stated above, this conflict is typical in the Neutral condition. In contrast, the Go Plus condition, which encouraged fast responses with less conflict control, showed no such relationship. The lower value assigned to inhibition in this condition probably reduces the need for control, as reflected by the higher probability of trigger failure estimated via BEESTS-WTF, consistent with a faster response strategy. These observations align with studies showing that pupil size increases before the instructing stimulus when correct performance is more highly rewarded or when greater effort is required due to stimulus uncertainty or incongruence, suggesting, in our case, the engagement of distinct motor-preparation processes to optimize rewarded actions (Schneider et al., 2018; Boehler et al., 2011; Van Slooten et al., 2018). In our study, pupil size and slope are both linked to a proactive strategy, as their modulation appears even before the Go signal (Eayrs et al., 2025). Our findings suggest that pupil slope reflects processes associated with cue evaluation—including motivational aspects and task-related demands—and with the anticipatory allocation of effort for a proper response. In line with the Expected Value of Control (EVC) model (Chen et al., 2022; Van Slooten et al., 2018), these two factors seem to strongly influence the effectiveness of the proactive control perceived by the participants in each condition. Specifically, the EVC model assumes that cognitive control allocation is guided by the overall value of the action execution and the perceived likelihood of success (i.e., efficacy) (Frömer et al., 2021; Shenhav et al., 2013). According to this framework, higher reward levels generally promote cognitive effort, but this is further modulated by perceived efficacy, i.e., how likely participants believe their effort will influence task success. This is consistent with prior studies that showed that the modulations in CNV and pupil size are related to reward, task difficulty, and perceived efficacy (Fröber and Dreisbach, 2014; Frömer et al., 2021; Shenhav et al., 2013). In our task, efficacy was not experimentally manipulated (Walsh et al., 2019; Fröber et al., 2020; Kostandyan et al., 2019; Frömer et al., 2021), yet it is plausible that the reward schedule shaped perceived efficacy across conditions.

While our results support the link between pupil slope and cognitive control, we acknowledge several limitations. First, our task was not specifically designed to disentangle cue-evaluation and motor preparatory processes, which may overlap in their contributions to pupil signals. Second, time constraints on responding may have limited the observable influence of proactive control on absolute pupil size. Third, the use of group-level model fitting limits the individual differences in inhibition dynamics. Future work could address these issues by introducing a delay between the Go signal and movement to be performed and use a block reward structure to better characterize cognitive effort related to cue-evaluation or to a motor response strategy used, by also analyzing a possible baseline (tonic) pupil change. These results show that reward and task difficulty shape both control strategy and autonomic correlates of anticipatory effort. This is consistent with previous studies showing that task-related variables influence the underlying race dynamics that determine performance in the SST (Fiori et al., 2024; Verbruggen and McLaren, 2018; Verbruggen et al., 2014; Marc et al., 2025; Marc et al., 2023; Verbruggen et al., 2006).

5. Conclusion

In summary, our results suggest that explicit reward Cues in the SST modulate both behavior and autonomic responses, as reflected by changes in reaction times and pupil size. Reward Cues elicited proactive control and removed trial-history-based adjustments, providing a clearer and more efficient strategy for reward maximization. Moreover, reward conditions influenced cognitive effort, as reflected by pupillary modulation. In this context, pupil dynamics provide a sensitive physiological marker of reward-modulated proactive control: slope analyses revealed distinct temporal clusters corresponding to cue evaluation and motor preparation, where anticipatory effort allocation is at play. This extends prior work by demonstrating that slope metrics capture phasic control adjustments that are not always visible in mean pupil size. Overall, our findings offer new insights into how reward shapes cognitive control strategies and highlights the potential of pupil size as a marker of cognitive effort.

CRediT authorship contribution statement

Valentina Giuffrida: Writing – review & editing, Writing – original draft, Software, Project administration, Investigation, Formal analysis, Data curation. **Isabel Beatrice Marc:** Writing – review & editing, Writing – original draft, Visualization, Validation. **Stefano Ferraina:** Writing – review & editing. **Emiliano Brunamonti:** Writing – review & editing. **Pierpaolo Pani:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Ethics approval and consent to participate

The study was ethically approved by the institutional review board of the Sapienza University of Rome, and written informed consent was obtained from all participants.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used the generative AI tool ChatGPT and Quillbot to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial, financial, or other relationships that could be construed as potential competing interests.

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Data availability

The datasets and analyses used during the current study are available in Zenodo at doi: https://doi.org/10.5281/zenodo.17415469.

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