The neural mechanisms underlying effort process modulated by efficacy

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ABSTRACT

Life is filled with uncertainty that imposes challenges for goal-directed effort. For example, whether effort reaps reward impacts the effort process. Real-life activities involve a long-term input of effort, implying that our effort process should be stably and consistently managed. The present study investigated how efficacy modulates the effort process from the perspective of overall performance and effort stability. Using a mini-block Stroop task and electroencephalography, we manipulated performance-reward contingency to pinpoint behavioral and neural features at each time stage (preparation, execution, and feedback-processing). Our findings revealed an efficacy-modulated effort process from three aspects. First, high efficacy induced a more prepared state before target presentation, which was identified by two neural indicators: contingent negative variation (CNV) and β oscillation (13–20 Hz). Then, drift rate and decision boundary reflected how people executed the task under different efficacy levels. Moreover, CNV and β oscillation affected sustained effort by modulating the drift rate, indicating preparatory state changed the execution to influence sustained effort. Finally, feedback-P3b captured shifts in the sustained effort after receiving different feedback. Taken together, these findings showed that efficacy modulates effort at each time course. Informative signals about efficacy and feedback are beneficial to trigger high-quality preparation and execution and drive effort adjustment.

1. Introduction

Goal-directed behavior reflects humans' internal models of understanding the world (Gweon, 2021; Liu et al., 2017). A ubiquitous model is that effort eventually pays off, shaping most people's code of conduct. Effort reflects the magnitude and intensity of participation in pursuing goals (Inzlicht et al., 2018). The value of effort guides effort-based decisions (Contreras-Huerta et al., 2020) and modulates the effort process. People face the challenge of evaluating the worthiness of effort and adjusting effort because there are multiple stochastic disturbances between the effort process and outcome. The worthiness of effort, related to a concept termed efficacy, is vital for control resource allocation (Shenhav et al., 2013, 2017). People can learn efficacy from past experiences under uncertainty and adapt control allocation (Grahek et al., 2021). Moreover, our behavior can be modulated by external cues that reveal efficacy. It has been found that people allocate more effort to obtain high-quality performance if their effort is effective. In contrast, low efficacy circumstances render certain behavior futile. The low motivational context induces lower accuracy and slower reaction time

(Frömer et al., 2021a,b). In general, people are capable of making adjustments in the ever-changing environment (Behrens et al., 2007; Browning et al., 2015; Gagne et al., 2020; Na et al., 2021).

To reveal the motivated effort process in a multidimensional way, researchers take advantage of more nuanced analysis than simple outcome-based evaluation (e.g., reaction time and accuracy). One way to improve our understanding of the efficacy-modulated effort process is to study neural implementation using electroencephalography (EEG). Decomposing the effort into multiple processes sheds light on how people exert effort. Each process has a representative index regarding the effect of efficacy. First, during the incentive processing stage, efficacy cues elicit neural activities which are related to behavioral performance. Specifically, cue-P3b is associated with incentive processing after cue presentation for 300–500 ms (Wei et al., 2021; Zhang et al., 2017; Zheng et al., 2017). A recent study suggested that cue-P3b processes reward and efficacy information and predicts task performance, such as accuracy and reaction time (Frömer et al., 2021a,b).

After the cue processing, preparatory state and executive strategy are important to enhance performance. Contingent negative variation

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(CNV) is a slow wave with a negative peak timed after cue onset and before target presentation (Leuthold et al., 2004; Walter et al., 1964). It is an index of proactive control that displays the maintenance of context or goal-relevant information (Braver, 2012). It represents motor initiation for highly motivated behavior (Novak and Foti, 2015). Recently, Grahek et al. (2021) suggested that CNV entirely demonstrates control adjustments. They excluded an alternative explanation for CNV that it is an incentive-processing signal. When effort yielded reward ineffectively, the value of the control was reduced, which was reflected in a smaller CNV amplitude and correlated to poor behavioral performance. Furthermore, another typical neural signature of motion preparation is the pre-motor oscillatory activity in the β-band (13–30 Hz) (Lasaponara et al., 2020; Tzagarakis et al., 2015). It is suppressed during the preparation and the initiation of motor responses (movement-related β-desynchronization, MRBD). Compared to the time-locked event-related potentials (ERPs), the oscillatory signals that are not synced across trials utilize more information in the EEG (Morales and Bowers, 2022). However, it is unclear whether the MRBD is modulated by efficacy and whether its function is similar to that of CNV.

Reward-induced increases in motivation promote cue maintenance and cognitive stability. Performance incentives have been found to impact not only how well people perform on a specific trial, but also how consistently they perform across trials (Fröber and Dreisbach, 2014; Hefer and Dreisbach, 2017, 2020; Notebaert and Braem, 2015). Sustained effort is essential in many domains, such as academic success, personal safety, and social communication (Esterman et al., 2013; Fortenbaugh et al., 2018). It is unclear whether there are neural signals that can predict stable performance across trials. This study investigated this question using a modified Stroop task. In our task, an efficacy cue was followed by a mini-block Stroop that allowed for self-paced responses, and the cue was only presented once before the first target in each mini-block. We aimed to examine whether CNV and β oscillation reflect the cue maintenance in consecutive trials in a mini-block.

Moreover, θ-band (4–8 Hz) activity represents the need for control, providing insights into how people perform the task when task information varies (Cavanagh and Frank, 2014; Wang et al., 2014). In addition to the neural implementation, sequential-sampling models, like the drift diffusion model (DDM), are well-established cognitive models that provide a mathematical description of people's execution strategy (Ratcliff and McKoon, 2008). The model translates accuracy, reaction time, and response time distribution to cognitive processing. For example, threshold adjustments are associated with the suppression of motor-related activity (Danielmeier et al., 2011). Incentive-related control adjustments can be explained by the selective attention to target stimuli and are reflected in drift rate (Manohar et al., 2015).

Preparation and feedback processing phases are critical for demonstrating human cognitive abilities (Pornpattananangkul and Nusslock, 2015; Wei et al., 2020; Zheng et al., 2017). In previous research, efficacy-based effort in the preparation stage has been examined. Notably, useful feedback, such as error feedback, serves as an indicator to facilitate adjustments of control intensity (Ritz et al., 2022). However, feedback in real-life might not completely represent what is right or wrong. Long-term performance evaluation is also important, requiring consistency and stability in the effort. How feedback under different efficacy is processed, and how it influences future adjustments of effort have been less discussed. One neural signal of feedback processing may shed light on the question (Schiffer et al., 2017). Feedback-P3b (fb-P3b) is a parietally distributed positive peak at 300–600 ms. A previous study suggested that fb-P3b is a subcomponent of P3 (Squires et al., 1975). P3 has been found to be sensitive to reward magnitude (Yeung and Sanfey, 2004). fb-P3b may capture top-down processing of unfavorable outcomes. In particular, P3b amplitude increased as the probability of the event decreased (Donchin, 1981). Recently, it has been found to be associated with the trial-by-trial behavioral shift (Frömer et al., 2021a,b; Ullsperger et al., 2014). Thus, we hypothesized that fb-P3b could function as a signal of reward-processing and predict behavioral change.

In this study, we explored the underlying neural mechanism of efficacy-modulated effort and the stability of effort. We focused on the temporal stages such as preparation, execution, and feedback-processing, exploring a nuanced description of the efficacy-modulated effort process. Specifically, we postulated four hypotheses: (1) high efficacy leads to better overall performance, and more stable effort; (2) efficacy cues modulate the incentive-processing, execution, and feedback-processing stages, respectively; (3) the interplay of time stages ultimately promotes high-quality performance; and (4) people can adjust their effort process based on efficacy and reward feedback.

2. Methods

2.1. Participants

We recruited 36 participants (20 female; age_{mean} = 21.5 years, age_{sd} = 2.08 years). The sample size was based on the previous studies (Frömer et al., 2021a,b). All participants were right-handed, without color blindness, and had normal or corrected vision. Two participants were excluded because of data corruption and loss. All the procedures involved were in accordance with the Declaration of Helsinki and were approved by the Institutional Review Board of the Institute of Psychology, Chinese Academy of Sciences.

2.2. Paradigm

Participants performed a self-paced Stroop task within a random duration (6–10 s). The number of trials was based on participants' actual performance. They were informed about how reward feedback depended on their performance (high efficacy cue, 100% performance-reward contingency; low efficacy cue, non-contingent). In high efficacy rounds, reward feedback was determined entirely by participants' performance. In low efficacy rounds, rewards were randomly distributed. With a yoked design, the number of rewards was balanced between the two efficacy conditions (Supplementary Fig.1). Specifically, rewards in low efficacy rounds were determined by sampling from a rolling window (size = 10) of the reward rate in high efficacy rounds. The reward standard was individually calibrated based on each participant's performance in the training session. During the training session, participants were instructed to respond as quickly as possible while maintaining accuracy. We calculated the mean response time and accuracy over 80 practice trials for each participant. In the formal experiment, we defined "good performance" as reaction time equal to or below the training mean reaction time and accuracy equal to or better than training accuracy. Under high efficacy, a good performance produced a high reward (¥10), while a low reward (¥0.1) indicated a failure to meet the pre-determined standard (Fig. 1). In a randomly selected 40% of all the rounds, participants received three survey questions after reward feedback to assess their self-awareness of effort and attention. These were "How much effort did you put in for this round?", "Please assess how nervous you were in this round", and "Please rate your attention level in this round", with a response range from 1 to 10 for each.

2.3. Behavioral analysis

To investigate the effect of efficacy (low vs. high) on overall performance, we used the paired sample *t*-test for accuracy, correct response time (CorrRT), and correct response per second (CorrPerSec) in each condition. CorrPerSec is a behavioral indicator of how much effort was made in the task (Leng et al., 2021), revealing whether performance enhancement is a trade-off between speed and accuracy. We further excluded the effect of potential confounding variables (e.g., task difficulty, gender, and age) using a linear mixed model (LMM) at the round-level and trial-level, respectively.
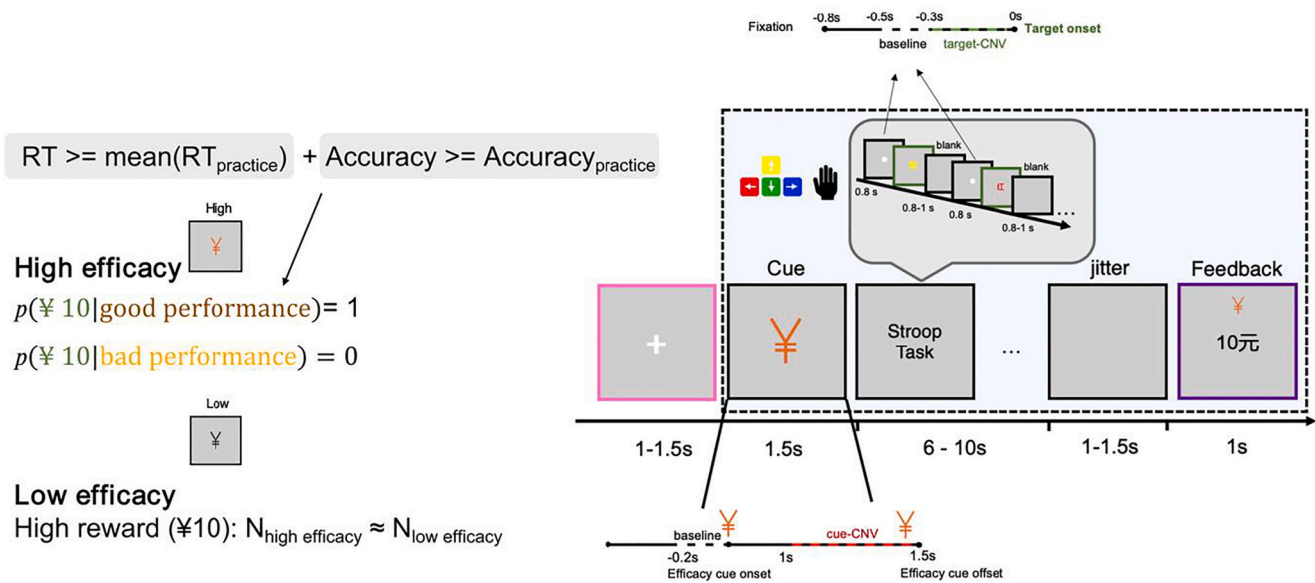
Fig. 1. Task procedure. For each trial, four Chinese characters ("红, 黄, 蓝, and 绿") were randomly presented in the center of the screen. Characters were displayed in one of four colors with equal probability. Participants were instructed to respond according to a color-key mapping [red (↑), yellow (↓), green (←), blue (→)]. Participants first completed a training session (80 trials) and repeated the session until their accuracy was above 90%. No accuracy feedback was provided in the formal experiment. The formal experiment had 6 blocks, each consisting of 10 or 12 rounds. Each round had an efficacy cue prior to a mini-block, with the two efficacy conditions randomly distributed with equal probability. Participants then completed a self-paced Stroop task with a random duration of 6–10 s. Before the reward feedback presentation, a blank screen was displayed for 1–1.5 s. The reward feedback was based on efficacy conditions and actual performance (¥10 or ¥0.10). Participants were allowed a self-paced rest at the end of each block. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

$$CorrPerSec = \frac{(Number\ of\ Correct\ Responses\ )round}{duration round}$$

We used the variation time course (VTC) proposed by Esterman et al. (2013) to explore how efficacy affects the sustained effort, measured through variations in reaction time. VTC was calculated as the deviation of response times from the average block response time and normalized to the block's standard deviation. Higher VTC values indicate more erratic behavior, while lower VTC values indicate more stable and focused behavior. We examined the effect of efficacy on effort stability using ANOVA and LMM.

$$VTC = \frac{RT_{trial} - \overline{RT}_{block}}{sd_{block}}$$

To see how efficacy and feedback contribute to behavioral adjustment regarding overall effort, we used the change in CorrPerSec (CorrPerSec change = CorrPerSec$_{(t+1)}$- CorrPerSec$_{(t)}$). The interaction of efficacy (low vs. high) and reward feedback (low vs. high) on overall effort adjustment was examined using LMM. We similarly examined how efficacy and reward feedback affect changes in sustained effort (VTC change = VTC$_{(t+1)}$- VTC$_{(t)}$) using LMM.

2.4. EEG data recording and analysis

2.4.1. EEG data recording

The EEG data were collected using a standard 10–20 system EEG cap with a 64-channel recording system (Brain Products, GmbH, Gilching, Germany; passband, 0.01–100 Hz; sampling rate, 500 Hz). The FCz channel was chosen as an online reference, and a vertical electrooculogram was recorded using an electrode placed below the right eye. All channel impedances were kept below 5 kΩ during the experiment. In preprocessing, the EEG data were re-referenced to the average signal of TP9 and TP10 offline. FCz was recovered for further analysis, and continuous data were high-pass filtered at 0.1 Hz.

Preprocessed EEG data were segmented in different epochs relative to the onset of these pre-determined markers: efficacy cue (−1000

ms–1500 ms), target (−500 to 300 ms), response (−200 to 800 ms), and feedback (−200 to 800 ms). All epochs were baseline-corrected using the mean amplitude before event onset (efficacy cue, −300 to 0 ms; target, −500 to −300 ms; response, −400 to 0 ms; feedback, −200 to 0 ms). Based on the literature, we focused on several EEG components in specific time windows: the cue-CNV (−500 ms pre-task, averaged across Fz, FCz, and Cz), cue-P3b (250–550 ms, averaged across Pz, P1, and P2), target-CNV (−300 ms pre-target for each trial in a mini-block, averaged across Fz, FCz, and Cz), and fb-P3b (400–550 ms, averaged across Pz, P1, and P2). EEG data preprocessing was performed using the EEGLAB functions in custom MATLAB scripts. Further quantitative analyses were conducted in R using paired t-tests and LMMs.

2.4.2. Time-frequency analysis

In addition to the above phase-locked brain responses, a time-frequency analysis was performed to explore the non-phase-locked brain responses elicited by efficacy cues. Time-frequency analysis was performed using custom scripts based on FieldTrip (Oostenveld et al., 2011). Time-frequency distributions (TFDs) of single-trial EEG signals were estimated using a MTMCONVOL (multi-taper-method convolution). The wavelet was constructed by time-point-wise multiplication of the (real) cosine and (imaginary) sine component at each frequency with a specified tapering function. MTMCONVOL performs time-frequency analysis on any time series trial data using a fixed 0.5 s Hanning taper. The time window of interest extends from −0.5 s to 0.5 s relative to the onset of the potency stimulus in steps of 0.01 s (10 ms). Frequency points ranged from 2 to 30 Hz in steps of 1 Hz. The spectrograms were baseline-corrected (reference interval: −0.5 s to −0.3 s relative to stimulus onset) at each frequency using the subtraction approach (Hu and Zhang, 2019). According to previous studies, fluctuations of proactive control and the need for control could be encoded by theta (θ, 4–8 Hz) and beta (β, 13–20 Hz) oscillations, i.e., event-related synchronization (ERS) of the θ band and the MRBD. We corrected for multiple comparisons using the false discovery rate and identified time-frequency windows that differed significantly between the two efficacy levels.

Further statistics of θ-ERS and MRBD (low efficacy vs. high efficacy) were assessed in R using paired t-tests. time stage using Bayesian multilevel mediation analysis (Vuorre and Bolger, 2018). We were interested in how different time stages interacted to produce good performance consistently.

2.4.3. Drift diffusion model (DDM)

We employed a DDM to reveal the cognitive mechanisms during task execution. This analysis was conducted in R using the hBayesDM package (Ahn et al., 2017). Behavioral data of the participants were fitted for each condition separately.

3. Results

3.1. High efficacy enhanced overall performance and sustained effort

According to participants' self-report, their effort was significantly greater in the high compared to low efficacy rounds (low: 6.69 ± 1.43, high: 7.26 ± 1.39; $t_{(33)} = -4.65$, $p < .01$). Using a nonparametric approach, we examined participants' self-report about how they felt about their effort investment in each condition (Galvin et al., 2003). However, they showed no metacognitive sensitivity, so they did not realize the difference in their effort in the high and low efficacy rounds

(Supplementary Fig. 2a and Supplementary Fig. 3). Therefore, detailed behavioral indexes, fine-grained neural signatures, and underlying cognitive strategies are important to provide thorough information.

For an evaluation of the overall effort, participants responded more accurately (accuracy$_{low}$: 0.96 ± 0.02, accuracy$_{high}$: 0.97 ± 0.03; $t_{(33)} = -2.49$, $p < .05$; Fig. 2a), and faster in high compared to low efficacy rounds (CorrRT$_{low}$: 0.68 ± 0.13, CorrRT$_{high}$: 0.62 ± 0.10; $t_{(33)} = 6.39$, $p < .001$; Fig. 2b). The results replicated previous findings that individual performance was enhanced when a high efficacy cue is explicitly presented. The significant enhancement of performance was not a trade-off between speed and accuracy, as evidenced by CorrPerSec. CorrPerSec was higher for high (1.52 ± 0.2) compared to low (1.38 ± 0.21) efficacy rounds ($t_{(33)} = -6.81$, $p < .001$; Fig. 2c and d, Supplementary Fig. 1). To eliminate confounding variables, we controlled for task difficulty (congruence of word and color) and demographic information by the LMM. The round-level LMM showed a significant effect of efficacy on correct response per second ($b = 0.15$, CI = $[0.01, 0.29]$, $p < .05$; Supplementary Table 1). We also constructed a trial-level LMM and found a similar effect of efficacy on performance enhancement ($b = 0.01$, CI = $[0, 0.01]$, $p < .001$; Supplementary Table 2).

VTC is an indicator of behavioral stability proposed by Esterman et al. (2013). It was used here to examine the effect of efficacy on sustained effort. Lower VTC represents a more stable effort. We found that
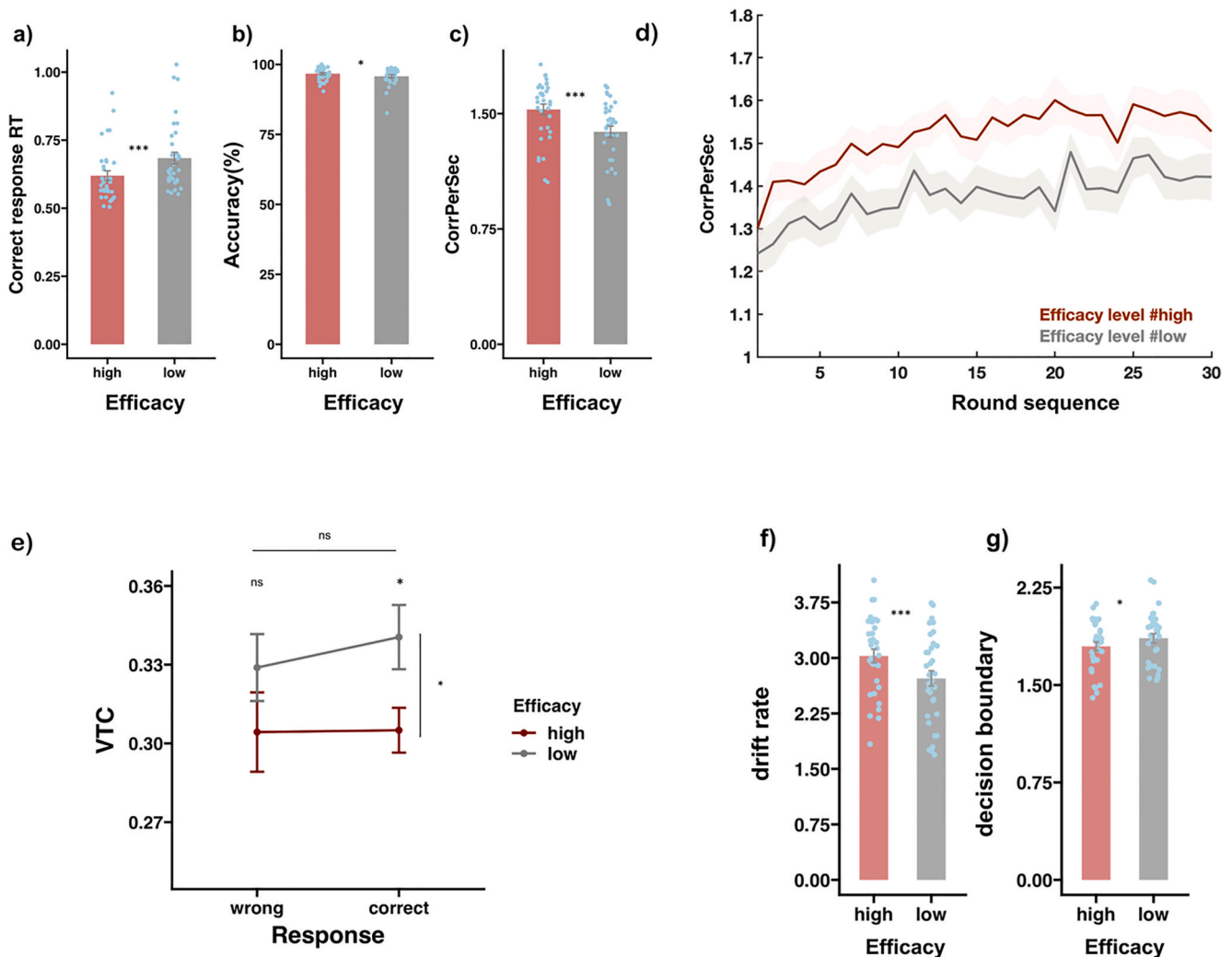

Fig. 2. Efficacy modulates behavioral performance. a, b, c) Mean value of correct response time (CorrRT), accuracy, and the correct response per second (CorrPerSec) under two efficacy conditions; **d)** the average behavioral fluctuation (mean CorrPerSec for all the participants) for the two efficacy levels across the whole experiment; **e)** the VTC calculated regarding response accuracy and efficacy levels; **f, g)** drift rate and decision boundary for the two efficacy levels. ***$p < .01$, **$p < .01$, *$p < .05$, and ns represents $p > .05$.

performance was more unstable in low efficacy rounds, compared to high efficacy rounds. Thus, participants were more focused when effort was effective ($F_{(1,32)} = 6.73, p < .05$). There was no interaction between response accuracy and efficacy ($F_{(1,32)} = 0.98, p = .33$). However, making correct responses in high efficacy rounds (0.30 ± 0.04) was more stable than that in low efficacy rounds (0.34 ± 0.07) ($t_{(32)} = 4.45, p < .001$). There were no significant differences in VTC depending on response accuracy ($F_{(1,32)} = 0.17, p = .68$) (Fig. 2e). In the following analysis, we only considered the VTC of correct responses.

We analyzed DDM parameters and found that drift rate in the high efficacy condition (3.03 ± 0.53) was significantly larger than that in the low efficacy condition (2.72 ± 0.60) ($t_{(33)} = 3.89, p < .001$; Fig. 2f). Meanwhile, decision boundary was significantly smaller in the high efficacy condition (1.80 ± 0.19) than in the low efficacy condition (2.25 ± 0.44) ($t_{(33)} = -2.43, p < .05$; Fig. 2g). The adjustments of drift rate and decision boundary were in line with experimental instruction as fast responses and high accuracy guaranteed high reward.

3.2. Efficacy modulated cue-processing and execution

As expected, high efficacy cues generated higher cue-P3b (6.98 ± 0.8 μV) than low efficacy cues (5.48 ± 0.6 μV) ($t_{(33)} = -2.05, p < .05$; LMM: $b = 1.5$, CI = [0.07, 2.93], $p < .05$; Fig. 3a; Supplementary Table 3). Interestingly, we found a marginally positive relationship

between drift rate and cue-P3b, particularly in the high efficacy rounds ($r = 0.33, p = .05$; Supplementary Fig. 4), showing that cue-induced attentional orientation was associated with the speed of evidence accumulation.

Next, our paradigm enabled us to explore the effect of cue maintenance by separating CNV into two types: cue-CNV (immediately following cue onset, −500 ms pre-task) and target-CNV (prior to the onset of the Stroop target, −300 ms pre-target). cue-CNV was not significantly different between efficacy conditions (low: 2.17 ± 0.09 μV, high: 2.9 ± 0.07 μV; $t_{(33)} = -0.84, p = .42$; LMM: $b = 0.76$, CI = [−1.01, 2.53], $p = .40$; Supplementary Fig. 5; Supplementary Table 5). In contrast, target-CNV was significantly larger in high than low efficacy condition (low: -0.42 ± 0.29 μV, high: 1.46 ± 0.29 μV; $t_{(33)} = 7.00, p < .001$; LMM: $b = -1.04$, CI = [−1.34, −0.75], $p < .001$; Fig. 3b; Supplementary Table 4). Therefore, the CNV, before every target onset (target-CNV), reflected motor preparation and it was consistently influenced by efficacy cues.

The β-band oscillation (−260 to 70 ms relative to target onset, 13–20 Hz) is another critical indicator representing a preparatory state before target onset. High efficacy condition generated significantly larger power (-0.35 ± 0.09 dB) than low efficacy condition (-0.13 ± 0.08 dB) ($t_{(33)} = 2.95, p < .001$; Fig. 3c, d, 3f), indicating a motor preparation similar to that of the target-CNV. As expected, θ-band (4–8 Hz) oscillation (210–500 ms relative to target onset) for the high efficacy condition
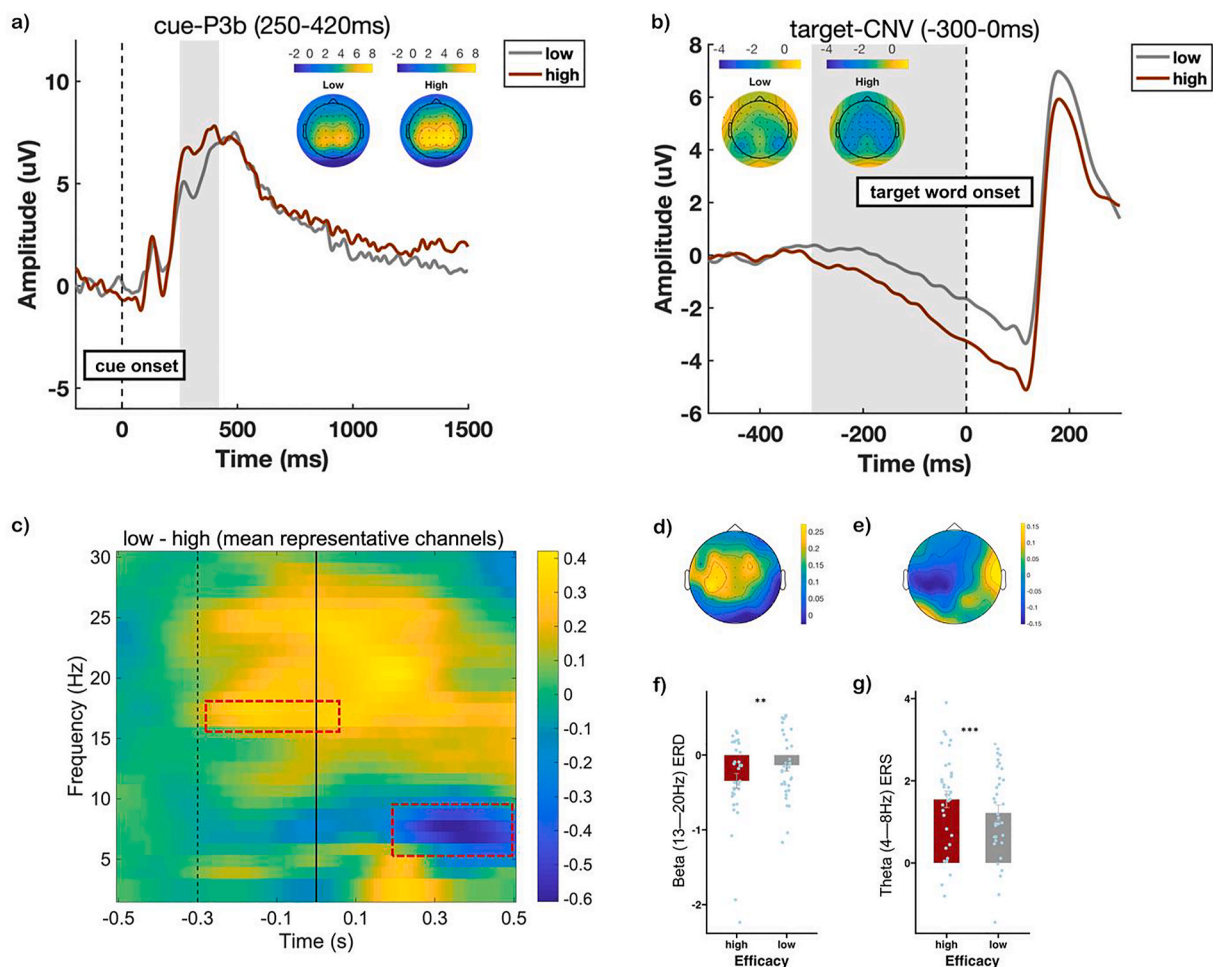

Fig. 3. Neural activities modulated by efficacy. a) Averaged cue-P3b (250–500 ms) choosing Pz, P1, and P2; **b)** averaged fronto-central target-CNV (−300 ms pre-target) choosing Cz, FCz, and Fz; **c)** averaged time-frequency results choosing peak channels of the topography (Cz, FCz, Fz, FC3, C3, C1, CP3, CP5) (The black dot line represents baseline, and the solid line represents target onset); **d, f)** the difference in two efficacy condition regarding motor-related beta desynchronization (MRBD) (−260 ms–70 ms relative to target onset, 13–20 Hz); **e, g)** the difference in two efficacy condition regarding θ-band ERS (210–500 ms relative to target onset, 4–8 Hz) (Supplementary Fig. 6a and 6b). ***$p < .01$, **$p < .01$, *$p < .05$, and ns represents $p > .05$.

(1.55 ± 0.19 dB) was larger than that for the low efficacy condition (1.22 ± 0.19 dB). The result indicated that more control was demanded and larger control resources were allocated in high than low efficacy condition ($t_{(33)} = -4.12$, $p < .001$; Fig. 3c, e, 3g).

3.3. The effect of preparation on sustained effort: the mediation role of drift rate

As a further link between the underlying cognitive process and behavioral performance, we found that drift rate was negatively correlated with VTC (high: $r = -0.61$, $p < .001$; low: $r = -0.66$, $p < .001$; Fig. 4a). Moreover, the decision boundary was positively correlated with VTC (high: $r = 0.41$, $p < .01$; low: $r = 0.58$, $p < .001$; Fig. 4b). Thus, we proposed that the quality of the preparation stage should influence the quality of the execution and ultimately be related to behavioral performance. We found that target-CNV, an index describing the preparatory stage, modulated sustained effort (Fig. 4c) (mediated effect = 0.39, $CI_{90} = [0.10, 0.77]$; proportion mediated effect = 0.86, $CI_{90} = [0.37, 1.45]$). The mediation significantly reduced the direct effect (c = 0.46, $CI_{90} = [0.15, 0.87]$; c' = 0.08, $CI_{90} = [-0.13, 0.27]$). Similarly, β-band oscillation (13–20 Hz) also contributed to adjusting drift rate for improved effort stability (Fig. 4d) (mediated effect = 0.31, $CI_{90} = [0.07, 0.62]$); proportion mediated effect = 0.77, $CI_{90} = [0.24, 1.51]$), and the mediation also significantly reduced the direct effect (c = 0.41, $CI_{90} = [0.12, 0.72]$; c' = 0.10, $CI_{90} = [-0.12, 0.34]$). Our results confirmed the hypothesis that the effort stability is predicted by preparation state and evidence accumulation during execution.

3.4. Behavioral adjustments of sustained effort based on feedback and efficacy

Reward feedback indicated whether participants meet the standard in high efficacy condition. This feedback can be used to trigger adjustments in the future, particularly in high efficacy rounds. To investigate this hypothetical behavioral adjustment, we analyzed the influence of previous reward feedback on the participant's current behavior change (round$_{(t+1)}$ – round$_{(t)}$) for the two efficacy conditions. We found an interaction between feedback and efficacy for the change in the CorrPerSec ($b = 0.14$, CI = [0.1, 0.18], $p < .001$; Supplementary Table 6) as well as for the change in VTC ($b = -0.05$, CI = [−0.07, −0.03], $p < .001$;

Fig. 5c). Low reward feedback in previous high efficacy rounds induced larger changes in overall effort (CorrPerSec) and effort stability (VTC). This relationship was not found in low efficacy rounds.

How neural activation reflects adjustments after feedback is received remains unknown. We predicted that fb-P3b would be sensitive to such behavioral changes. We found that fb-P3b amplitude was significantly higher ($F_{(1,33)} = 8.72$, $p < .05$; Fig. 5b) when processing low reward (13.89 ± 1.19 μV) compared to high reward (11.74 ± 0.93 μV). Moreover, the standardized fb-P3b interacted with reward feedback and partially predicted the VTC change (ΔVTC; $b = -0.34$, CI = [−0.67, −0.01], $p < .05$; Fig. 5d, Supplementary Table 7). When the reward feedback in the previous round was ¥10, the VTC in the next round increased, indicating more erratic behavior (ΔVTC>0; Fig. 5d orange dots). Conversely, when the reward feedback in the previous round was ¥0.1, the VTC in the next round decreased, indicating more stable behavior (ΔVTC< 0; Fig. 5d green dots).

Moreover, the absolute value of VTC adjustments (|ΔVTC|) decreased with increasing fb-P3b. However, this decrease was observed in the reversed direction, indicating the fb-P3b captured VTC change modulated by reward feedback (Fig. 5d). Specifically, when receiving ¥10 in the previous round, the positive value of ΔVTC became smaller with larger fb-P3b. In contrast, when receiving ¥0.1 in the previous round, the negative value of ΔVTC became smaller with larger fb-P3b.

4. Discussion

This study showed the neural mechanisms of efficacy-modulated effort and the ability to modify effort to achieve goals stably. Our results were aligned with previous studies, that CNV is a neural feature of motion preparation linked to improved performance in high compared to low efficacy condition. Also, β oscillation, a marker of motor preparation, was more suppressed in cases of high efficacy. Moreover, the two EEG signatures of proactive control contributed to sustained effort through the mediation of drift rate. In conclusion, our findings provided a temporal analysis to understand the influence of efficacy on effort, illuminating how humans adjust effort over time when knowing effort yields rewards effectively.

Generally, participants put in more effort, and their behavior was more stable when efficacy was higher. Informative cues about efficacy can bolster competence and perceived autonomy (Houlfort et al., 2002).
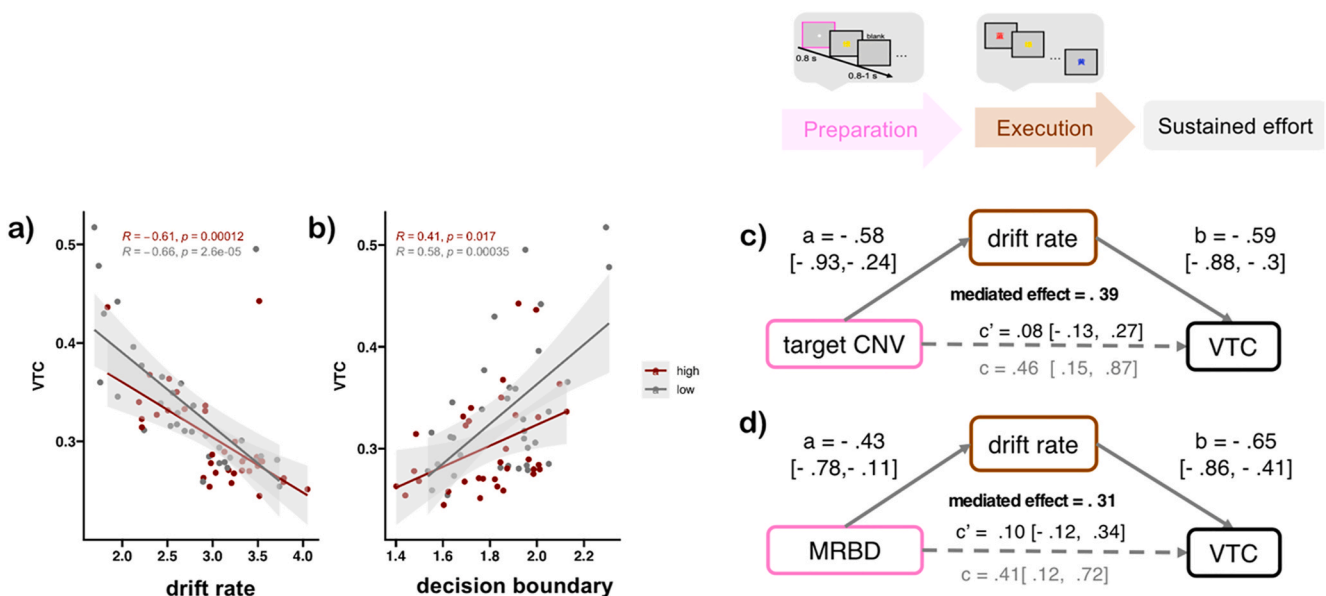

Fig. 4. Sustained effort modulated by drift rate and neural activities. a) Correlation between drift rate and VTC; **b)** Correlation between decision boundary and VTC; **c, d)** The mediation effect of drift rate on how the preparation state reflected by the CNV and the MRBD influenced sustained effort.
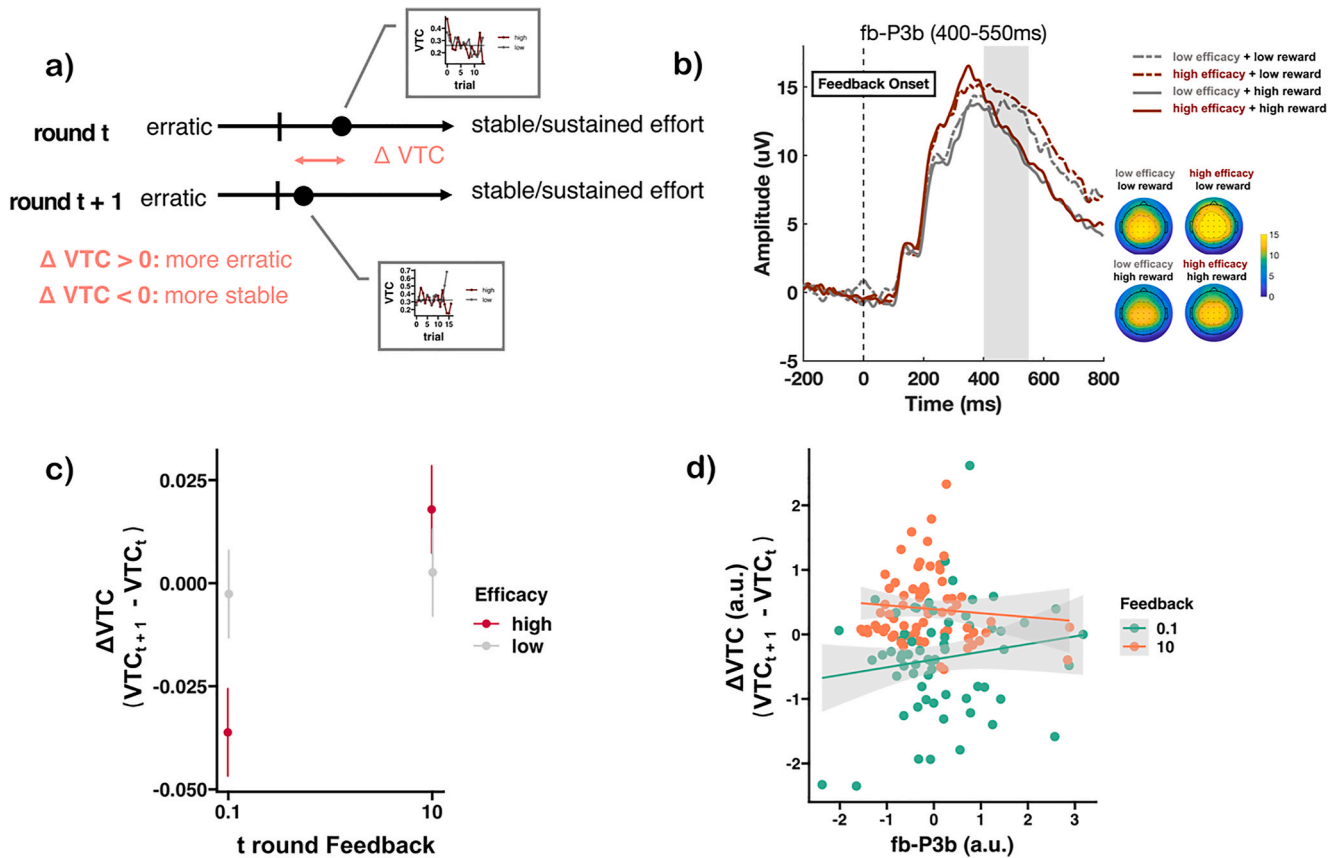
Fig. 5. Behavioral adjustments based on feedback and efficacy. **a)** Hypothetical VTC change: $\Delta VTC = VTC_{(t+1)} - VTC_{(t)}$. The grey boxes showed examples of VTC variation across trials in one mini-block; **b)** the fb-P3b amplitudes of the two efficacy conditions; **c)** the interaction of efficacy and feedback on ΔVTC; **d)** the interaction effect of standardized fb-P3b and feedback in predicting standardized ΔVTC.

However, our results did not show participants' metacognitive sensitivity to understand their effort investment under different efficacy levels. Through neural signals and cognitive model parameters, we provided a nuanced description of the efficacy-motivated effort process. First, the cue-P3b signal indicated the processing of efficacy cues, and it was larger for high efficacy cues. We also analyzed the cognitive processes underlying behavior patterns using DDM. The drift rate was higher in high than low efficacy condition, indicating participants were more unfocused in uncontrollable situations. Furthermore, decision boundary was higher in low efficacy rounds. From the perspective of parameter estimation, drift rate and decision threshold are not independent in calculation and data description. Thus, there is a trade-off in the value of decision boundary and drift rate. Overall, the strategies are combined to generate good performance (Dutilh et al., 2012; Fischer et al., 2018; Ullsperger et al., 2014).

In the preparatory phases before target presentation, efficacy cues also influenced proactivity represented by two critical indexes: CNV and β-band oscillation. CNV is suggested to be a marker of motor readiness, modulating and optimizing perceptual cognitive and motor processes (Botvinick and Braver, 2015; Notebaert and Braem, 2015). Specifically, early CNV is assumed to be an indicator of cortical arousal during orientation and attentional processes, whereas late CNV is hypothesized to reflect anticipation and response preparation (Wagner-Altendorf et al., 2020). Recent work indicated that CNV is more complex than previously recognized. For example, CNV has been found to manifest a value-guided control allocation (Duma et al., 2020; Frömer et al., 2021a, b). This study confirmed that CNV represented the proactive control that was induced consistently by cue before target, which was larger in high efficacy condition. In addition, β-oscillation (MRBD) prior to target onset, was more suppressed in the high efficacy condition, representing

a similar effect of efficacy on motor preparation as CNV.

This work established an essential mechanism of how people adjust sustained effort. We postulated that task preparation is associated with execution and predicts performance. Consistent with this proposal, our mediation analysis showed that the preparatory state predicted sustained effort. The state of preparation was identified with two EEG signatures, as both target-CNV and MRBD were neural features for predicting stable effort. Moreover, the drift rate mediated this predictive effect. Thus, the goal-directed effort process is modulated by adjusting the preparation state and executive strategies for better performance.

People depend on feedback to make changes (Diehl and Sterman, 1995). Our data showed that the interplay between efficacy and feedback affected future adjustments. Low reward feedback prompted significant adjustments in the high efficacy condition. In this study, the fb-P3b was sensitive to feedback processing, especially for low rewards. Also, fb-P3b predicted changes in effort stability after reward feedback was received, and this predictive effect was modulated by different reward feedback. This idea is also in line with recent findings that fb-P3b indicates the main effect of feedback on behavioral adjustment (Ullsperger et al., 2014).

To summarize, this study provided a detailed description of the efficacy-modulated effort process. The efficacy of effort impacts individual proactivity, and feedback is an effective signal for future adjustments. Our findings lay the groundwork for understanding effort based on temporal processes, rather than solely on behavioral performance. Efficacy information and performance feedback are useful to motivate high-quality preparedness and promote sustained effort. Whether people flexibly adjust their effort process in a social environment remains unknown. In broader social environments, how does nonsocial and social efficacy modulate the perception of effort worthiness

and influence effort-making processes? Future research can investigate this question by measuring perceived efficacy and manipulating efficacy in a social context.

Credit author statement

Siqi Cao: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.; Xun Liu and Haiyan Wu: Funding acquisition, Methodology, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuropsychologia.2022.108314.

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