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Feeling the task: Joint effects of subjective experiences and objective difficulty on effort and performance under low cognitive demand

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Abstract

Effort investment and task performance are shaped not only by objective task difficulty but also by individuals' subjective experiences during task execution. However, it remains unclear how these objective and subjective factors jointly regulate effort and performance across successive trials. This study investigated how objective task difficulty and three trial-level subjective factors: perceived difficulty, perceived effort, and emotional states, interact to influence subsequent effort investment and task performance across trials. Thirty-four participants completed a modified random-dot motion task in which objective difficulty was manipulated on a trial-by-trial basis (easy vs. hard). After each trial, participants rated their perceived difficulty, effort, and emotional experience. Linear Mixed Models (LMMs) analyses revealed that hard trials elicited lower accuracy, slower reaction times, higher perceived difficulty, higher perceived effort, and more negative emotions, compared to easy trials. Effort investment (the number of mouse clicks) in the current trial was modulated by the interaction between the objective difficulty of the preceding and current trials, and was further modulated, in exploratory analyses, by the preceding trial's perceived difficulty. In contrast, reaction times were not significantly influenced by the objective difficulty of the preceding trial alone, but were modulated by interactions of preceding-trial perceived effort or affective valence with current-trial difficulty. Notably, these carryover effects were particularly pronounced when both the preceding and current trials were easy. Moreover, perceived difficulty and perceived effort were positively associated under both easy and hard conditions, whereas the positive association between perceived effort and positive emotions was selectively evident only under the easy condition. These findings suggest that under low cognitive demand, subjective appraisals play a more prominent role in regulating effort investment and task performance, plausibly through an ongoing cost-benefit evaluation process.

Introduction

Effort investment, the active allocation of cognitive or physical resources toward a goal, is a fundamental psychological construct in outcome-driven behavior (Von Kriegstein, 2017). In cognitive contexts, effort can be defined as the subjective intensity of mental or physical activity that individuals intentionally or unintentionally deploy and sustain in pursuit of a goal (Kurzban et al., 2013; Kool & Botvinick, 2014; Inzlicht et al., 2018; Shepherd, 2021). In cognitive contexts, effort reflects the mobilization of cognitive resources necessary for task engagement and serves as a pivotal mediator between capability and actual performance (Shenhav et al., 2017; Székely & Michael, 2021). Empirical research consistently demonstrates that strategic effort allocation enables individuals to maintain or enhance task performance under challenging conditions (Clay et al., 2022; Inzlicht et al., 2018; Van Iddekinge et al., 2023; Preston & Wegner, 2009). Yet, despite its potential rewards, effort is inherently costly, and individuals show a robust tendency to minimize it whenever possible (Inzlicht et al., 2018; Kool et al., 2010; Shenhav et al., 2017; Székely & Michael, 2021; Zipf, 2016). This tendency is captured by neuroeconomic and control-allocation accounts that conceptualize effort investment as the output of a cost-benefit decision process (Inzlicht et al., 2018; Shenhav et al., 2017). In agreement with this frmaework, numerous studies have demonstrated that individuals typically prefer tasks with lower

cognitive demands, as these require less effort (Arrington & Logan, 2004; Kool & Botvinick, 2018; Schouppe et al., 2014; Vermeylen et al., 2022).

Most experimental work on effort regulation has focused on the role of objective difficulty in shaping effort. Increasing objective demand typically reduces accuracy and slows responses, reflecting higher computational load imposed by the task (Shenhav et al., 2017). However, task performance is not fully determined by objective characteristics alone. Individuals integrate objective demands with their own subjective experiences associated with task engagement (Kool & Botvinick, 2014). In this regard, subjective appraisals of effort-related costs, as indicated by perceived difficulty, perceived effort exertion, and affective states, are considered to play a crucial role in the substantial variability in effort allocation (Zipf, 2016; Shenhav et al., 2013). Neuroimaging evidence further highlights the role of the anterior cingulate cortex (ACC) in integrating objective task demands with subjective value signals during effort-based decision making (Basten et al., 2010; Croxson et al., 2009). This integrative process explains why increasing objective difficulty does not always translate into a proportional increase in effort investment, while the relationship is filtered through internal appraisal. Effort regulation therefore reflects both external demands and the internal evaluations that dynamically shape performance. Moreover, effort regulation can evoke subjective evaluations that vary across individuals (Zipf, 2016), pointing out that people may perceive and emotionally respond to the same effortful process in distinct ways.

Of note, three subjective experiences are consistently implicated in effort regulation. First, perceived difficulty reflects a metacognitive appraisal of task demands and shapes willingness to engage (Steele, 2020). Second, perceived effort is the phenomenological sense of exertion and is widely viewed as a proximal read-out of the degree to which cognitive or physical resources have been mobilized (Chong et al., 2017; Dreisbach & Jurczyk, 2022; McLaughlin et al., 2021; Summerside & Ahmed, 2021). Behavioral and physiological studies further documented that individuals tend to scale effort with difficulty, but withdraw effort when the anticipated outcome became impossible to obtain (Richter, 2008; Bouzidi et al., 2022; Richter et al., 2016; Schmidt & Dolis, 2009). Third, affective states, whether the experience of exertion feels positive or negative, biases interpretations of effort and influences persistence (Dreisbach, 2012; Inzlicht, 2018; Yang, 2022; Cacioppo et al., 1996). Notably, the same effortful activity may be experienced as rewarding/positive when linked to meaningful progress but as aversive when perceived as futile (Richter et al., 2016; David et al., 2024). For instance, when individuals perceive meaningful progress toward achievable objectives, they are more likely to reinterpret effort expenditure as rewarding rather than depleting (Brehm & Self, 1989). Hence, there is a close association between subjective emotions and effort investment, as well as the potential carryover effect of subjective emotions on subsequent effort investment.

Importantly, these three subjective evaluations are not merely outcomes of effort; they can themselves serve as regulatory signals that shape subsequent task engagement (Lemaire, 2021; Newton et al., 2020). Two tasks of identical objective difficulty may be experienced, and thus responded to, very differently depending on are appraised. Despite wide theoretical agreement on this point, most empirical

studies have focused on how objective difficulty modulates task performance (Benikos et al., 2013) and have paid less attention to how subjective experiences fluctuate across trials and interact with objective demand to shape ongoing engagement. More specifically, little is known about how fluctuations in perceived difficulty, perceived effort, and emotional states, arising directly from the task, carry over across trials and interact with objective demands to regulate engagement. Additionally, there are persistent methodological limitations in how effort is quantified. Many studies rely on indirect proxies, such as response times or accuracy, which may not fully capture the complexity of effort expenditure. Thus, more direct and ecologically valid measures are needed to better understand how individuals dynamically adjust their effort in respond to challenging task demands and subjective experiences.

Following an effort regulation framework in which effort is the outcome of a dynamic cost-benefit evaluation (Shenhav et al., 2017; Inzlicht et al., 2018), the present study sought to elucidate how the objective difficulty of one trial, and the subjective experiences formed during that trial, jointly shape effort investment and task performance on the following trial. More specifically, we adopted a modified dot-motion experimental paradigm (see Corlazzoli, 2023), wherein objective difficulty were manipulated at the trial level. At the same time, we collected trial-wise subjective ratings of perceived difficulty, perceived effort, and affective states. Additionally, mouse clicks during task execution were served as an ecologically valid indicator of effort investment (see Nizamis et al., 2017; Søgaard et al., 2001). We conceptualized each trial as an integrated effortful decision, execution event, comprising a perceptual decision on a random-dot motion display and a continuous response-execution phase during which participants physically click a mouse to register their choice. This integration follows the original treatment of the paradigm by Corlazzoli et al. (2023) and is supported by a substantial literature showing that post-decisional confidence, itself shaped by the difficulty of the preceding decision, systematically influences subsequent response-execution behavior and the allocation of control resources (Desender et al., 2018, 2019; Pleskac & Busemeyer, 2010; Shenhav et al., 2013, 2017). Under this integrated-event view, trial-level objective difficulty (driven by dot-motion coherence) shapes not only the decision phase but also the downstream execution phase.

By this design, we hypothesized that hard trials (low coherence) would elicit lower accuracy, slower RTs, higher perceived difficulty, higher perceived effort, and more negative emotions than easy trials (high coherence). Moreover, we expected that the interaction of previous-trial and current-trial objective difficulty would current-trial objective effort, with trail-by-trial persistence of effort mobilization producing more clocks when previous and current difficulty match. Additionally, the previous trial's subjective experiences (perceived difficulty, perceived effort, and emotional states) would shape current-trial objective effort and task performance (RTs, accuracy), with carryover effects being moderated by current-trial objective difficulty. Drawing on cost-benefit accounts, we predicted that subjective-appraisal carryover effects would be more pronounced under low current demand, where cognitive resources remain available to translate internal evaluation into strategic adjustment, than under high current demand, where limited remaining resources leave less room for appraisal-driven adjustments.

Methods

Participants

The sample size was determined a prior using MorePower 6.0 (Campbell & Thompson, 2012). For a 2 (Previous difficulty) × 2 (Current difficulty) within-subject design with α = .05, target power = .80, and a medium effect size (*F* = 0.25), a minimum of 26 participants was required to detect the primary two-way interaction. We recruited 49 participants to allow for exclusions. Of these, 12 were excluded due to low accuracy rates (i.e., smaller than 65%), and 3 for irregular task operation, defined a priori as 1) clicking the mouse faster than 20 times within any single 500 ms window on more than 10% of trials, or 2) clicking on the wrong side of the response screen on more than 25% of trials despite correctly answering the motion direction. The final sample comprised 34 participants (4 men, 18–30 years, *M* = 21.9, *SD* = 2.9), all right-handed, with normal or corrected-to normal vision and no history of neurological or psychiatric disorders. Each participant received a compensation of ¥18 for their participation in the end and provided written informed consent. The study was approved by the Ethical Committee of the Institute of Brain and Psychological Sciences at Sichuan Normal University (No. 2025LS0012).

Stimuli and task

All stimuli were presented on a white background on a 21.5-inch monitor with vertical refresh rate of 60 Hz. The experimental program was developed with Psychtoolbox3 (Kleiner, 2007) in Matlab R2021b. The random dot motion stimuli were generated using the Random Dot Kinematogram (Rajananda et al., 2018). The stimuli and task of this study were adapted from previous research (see Corlazzoli et al., 2023).

Each trial started with a fixation cross displayed for 500 ms, followed by presentation of black random dots moving either left or right for 3000ms. The proportion of coherently moving dots was manipulated to create two levels of difficulty: an easy condition (38% − 42% coherence) and a hard condition (8% − 12% coherence). Each integer value with these ranges presented equally often in the formal experiment to ensure balanced stimulus distribution. After the motion display, a response screen appeared, presenting two gray vertical bars (150 pixels in width, 730 pixels in height). Participants were instructed to judge the dominant motion direction (left or right) by repeatedly clicking the corresponding mouse button with their right index finger. The first mouse click indicated the correctness of their response. Each click progressively filled the gray bar with red, while the bar simultaneously emptied at a fixed rate. Participants were required to keep clicking until the gray bar was completely filled within the 5000ms response period.

The number of mouse clicks used as a measure of physical effort exerted (see Nizamis et al., 2017; Søgaard et al., 2001). To account for individual differences in effort exertion, the effort threshold was calibrated for each participant during the practice session (see details in “Procedure” section below). Participants were instructed to respond as quickly and accurately as possible. Following their responses of each trial, participants were provided three subjective ratings in sequence: (1) the perceived Difficulty of judging the motion direction, (2) the perceived level of Effort invested in filling the vertical bar, and (3) their subjective Emotions during the task. Ratings were recorded on a 0-100 scale, where higher scores

represented greater perceived Difficulty or Effort. For subjective Emotions ratings, lower scores indicated more negative emotions, while higher scores indicated more positive emotions (see Figure.1).

Insert Fig. 1 about here

Procedure

After signing the informed consent, each participant started with a practice session designed to familiarize them with the task and ensure proper calibration of individual parameters. The practice session comprised 16 trials, evenly split between the easy (8 trials) and hard (8 trials) conditions. Participants received feedback (i.e., “Correct” or “Incorrect”) after each response. In addition, they rated the perceived difficulty, effort investment, and emotions for the last three trials of the practice session. At the end of the practice session, participants were provided with feedback on their average accuracy.

During the practice phase, the speed at which the vertical bar emptied was tailored to each participant’s response speed. The initial bar-emptying speed was set to a low value, requiring participants to click repeatedly to completely fill the bar in all trials. This adjustment allowed the experimental program to determine an appropriate bar-emptying speed for each participant, which was carried forward into the adaptation phase. The adaption phase followed the practice phase, consisting of 5 trials randomly selected from the formal task pool. The structure and requirements of the adaptation phase were identical to those of the subsequent formal experiment. Participants started the formal experiment only if their accuracy exceeded 60%; otherwise, they repeated the hard condition practice trials (8 additional trials) until reaching the accuracy threshold. The formal experiment consisted of 81 trials in a pseudo-random. The design ensured an equal number of four trial types based on the difficulty (easy, hard) of the previous and current trials: Easy-Easy (EE), Easy-Hard (EH), Hard-Easy (HE), and Hard-Hard (HH), with 20 trials in each condition.

Data analysis

Data preprocessing, visualization and analysis were carried out in R (R Core Team, 2024), using the lme4 (Bates et al., 2003), lmerTest (Kuznetsova et al., 2017), car (Fox et al., 2001), emmeans (Lenth, 2017), tidyverse (Wickham, 2016), dplyr (Yarberry, 2021), ggplot2 (Wickham et al., 2016), ggiraphExtra (Moon, 2016), ggeffects (Lüdecke, 2017), GGally (Schloerke et al., 2018), and afex (Singmann et al., 2012) packages. We used the Linear Mixed-effects Models (LMMs; Bates et al., 2015) to analyze subjective ratings and behavioral data. All factors included in the LMMs were re-coded, and the random intercept for each subject was added as the random effect for all models. p-values were obtained by likelihood ratio tests of the full model with the effect in question against the model without the effect in question. A standard alpha level of 0.05 was used for all statistical tests.

Manipulation check

For each subject separately, subjective ratings of difficulty perception, effort investment perception, and emotions were used as dependent variables respectively in three separate different models, with Task difficulty (low vs. high) included as the independent variables in each model.

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Behavioral data analysis

For each subject separately, the first trial of each block, error trials, unfilled trials and outlier trials (over ± 3SD from the mean) were excluded. The dependent variables (i.e., the number of mouse clicks and Reaction times) were log-transformed.

First, we investigated the effects of the number of mouse clicks (a proxy of objective effort; see Nizamis et al., 2017; Søgaard et al., 2001) by objective factors across successive trials. The fixed effects of LMM were created based on two objective factors (i.e., Previous difficulty [easy vs. hard] and Current difficulty [easy vs. hard]), and the two main effects and their interaction were added (see Table 1 for the objective factors as fixed effects). On this basis, we further investigated the combined influences of objective factors with subjective factors at the previous trial on the number of mouse clicks. Accordingly, we additionally added the subjective ratings of Difficulty perception, Effort investment perception, and Emotions at the previous trial into three different LMMs separately as the fixed effects (see Table 1 for the objective × subjective factors as fixed effects).

Table 1
Results of the LMM analysis for the number of Mouse Clicks.

Objective factors (Task difficulty)			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	6162.354	1	.001***
PreDif	0.628	1	.428
CurDif	1.102	1	.294
PreDif: CurDif	5.647	1	.018*
Objective factors × Subjective Difficulty perception			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	6157.370	1	.001***
PreDif	0.381	1	.537
CurDif	0.090	1	.765
Dif_rating	0.012	1	.912
PreDif: CurDif	6.476	1	.011*
PreDif: Dif_rating	0.263	1	.608
CurDif: Dif_rating	0.750	1	.387
PreDif: CurDif: Dif_rating	4.065	1	.044*
Objective factors × Subjective Effort perception			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	6156.829	1	.001***
PreDif	0.913	1	.339
CurDif	1.170	1	.279
Eff_rating	3.929	1	.047*
PreDif: CurDif	5.386	1	.020*
PreDif: Eff_rating	0.009	1	.924

PreDif: Task difficulty of preceding trial; CurDif: Task difficulty of current trial; Dif_rating: the subjective perceived Difficulty of preceding trial; Eff_rating: the subjective perceived Effort of preceding trial; Emo_rating: the subjective perceived Emotional experiences of preceding trial.

Objective factors (Task difficulty)			
CurDif: Eff_rating	0.0002	1	.988
PreDif: CurDif: Eff_rating	0.102	1	.749
Objective factors × Subjective Emotional experience			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	6177.247	1	.001***
PreDif	0.806	1	.369
CurDif	1.601	1	.206
Emo_rating	0.153	1	.695
PreDif: CurDif	4.888	1	.027*
PreDif: Emo_rating	0.762	1	.383
CurDif: Emo_rating	0.319	1	.572
PreDif: CurDif: Emo_rating	1.694	1	.193
'***' < .001; '**' < .01; '*' < .05; '.' < .1			
PreDif: Task difficulty of preceding trial; CurDif: Task difficulty of current trial; Dif_rating: the subjective perceived Difficulty of preceding trial; Eff_rating: the subjective perceived Effort of preceding trial; Emo_rating: the subjective perceived Emotional experiences of preceding trial.			

Insert Table 1 about here

For reaction times (RTs) data analysis, we first investigated the influence of objective difficulty across successive trials on RTs. The fixed effects in the LMM were created based on two objective factors (i.e., Previous difficulty [easy vs. hard] and Current difficulty [easy vs. hard]), with both main effects and their interaction included in the model (see Table 2 for the objective factors as fixed effects). Then, we investigated how three subjective factors associated with the objective difficulty influenced RTs. Three separate LMMs were constructed, each incorporating Previous difficulty, Current difficulty and one of the subjective ratings (i.e., Difficulty perception, Effort investment perception, or subjective Emotions) from the previous trial as fixed effects (see Table 2 for the objective × subjective factors as fixed effects). Moreover, to further explored the combined influence of objective and subjective effort at the previous trial on RTs at the current trial, the number of mouse clicks and the subjective ratings of Effort investment in the previous trial, together with Previous difficulty, Current difficulty were included as fixed effects in the LMM (see Table 3).

Table 2
Results of the LMM analysis for the RTs data.

Objective factors (Task difficulty)			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	8304.287	1	.001***
PreDif	0.048	1	.827
CurDif	47.783	1	.001***
PreDif: CurDif	0.237	1	.627
Objective factors × Subjective Difficulty perception			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	8183.024	1	.001***
PreDif	1.073	1	.300
CurDif	45.198	1	.001***
Dif_rating	3.260	1	.071 .
PreDif: CurDif	0.039	1	.844
PreDif: Dif_rating	0.003	1	.953
CurDif: Dif_rating	0.526	1	.468
PreDif: CurDif: Dif_rating	0.251	1	.617
Objective factors × Subjective Effort perception			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	8140.823	1	.001***
PreDif	0.123	1	.726
CurDif	49.913	1	.001***
Eff_rating	0.901	1	.342
PreDif: CurDif	0.311	1	.577
PreDif: Eff_rating	0.132	1	.716
CurDif: Eff_rating	0.217	1	.642

PreDif: Task difficulty of preceding trial; CurDif: Task difficulty of current trial; Dif_rating: the subjective perceived Difficulty of preceding trial; Eff_rating: the subjective perceived Effort of preceding trial; Emo_rating: the subjective perceived Emotional experiences of preceding trial.

Objective factors (Task difficulty)			
PreDif: CurDif: Eff_rating	4.526	1	.033*
Objective factors × Subjective Emotional experience			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	8742.855	1	.001***
PreDif	0.385	1	.535
CurDif	42.776	1	.001***
Emo_rating	3.143	1	.076 .
PreDif: CurDif	0.189	1	.664
PreDif: Emo_rating	0.014	1	.907
CurDif: Emo_rating	0.065	1	.799
PreDif: CurDif: Emo_rating	4.086	1	.043*
'***' < .001; '**' < .01; '*' < .05; '.' < .1			
PreDif: Task difficulty of preceding trial; CurDif: Task difficulty of current trial; Dif_rating: the subjective perceived Difficulty of preceding trial; Eff_rating: the subjective perceived Effort of preceding trial; Emo_rating: the subjective perceived Emotional experiences of preceding trial.			

Table 3
Results of the LMM analysis for the RTs data considering objective and subjective effort.

Objective factors (Task difficulty) × Subjective Effort × Objective Effort			
Predictor	*Chisq*	*Df*	*Pr(> Chisq)*
(Intercept)	8212.935	1	.001***
PreDif	0.651	1	.420
CurDif	46.543	1	.001***
NClicks	0.271	1	.603
Eff_rating	0.528	1	.468
PreDif: CurDif	0.059	1	.808
PreDif: NClicks	0.176	1	.675
CurDif: NClicks	0.213	1	.644
PreDif: Eff_rating	0.0006	1	.981
CurDif: Eff_rating	0.307	1	.579
NClicks: Eff_rating	8.600	1	.003**
PreDif: CurDif: NClicks	1.236	1	.266
PreDif: CurDif: Eff_rating	4.810	1	.028*
PreDif: NClicks: Eff_rating	8.215	1	.004**
CurDif: NClicks: Eff_rating	3.774	1	.052 .
PreDif: CurDif: NClicks: Eff_rating	5.922	1	.015 *
'***' < .001; '**' < .01; '*' < .05; '.' < .1			
PreDif: Task difficulty of preceding trial; CurDif: Task difficulty of current trial; NClicks: the number of Mouse Clicks of the preceding trial; Eff_rating: the subjective perceived Effort of preceding trial.			

Insert Table 2 about here

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Insert Table 3 about here

Correlation analyses

In order to explore the relationships between Difficulty perception and Effort investment perception, as well as Effort investment perception and subjective Emotions in the easy and hard conditions, separately, Pearson correlation analyses were performed for each pair of subjective measures with the easy and hard conditions.

Results

Manipulation check

For the three subjective factors (i.e., Difficulty perception, Effort investment perception, and subjective Emotions), the LMM results consistently showed significant main effects of Task difficulty (χ^2s ≥ 17.034, *p*s < 0.001). They indicated that in the hard condition, subjective ratings of difficulty perception, effort investment perception, and negative emotions were higher compared to the easy condition (see Fig. 2A-C).

Insert Fig. 2 about here

Behavioral data

The number of mouse clicks

The results of LMM examining the effects of objective factors across successive trials found a significant interaction between Previous difficulty and Current difficulty (χ^2 (1) = 5.647, *p* = 0.018; see Fig. 2D). It indicated that when previous difficulty was easy, participants made more number of mouse clicks in the current easy condition but fewer in the current hard condition (*SE* = 0.006, *p* = 0.341). In contrast, when the previous difficulty was hard, participants showed the opposite pattern, with fewer mouse clicks in the current easy condition and more mouse clicks in the current hard condition (*SE* = 0.006, *p* = 0.016).

Moreover, when Difficulty perception ratings of the previous trial were included in the LMM, we found a significant three-way interaction between Previous difficulty, Current difficulty and Difficulty perception ratings (χ^2 (1) = 4.065, *p* = 0.044). Further LMM analyses revealed that when Previous difficulty was easy (Fig. 2E, left panel), the interaction between Current difficulty and Difficulty perception ratings was significant (χ^2 (1) = 3.903, *p* = 0.048). This effect indicated that in the current hard conditions, higher difficulty perception ratings were associated with fewer number of mouse clicks (*slope* = -0.003),

whereas in the current easy conditions, higher difficulty perception ratings were associated with more mouse clicks (*slope* = 0.009). However, when the Previous difficulty was hard (Fig. 2E, right panel), we did not find any significant effect (χ^2 s ≤ 0.127, *p*s ≥ 0.422). When ratings of Effort investment were included in the LMM, we found a significant main effect of Effort investment ratings (χ^2 (1) = 3.929, *p* = 0.048), with higher ratings of effort investment were associated with larger number of mouse clicks (see Fig. 2F). Lastly, when Emotions ratings were included in the LMM, we did not find any significant effect (χ^2 s ≤ 1.694, *p*s ≥ 0.193).

RTs

The results of the LMM examining the effects of objective Difficulty across successive trials only found a significant main effect of Current difficulty (χ^2(1) = 47.783, *p* < 0.001), with faster RTs in the easy compared to hard conditions (Fig. 3A).

Insert Fig. 3 about here

Moreover, when Difficulty perception ratings were included in the LMM, we did not find any significant effect with Difficulty perception ratings (χ^2 s ≤ 3.260, *p*s ≥ 0.071). Then, when Emotions ratings were included in the LMM, we found a significant three-way interaction between Previous difficulty, Current difficulty, and Emotions ratings (χ^2 (1) = 4.086, *p* = 0.043). Further LMM analyses revealed that when Previous difficulty was hard (Fig. 3B, right panel), we did not find any significant effects in relation to Emotions ratings (χ^2s ≤ 1.659, *p*s ≥ 0.198). Whereas when Previous difficulty was easy (Fig. 3B, left panel), we found a marginally significant interaction between Current difficulty and Emotions ratings (χ^2 (1) = 2.808, *p* = 0.094). This effect indicated that under the current easy condition, RTs became faster as emotional ratings increased (*slope* = -0.03); whereas under the current hard condition, emotional ratings did not significantly influence RTs. Lastly, when Effort investment ratings were included in the LMM, we found a significant three-way interaction between Previous difficulty, Current difficulty, and Effort investment ratings (χ^2 (1) = 4.526, *p* = 0.033). Further LMM analyses revealed that when Previous difficulty was hard (Fig. 3C, right panel), no significant effects were observed (χ^2 s ≤ 1.263, *p*s ≥ 0.261). In contrast, when Previous difficulty was easy (Fig. 3C, left panel), the two-way interaction between Current difficulty and Effort investment ratings was significant (χ^2 (1) = 4.013, *p* = 0.046). This effect revealed that as effort investment ratings increased, RTs decreased under the current easy condition (*slope* = -0.011); but increased under the current hard condition (*slope* = 0.028).

On this basis, we included the number of mouse clicks from the previous trial into this LMM and found a significant four-way interaction between Previous difficulty, Current difficulty, Mouse clicks and Effort investment ratings (χ^2 (1) = 5.922 *p* = 0.015). Further LMM analyses revealed that when Previous

difficulty was hard, no significant effects were found (χ^2 s ≤ 1.318, *p*s ≥ 0.251). In contrast, when Previous difficulty was easy, the three-way interaction between Current difficulty, Effort investment ratings and Mouse clicks was significant (χ^2 (1) = 9.146, $p = 0.003$). In the current easy condition (Fig. 3D), the two-way interaction between Mouse Clicks and Effort Investment ratings was significant (χ^2 (1) = 24.09, $p < 0.001$), indicating that for participants with above-average the number of mouse clicks, RTs decreased as effort investment ratings increased; whereas for those with below-average mouse clicks, RTs increased as effort investment ratings increased. In the current hard condition, the main effect of Mouse Clicks was marginally significant (χ^2 (1) = 3.017, $p = 0.082$), indicating that participants with more mouse clicks tended to have slower RTs.

Correlation analyses

The results showed a significant positive correlation between Difficulty perception ratings and Effort investment ratings in both the hard (r = 0.603, $p < 0.001$) and the easy conditions (r = 0.466, $p = 0.005$; see Fig. 3E). Moreover, Emotion ratings were significantly positively correlated with Effort investment ratings in the easy condition (r = 0.388, $p = 0.023$), and this correlation was only marginally significant in the hard condition (r = 0.311, $p = 0.073$; see Fig. 3F).

Discussion

This study investigated how objective task difficulty and three trial-level subjective experiences (perceived difficulty, perceived effort, and subjective emotions) jointly shape effort investmentand task performance across successive trials. By capturing trial-by-trial behavioral measures (i.e., RTs) with three types of subjective ratings (i.e., perceived task difficulty, perceived effort investment, and emotions), we identified some key patterns that advance understanding of how individuals regulate effort through the dynamic interplay between objective task difficulty and subjective experiences associated with task completion. Consistent with our first hypothesis, we found faster RTs and lower effort investment in the easy compared to the hard conditions. At the subjective level, participants also reported perceiving the easy task as less difficult and requiring less effort, while also experiencing more positive emotions. These findings confirm the validity of our task difficulty manipulation, as well as the close association between difficulty and effort. Notably, effort investment on the current trial was influenced by the difficulty of the preceding trial, both at the objective and subjective levels. In contrast, task performance (as indicated by RTs) was unaffected by the objective difficulty of the preceding trial. Rather, it was selectively modulated by participants' subjective perceptions of effort investment and emotional states.

More specifically, participants exhibited increased effort investment (i.e., more mouse clicks) for the current easy condition when the preceding trial was also easy, and similarly, it increased for the current hard condition when the preceding trial was hard. This pattern suggests that participants tended to allocate more effort to the specific task/condition they had previously encountered, probably as a strategic attempt to enhance performance. While this finding partially contrasts with Resource Depletion Models, which propose that cognitive resources decline following cognitively demanding tasks (Muraven

et al., 1998). Thus, it raises the possibility that subjective evaluations may play a crucial role in shaping this dynamic process (Shenhav et al., 2013). Of note, however, we failed to observe significant influence of preceding objective difficulty on current task performance as indicated by RTs, suggesting that the influence of preceding task difficulty is primarily reflected in effort investment rather than in direct performance outcomes.

In agreement with the point that subjective evaluations influence dynamic effort investment, we observed that when the preceding trial was easy, participants' effort investment in the current trial was also shaped by their subjective perception of the preceding trials' difficulty. More specifically, higher perceived difficulty in the preceding easy trial was associated with increased effort investment in the current easy condition, but decreased effort investment in the current hard condition. It is plausible that subjective appraisals of objective difficulty exert distinctive impacts on the subsequent effort investment, depending on whether the current task is easy or hard. In this regard, previous studies on cognitive fatigue indicated that subjective appraisals can amplify objective demands (Marcora et al., 2009). Our findings indicate that such amplification effect primarily occurs in tasks with relatively low cognitive demands. In easy tasks, where cognitive resource depletion is minimal, participants may rely more on subjective evaluations of difficulty, which subsequently influence their effort investment. This accords well with theoretical models proposing that effort investment is guided by a cost-benefit analysis (Lieder & Griffiths, 2020; Székely & Michael, 2021). However, subjective difficulty perception of the preceding hard trial did not significantly influence subsequent effort investment. In high-demand situations, objective difficulty, rather than subjective perception, appears to dominant effort investment. One possible explanation is that cognitively demanding tasks deplete resources to such an extent that subjective evaluations play a diminished role in guiding subsequent effort investment (Kool & Botvinick, 2018). Interestingly, despite subjective difficulty shaped effort investment, it did not significantly affect subsequent performance. It is thus suggested that while subjective perception of difficulty can influence how much effort individuals are willing to invest, it may not directly translate into performance benefits.

Consistent with prior findings regarding the strong association between cognitive load and subjective emotions across various tasks (Botvinick, 2007; Dreisbach, 2012; Inzlicht, 2015; Yang, 2022), participants experienced more negative emotions after completing a high-cognitively demanding task (i.e., hard condition) and more positive emotions after completing a low-cognitive demanding task (i.e., easy condition). While regarding the impact of these emotions on subsequent effort investment and performance, we found that subjective emotions did not significantly affect effort investment, they did, however, influence task performance. More specifically, positive emotions following an easy task were associated with faster RTs in the next easy trial, suggesting a motivational boost that enhanced performance in low-demand contexts. This aligns with previous the finding indicating that positive affect facilitates engagement (Byrne et al., 2023). In contrast, negative emotion generated from high-demand task (i.e., hard condition) did not significantly impact subsequent performance. One plausible explanation is that under high-demand conditions, where cognitive resources are heavily depleted, subjective emotions function more as a byproduct of task difficulty rather than as a driving force for subsequent performance (Botvinick & Braver, 2015; Pessoa, 2009). Accordingly, performance in high-

demand tasks seems to be primarily determined by objective difficulty than by emotional states. This interpretation is consistent with cognitive load theory (see Sweller, 2011), which suggests that high cognitive demands constrain the availability of cognitive resources for affective processing. Relatedly, previous studies that manipulated negative emotions independently of high-demand tasks have similarly reported no significant impact on performance or effort-related indices (González-García et al., 2021).

As expected, participants reported higher subjective effort in the hard condition, consistent with their greater objective effort investment. This alignment underscores the validity of our effort measures and suggests that under high-demand condition, participants are acutely aware of their effort exertion. Moreover, the subjective perception of effort investment in the preceding trial significantly influenced subsequent effort investment. More specifically, higher subjective effort in the preceding trial led to greater effort allocation in the next, reinforcing the notion that effort regulation involves a series of ongoing subjective evaluations (Chong et al., 2017; Wang et al., 2017; Zipf, 2016). This is in line with prior empirical research and theoretical models suggesting that subjective effort perception is closely linked to the perceived value of effort exertion and is encoded in neural systems associated with reward processing (Kurzban et al., 2013; Mlynski et al., 2025; Shenhav et al., 2013; Inzlicht et al., 2018). Importantly, the present results revealed that subjective effort perception also significantly influenced subsequent performance, but only in the easy condition. More specifically, higher perceived effort in a preceding easy trial was associated with faster RTs in a subsequent easy trial, but with slower RTs in a subsequent hard one. This pattern suggests that subjective evaluations of effort appear to help calibrate performance when cognitive demands are low but is less impactful when demands are high.

Interestingly, it is noted that the modulatory effect of subjective effort perception on dynamic performance closely parallels the modulation of subjective difficulty perception on dynamic effort investment. That is to say, both effects were most evident when cognitive demands were low in both the preceding and current trials, highlighting that subjective evaluations are particularly beneficial for regulating cognition in manageable contexts. Moreover, our results suggest a functional dissociation between subjective perceptions of difficulty and effort investment: subjective difficulty primarily influenced dynamic effort investment, while subjective effort influenced dynamic performance. This dissociation implies that task engagement and performance are guided by distinct but complementary facets of subjective evaluations. Moreover, we observed an interaction between subjective and objective effort on performance. When both preceding and current trials were easy, participants who both invested high objective effort and perceived their effort as high showed faster RTs. Conversely, when subjective effort exceeded objective investments, potentially reflecting overexertion or misjudgment, performance declined. Such effects may be closely related to metacognitive miscalibration, whereby inaccurate self-monitoring disrupts optimal effort allocation (Smallwood & Schooler, 2015; Westbrook & Braver, 2015; Yeung & Summerfield, 2012). When individuals overestimate their effort expenditure, they may inefficiently allocate cognitive resources, impairing subsequent performance.

Our correlation analyses revealed a positive relationship between perceived difficulty and perceived effort: participants who rated tasks as more difficult also reported exerting more effort, regardless of the

objective task difficulty. This finding aligns with previous research demonstrating a stable link between subjective difficulty and subjective effort across various cognitive domains (Ayasse & Wingfield, 2018; Sarrazin et al., 2002; Hughes et al., 2024). Interestingly, the relationship between perceived effort and emotional states exhibited a context-dependent pattern. In the easy condition, greater perceived effort was significantly associated with more positive emotions, suggesting that under low-demand contexts, increased effort may be more likely to be appraised as meaningful or rewarding. When individuals can clearly link their effort to successful task performance, this may foster a sense of competence or satisfaction, thereby enhancing positive emotions (Inzlicht et al., 2018). In such cases, the emotional benefits may offset the subjective costs of expending effort, making sustained effort investment feel valuable and less aversive. In contrast, this positive association between effort and positive emotions was absent in the hard condition. Under high cognitive demand, increased effort does not necessarily translate into better outcomes, and the elevated subjective costs may outweigh any emotional gains, potentially leading to feelings of frustration (Kool et al., 2010; Shenhav et al., 2013). As a result, when task demands exceeds an individual's perceived capacity to succeed, the motivational value of effort may diminish, weakening its link to positive emotions.

We note two limitations of the present study. First, the three subjective constructs were measured with single-item ratings. Although single-item scales are common in trial-by-trial paradigms for practical reasons, they cannot distinguish between subcomponents of each construct (e.g., fatigue vs. frustration for affective valence). A multi-item or multi-modal approach—combining subjective ratings with autonomic (skin conductance, heart rate variability), facial-EMG, or pupillometric indices (Dignath et al., 2020; Marcora et al., 2009)—would substantially strengthen inference. Second, rating procedures can themselves be reactive: asking participants to reflect on their difficulty, effort, and affect may subtly alter those very states. This is a general limitation of self-report designs but worth noting for trial-by-trial applications.

In summary, this study underscores the dynamic interplay between objective task difficulty and three key subjective factors (i.e., perceived difficulty, perceived effort, and emotional states) in shaping effort investment and task performance across successive trials. The results demonstrate that effort investment (as indicated by the number of mouse clicks) was influenced by the interaction between the objective difficulty of the preceding trial and both the objective and subjective difficulty of the current trial. In contrast, task performance (as indicated by RTs) was modulated by the interplay between the objective difficulty of the preceding trial and either subjective effort perception or emotional states associated with that trial. Notably, these interactions between objective and subjective factors were particularly prominent when both the preceding and current tasks were low in cognitive demand. Under such low-demand conditions, performance was jointly influenced by both the objective and subjective effort exerted in the preceding trial, highlighting the lingering effects of earlier effort exertion on subsequent cognitive functioning. Taken together, these findings suggest that subjective experiences closely tied to task completion, such as how difficult or effortful a task feels, and the emotions it elicits, interact with objective difficulty to shape further effort allocation and performance. Crucially, the extent of these interactive effects appears to depend on the cognitive demands of the task, emphasizing the

importance of cognitive resource availability in shaping how past experiences influence ongoing task engagement.

Declarations

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Declaration of Competing Interest

All authors declared no competing interests.

Informed consent

All participants provided written informed consent prior to participation.

Ethical approval

This study was approved by the Ethical Committee of the Institute of Brain and Psychological Sciences at Sichuan Normal University (Number: 2025LS0012).

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Data Availability

Data are openly available at the project's Open Science Framework page (https://osf.io/z26u5/).

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Figures

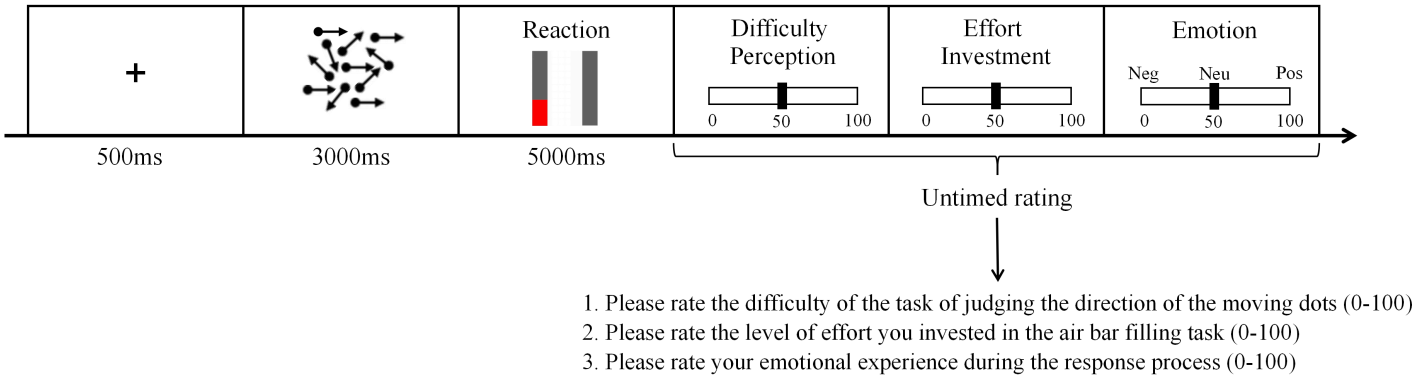


Figure 1

Task procedure. Each trial started with a fixation cross displayed for 500ms, followed by the black moving dots for 3000ms. Then, participants responded according to the direction of the motion dots, while filling in the air bar within 5000ms. Afterwards, participants completed three subjective ratings in relation to the task.

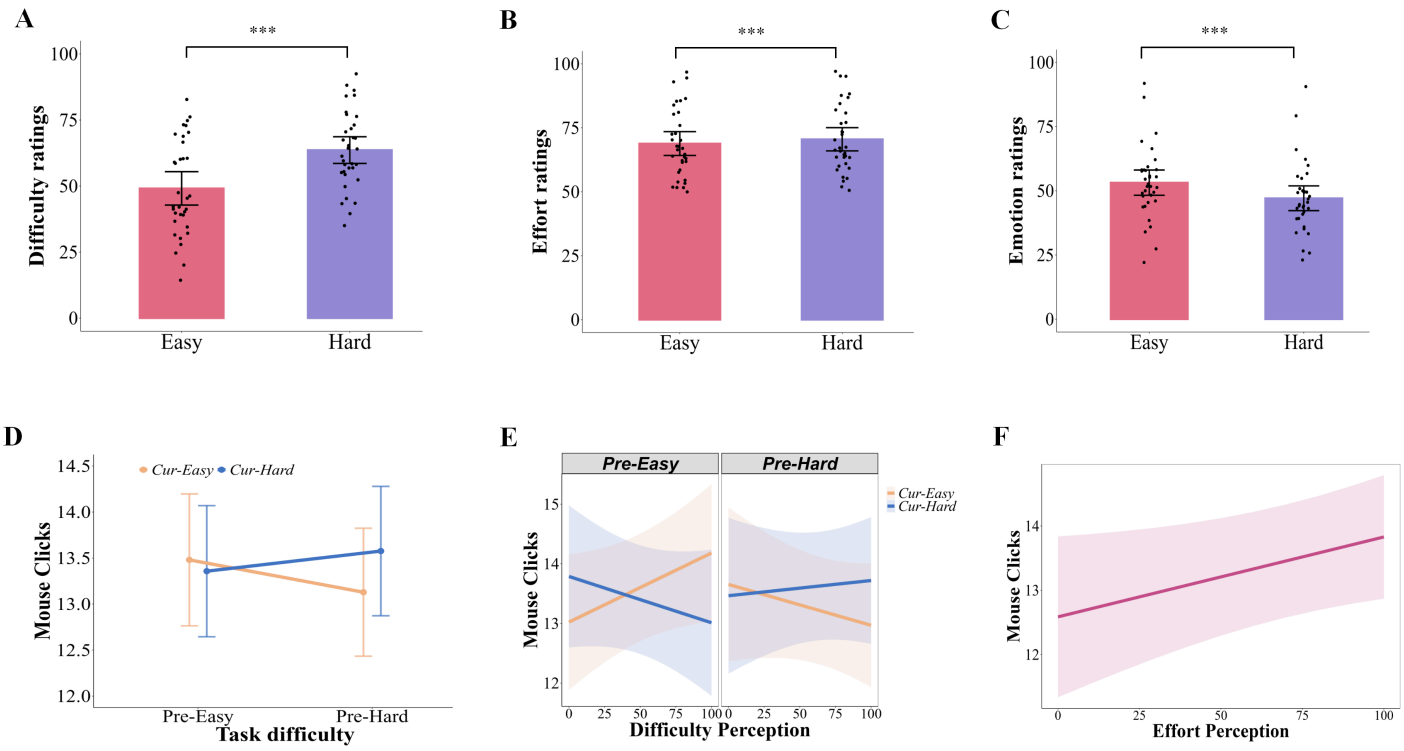


Figure 2

A-C. Manipulation checks for the objective task difficulty: In the hard condition (compared to the easy condition), subjective ratings of perceived Difficulty (A) and perceived Effort (B) were significantly higher, while subjective ratings of emotions (C) were significantly more negative. D-F. LMM results for the number of Mouse Clicks. **D**. The significant interaction between Previous difficulty and Current difficulty. **E**. When the Previous task difficulty was easy (left-panel), the interaction between the Current task difficulty and perceived Difficulty was significant. When the Previous task difficulty was hard (right-panel), the interaction was not significant. **F**. The main effects of perceived Effort of the preceding trial on the number of Mouse Clicks.

Note. In these graphs, '***' indicates $p < 0.001$. Shaded areas represent 95% confidence intervals. Individual subject data are depicted as black dots. "Pre-Easy" and "Pre-Hard" refer to the easy and hard conditions of the preceding trial, respectively, while "Cur-Easy" and "Cur-Hard" refer to the easy and hard conditions of the current trial, respectively.

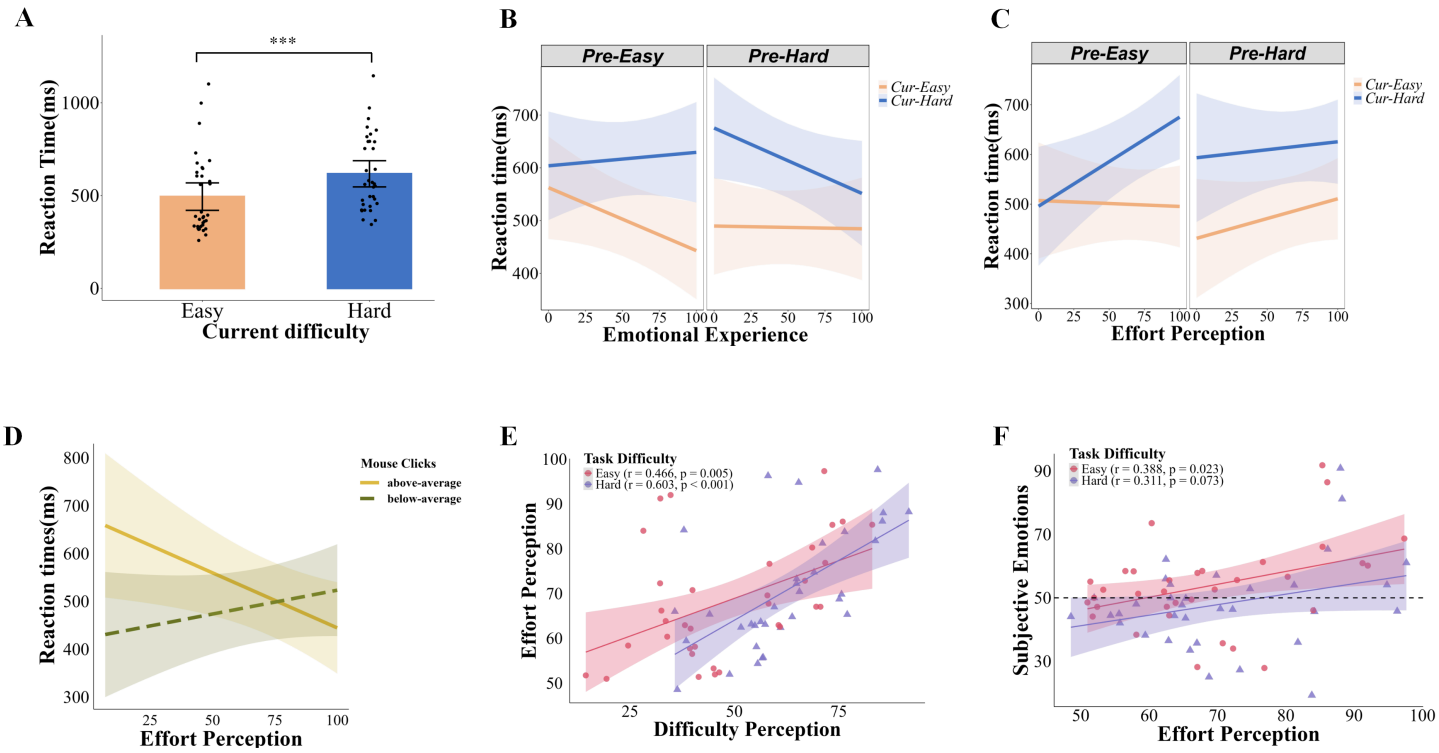


Figure 3

The results of RTs and correlations. A-D. **A.** The main effect of the Current task difficulty on RTs. **B.** When the Previous task difficulty was easy (left-panel), the interaction between the Current task difficulty and the subjective Emotional states was significant. Right panel. When the Previous task difficulty was hard (right-panel), the interaction was not significant. **C.** When the Previous task difficulty was easy (left-panel), the interaction between the Current task difficulty and perceived Effort was significant. When the Previous task difficulty was hard (right-panel), the interaction was not significant. **D.** The significant

interaction between the number of Mouse Clicks and perceived Effort of the preceding trial. **E.** Significant positive correlations between perceived Difficulty and perceived Effort were observed in both easy and hard conditions. **F.** The positive correlation between perceived Effort and subjective positive Emotions was significant only in the easy condition.

Note. In these graphs, '***' indicates $p < 0.001$. Shaded areas represent 95% confidence intervals. Individual subject data for RTs are depicted as black dots, individual subject data for subjective ratings in the easy condition are represented by red dots, while those in the hard condition are represented blue triangles. "Pre-Easy" and "Pre-Hard" refer to the easy and hard conditions of the preceding trial, respectively.