Instilling the value of effort

Stage 1 Registered Report (in-principle-acceptance)

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Abstract

People who take on challenges and persevere longer are more likely to succeed in life. But individuals often avoid exerting effort, and there is limited experimental research investigating whether we can learn to value effort. Because existing research focuses on enhancing cognitive performance rather than increasing the value of effort, it also remains unclear whether individuals can learn to care more about challenging themselves than performing well. We developed a paradigm to test an intuitive idea: that people can learn to value effort and will seek effortful challenges if directly incentivized to do so. Critically, we dissociate the effects of rewarding people for choosing effortful challenges and performing well. We predict that rewarding effortful choices will increase willingness to engage in challenging tasks. We also predict near- and far-transfer effects, as reflected in changes in preferences on unrewarded and unrelated tasks.

Introduction

Many people value effort. By exerting effort and persevering over time, we learn to approach challenges, become resilient, and develop self-regulatory skills. These qualities correlate not only with academic attainment [1–3], but also outcomes as disparate as health, wealth, and criminal offending [4–6]. But despite growing awareness of the importance of these qualities for individuals and societies [7–11], it remains unclear whether and how individuals can learn to value effort and approach challenges.

Although effort is costly [12–17], much evidence suggests that humans and other animals can (learn to) value effort [18–21]: We sometimes willingly challenge ourselves with tasks that are difficult to perform (e.g., endurance sports) precisely because these tasks require effort and perseverance, contrary to the notion that we avoid tasks with high perceived effort or low success likelihood [14,22,23]. This so-called effort paradox [19] raises questions about how people (and other animals) come to value effort for its own sake.

Our goal is to develop a paradigm to investigate whether people can learn to seek out effortful tasks in an experimental context. Our approach contrasts with and addresses problems with existing interventions that aim to enhance cognitive skills and performance [24–26]. These interventions typically improve performance on trained tasks (i.e., near-transfer effects) but not untrained tasks even when the tasks are closely related [27–32]. Crucially, it is unclear whether these interventions benefit everyday behavior and cognition [33] (i.e., far-transfer effects), nor is it clear whether emphasizing performance helps or hinders the learning of the value of effort and willingness to embrace effortful challenges.

Interventions that focus directly on improving these qualities have also provided mixed results. For example, training self-control regularly (by repeatedly practicing overriding specific habitual responses for extended periods) does not reliably improve self-control performance in the laboratory or willingness to exert effort in everyday life [33–35]. Similarly, some work suggests that instilling grit or growth mindsets in students improves academic outcomes [36–39]; however, these effects might be less robust than previously thought [40–43]. Moreover, these interventions often target many skills concurrently (e.g., grit, goal setting, emotion regulation), making it difficult to evaluate how and why they have (not) worked, and thus, provide little insights into whether people can be trained to value effortful challenges.

Decades of research on learning suggests that rewards [44–46]—if they appropriately shape environmental contingencies—can change humans and non-human animals' preferences for challenge and exerting effort. For example, when infants observe adults persevere longer to achieve their goals, they subsequently work harder on a novel task [47], suggesting that conducive environments can help individuals value effort [48,49].

So why do people tend to avoid exerting effort even when they know that it is associated with positive, rewarding outcomes? We suggest that people have acquired associations that inadvertently encourage effort-avoidant behavior. Rewards are often used to motivate good performance rather than instill the value of taking on effortful challenges. Many studies show that rewards improve immediate task performance [50–56], but they often fail to consider how rewards could also reduce the intrinsic value of effort [57–59], especially when rewards are later removed. Moreover, performance-based rewards could make us avoid taking on challenges (and prefer easier tasks) because it is more difficult to perform well on harder tasks (and easier to perform well on easier tasks). Thus, performance-based rewards might make individuals avoid beneficial but effortful tasks (e.g., doing homework) that are challenging or invoke feelings of frustration [60,61].

A more promising approach is to directly reinforce behaviors that emphasize the value of engaging in effortful challenges [62,63]. For example, when rewarded for performing harder tasks, children and rats persisted longer or worked harder on subsequent unrelated effortful tasks [64–66]. These studies might not have teased apart or controlled for the value of performing well, but they nevertheless provided initial evidence for the idea that rewards can be used to reinforce behaviors that emphasize the value of taking on effortful challenges.

Moreover, when the act of engaging in effortful challenges is repeatedly associated with reward, effort itself can become a secondary reinforcer, making it rewarding in its own right [19,45]. Effort becoming a secondary reinforcer might help explain why we often willingly engage in effortful tasks like endurance sports or crossword puzzles. This approach can not only potentially increase effort's value, but also provide insights into how to foster qualities like perseverance and conscientiousness [67], which might be particularly important for at-risk populations (e.g., low-income students [68,69]).

What is emerging is a simple idea: People should become more willing to choose to perform effortful tasks if directly incentivized to do so. Crucially, this idea can be tested experimentally. We designed a three-section experimental paradigm (pre-training, training, post-training) that rewards participants for either choosing to engage in hard tasks (*effort* condition) or performing well (*performance* condition) during training. We also included a *neutral* condition where participants will receive the same amount of rewards regardless of their choice and performance. This design allows us to dissociate the effects of these three types of rewards. While the results of this experiment cannot offer strong conclusions regarding how to intervene in real-world settings [70], they could nevertheless establish that it is possible to reinforce choosing to engage in demanding tasks and provide insights into how to design future intervention studies.

We predict that rewarding willingness to choose and engage in hard tasks during training will instill in participants the value of effort, which will manifest in increased willingness to engage in hard tasks—even ones that have not been associated with rewards and in the absence of rewards. We will test eight related hypotheses that provide different levels of evidence for our core idea: Participants who have been rewarded for engaging in effortful tasks (effort condition) will choose harder tasks over easier tasks more frequently than participants in the performance and neutral conditions. The outcome measures for our hypotheses are related measures of effort preferences (i.e., the percent of choices whereby participants choose the hard task).

Importantly, we will also assess participants' baseline effort preferences during a no-reward pre-training section so we can include pre-training effort preferences as a covariate in our models. That is, we will statistically control for idiosyncratic preferences that might influence choice (e.g., participants might choose to perform a task because they like certain low-level stimulus properties associated with the task cue). This approach not only allows us to accurately estimate the direct effects of our experimental manipulations but also further increases statistical power and mitigates against false negatives. Specifically, after controlling for baseline effort preferences in the pre-training section, we expect the following (see Table 1 for details):

1. On *rewarded* trials during the *training* section (rewarded trials are interleaved with probe trials), participants in the effort condition will choose the hard task more frequently than those in the performance and neutral conditions (Table 1, rows 1 and 2). This analysis mainly reveals whether participants have learned the task and reward contingencies.
2. On *probe* (i.e., unrewarded) trials during the *training* section (rewarded trials are interleaved with probe trials), participants in the effort condition will choose the hard task more frequently than those in the performance and neutral conditions (Table 1, rows 3 and 4), reflecting *within*-block *near*-transfer effects. Differences in effort preferences across conditions will likely reflect carryover effects (due to the interleaved reward and probe trials within a block) and actual changes in effort preferences (i.e., near-transfer).

3. On trials during the *post-training* section (completely unrewarded section), participants in the effort condition will choose the hard task more frequently than those in the performance and neutral condition (Table 1, rows 5 and 6). This analysis examines *across*-block *near*-transfer effects: Differences in effort preferences across conditions on these trials are less likely to be driven by carryover effects, since rewards are completely absent in this section.
4. In a separate block during the *post-training* section (completely unrewarded section), we will examine *across*-block *far*-transfer effects by presenting participants with a different cognitive task that had not been paired with rewards during the training section. We expect participants in the effort condition to choose the hard task more frequently than those in the performance and neutral conditions (Table 1, rows 7 and 8). Since this cognitive task has not been associated with rewards in the training section, this analysis provides evidence for whether the manipulations can lead to domain-general changes in effort preferences that transfer to unrelated tasks.

Two of the eight hypotheses in Table 1 (rows 6 and 8) most directly test our claims because they predict that in the absence of rewards (i.e., post-training section), effort preferences will be higher in the effort than neutral condition on the inhibition task (Hypothesis 6) and updating task (Hypothesis 8). If Bayesian analyses provide positive evidence for only one of the two hypotheses, the results will not refute our overarching claims—instead, they will provide support for only across-block near-transfer (Hypothesis 5) or across-block far-transfer effects (Hypothesis 7). Nevertheless, any pattern of positive results for Hypotheses 3 to 8 should also provide some evidence for transfer effects and will be theoretically informative, given that transfer-effects are rarely reported in the literature. However, four broad patterns of results will be the most informative.

First, if we find positive results for Hypotheses 3 and 4 but not 5 to 8, the results will provide evidence for only within-block near-transfer effects. That is, changes in effort preferences are only observed during the training block but not during the post-training block. Although the lack of far-transfer effects (Hypotheses 5 to 8) is inconsistent with the core hypotheses, the within-block near-transfer effects (Hypothesis 3 and 4) suggest that longer or more intense interventions (e.g., longitudinal studies) might be better suited to testing our hypotheses and examining the possibility of across-block near- and far-transfer.

Second, in addition Hypotheses 3 and 4, we might also find support for Hypotheses 5 and 6. Positive results for these four hypotheses provide evidence for within-block (Hypotheses 3 and 4) and across-block (Hypotheses 5 and 6) effects that are limited to only the task that has been associated with rewards during training (i.e., only near- but not far-transfer). Thus, changes in effort preferences on one task carry over to the same task in a different block but do not generalize to a different task.

Third, we might obtain positive results only during the post-training block (Hypotheses 4 to 8) and not during the training block (Hypotheses 3 and 4), which provide evidence for across-block but not within-block transfer effects. If so, we speculate that consolidation processes that occur between the training and post-training sections might be necessary for changing effort preferences, and further analyses and studies will be necessary to examine this possibility.

Finally, we might find positive results only when contrasting the effort and performance conditions (Hypotheses 1, 3, 5, 7) but not the effort and neutral conditions (Hypotheses 2, 4, 6, 8). These results could suggest the presence of different processes: The reward-effort manipulation increases effort preferences but the reward-performance manipulation decreases effort preferences.

Methods

Ethics information

The research complies with the university's ethics regulations. All participants will provide informed consent in accordance with the regulations of the ethics unit. Undergraduate participants at the university will receive course credits for completing the study and participants recruited via online platforms (e.g., Amazon Mechanical Turk, Prolific) will be paid $12.50. All participants will also receive a cash bonus (between $1 and $5), which will be determined by the number of points earned.

Pilot data

Results from a pilot study using the dot-motion inhibition task demonstrate the feasibility of the proposed paradigm because the value functions (Fig. 1c) led to different effort preferences that are consistent with Hypothesis 1. Participants in the effort condition ($n = 59$) had higher effort preferences than those in the performance condition ($n = 60$), $b = 13.89$, 95% HPD = [5.62, 22.06], $d = 0.63$, BF = 29.79 ($p < .001$).

That is, participants who experienced the reward-effort value function (Fig. 1c, first panel) chose the hard version of the dot-motion inhibition task more frequently than those who experienced the reward-performance value function (Fig. 1c, second panel). See Supplementary information for details.

Design

This experimental paradigm uses a mixed (between-within subjects) design. All participants will complete three sections in this order (*within*-subject): pre-training, training, and post-training. The pre-training section presents participants with two unrelated cognitive tasks in two separate blocks to evaluate participants' baseline effort preferences on these two tasks (Fig. 1a). Next, the training section consists of a single block and is the only block in the experiment that delivers rewards (Fig. 1b). Participants are randomly assigned (*between*-subject assignment) to the effort, performance, or neutral condition. Finally, the post-training section has two blocks that assess whether the reward manipulation (Fig. 1c) during the previous training section affects effort preferences on the two tasks presented during pre-training (Fig. 1a). Data collection will be performed blind to the conditions of the experiment; data analysis, however, will not be performed blind.

Pre-training section and post-training section

Both the pre-training the post-training sections each consist of two blocks of demand selection tasks [14] (Fig. 1a). In each section, two cognitive tasks requiring primarily inhibition and updating abilities are presented in two separate blocks (order counterbalanced across participants). Each pre-training block has 40 trials. Behavioral indices (e.g., choices) obtained from the two pre-training blocks provide baseline measures of effort preferences and performance on the two cognitive tasks. The post-training section is similar to the pre-training section, but only has 20 trials in each block and is presented after the training section. This block allows us to measure how behavior changes as a function of our experimental manipulation in the training section (Fig. 1b). On each trial in each block, participants will press either the left or right key to select the cue shown on the left or right of the display (3000 ms response deadline), which represents either the easy or hard version of the cognitive task. Participants will then perform the task they have selected and no performance feedback will be provided at the end of each trial (Fig. 1a). The mappings between cues and task difficulty will be counterbalanced across participants and the locations (left or right) of the cues will be randomly determined on every trial. For each participant and each task, two cues will be randomly chosen from a set of six cues to represent the easy and hard tasks (i.e., different sets of six cues for the inhibition and updating tasks). The cues representing the inhibition and updating tasks will also be visually distinct (Fig. 1a), ensuring that stimulus-driven carryover effects will be minimal.

The inhibition task in one of the demand selection blocks is a Simon-like dot-motion conflict task [71,72]. After choosing a cue (reflecting either the easy or hard version of the inhibition task), participants will perform three repetitions of the selected task (Fig. 1a). On each repetition, participants will see an array of colored moving dots and have up to 1500 ms to respond. Depending on their choice (easy or hard task), they will have to press either the left or right key to indicate the dot motion direction (leftward or rightward; 300 dots with 75-100% motion coherence, sampled from a uniform distribution) or the color of the dots (presented in one of four colors, with two colors mapped to each key). Another 20 to 50 (sampled from a uniform distribution) distractor dots in a different color will move in a direction that is consistent with or opposite to the majority of the dots. The easy version requires little controlled attention because participants simply have to indicate the motion direction of the majority of the dots while ignoring the color of the dots. However, the hard version requires controlled attention because it requires participants to indicate the color of the dots while overriding their automatic tendency to indicate motion direction; critically, the key for the correct color response could be congruent with the dot motion direction or it could be incongruent with the dot motion direction (65% chance it will be incongruent on each repetition). Color-response mappings will be counterbalanced across participants.

The updating task in the other demand selection block is a working memory and attention control task [73]. After choosing one of the cues (reflecting either the easy of hard version of the updating task), participants will perform the selected task (Fig. 1a). On each trial, participants will add a digit to three serially presented digits. The easy version requires participants to add 0 to each digit (e.g., 7, 8, 6) and to use the left, right, up, or down key to choose the correct response (i.e., 786) out of four similar responses (3000 ms response deadline). The hard version requires participants to add 3 or 4 to each digit (e.g., add 4 to each digit: 7 becomes 1, 8 becomes 2, 6 becomes 0, etc.); two digits are used for the hard task to minimize practice effects and a digit will be selected randomly at the start of each trial.

Training section

In the training section, participants will complete one block (60 trials) of demand selection task with the inhibition task (but not the updating task; see explanation below). At the beginning of each trial, participants will see one of two cues—reward trial cue or probe trial cue (Fig. 1b)—explicitly signaling to participants the presence or absence of rewards on that trial, respectively. Next, participants will choose to perform either the easy or hard version of the inhibition task (represented by the same cues seen in the pre-training section), and perform their chosen task. Finally, they will see either the reward or probe trial feedback, depending on whether it is a reward or probe trial, respectively. Rewarded (n = 40) and probe (n = 20) trials will be pseudo-randomly interleaved in this block, such that the first trial will always be a reward trial and probe trials occur after every one to three reward trials.

To test our hypotheses, we will randomly assign participants to the effort, performance, or neutral condition. The three conditions have identical task instructions, structure, sequence, and cues (reward, probe, feedback); the only difference is how the points are delivered on rewarded trials (Fig. 1b, Reward trial cue). On these trials, participants in the effort condition will experience the reward-effort value function (Fig. 1c, first panel). Those in the performance condition will experience the reward-performance function (Fig. 1c, second panel). Those in the neutral condition will receive the same amount of rewards for choosing the easy or hard task and regardless of their performance (Fig. 1c, third panel).

Specifically, on rewarded trials (Fig. 1b, reward trial cue), participants in the effort condition will receive more points for choosing the hard relative to the easy task (e.g., 370 vs. 230 points, respectively, plus jitter drawn from a normal distribution, $N(\mu = 0, \sigma = 5)$), regardless of their reaction times (RTs). However, participants in the performance condition will receive points that scale with their own RTs (plus jitter drawn from the same normal distribution as above), regardless of their choice (easy or hard version of the task). Participants in the neutral condition will receive the same points (plus jitter) regardless of their choice or performance. Critically, the expected reward across conditions is identical. Because participants will perform three repetitions of the inhibition task after each choice (Fig. 1b), the feedback (Fig. 1b, reward trial feedback panel) received at the end of each rewarded trial is the mean of the points received on three repetitions of the inhibition task. On rewarded trials, 0 points will be given for incorrect or missed responses (RT deadlines are participant-specific; see next paragraph).

Participant-specific RT criteria will be used to allocate points on rewarded trials, ensuring participants' RTs are evaluated against their own RT benchmarks on the inhibition task. These benchmarks will be based on each participant's RTs across the easy and hard versions of the task. In addition, if participants respond incorrectly or too slowly, they will receive 0 points (i.e., no "empty praises"). This approach ensures incentive compatibility and that participants have to perform relatively well, even when RT performance is uncorrelated with points earned (Fig. 1c, first and third panels). That is, choosing the hard task and then slacking off is a bad strategy that will likely result in no rewards.

The distribution of RTs used for benchmarking includes RTs on only correct responses (correct RTs) of the inhibition task in the pre-training section demand selection task (Fig. 1a); very fast and slow correct RTs (±1 times the median absolute deviation) will also be excluded [74]. RT deadlines will be determined separately for each participant, and the easy and hard versions of the inhibition task will have the same deadline (i.e., maximum RT [after applying exclusion criteria above] plus 150 ms).

This RT-benchmarking procedure helps to ensure each participant has neither too much nor too little time to respond on each trial. For example, two participants—one fast, one slow (with median RTs of 500 ms and 700 ms, respectively)—will have different RT deadlines (e.g., 750 ms and 950 ms respectively), but both will receive the same number of points on a trial if they respond correctly at their own median RTs (500 ms and 700 ms, respectively). Thus, task difficulty and rewards will be tailored to each participant's ability, such that participants will receive, on average, the same number of points, regardless of individual differences in average RTs.

We chose to train participants on only the inhibition task but not the updating task for two reasons. First, our paradigm requires participants to feel efficacious on reward-performance trials—exerting more effort should lead to more accurate and faster responses, and the inhibition task allows for a much tighter coupling between performance and rewards obtained than the updating task. Second, we are interested in whether the effects of training on a highly controlled inhibition task generalize to the updating task, which is more ecologically valid because solving mathematics problems resemble real-life problems more than indicating the motion or color of dots.

Procedure

Participants will be recruited to take part in a study titled "What are your cognitive preferences and abilities?" and will see the following study description: "We are examining how you make decisions and perform different cognitive tasks. You'll be doing cognitive tasks on the computer and answering a few questions about yourself after completing the tasks.”

At the beginning of the experiment, participants will be told that they are adventurous space explorers who have to complete various missions in space. Before the pre-training section (Fig. 1a), participants will practice and learn the four different cues associated with the easy and hard versions of the inhibition and updating tasks. Each practice block (maximum 80 trials per block) will terminate when participants have either completed all trials or performed well above chance levels in the preceding 20 trials (≥ 80% and 70% correct in the last 20 trials on the inhibition and updating tasks, respectively; see Exclusion criteria section below). During practice, participants will be encouraged to be adventurous by trying different tasks instead of always choosing one task. Participants will then complete the two actual blocks in the pre-training section (Fig. 1a).

After which, they will begin the training section, where they will first learn the cues associated with the reward and probe trials (Fig. 1b): “If you see a landed spaceship, an alien will be delivering rewards. If the spaceship hasn’t landed, you WON’T be receiving rewards.” They will be told that in the upcoming mission, their “goal is to earn as many points as possible” and that the earned points will be converted to a cash bonus at the end of the study. They will also read the following instructions: “How many points you could earn from the aliens depends on some combination of WHICH ROCKET YOU CHOOSE or/and HOW WELL YOU PERFORM (accuracy and reaction time). If you respond inaccurately or too slowly, you will receive 0 points for that response. So if the alien gave you very few points, it's likely because you made too many mistakes or/and were slow. Therefore, to maximize your earnings, try to use the feedback/points you receive from the aliens to improve HOW WELL YOU PERFORM and inform WHICH ROCKET TO CHOOSE in the future”. After completing 10 practice trials (5 rewarded trials, 5 probe trials) where they are encouraged to explore different strategies, they will complete the actual training section (Fig. 1b).

Before beginning the post-training section, participants will be briefly reminded of the four cues (from the pre-training section) associated with the easy and hard versions of the inhibition and updating tasks. To inform participants that no rewards will be delivered in this section, they will be explicitly told that “the aliens have retreated so they won't be around to deliver points or rewards” before they complete the two blocks in this section.

Finally, they will then complete demographic, personality, and debriefing questionnaires: Need for Cognition [75], Distress Tolerance [76], Conscientiousness [77], Grit

[78], and Implicit Theories of Intelligence [79]. They will then be compensated for their participation and points earned during the training section.

Sampling plan

We will use the Bayes Factor Design Analysis approach [80] to determine the number of participants required to provide compelling evidence for Hypotheses 6 and 8 (Table 1, Design Table), which predict that relative to participants in the neutral condition, those in the effort condition will choose the hard over the easy version of the inhibition task (Hypothesis 6) and updating task (Hypothesis 8) more frequently in the post-training section. This criterion reflects our belief that these two hypotheses test our ideas most directly.

We will use the sequential design with maximum participant approach to recruit additional participants until either (a) the Bayes factor (BF) provides strong evidence for the null hypothesis (BF < 0.1) or alternative hypothesis (BF > 10), or (b) a total of 750 participants has been reached. That is, the BF for Hypotheses 6 and 8 must each exceed one of the thresholds; if not, we will stop only after we have recruited 750 participants in total. We will compute BFs using the BayesFactor package [81] for the R Environment for Statistical Computing [82], and will use the default JZS prior [83]. We will compare the full linear regression model (outcome ~ condition + baseline) against null model (outcome ~ baseline) to determine whether the BF has exceeded either threshold.

Participants who fail to meet the criteria below will be excluded from the sequential sampling procedure and all analyses. They will be excluded if they perform poorly during pre-training practice blocks. Specifically, those who do not respond with at least 80% and 70% correct in the last 20 practice trials on the inhibition and updating tasks, respectively, will be excluded from all analyses. We will also exclude participants who perform better (i.e., faster median correct RT) on the hard relative to the easy version of either of the two cognitive tasks in the last 20 practice trials. This criterion is necessary because our paradigm hinges on the fact our hard tasks should require more effort (i.e., as reflected in slower median correct RT) than the easy tasks, and thus, more rewards will be necessary to offset the costs associated with performing the hard tasks.

To further ensure data quality is high, we will ask participants to indicate honestly the extent to which they had tried to follow all task instructions on a continuous slider scale with three equally-spaced anchors (never, mostly, always); participants who respond below the midpoint of the scale (mostly) will be excluded from all analyses. As a final check, participants will be asked to recall the four tasks (easy and hard versions of the inhibition and updating tasks) and describe the corresponding cues look like; participants who fail to describe the cues correctly will also be excluded from all analyses.

Analysis plan

We will exclude trials with no responses (i.e., because participants fail to respond in time) before performing any aggregation. To compute effort preferences on the different trial types in the different blocks, we will calculate for each participant the percent of choices whereby they choose the hard task. To test each hypothesis in Table 1, we will fit a Bayesian linear regression to test the effect of condition (effort versus performance or neutral condition) on effort preferences. To obtain the direct effect [84] of condition, we will include effort preferences in the pre-training demand selection blocks as a covariate (i.e., linear regression with one covariate and the condition regressor, i.e., analysis of covariance). Specifically, effort preferences on the pre-training inhibition task will be included as the covariate in Hypotheses 1 to 6, whereas effort preferences on the pre-training updating task will be the covariate in Hypothesis 7 and 8.

We will fit the models with the R package brms [85] and will report the following statistics that will be calculated from the posterior samples: beta estimate and its Bayesian 95% highest-posterior-density (HPD) interval and Cohen's d effect size. We will use default brms priors (i.e., improper flat priors over the reals) because with sufficient data, the priors are unlikely to influence parameter estimates (but they always influence the BF). For each effect, we will also report the BF, which will be computed using the BayesFactor package and the default JZS prior [81,83]. BF = 1 indicates the data do not favor either the experimental or null hypothesis. BFs between 3 and 10 provide moderate evidence for the experimental hypothesis, whereas BFs between 0.3 and 0.1 provide moderate evidence for the null hypothesis. BFs greater than 10 or smaller than 0.1 provide at least strong evidence for the experimental and null hypothesis, respectively [80]. We will also report frequentist probability values.

Data availability statement

All data and materials will be publicly shared on a Github repository upon acceptance for publication of the Stage 2 manuscript.

Code availability statement

All code will be publicly shared on a Github repository upon acceptance for publication of the Stage 2 manuscript.

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Author contributions

All authors contributed to the conception and design of the work. The last two authors provided critical oversight and feedback of the work. The first author wrote the manuscript. The last two authors provided critical feedback.

Competing interests

The authors declare no competing interests.

Figures

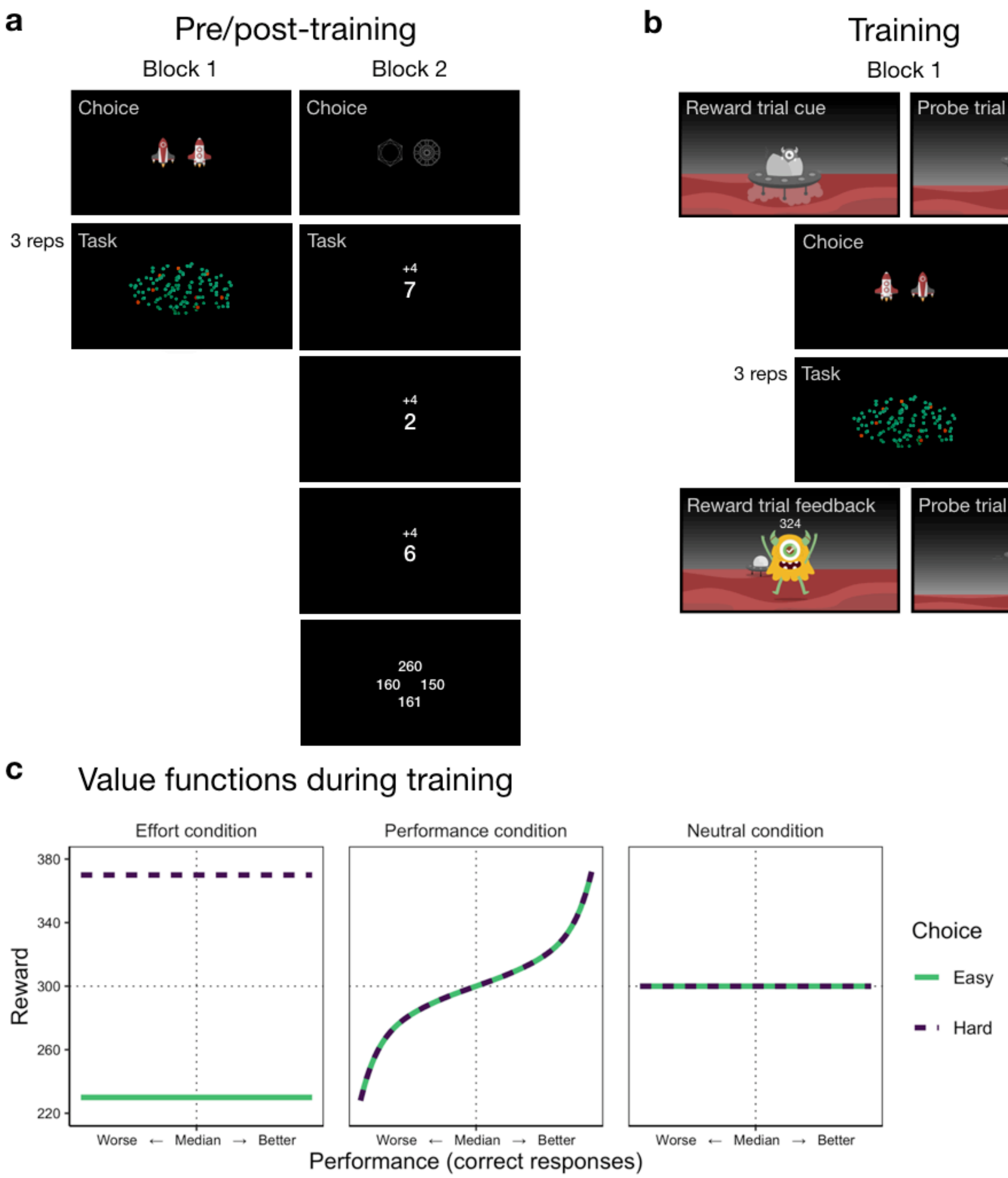


Figure 1 | Design. The experiment has pre-training, training, and post-training sections. Rewards are delivered only during the training section, but not the pre-training and post-training sections. **a,** The pre- and post-training sections consist of two demand selection task blocks each; these two blocks assess effort preferences on two unrelated cognitive tasks (to aid visualization, fewer and larger dots are shown than in the actual dot-motion inhibition task). On each trial, participants choose the version of the task (easy or hard) they prefer and then perform their chosen task. Effort preference is defined as the percent of choices whereby participants choose the hard task. **b,** The training section has only one block that consists of two distinct and pseudo-randomly interleaved trial types: rewarded trial (n = 40) and probe trial (n = 20). At the beginning of each trial, participants will see one of two cues (reward trial cue or probe trial cue) explicitly signaling the presence or absence of rewards on that trial. Next, they will be presented with two options (easy or hard); they will choose the version they prefer and then perform their chosen task. If it is a rewarded trial (signaled by the reward-trial cue), participants can earn rewards or points; if it is a probe (i.e., unrewarded) trial (signaled by the probe-trial cue), participants will be fully aware that they will not receive any points (see also probe trial feedback panel), no matter their choice and performance. **c,** Value functions show how rewards on rewarded trials in the training section differ across the three experimental conditions. Choice (easy vs. hard) determines rewards in the effort condition; performance (correct reaction times) determines rewards in the performance condition; neither choice nor performance determines rewards in the neutral condition. Critically, the expected reward is identical across conditions. No points are given for incorrect or missed responses (reaction times deadlines are participant-specific). All conditions have identical task instructions, structure, sequence, and cues. The only difference is whether rewards are assigned based on the reward-effort value function (effort condition), reward-performance value function (performance condition), or a uniform distribution (neutral condition).

Table 1. Design Table

Question	**Hypothesis**	**Sampling plan**	**Analysis**	**Interpretation given to different outcomes**
1. Do effort preferences on *rewarded trials* in the *training section* differ between the *effort* and *performance* conditions?	Effort preferences will be higher in the *effort* condition than *performance* condition.	We will stop sampling or recruiting participants when the Bayes factors for Hypotheses 6 and 8 (i.e.,	The outcome measure is effort preferences (% hard choices) on *rewarded trials* in the training section. We	The results are consistent with the hypothesis if Bayes factor ≥ 3. The results are consistent with the null hypothesis if

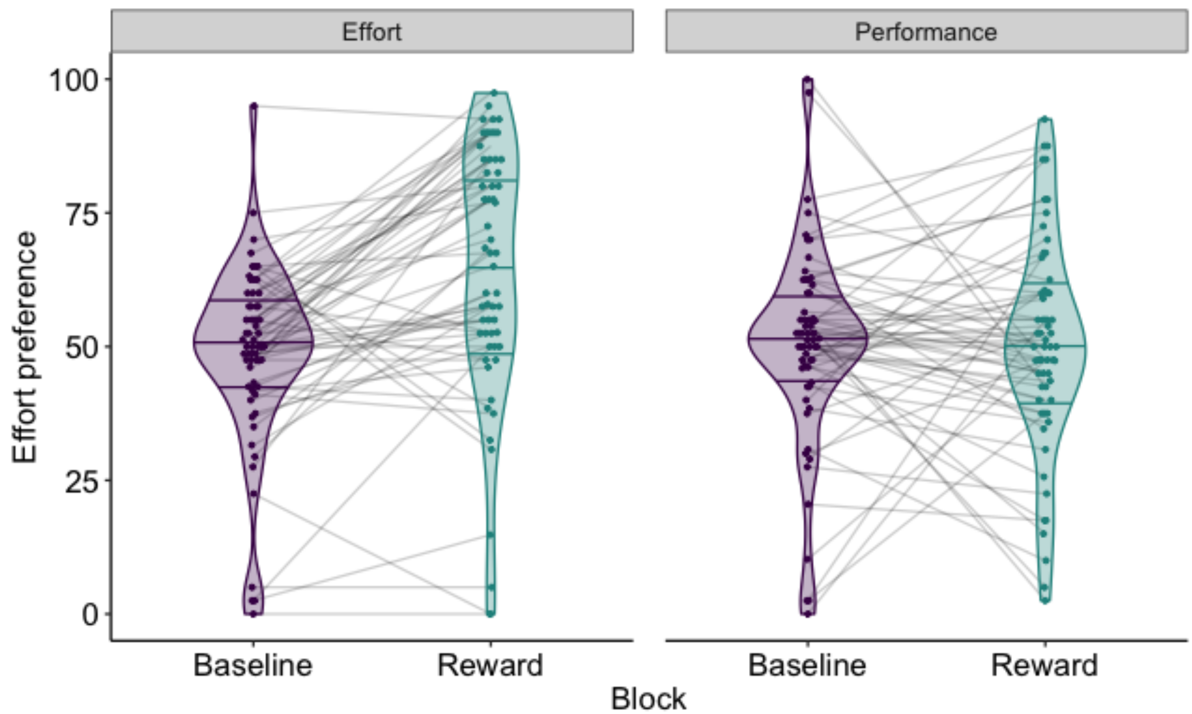
		rows 6 and 8 of this table) exceed a threshold (10 or 0.1) or when a total of 750 participants has been recruited.	will fit a Bayesian linear regression model with condition as the main regressor and effort preferences on the pre-training inhibition task as the covariate.	the Bayes factor ≤ 0.3. Specifically, Bayes factors larger than 1, 3, or 10 (or less than 1, 0.3, 0.1) provide anecdotal, moderate, and strong evidence for the experimental hypothesis (or null hypothesis).
2. Do effort preferences on *rewarded trials* in the *training section* differ between the *effort* and *neutral* conditions?	Effort preferences will be higher in the *effort* condition than *neutral* condition.	Same as above.	Same as the row above.	Same as above.
3. Do effort preferences on *probe (unrewarded) trials* in the *training section* differ	Effort preferences will be higher in the *effort* condition than *performance* condition.	Same as above.	The outcome measure is effort preferences (% hard choices) on *probe trials* in	Same as above.

between the *effort* and *performance* conditions?			the training section. We will fit a Bayesian linear regression model with condition as the main regressor and effort preferences on the pre-training inhibition task as the covariate.	
4. Do effort preferences on *probe (unrewarded) trials* in the *training section* differ between the *effort* and *neutral* conditions?	Effort preferences will be higher in the *effort* condition than *neutral* condition.	Same as above.	Same as the row above.	Same as above.
5. Do effort preferences on the *inhibition task* in the *post-training section* differ	Effort preferences will be higher in the *effort* condition than *performance*	Same as above.	The outcome measure is effort preferences (% hard choices) on	Same as above.

between the *effort* and *performance* conditions?	condition.		the inhibition task in the post-training section. We will fit a Bayesian linear regression model with condition as the main regressor and effort preferences on the pre-training inhibition task as the covariate.	
6. Do effort preferences on the *inhibition task* in the *post-training section* differ between the *effort* and *neutral* conditions?	Effort preferences will be higher in the *effort* condition than *neutral* condition.	Same as above.	Same as the row above.	Same as above.
7. Do effort preferences on the *updating task* in the *post-training*	Effort preferences will be higher in the *effort* condition than	Same as above.	The outcome is effort preferences (% hard choices) on	Same as above.

section differ between the *effort* and *performance* conditions?	*performance* condition.		the updating task in the post-training section. We will fit a Bayesian linear regression model with condition as the main regressor and effort preferences on the pre-training updating task as the covariate.	
8. Do effort preferences on the *updating task* in the *post-training section* differ between the *effort* and *neutral* conditions?	Effort preferences will be higher in the *effort* condition than *neutral* condition.	Same as above.	Same as the row above.	Same as above.

Supplementary information



Supplementary Figure 1 | Pilot results. Participants were randomly assigned to either the effort (left panel) or performance (right panel) condition. They first completed a baseline block (dot-motion inhibition task) where no rewards were offered before completing a reward block where rewards were delivered at the end of each trial. In the reward block, those in the effort condition experienced only the reward-effort value function, whereas those in the performance condition experienced only the reward-performance value function. Effort preference (percent of choices whereby participants chose the hard task) in the reward block was higher for the effort than performance condition. Each dot is one participant. The three horizontal lines in each violin plot are the 0.25, 0.50, and 0.75 quantiles. Each gray line connects the baseline and reward blocks' effort preferences for one participant: Positive and negative slopes indicate that the condition manipulation increased and decreased effort preferences, respectively.

Participants were randomly assigned to either the effort or performance condition (Supplementary Fig. 1). Each participant first completed a baseline block (40 trials) where no rewards were offered. On each trial, they chose to perform the easy or hard version of the dot-motion inhibition task (equivalent to Block 1 in Fig. 1a). They then completed a reward block (40 rewarded trials) where they saw the reward trial cue and feedback (Fig. 1b) on every trial. Those in the effort condition experienced only the reward-effort value function (Fig. 1c, left panel), whereas those in the performance condition experienced only the reward-performance value function (Fig. 1c, right panel). In the main text (Pilot data section), we reported that effort preferences in the reward block were higher in the effort than performance condition, demonstrating the feasibility of the proposed paradigm. Below, we report the results from additional models.

When we include effort preferences in the baseline as a covariate in our model, we found strong evidence for the effect of condition, $b = 14.64$, 95% HPD = [7.28, 22.33], $d = 0.73$, BF = 144.02 ($p < .001$). When we modeled effort preferences as a change score (reward block minus baseline block), the results were similar, $b = 15.45$, 95% HPD = [7.54, 23.72], $d = 0.70$, BF = 107.86 ($p < .001$), indicating the robustness of the condition manipulation.

We also modeled effort preferences as a function of condition, block, and condition-block interaction. There was an interaction effect, $b = 15.39$, 95% HPD = [5.29, 25.19], $d = 0.38$, BF = 10.14 ($p = .005$), which was driven by an increased in effort preferences across blocks in the effort condition, $b = 15.64$, 95% HPD = [7.64, 23.21], $d = 0.75$, BF = 225.90 ($p < .001$), but no change in effort preferences in the performance condition, $b = 0.13$, 95% HPD = [-6.56, 7.57], $d = 0.01$, BF = 0.19 ($p = .971$).