Rewarding cognitive effort increases the intrinsic value of mental labor

Georgia Clay[a,b,1], Christopher Mlynski[b,1], Franziska M. Korb[a], Thomas Goschke[a,2], and Veronika Job[b,2,3]

[a]Faculty of Psychology, Technische Universität Dresden, 01069 Dresden, Germany; and [b]Faculty of Psychology, University of Vienna, Vienna 1010, Austria

Edited by Timothy Wilson, Department of Psychology, University of Virginia, Charlottesville, VA; received June 28, 2021; accepted November 29, 2021

Current models of mental effort in psychology, behavioral economics, and cognitive neuroscience typically suggest that exerting cognitive effort is aversive, and people avoid it whenever possible. The aim of this research was to challenge this view and show that people can learn to value and seek effort intrinsically. Our experiments tested the hypothesis that effort-contingent reward in a working-memory task will induce a preference for more demanding math tasks in a transfer phase, even though participants were aware that they would no longer receive any reward for task performance. In laboratory Experiment 1 ($n = 121$), we made reward directly contingent on mobilized cognitive effort as assessed via cardiovascular measures (β-adrenergic sympathetic activity) during the training task. Experiments 2a to 2e ($n = 1,457$) were conducted online to examine whether the effects of effort-contingent reward on subsequent demand seeking replicate and generalize to community samples. Taken together, the studies yielded reliable evidence that effort-contingent reward increased participants' demand seeking and preference for the exertion of cognitive effort on the transfer task. Our findings provide evidence that people can learn to assign positive value to mental effort. The results challenge currently dominant theories of mental effort and provide evidence and an explanation for the positive effects of environments appreciating effort and individual growth on people's evaluation of effort and their willingness to mobilize effort and approach challenging tasks.

mental effort | cognitive control | value of control | learned industriousness | achievement motivation

The pursuit of many of our most important goals in daily life requires the persistent recruitment of cognitive effort. This holds in particular when automatic routine behaviors do not suffice to achieve a goal or when novel and unpracticed tasks must be completed, which require planning, problem solving, or self-control. Likewise, most extraordinary human skills like reading, writing, mastering an instrument, playing tennis, making medical diagnoses, or solving differential equations are the result of thousands of hours of deliberate practice and continued high-effort exertion (1). The societal relevance of cognitive effort becomes particularly obvious when considering that, according to the World Economic Forum Future of Jobs Report 2020, over the next few years, the fourth Industrial Revolution will radically change the skills required in most industries, with complex problem solving, creativity, and critical thinking as well as self-management and active learning being top competencies needed in the workplace of the future.

While cognitive effort is and will continue to be extremely useful, most current models of cognitive control in psychology, cognitive neurosciences, and behavioral economics describe the exertion of effort as generally aversive and as something people strive to avoid whenever possible (2–5). For example, Kool and colleagues (3) demonstrated that when faced with the choice between two tasks of varying cognitive demands, participants clearly preferred the less demanding task (see also refs. 6 and 7). These findings have been interpreted as strong support for the assumption that cognitive effort incurs intrinsic cost and that humans generally aim to minimize cognitive effort investment (2).

In stark contrast to the view that effort is generally aversive, there are situations in daily life in which people appear to freely choose to exert effort, even without any obvious external reward. For example, individuals may enjoy completing the daily newspaper crossword puzzles every morning, students are often motivated by challenging intellectual problems, and amateur pianists may spend hours striving for perfection in the absence of any obvious extrinsic reward. Recently, some scientists have started to call into question that effort is always aversive and argued instead that cognitive effort can at least under certain circumstances be experienced as intrinsically rewarding and valuable (8).

However, to date, there has been surprisingly little empirical research to test the assumption that cognitive effort can be intrinsically rewarding. Indirect evidence for the effects of effort on the processing of reward stems from recent neuroimaging studies showing that extrinsic rewards elicit stronger activation in reward-related brain regions including the ventral striatum after the exertion of high compared to low effort (9). However, while this result shows that high effort may increase the value of external reward for completing a task, it does not address the question whether effort as such can be or become intrinsically rewarding.

In the present research, we draw on traditional learning theories, which suggest that specific behavior may acquire intrinsic value and become a so-called *secondary reinforcer* if it is

Significance

Many extraordinary human skills like reading, mastering an instrument, or programming require thousands of hours of practice and continued exertion of mental effort. However, the importance of mental effort often contrasts with currently dominant theories suggesting that effort is aversive and something people avoid whenever possible. Here, we show that rewarding participants for the exertion of effort in a cognitive task increased their preference for more demanding tasks in a transfer phase. This provides evidence that people can learn to positively value effort and demanding tasks in the absence of extrinsic reward. These findings challenge currently dominant theories of mental effort and point to the role of learning environments for the development of effort-related motivation.

Author contributions: T.G. and V.J. developed the study concept; G.C., C.M., F.M.K., T.G., and V.J. designed research; G.C. and C.M. performed research; G.C. and C.M. analyzed data; and G.C., C.M., F.M.K., T.G., and V.J. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

[1]G.C. and C.M. contributed equally to this work.

[2]T.G. and V.J. contributed equally to this work.

[3]To whom correspondence may be addressed. Email: veronika.job@univie.ac.at.

This article contains supporting information online at http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2111785119/-/DCSupplemental.

Published January 31, 2022.

repeatedly paired with reward (10). Numerous studies on reinforcement learning and chaining, with intermitted reinforcement plans, demonstrated that animals acquire all kinds of behavior that persists even after the reward has been removed (11, 12). Theoretically, it could thus be possible to promote the intrinsic motivation for effort exertion itself by experiences of effort-contingent extrinsic reward.

Note that when we propose that effort-contingent reward via mechanisms of associative learning enhances the intrinsic value of effort, this does not imply that such an effect would be visible as enhanced intrinsic task motivation. People might not be willing to continue working on a previously incentivized task without extrinsic reward. A large body of research documents that via mechanisms of cognitive evaluation (i.e., overjustification), intrinsic task motivation may be undermined by extrinsic rewards (13, 14). Thus, to observe effects on intrinsic value of effort, it is crucial to assess effort seeking on a different transfer task.

Quite surprisingly, there is little research which directly tested the hypothesis that people can learn to value effort through effort-contingent reinforcement. Notable exceptions are a few studies on the so-called *learned industriousness* effect (15–17). Mostly focusing on animals (physical tasks) or children in field settings (cognitive tasks), these studies yielded suggestive evidence for an increase in effort-seeking tendencies on a novel task in the same performance realm, depending on the effort required to achieve a fixed reward on a preceding task. These results are consistent with classical theories of achievement motivation, which also proposed that positive learning experiences with demanding tasks early during ontogenesis may contribute to stable interindividual differences in the motivation to engage in challenging activities (18). However, evidence from the achievement motivation literature on the development of motivation to mobilize cognitive effort is sparse and exclusively correlational (19). Overall, there is a lack of well-controlled experimental studies with humans investigating the learning mechanisms that can induce an individual to seek effort without a prospect of extrinsic reward.

The Present Experiments. The aim of this research is to challenge the predominant view that people generally avoid effort and to test the hypothesis that individuals can learn to seek effort intrinsically. Importantly, we attempt to show that cognitive effort is not merely approached when it leads to higher extrinsic (e.g., monetary) reward, but our key hypothesis is that people can become motivated to exert effort itself even if there is no prospect of further extrinsic reward. More specifically, we propose that one can increase the intrinsic value of effort with a learning phase during which participants receive reward that is made contingent on the degree of exerted effort. We approached this research question from two distinct perspectives.

First, a laboratory experiment utilized cardiovascular (CV) measures to directly incentivize mobilized effort on a working-memory task as indicated by β-adrenergic sympathetic activity (20). Empirical support for this measurement of effort mobilization on cognitive tasks has substantial support from well over 100 experiments utilizing diverse protocols and participant populations (for reviews, see ref. 21). Second, we conducted a series of online studies in which effort during the learning phase was operationalized via varying task demands on the same working-memory task used previously. In both studies, effort seeking was operationalized as demand selection on a follow-up math task with varying task demands.

Taken together, this pair of studies allowed us to test the hypothesis in situations in which either experimental control or generalizability were high, providing us with a more complete picture of the phenomenon. All studies were designed to control for interindividual differences in math ability, the subjective value of performing well on a demanding task, and social desirability to choose a demanding task in an experimental setting. Most importantly, in the test phase in which participants were free to choose tasks requiring different degrees of cognitive effort, we eliminated any extrinsic incentives which otherwise could have motivated the choice of higher task demands. This constitutes a set of studies that directly tested the hypothesis that rewarding individuals for recruiting effort can render the exertion of mental effort intrinsically valuable.

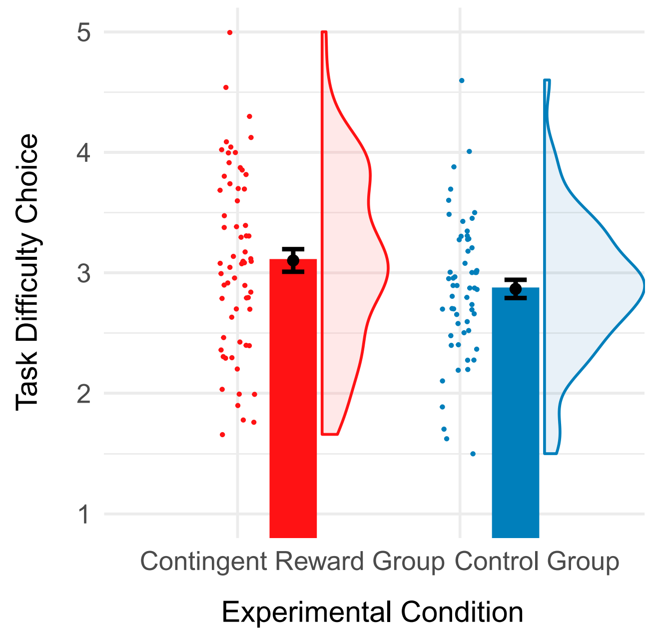

Fig. 1. Average task difficulty choice during the MET for participants in either the contingent reward or control groups. Error bars indicate SEs.

Experiment 1

In Experiment 1 (n = 121), as an objective indicator of cognitive effort mobilization, we assessed the CV response of β-adrenergic sympathetic activity through the force of contractions in the left ventricle (22) along with blood pressure and heart rate responses. We operationalized heart contraction force (contractility) in terms of heart pre-ejection period (PEP) (22). PEP is the time interval between the onset of ventricular depolarization (i.e., beginning of electrical stimulation to the left ventricle) and cardiac ejection of blood from the heart (i.e., the opening of the aortic valve).

During the learning phase (15 min), participants were presented a series of working-memory tasks (N-back) varying in task difficulty (1-, 2-, or 3-back, 5 blocks each). After each block, participants received a monetary reward ranging from 1 to 60 cent (CT). In the experimental group, unbeknownst to the participants, rewards were made contingent on participants' effort mobilization as inferred from their PEP reactivity (changes compared to the baseline). In the control group, rewards were selected randomly. In both groups, rewards were granted independently of participants' performance provided that they passed the low threshold of 50% accuracy. This threshold was met on virtually all (99.89%) blocks, suggesting that all participants were generally engaged in the task (see *SI Appendix, Learning Phase* for a manipulation check and detailed analyses of reward allocation).

In the second phase of the experiment, participants completed the math effort task (MET) (23). They could choose the level of difficulty for blocks of mathematical problems from a continuum of five difficulty levels. Importantly, participants were informed that they would no longer be rewarded and that they would receive no indication of their performance during this second task. Finally, we obtained self-report measures of demand seeking as indicated by the hope of success dimension of achievement motivation (AMS-R) (24) (e.g., "I enjoy situations in which I can make use of my abilities.") and assessed their math self-concept (25) (e.g., "I feel that I am naturally good at math.")

Main Analyses. The data and analyses scripts are available at https://osf.io/8pcex/. A one-way ANCOVA was conducted to determine the influence of experimental group on difficulty choice. Math self-concept was included as a covariate to control for participants' preexisting differences in valuation of math. The analysis yielded a significant main effect of group, $F(1, 118) = 4.88$, $P = 0.029$, $\eta^2 = 0.033$ (Fig. 1). As predicted, participants in the effort-contingent reward group selected higher difficulty levels in the MET ($M = 3.10$, $SD = 0.74$) as compared to participants in the control group ($M = 2.87$, $SD = 0.58$).[*]

Exploratory Analyses.

Difficulty choice across time. A growth curve model was estimated (Table 1) to predict difficulty choice by time and group. To make the coefficients more interpretable, time was rescaled as the proportion of trials completed. On a visual inspection of the pattern of difficulty choice over time (inverted U shape), there was a clear need to include a quadratic term for time (Fig. 2). We found that group had a significant main effect, with those in the control group selecting lower difficulty levels. This was supported by a nonsignificant interaction between group and trial with the 95% CI not excluding zero, providing an indication that the group effect was stable across time.

Predicting difficulty choice with effort mobilization. Next, we tested whether exerted effort on the *N*-back task would correlate with difficulty choice differently in the two groups. If relative PEP reactivity (within each level of difficulty) during the *N*-back task correlated with difficulty choice on the MET in the experimental group but not in the control group, this would provide further evidence for our assumption that incentivizing effort exertion and not merely working on a difficult task enhanced participants effort motivation. In order to obtain a measure of relative PEP reactivity, we first residualized the average PEP scores obtained during each *N*-back block by predicting them with the associated difficulty of said block. We then averaged these residualized scores for each participant and used the average score to predict difficulty choice. In the experimental group, this residualized PEP score was significantly correlated with demand selection in the math effort task in the expected direction ($r = -0.262$, $P = 0.038$). Higher mental effort, as indicated by lower PEP values, was associated with a tendency to select more demanding tasks. In the control group, PEP and demand selection in the MET were not correlated ($r = -0.001$, $P = 0.994$). The interaction between group and relative *N*-back effort was not significant ($F(1, 117) = 1.78$, $P = 0.19$), which might be due to the lack of power for moderation analyses (26).

Table 1. Coefficients of group in quadratic hierarchical linear model predicting difficulty choice across trials on the MET in Experiment 1

Variable	B	SE	T	p	95% CI
Intercept	**1.50**	**0.23**	**6.53**	**<0.0001**	**[1.05, 1.95]**
Math self-concept	**0.06**	**0.01**	**5.22**	**<0.0001**	**[0.04, 0.09]**
Group	**-0.40**	**0.13**	**-2.93**	**0.004**	**[-0.66, -0.13]**
Time	**2.28**	**0.23**	**10.01**	**<0.0001**	**[1.83, 2.72]**
Time^2	**-1.92**	**0.19**	**-9.89**	**<0.0001**	**[-2.30, -1.54]**
Group:Time	0.26	0.33	0.78	0.44	[-0.39, 0.90]
Group:Time^2	0.06	0.28	0.22	0.82	[-0.49, 0.61]

Group: 0 = experimental condition, 1 = control condition. Time = number of trials completed/total number of trials. Variables with 95% CI excluding zero shown in bold.

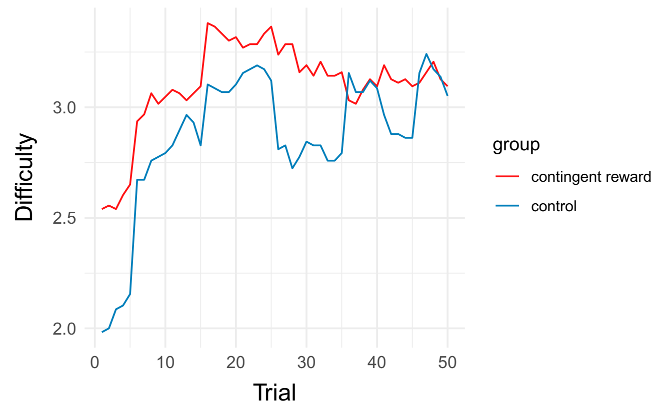

Fig. 2. Average task difficulty choice throughout the MET for participants in either the contingent reward group or the control group in Experiment 1.

Group differences in effort and performance. We conducted hierarchical models to test for group differences in effort and MET performance across single MET blocks controlling for block difficulty (see *SI Appendix*, *Subsequent Performance Task* for detailed analyses). None of the analyses found a difference between the two experimental groups, neither for PEP reactivity, $B = 1.49$, $SE = 1.37$, $t = 1.09$, $P = 0.28$, nor for accuracy, $B = -0.036$, $SE = 0.18$, $z = -0.20$, $P = 0.84$.

Relationship between task difficulty, effort, and performance. We further carried out multilevel analyses to explore the nature of the relationship between task difficulty, mobilized effort, and performance in the *N*-back task. The results show that the level of difficulty was a predictor of effort mobilization, $F(2, 1{,}591) = 6.41$, $P = 0.0017$, $\eta_p^2 = 0.008$, as well as for performance, $F(2{,}1{,}678) = 492.07$, $P < 0.001$, $\eta_p^2 = 0.37$. Not surprisingly, higher difficulty levels were associated with greater effort mobilization and lower performance. Effort, however, was not predictive of performance $F(1, 263) = 0.004$, $P = 0.95$, $\eta_p^2 = 0.00002$.[†]

Achievement motivation. An exploratory analysis of self-reported achievement motivation revealed a significant difference between experimental groups after controlling for math self-concept, $F(1, 118) = 11.68$, $P < 0.001$, $\eta^2 = 0.062$. Participants in the effort-contingent reward group reported slightly higher achievement motivation ($M = 3.18$, $SD = 0.56$) than their control counterparts ($M = 2.90$, $SD = 0.60$).

In sum, Experiment 1 provides first evidence for our intrinsic value of effort hypothesis in a controlled laboratory setting. When participants received rewards contingent on physiological indicators of cognitive effort mobilization, they subsequently showed a higher preference for more demanding tasks than participants in the control group did, even though they were aware that they would no longer receive any extrinsic rewards.

*Without controlling for math self-concept, the main effect for group was marginally significant, $F(1, 119) = 3.76$, $P = 0.055$.

†While a similar analysis would theoretically make sense during the MET, the much more rapid switching between difficulty levels and the slight delay in PEP reactivity to changes in task difficulty make the results harder to interpret. However, as in the *N*-back task, we did find that PEP was unrelated to performance, $F(1, 201) = 0.17$, $P = 0.69$, $\eta_p^2 = 0.0008$.

https://doi.org/10.1073/pnas.2111785119

Experiments 2a to 2e

While Experiment 1 allowed us to obtain objective (physiological) measures of effort investment, the aim of Experiments 2a to 2e was to enhance generalizability and demonstrate replicability of our findings. To this end, we adapted our effort-contingent reward paradigm for an online study and recruited multiple community samples (Experiments 2a to 2e, all studies that we conducted with this paradigm) on Amazon Mechanical Turk. Experiments 2b to 2e were preregistered on aspredicted.org (https://aspredicted.org/WXA_MZE, https://aspredicted.org/M21_MGH, https://aspredicted.org/HXG_YQ4, and https://aspredicted.org/TTE_URQ).

The learning phase of Experiment 2 was identical to that employed in Experiment 1, with the exception that in the experimental group, reward was contingent solely on the difficulty of the task in a given block since the online format precluded the measurement of cardiovascular responses. The 50% accuracy threshold in the *N*-back task was met in more than 93% of blocks over all five studies. The MET was also identical to Experiment 1 and was followed by the math self-concept scale (25) in addition to other questionnaires which were added for exploratory reasons and varied across samples (see *SI Appendix* for details).

Main Analyses. A one-way ANCOVA was conducted to determine the influence of group on difficulty choice following the preregistered analysis plan. Math self-concept was again included as a covariate. The first four smaller samples (n = 228, 255, 241, 233) yielded mixed results, with a marginally significant main effect for experimental group in Experiment 2a, $F(1, 225) = 3.04$, $P = 0.083$, $\eta_p^2 = 0.013$, a nonsignificant effect for group in Experiment 2b, $F(1, 252) = 0.10$, $P = 0.75$, $\eta_p^2 = 0.0004$, a significant main effect for group in Experiment 2c, $F(1, 238) = 5.02$, $P = 0.026$, $\eta_p^2 = 0.021$, and a nonsignificant effect for group in Experiment 2d, $F(1, 230) = 2.67$, $P = 0.10$, $\eta_p^2 = 0.011$. Experiment 2e was conducted with a larger sample ($n = 500$) and yielded a highly significant main effect for group, $F(1, 497) = 10.25$, $P = 0.001$, $\eta_p^2 = 0.020$.

A meta-analysis that was conducted across all five samples on the group difference in difficulty choice, controlling for math self-concept, yielded a significant difference, $d = 0.22$, 95% CI [0.12, 0.33], $z = 4.24$, $P < 0.0001$ (Fig. 3), indicating that the experimental group selected more difficult levels compared to the control group.

Exploratory Analyses.

Difficulty choice across time. As in Experiment 1, a growth curve model was estimated to predict difficulty choice by time and group. Each of Experiments 2a to 2e indicated a significant negative quadratic term for time. A meta-analysis on the group by quadratic time interaction term revealed a negative coefficient, $d = -0.24$, 95% CI = [−0.40 to −0.08], $z = -2.93$,

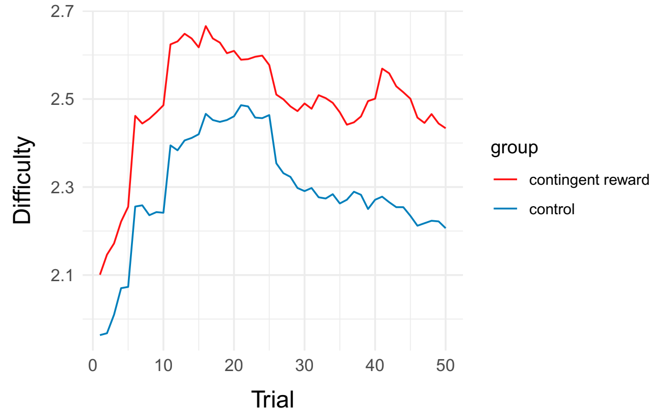

Fig. 4. Average task difficulty choice throughout the MET aggregated across Studies 2a to 2e.

$P = 0.0034$, suggesting a stronger quadratic function for the control group compared to the experimental group (Fig. 4).

MET performance. A logistic hierarchical linear model with random slopes and intercepts was used to analyze accuracy on the MET, with math trials nested within participant. Experimental group was the Level 2 predictor, and difficulty level was the Level 1 control variable. In all Experiments 2a to 2e, the expected main effects of difficulty level were present, with accuracy decreasing as difficulty level increases. The main effect of group was subjected to a meta-analysis for Experiments 2a to 2e and produced a nonsignificant effect, $B = 0.003$, 95% CI [−0.19, 0.20], $z = 0.03$, $P = 0.97$ (see *SI Appendix* for detailed analyses), demonstrating that participants in both experimental and control conditions performed equally well on the MET accounting for difficulty level.

Achievement motivation. Experiments 2d and 2e included measures of achievement motivation for purposes of exploratory analysis; both experiments showed that there was no significant difference between groups controlling for math self-concept, $P > 0.53$, $\eta^2 < 0.0013$.

In sum, following a preregistered procedure and analysis plan in a large community sample, Experiment 2 provides further evidence for the assumption that rewarding effort as indicated by task difficulty can enhance effort seeking.

Discussion

The two studies presented here provide experimental evidence that rewarding participants for the exertion of cognitive effort enhances their motivation to engage in demanding tasks. Importantly, participants in the experimental group did select more demanding novel transfer tasks without any prospect of gaining further extrinsic rewards for their performance in these

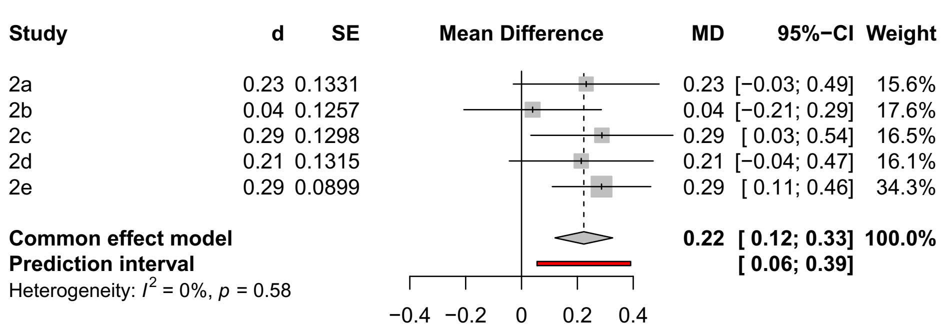

Fig. 3. Meta-analysis of difference between mean difficulty choice residualized by math self-concept in Studies 2a to 2e (positive value indicates higher difficulty choice in experimental condition).

tasks. Despite the very short training phase, the effect was stable and persisted throughout the transfer task and, if anything, in the online studies became even more pronounced over time. These results suggest that the manipulation increased the intrinsic value of cognitive effort itself as indicated by the fact that it enhanced participants' tendency to seek effortful tasks even in the absence of any extrinsic reward. The findings are consistent with our assumption derived from learning theory that effort can gain the quality of a secondary reinforcer and become gradually intrinsically rewarding when it frequently leads to extrinsic reward (15).

As in previous research discussing the intrinsic cost of effort (3), we also used demand selection as the primary outcome measure. This approach does not allow to draw conclusions as to how people subjectively experience the exertion of effort, that is, whether they experience it as pleasurable or aversive. The subjective quality of intrinsic value or cost of effort, respectively, has yet to be elucidated. It is possible that effort-contingent reward will lead to more pleasure and hedonic experiences during the exertion of effort as indicated by self-report or facial expressions (corresponding to enhanced "liking" according to ref. 27). However, it is also possible that the frequent experience of effort-contingent reward sensitizes the individual to perceiving effort as a cue that (implicitly) signals the prospect of reward. It may thus energize effortful behavior because of a generalized reward anticipation ("wanting" in terms of ref. 27), even without the individual necessarily experiencing effort as subjectively pleasurable. While the present data do not allow to distinguish between these two possibilities, they clearly show that effort can acquire an intrinsic value in the sense that participants choose more effortful tasks even being fully aware of the absence of extrinsic reward.

Our experimental design allowed us to exclude several potential alternative explanations. First, controlling for math self-concept allowed us to control for any preexisting math-related preferences. Second, we can exclude that participants in the effort-contingent reward group only showed a pseudo preference for effort exertion by selecting more difficult tasks without actually investing cognitive effort when completing them. As indicated by the performance results in both experiments and the PEP reactivity results in Experiment 1, participants in the experimental groups not only chose more difficult tasks but performed as well as their control counterparts on these tasks and mobilized equally high levels of effort to complete them.

One might expect that a higher intrinsic value of effort should also be reflected in better performance in the experimental compared to the control group. However, when interpreting performance on the math effort task, it is important to take into consideration that participants in the experimental group selected on average more difficult tasks. Due to a random assignment of participants to the experimental groups and null findings concerning group differences in math self-concept, we can exclude systematic differences in math ability between groups. Thus, if participants in the experimental group had invested the same amount of effort as the control group while at the same time selecting on average more difficult tasks, they should have shown lower average performance compared to the control group (because of the higher average task difficulty). However, multilevel analyses controlling for difficulty level in predicting accuracy on each trial revealed no reliable performance differences between the experimental and the control groups. This constitutes converging evidence that participants in the experimental group actually exerted more effort to achieve the same performance level despite the higher demands they had set themselves in the MET.

The pattern of present findings is fully consistent with our intrinsic value of effort hypothesis. Nevertheless, we should note that we cannot completely exclude the possibility that participants may have learned to associate reward with demanding task contexts rather than effort per se. To sustain this alternative interpretation, one would have to explain, however, why an association between task demand and reward still exerts a biasing influence on demand selection in the transfer task, even though participants are fully aware that they will no longer receive an extrinsic reward. One possible explanation could be that the association between task demand and reward gained a habit-like quality and biased choice behavior toward more demanding tasks irrespective of participants' lack of a conscious reward expectancy. While it appears unlikely that the brief reward manipulation in our experiments was sufficient to lead to the formation of a habit-like choice bias, we cannot fully exclude the possibility of a perseverating short-term bias effect of an association between task demand and reward.

We observed the predicted effect of effort-contingent reward after a brief learning phase of 12 min only. In real life, effort-rewarding socialization practices occur over years of learning to promote the development of a strong and generalized intrinsic motivation to seek demanding tasks. Such a generalized intrinsic motivation to seek effort has been investigated as a personality characteristic called achievement motive (or hope of success). It predicts task choice and engagement on demanding tasks (18, 19, 28). The present research investigates experimentally the concrete learning mechanisms involved in the development of individual differences in the achievement motive. For explorative reasons, we included self-reported achievement motivation in our analyses and obtained some evidence that even a brief experience with effort-contingent reward in a laboratory setting (Experiment 1) might transiently increase people's self-reported achievement motivation. However, since the effect did not replicate in the online experiments, a stable change of peoples' achievement motive likely requires a more extensive learning phase.

Our results have implications both for theories of motivation and effort as well as for a range of applied domains. Currently, the most elaborate computational framework specifying when effort is recruited and how it is allocated is the expected value of control theory (4). According to this theory, the mobilization of effort depends on the expected value of control, which is a function of the expected payoff of completing a task, the amount of control that must be invested to achieve this payoff, and the intrinsic cost of effortful control. While we agree with this general idea, our present findings indicate the need to expand this theory by including not only a parameter for an intrinsic cost of effort but also for individual differences in the intrinsic value of effort.

If effort-contingent rewards boost intrinsic effort motivation, why then do people often avoid effort and appear to include it as a cost factor in their task choices (2, 3, 5)? Our results would stand in conflict with these findings only if effort in daily life would always lead to reward (as in our experimental group). Even though people may intuitively believe that effort in daily life is typically rewarded and idleness punished, research on effort–performance relationships suggests that this is not generally the case. While investing more effort as compared to disengagement does in fact often improve performance in a given task (e.g., learning for an examination) (29), it is also true that tasks requiring high effort (due to their higher difficulty) involve a greater risk of failure as compared to easier tasks and thus often lead to lower reward (28, 30). Our exploratory analyses of the relation between difficulty, effort, and performance on the *N*-back task confirm this rationale by showing that task difficulty was positively related to effort and negatively related to performance. If in everyday life, reward is based primarily on success, people will learn that high effort signals that a task involves a high likelihood of failure. Consequently, effort becomes a secondary punisher promoting effort avoidance.

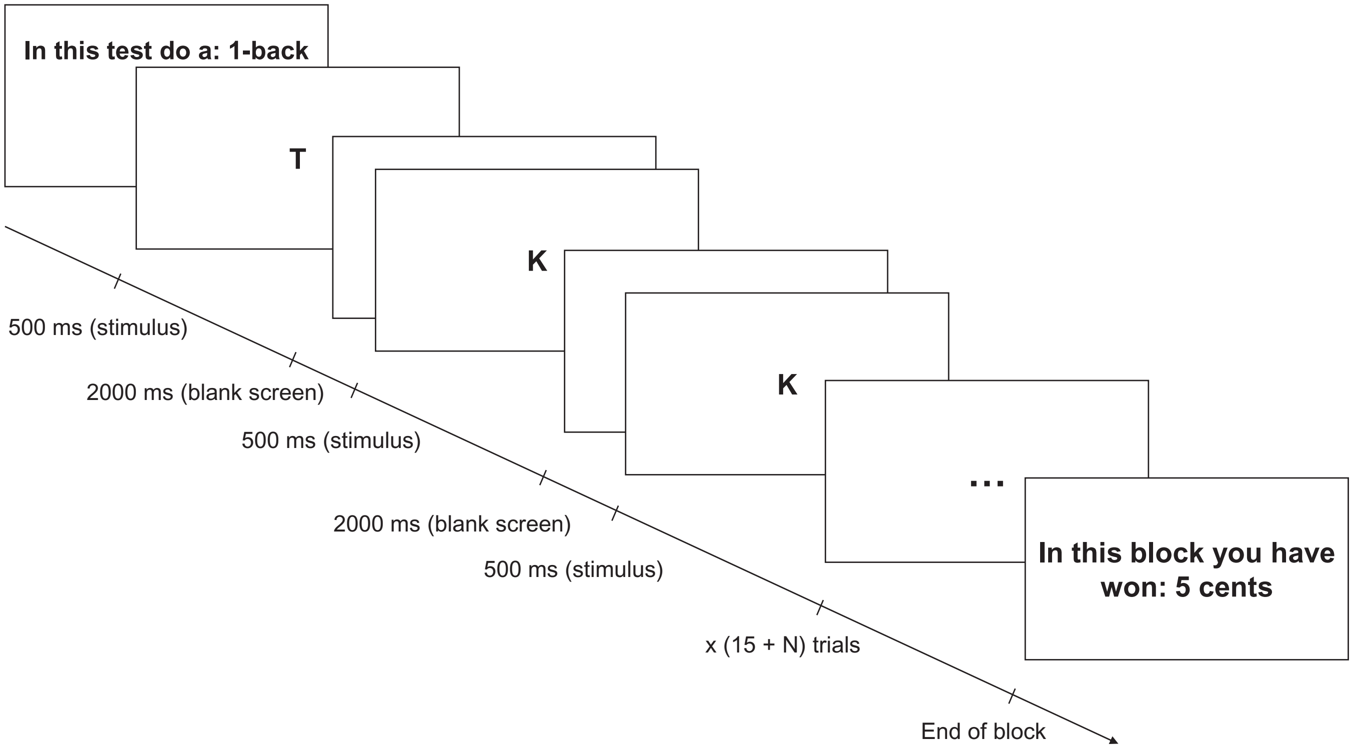

Fig. 5. Protocol for one *N*-back block. Each block consisted of 15+ N letters. CV values were recorded during the entirety of the block.

In most educational and work environments, grades and bonuses are granted for task success and not merely for the exertion of effort per se. This might explain previous findings documenting general tendencies of effort avoidance (2, 3). However, incentive cultures, for example, in educational or occupational settings, that focus more on intraindividual improvement and growth and less on brilliant outcomes may harness the here-described learning mechanism and promote intrinsic effort motivation [e.g., Montessori schools (31) and growth mindset cultures (32)].

Taken together, the present studies provide consistent evidence that even after a short period of experiencing effort-contingent reward, people begin to value effort positively and choose to engage in tasks requiring high-effort exertion in the absence of any extrinsic reward. This calls into question the prominent view of effort exertion as generally costly, which dominates current theories of decision-making and cognitive control in neuroscience and economics (2–4). Humans might not have an inherent tendency to follow the path of least effort. Their inclinations to avoid demanding tasks might be a product of their individual learning histories and the social context rather than a universal law that dooms all ambitious striving to be painful and agonizing.

Methods

All experiments were approved by the Technical University of Dresden ethics committee (EK573122019). All participants provided informed consent before viewing any study materials.

Experiment 1.

Participants. A total of 129 students from a German university participated for course credit or €12. Eight participants from the sample of 129 were excluded due to reasons determined through debriefing. Seven of these participants reported a belief that the experimenter could watch their performance on the MET. One further participant was excluded for thinking that participants would receive a monetary incentive for their performance on the MET. The final sample comprised 121 participants (37 males, 82 females, and two participants who did not provide gender information; $M_{age} = 23.82$, $SD = 6.42$). Participants were divided randomly into either the experimental group ($n = 63$) or control group ($n = 58$) by a computer program.

Cardiovascular measurement. We noninvasively measured impedance cardiogram and electrocardiogram signals with a Cardioscreen 1000 system (Medis) to assess heart rate (HR) and PEP. B-point location was estimated based on the interval between the R peak of the electrocardiogram and the Z peak of the impedance cardiography dZ/dt waveform of valid heartbeat cycles (33). PEP (in milliseconds) was determined as the interval between R onset and B point (34). This is generally accepted as the gold standard for measuring beta-adrenergic activation due to the lack of influence from changes in parasympathetic activity or vascular resistance, as is the case in other common beta-adrenergic activation measures (e.g., systolic blood pressure and HR).

HR was determined on the basis of interbeat intervals assessed with the Cardioscreen system. Additionally, systolic blood pressure (SBP), diastolic blood pressure, mean arterial pressure, and HR were oscillometrically assessed with a Dinamap Carescape V100 monitor (GE Healthcare).

Materials and procedure. Participants were seated at a desk containing a computer monitor and mouse, two consent forms, and a baseline mood checklist. Following the outbreak of the Coronavirus, a third information form concerning health and safety was presented to participants in addition to the other forms. Participants were asked to read over and complete the forms. The checklist consisted of items from the Multidimensional Mood State Questionnaire (Mehrdimensionaler Befindlichkeitsfragebogen; MDBF). Responses were made on five-point scales containing endpoints of 0 (not at all) and 10 (very).

When participants finished, the experimenter returned and placed electrodes and the arm cuff on the participant for CV assessments. The experimenter then explained that the protocol included an initial baseline period. During the baseline period, participants were to sit and listen to a predetermined playlist on YouTube selected for its affectively neutral content. After delivering baseline instructions, the experimenter returned to the control room, started a stopwatch, and made baseline CV assessments. Experimenters recorded CV response continuously during the 10-min period, taking as baseline for each CV parameter the mean of values obtained in the final 2 min.

Once the baseline period was over, the experimenter informed the participant that they would complete two tasks presented to them on the computer. The experimenter stressed that the two tasks would be completed in isolation with the experimenter unable to see their screen or responses to either task. In actuality, the experimenter was able to see an exact mirror of the

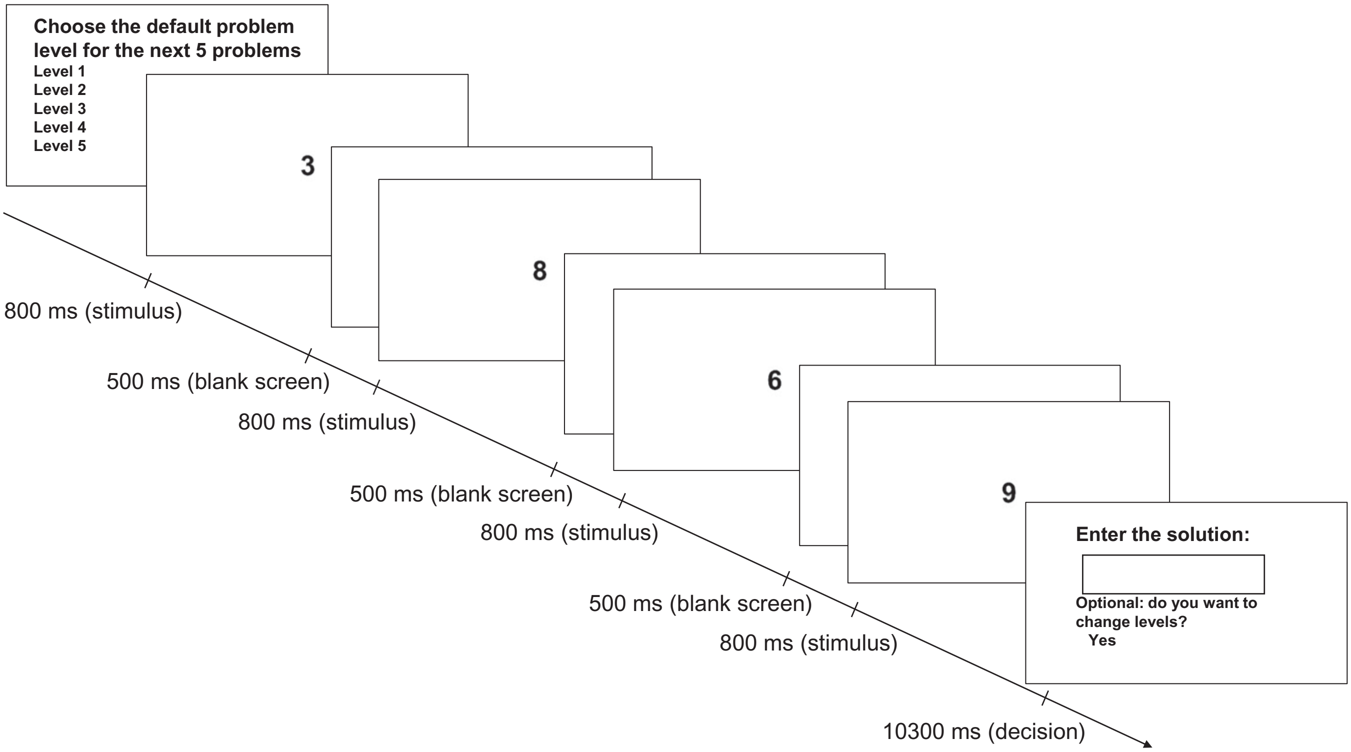

Fig. 6. Protocol for the MET. CV values recorded during the entirety of the task.

participant's screen in the experimental chamber. This piece of deception was included to allow the experimenter to reward the participants based on their effort mobilization, while also controlling for the influence of social desirability on the participant's effort exertion. The experimenter returned to the experimental chamber and noted to which group the program had randomly assigned the participant. From this moment on, no interaction between experimenter and participant occurred until debriefing. The program began with the *N*-back task. Participants first practiced one block at each level of difficulty, receiving feedback on their performance following each block. Finally, they were given the option to repeat the practice if they wished.

Participants then began the actual task, and the experimenter started a stopwatch and began to record CV responses. The *N*-back script was based on the single-task version of the *N*-back procedure (35) (Fig. 5). Participants were shown a sequence of letters and were required to determine whether the current letter was the same as that presented *n* letters ago (such letters are referred to as "targets"). Participants had 2,500 ms to press the "A" key if the letter is a target; no response was required for nontargets. Participants were tested on 15 blocks consisting of five blocks of each 1-, 2- and 3- backs in a randomized order. Participants were made aware that they would earn a reward after completing each block but were not instructed on what determined the reward.

The participants completed the 15 blocks of the learning phase in a randomized order (approximately 15 min.). Following each block, the amount they had earned appeared on the screen. In the experimental group, reward ranges were aligned with the difficulty of the block, with reward ranges increasing with *N*-back difficulty level (1 to 5, 10 to 15, and 40 to 60 ct. for the 1-, 2- and 3- back respectively). The exact amount that participants received from each range on a block was determined by their CV reactivity. This was determined by inputting CV values obtained during the *N*-back task into an Excel spreadsheet that would automatically subtract the average CV response obtained during the final 2 min of a baseline period from the CV responses obtained during approximately four measurement points that occurred during each *N*-back block. The average of these four values determined their CV reactivity score for each block. Depending on the magnitude of reactivity, participants received no reward (only if disengagement was observed through a drop in effort-related CV response as denoted by all CV measures), a small reward (lowest value possible for difficulty range), a medium reward (mean value of difficulty range), or a high reward (highest value possible for difficulty range). Reward determination was primarily made based off of PEP reactivity. During 1-back blocks, PEP reactivity of 0 to −0.5 was provided a low reward, −0.6 to −1.5 was provided a medium reward, and anything less than −1.5 was provided a large reward. During 2-back blocks, PEP reactivity of 0 to −1.5 was provided a low reward, −1.6 to −3.0 was provided a medium reward, and anything less than −3.0 was provided a large reward. During 3-back blocks, PEP reactivity of 0 to −2.5 was provided a low reward, −2.6 to −4.0 was provided a medium reward, and anything less than −4.0 was provided a large reward. The B-point formula used to determine PEP in real time has been shown to correlate highly with hand-determined PEP (33) but can cause errors in specific individuals with unusual morphologies. In these cases, when PEP reactivity scores contradicted the other CV measures, SBP reactivity was instead used to determine incentivization using the same scoring scheme as PEP reactivity. In the control group, participants were offered the same reward ranges (i.e., 1 to 5, 10 to 15, and 40 to 60 ct.) and the same reward amounts (i.e., lowest, mean, or highest value possible from current range). However, the ranges from which the reward was selected and the reward itself was assigned at random, with each reward range and each reward value from that range having a 33.3% chance of occurring. To determine the accuracy of our manipulation, we utilized a hierarchical linear model, which confirmed that mobilized effort only predicted reward in our experimental group (see *SI Appendix, Learning Phase* for detailed results).

While the experimenter was aware of the condition, we do not feel experimenter awareness biased the results of the study for three reasons. 1) The experimenter did not learn of the condition until after they explained how the computer program worked, which was the last time they interacted with the participant until debriefing. 2) The experimenter had no influence on the control condition. 3) The experimenter desired to increase participants' effort seeking, and thus, rewarding participants for more effort mobilization is the only route to achieve such a desired result. If the experimenter was to reward the experimental condition no matter the effort mobilization, individuals would be taught that not trying also produced a large reward, weakening our outcome as opposed to strengthening it (please see *SI Appendix* for additional analyses supporting the relationship between CV reactivity and reward).

Subsequently, the participants completed the MET (23) (Fig. 6). In the MET, participants work through 50 trials of addition problems, each consisting of four numbers displayed one by one on the screen. The numbers in each trial are selected randomly from a range that is determined by the level of difficulty. Level 1 includes numbers 1 to 3, Level 2 includes numbers 3 to 9, Level 3 includes numbers 7 to 15, Level 4 includes numbers 7 to 25, and Level 5 includes numbers 7 to 35. This phase lasted ∼20 min, with CV measurements being made during the entirety of the task.

The program concluded with a series of questionnaires. It started by having participants complete the MDBF again to gauge the effect that the experimental manipulation had on well-being. This was followed by a four-item math self-concept scale to capture the participant's self-report of mathematical capabilities (25). Responses were made on six-point scales containing endpoints of 1 (Strongly disagree) and 6 (Strongly agree) ($\alpha = 0.88$). Next, as a self-report measure of demand seeking, participants completed the revised AMS-R (24). Responses were made on four-point scales containing endpoints of 1 (Strongly disagree) and 4 (Strongly agree) ($\alpha = 0.84$). Finally, a post-task questionaire was administered that asked participants how difficult they found the MET, how enjoyable the overall task was, and how enjoyable it was to complete each level of the MET, with an additional option stating that they had not chosen this level. All questions utilized a four-point scale from *Not at all* to *Very*. The completion of the questionnaires took ~10 min.

When the program finished, the experimenter returned to the experimental chamber for debriefing. After the debriefing, experimenters awarded research credits or €12 base payment. Furthermore, all participants received the full €3 no matter the amount of reward earned during the learning phase.

Experiment 2.

Participants and design. In recent years, serious concerns about research replicability led to suggestions for new approaches to evaluating hypotheses, including conducting internal meta-analyses and focusing on effect sizes and CIs rather than strictly relying on *P* values (see ref. 36). Maner (37) suggests that results of a meta-analysis should hold more weight than inconsistent individual tests of statistical significance (see also ref. 38). With this in mind, we collected data from five samples on Amazon Mechanical Turk and conducted a meta-analysis on the results. The studies were conducted successively over a timeframe of 8 mo. Studies 2b to 2e were preregistered online (https://aspredicted.org/WXA_MZE, https://aspredicted.org/M21_MGH, and https://aspredicted.org/HXG_YQ4, https://aspredicted.org/TTE_URQ).

The calculation of sample size for Studies 2a to 2d was based on an independent samples Student's *t* test with a potentially small effect d = 0.29, $\alpha = 0.05$ (one tailed) and a power of $1 - \beta = 0.80$, suggesting 296 participants. After exclusions, our final samples sizes were 228, 255, 241, and 233, respectively. For Study 2e, a power analysis based on the first four samples was carried out; for an ANCOVA with a small effect size of partial eta squared = 0.015, $\alpha = 0.05$ (one-tailed) and a power of $1 - \beta = 0.80$, 518 participants were required. After exclusions, our final sample size of Study 2e was 500.

According to our preregistered exclusion criteria, participants were required to earn at least 200 cents on the *N*-back task; this measure served to guard against disengagement from the task, which would render our manipulation ineffective.

Materials and procedure. Participants were randomly assigned to one of the two groups (experimental group sample sizes were 107, 138, 129, 113, and 258, control group sample sizes were 121, 117, 112, 120, and 242 in Studies 2a to 2e, respectively) and received detailed instructions on how to complete the *N*-back task. They practiced one block at each level of difficulty, receiving feedback on their performance following each block. They were then given the option to repeat the practice if they wished. Following this, the participants completed the 15 learning blocks in a randomized order, finding out after each block how much they had earned for that block. No feedback was provided concerning their performance. This phase lasted ~15 min.

Subsequently, the participants completed the MET following the same procedure as in Experiment 1. The experiment concluded with the assessment of math self-concept ($\alpha = 0.81$) followed by some additional variables that varied across samples and were included for exploratory purposes. Since they are relevant to the present research question, we do not report them here; however, all data are available at https://osf.io/8pcex/.

Data Availability. Numeric data in cvs format and the R script for analysis have been deposited in Open Sciene Framework (https://osf.io/8pcex/).

ACKNOWLEDGMENTS. We thank Carol Dweck for providing very helpful comments on a previous version of the manuscript.

1. K. A. Ericsson, R. T. Krampe, C. Tesch-Römer, The role of deliberate practice in the acquisition of expert performance. *Psychol. Rev.* **100**, 363–406 (1993).
2. W. Kool, M. Botvinick, Mental labour. *Nat. Hum. Behav.* **2**, 899–908 (2018).
3. W. Kool, J. T. McGuire, Z. B. Rosen, M. M. Botvinick, Decision making and the avoidance of cognitive demand. *J. Exp. Psychol. Gen.* **139**, 665–682 (2010).
4. A. Shenhav *et al.*, Toward a rational and mechanistic account of mental effort. *Annu. Rev. Neurosci.* **40**, 99–124 (2017).
5. A. Westbrook, T. S. Braver, Cognitive effort: A neuroeconomic approach. *Cogn. Affect. Behav. Neurosci.* **15**, 395–415 (2015).
6. T. L. Dunn, C. Gaspar, E. F. Risko, Cue awareness in avoiding effortful control. *Neuropsychologia* **123**, 77–91 (2019).
7. A. Tversky, D. Kahneman, Judgment under uncertainty: Heuristics and biases. *Science* **185**, 1124–1131 (1974).
8. M. Inzlicht, A. Shenhav, C. Y. Olivola, The effort paradox: Effort is both costly and valued. *Trends Cogn. Sci.* **22**, 337–349 (2018).
9. E. Dobryakova, R. K. Jessup, E. Tricomi, Modulation of ventral striatal activity by cognitive effort. *Neuroimage* **147**, 330–338 (2017).
10. K. W. Spence, The role of secondary reinforcement in delayed reward learning. *Psychol. Rev.* **54**, 1 (1947).
11. B. F. Skinner, "Operant conditioning" in *The Encyclopedia of Education*, L. C. Deighton, Ed. (Macmillan and Free Press, 1971), vol. 7, pp. 29–33.
12. J. E. R. Staddon, D. T. Cerutti, Operant conditioning. *Annu. Rev. Psychol.* **54**, 115–144 (2003).
13. M. R. Lepper, D. Greene, R. E. Nisbett, Undermining children's intrinsic interest with extrinsic reward: A test of the "overjustification" hypothesis. *J. Pers. Soc. Psychol.* **28**, 129 (1973).
14. K. Murayama, M. Matsumoto, K. Izuma, K. Matsumoto, Neural basis of the undermining effect of monetary reward on intrinsic motivation. *Proc. Natl. Acad. Sci. U.S.A.* **107**, 20911–20916 (2010).
15. R. Eisenberger, Learned industriousness. *Psychol. Rev.* **99**, 248–267 (1992).
16. R. Eisenberger, J. Carlson, M. Guile, N. Shapiro, Transfer of effort across behaviors. *Learn. Motiv.* **10**, 178–197 (1979).
17. R. Eisenberger, M. Adornetto, Generalized self-control of delay and effort. *J. Pers. Soc. Psychol.* **51**, 1020–1031 (1986).
18. D. C. McClelland, *Human Motivation* (CUP Archive, 1987).
19. D. C. McClelland, D. A. Pilon, Sources of adult motives in patterns of parent behavior in early childhood. *J. Pers. Soc. Psychol.* **44**, 564–574 (1983).
20. P. A. Obrist, Presidential Address, 1975. The cardiovascular-behavioral interaction–as it appears today. *Psychophysiology* **13**, 95–107 (1976).
21. M. Richter, G. H. E. Gendolla, R. A. Wright, *Three Decades of Research on Motivational Intensity Theory* (Elsevier Ltd, 2016).
22. R. M. Kelsey, "Beta-adrenergic cardiovascular reactivity and adaptation to stress: The cardiac pre-ejection period as an index of effort" in *How Motivation Affects Cardiovascular Response: Mechanisms and Applications*, R. A. Wright, G. H. E. Gendolla, Eds. (American Psychological Association, 2012), pp. 43–60.
23. M. Engle-Friedman *et al.*, The effect of sleep loss on next day effort. *J. Sleep Res.* **12**, 113–124 (2003).
24. J. W. B. Lang, S. Fries, A revised 10-item version of the achievement motives scale: Psychometric properties in German-speaking samples. *Eur. J. Psychol. Assess.* **22**, 216–224 (2006).
25. J. Benson, Structural components of statistical test anxiety in adults. *J. Exp. Educ.* **57**, 247–261 (1989).
26. A. Ledgerwood, "New developments in research methods" in *Advanced Social Psychology*, R. F. Baumeister, E. J. Finkel, Eds. (Oxford University Press, ed. 2, 2019), pp. 39–61.
27. K. C. Berridge, T. E. Robinson, Parsing reward. *Trends Neurosci.* **26**, 507–513 (2003).
28. J. W. Atkinson, Motivational determinants of risk-taking behavior. *Psychol. Rev.* **64**, 359–372 (1957).
29. C. C. Stewart, R. A. Wright, S.-K. A. Hui, A. Simmons, Outcome expectancy as a moderator of mental fatigue influence on cardiovascular response. *Psychophysiology* **46**, 1141–1149 (2009).
30. J. W. Brehm, E. A. Self, The intensity of motivation. *Annu. Rev. Psychol.* **40**, 109–131 (1989).
31. A. Lillard, N. Else-Quest, The early years. Evaluating Montessori education. *Science* **313**, 1893–1894 (2006).
32. L. Bian, S.-J. Leslie, M. C. Murphy, A. Cimpian, Messages about brilliance undermine women's interest in educational and professional opportunities. *J. Exp. Soc. Psychol.* **76**, 404–420 (2018).
33. D. L. Lozano *et al.*, Where to B in dZ/dt. *Psychophysiology* **44**, 113–119 (2007).
34. G. G. Berntson, K. S. Quigley, G. J. Norman, D. L. Lozano, "Cardiovascular psychophysiology" in *Handbook of Psychophysiology*, J. T. Cacioppo *et al.*, Eds. (Cambridge University Press, ed. 4, 2017), pp. 183–216.
35. S. M. Jaeggi *et al.*, The relationship between n-back performance and matrix reasoning — Implications for training and transfer. *Intelligence* **38**, 625–635 (2010).
36. G. Cumming, The new statistics: Why and how. *Psychol. Sci.* **25**, 7–29 (2014).
37. J. K. Maner, Let's put our money where our mouth is: If authors are to change their ways, reviewers (and editors) must change with them. *Perspect. Psychol. Sci.* **9**, 343–351 (2014).
38. S. L. Braver, F. J. Thoemmes, R. Rosenthal, Continuously cumulating meta-analysis and replicability. *Perspect. Psychol. Sci.* **9**, 333–342 (2014).