**Mapping the dose–response relationship between monetary reward and
cognitive performance**

Erik Bijleveld¹, Florance N. van Breukelen¹, David de Segovia Vicente¹, and
Dennis J.L.G. Schutter²

¹Behavioural Science Institute, Radboud University

²Department of Experimental Psychology, Utrecht University

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David de Segovia Vicente is now at the Department of Communication
Sciences, Ghent University.

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Correspondence concerning this article should be addressed to Erik
Bijleveld at erik.bijleveld@ru.nl

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Abstract

The relationship between reward value and cognitive performance is often thought to be curvilinear, shaped like an inverted U. Moderately valuable rewards should facilitate, but extremely valuable rewards should harm, performance. Despite the popularity of this idea, the dose–response relationship between reward value and cognitive performance is not yet well-understood. Here we present a set of experiments (total $N = 254$) that examine the effects of monetary reward (no reward, medium reward, extreme reward) on task-switching performance. Overall, more valuable rewards led to better performance. Yet, when physical reward cues were present (i.e., when the money at stake was placed on the table), we observed the predicted inverted-U-shaped relationship. Together, our results suggest that (a) people are often able to maintain good cognitive performance when the stakes are high, and that (b) physical reward cues may play a key role in triggering ‘choking under pressure’.

Keywords: motivation, incentives, Yerkes–Dodson law, meta-control, cognitive flexibility, value-driven attentional capture

Introduction

Monetary rewards boost human performance on a wide variety of tasks across a wide variety of conditions (Frömer et al., 2021; Garbers & Konradt, 2014; Liljeholm & O’Doherty, 2012; Zedelius et al., 2014). At the same time, monetary rewards also have well-documented undesirable effects. One of these effects is *choking under pressure*, i.e., performance impairments that occur when the stakes are very high (Beilock et al., 2004; Mobbs et al., 2009). So, rewards can both boost and impair human performance. To explain this pattern, researchers often assume that the relation between reward value and performance follows an inverted-U: Moderately valuable rewards should facilitate, but extremely valuable rewards, should interfere with performance. This assumption is widely known as the “Yerkes–Dodson law”, also among the general public, which has learned about it through popular science books (Ariely, 2011; Kohn, 1993).

Here we examine the shape of the dose–response relationship between reward value and human performance. We focus on cognitive performance, and we contribute to the literature in three ways:

First, despite that the Yerkes–Dodson law is often used as a post-hoc explanation for various behavioral phenomena (Corbett, 2015; Teigen, 1994), the empirical evidence for its validity is thin. That is, most studies on the link between reward and cognitive performance have used only two levels of reward (e.g., low and high; Chiew & Braver, 2014; Fröber & Dreisbach, 2016; Ruzs et al., 2018), and thus cannot detect nonlinear relationships. The studies that did use three (or more) levels of reward on performance either focused only on motor performance (Chib et al., 2012, 2014; Dunne et al., 2019; Lee & Grafton, 2015) or suffered from methodological limitations (e.g., between-subjects design with small cell sizes; Ariely et al., 2009). Thus, the field needs studies that test the effect of at least three levels of reward—i.e., no reward, medium reward, and extreme reward—on

cognitive performance, preferably within-subjects. Here we report a set of such studies.

Second, we propose that the presence of reward cues—i.e., visual displays of the rewards that are at stake—should affect how rewards impact cognitive performance. This proposal is based on research on *value-driven attentional capture*, which shows that distractors that were previously associated with reward, are more likely to capture attention, and are thus more likely to disrupt the primary task (Anderson et al., 2011; Ruzs et al., 2020). So, the presence of physical reward cues—e.g., coins and banknotes that can be earned—may augment the tendency of (extremely valuable) rewards to impair cognitive performance through distraction. Here we test this possibility.

Third, if extremely valuable rewards can harm cognitive performance, different cognitive control mechanisms may explain this interference effect. Specifically, based on meta-control models (Dreisbach & Fröber, 2019; Eppinger et al., 2021; Hommel, 2015), we assume that rewards can affect cognitive control by biasing the control state towards either *stability* or *flexibility*. On the one hand, studies show that rewards can increase stability (Hefer & Dreisbach, 2017). If this happens, people will be better able to shield their goal (i.e., to follow task instructions) from distractions. However, increased persistence comes at the cost of becoming too rigid when tasks require people to respond to new information, or when people need to switch back and forth between different tasks. On the other hand, rewards can plausibly also increase flexibility. If this happens, people should become better at quickly and accurately responding to new information and switching back and forth between tasks. However, increased flexibility comes at the cost of distractibility (Hommel, 2015); indeed, distraction (by task-irrelevant thoughts) is a mechanism that explains choking under pressure (Beilock et al., 2004; Bijleveld & Veling, 2014). Here we use a rewarded task-switching task, in which we can examine performance impairments stemming from (too much) stability vs. (too much) flexibility.

Experiments 1a and 1b provide a first examination of the dose–response relationship between reward value and cognitive performance. Experiment 1a uses a gain frame and Experiment 1b a loss frame (as gains vs. losses may trigger different speed–accuracy tradeoffs; Leng et al., 2021), but are otherwise identical. Experiment 2 examines whether the presence of physical reward cues changes the shape of the relationship between reward value and cognitive performance. Finally, we provide a pooled analyses of all data that we have collected with this paradigm.

Experiments 1a and 1b

Method

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We preregistered our hypotheses and analysis plans (Experiment 1a: <https://aspredicted.org/ya8tw.pdf>; Experiment 1b: <https://aspredicted.org/tw6ky.pdf>). Materials, data, and analysis scripts are available at <https://osf.io/5368s/>.

Participants and design

To determine sample size, we carried out a simulation-based power analysis (based on pilot data; see Supplementary Information and Green &

MacLeod, 2016), which suggested that we could detect ≥ 50 ms increases in reaction times (RT; for extreme reward vs. medium reward, within-subjects) with $\geq 90\%$ power with 35 participants per study. Effects of at least this magnitude are plausible based on prior work on choking under pressure (van de Groep et al., 2017). To account for potential equipment failure and no-shows, we scheduled 40 participants per study. Thirty-nine participants (28 females; mean age = 21.9) took part in Experiment 1a; 37 participants (28 females; mean age = 22.0) in Experiment 1b. Participants were recruited from the university community.

Both studies had a within-subjects design. All participants carried out an incentivized task-switching task (adapted from van de Groep et al., 2017), which consisted of 3 no-reward blocks, 3 medium-reward blocks, and 3 extreme-reward blocks. In Experiment 1a, rewards were presented as potential gains; in Experiment 1b, as potential losses. The experiments were otherwise identical. All experiments were approved by the local ethics committee.

Task

Participants completed 18 blocks (9 practice blocks, 9 experimental blocks; see below) of 17 trials each. On each trial of the task, a letter and a digit appeared in one quadrant of the screen (Figure 1). In the first trial of each block, these stimuli appeared in the top-left quadrant; in the remaining 16 trials, the stimuli appeared clockwise in the next quadrant. If the stimuli appeared in either of the top quadrants, participants had to do the *letter task*, i.e., they had to indicate whether the letter was a vowel or a consonant. If the stimuli appeared in either of the bottom quadrants, participants had to do the *digit task*, i.e., they had to indicate whether the digit was odd or even. Thus, the task consisted of *repeat trials* on which participants did the same task as on the previous trial and *switch trials* on which participants did the other task.

Participants responded by pressing ‘Z’ (vowel or odd) or ‘M’ (consonant or even) on the keyboard. Letters and digits were drawn randomly from predetermined sets (GKMRAEIU and 23456789). This draw was done with replacement, but with the restriction that letters and digits were never the same as those that were presented on the preceding trial. Each response by participants was followed a 150ms blank screen. After that, the next trial started immediately.

Procedure

After giving informed consent, participants were seated in cubicles. Participants first familiarized themselves with the task by completing 9 practice blocks. After each practice block, participants received feedback on their performance. After practice blocks 1–3, participants received feedback on the total time in which they completed the block (in seconds) and on their accuracy (in number of errors). Before starting practice block 4, participants learned that, from then on, their speed and accuracy would be converted into *points*. Accordingly, after each of the remaining practice blocks (4–9), participants received feedback only on the number of points they scored.

Figure 1. Schematic representation of one block. In each block, participants first learned their point target and the magnitude of the reward. Then, they completed 17 trials. Finally, participants received feedback on their score and their reward.

Points were computed after each block, as follows. We first computed a base score $A = 500 - (\text{total response time in milliseconds} / 100)$. Next, we computed an error penalty $B = 2 * (\text{number of mistakes})^2$. The error penalty reflected the percentage of the base score that participants would lose due to their errors. As such, we computed a final score $S = A * ((100 - B) / 100)$ with $S \leq 0$. Put simply, participants received a higher score when they were faster and/or made fewer errors.

After the practice blocks, participants carried out 9 experimental blocks. In the experimental blocks, participants could earn money (Experiment 1a) or avoid losing money (Experiment 1b) by being fast and accurate. Specifically, before each block, participants saw a target score (in points) and the monetary reward that was at stake (Figure 1). Blocks varied in the value of the reward that was at stake—i.e., participants could earn either *no reward* (€0.00), a *medium reward* (€0.50), or an *extreme reward* (€10.00) by being fast and accurate during that block. Each reward level occurred three times, in random order. Between blocks, there were brief breaks (5 s).

On average, participants needed 17 seconds ($SD = 3$) to complete one block. A rate of €10 per 17 seconds of work translates to ±€2100 per hour. For comparison, the minimum wage in the Netherlands is currently about €10 per hour. Therefore, we felt that a €10-per-block reward could reasonably be described as ‘extreme’ in the context of our task.

Experiment 1a used a *gain frame*. Participants started out with €0. By attaining or exceeding the target score of a block, they earned the amount of money that was at stake at that block. Experiment 1b used a *loss frame*. Participants started out with €31.50. By attaining or exceeding the target score, they avoided losing the monetary reward at stake. As such, in both experiments, participants could earn (or keep) anywhere between €0 and €31.50.

To ensure that the task was challenging for all participants, point targets were set individually, based on performance during the practice blocks. Specifically, the target was the highest score from the 9 practice blocks, with uniform noise (range: –10 to +10 points). The noise was added to make sure that targets would not be exactly the same each block.

Analyses

To preserve the nested structure of our data (trials within participants), we used mixed-level linear models, in which the trial was the level of analysis. We analyzed response times and accuracy separately. For both RTs and accuracy, we started out with a model that included the fixed main effect of trial type (repeat vs. switch) and the fixed main effect of reward value (no reward, medium reward, and extreme reward), to test our primary hypothesis. Then, a secondary analysis, we ran a model that included the trial type $\times$ reward interaction, in addition to the main effects, to examine whether rewards had different effects on repeat vs. switch trials. As for the random effects, we used a maximal model—that is, a model that includes a random intercept and random slopes for all within-subjects predictors (Barr et al., 2013). We chose this random-effects structure to take into account that some people may generally perform better than others, and that some people respond more strongly to reward than others.

All models were implemented using the *lme4* package for R (Bates et al., 2014). Before analyzing RTs, we excluded RTs from trials on which participants were not accurate, and RTs that fell outside 3 SD of the participant's mean (1.6% of trials in Experiment 1a; 1.5% in Experiment 1b). To compute p-values, we estimated degrees of freedom using Satterthwaite's method (Kuznetsova et al., 2017).

We further explored how reward value affected *switch costs* (operationalized as the RT difference between switch and repeat trials). As we had no hypotheses about switch costs, these analyses appear in the Supplemental Material.

Results

Experiment 1a

RTs. Data from Experiment 1a are summarized in Figure 2a. There was a significant main effect of reward on RTs, $\chi^2(2) = 14.00, p < .001$. Specifically, there was no significant difference in RTs between no-reward blocks and medium-reward blocks, $b = -11, SE = 13, t(37.4) = -0.84, p = .409$; however, participants were faster in extreme-reward blocks compared to medium-reward blocks, $b = -40, SE = 15, t(37.7) = -2.58, p = .014$. Furthermore, there was a main effect of trial type, $b = -147, SE = 12, t(37.8) = -12.47, p < .001$, which indicated that participants were faster on repeat trials than on switch trials. The reward $\times$ trial type interaction was not significant, $\chi^2(2) = 4.93, p = .085$, indicating that there was no evidence that the effect of reward was stronger on either of the trial types.

Accuracy. Participants were highly accurate under all conditions ($M = .95$). The main effect of reward was not significant, $\chi^2(2) = 0.20, p = .905$, suggesting that there was no evidence that accuracy depended on the amount of money that could be earned on that block. The main effect of trial type was significant, $b = 0.5, SE = 0.1, z = 5.35, p < .001$, indicating that participants were more accurate on repeat trials ($M = .97$) than on switch trials ($M = .93$). The reward $\times$ trial type interaction was not significant, $\chi^2(2) = 0.94, p = .625$.

Experiment 1b

RTs. Data from Experiment 1b are summarized in Figure 2b. We found a significant main effect of reward, $\chi^2(2) = 14.20, p < .001$. Specifically, participants were significantly faster in medium-reward blocks compared to no-reward blocks, $b = -54, SE = 19, t(34.2) = -2.86, p = .007$. However, there was no significant

difference in RTs between medium-reward blocks and extreme-reward blocks, $b = -15$, $SE = 19$, $t(32.8) = -0.78$, $p = .440$. Furthermore, there was a significant main effect of trial type, $b = -179$, $SE = 15$, $t(36.0) = -12.14$, $p < .001$, which indicated that participants were faster on repeat trials than on switch trials. The reward $\times$ trial type interaction was not significant, $\chi^2(2) = 1.79$, $p = .408$, suggesting that there was no evidence that the effect of reward was stronger on either of the trial types.

Accuracy. Participants were very accurate under all conditions ($M = .95$). The main effect of reward was significant, $\chi^2(2) = 8.66$, $p = .013$. Specifically, participants were slightly more accurate in medium-reward blocks ($M = .95$) and extreme-reward blocks ($M = .95$) compared to no-reward blocks ($M = .94$). The main effect of trial type was significant, $b = -0.5$, $SE = 0.1$, $z = 5.32$, $p < .001$, again indicating that participants were more accurate on repeat trials ($M = .97$) than on switch trials ($M = .93$). The reward $\times$ trial type interaction was not significant, $\chi^2(2) = 1.61$, $p = .447$.

Figure 2. Reaction times (ms) as a function of reward and trial type. Error bars indicate within-subjects confidence intervals (Cousineau, 2005). Light horizontal bars indicate individual subjects' means. 0 = no reward; \$ = medium reward; \$\$ = extreme reward. A) Data from Experiment 1a. B) Data from Experiment 1B.

Discussion

We found no evidence for an inverted-U-shaped relationship between reward value and performance, neither in a gain frame (Experiment 1a) nor in a loss frame (Experiment 1b). Rather, more valuable rewards increased performance. For gains, the increase in performance was clearest between no reward and a medium reward; for losses, the increase in performance was clearest between medium reward vs. extreme reward. This pattern may be explained post-hoc by loss aversion: Losses have a greater subjective impact than gains (Kahneman & Tversky, 1984); so, for losses, performance effects may manifest at comparatively

lower values. We found no evidence that the relationship between reward value and performance had a different shape for repeat trials vs. switch trials.

These results surprised us, as they contradicted previous research on choking under pressure (Ariely et al., 2009; Beilock et al., 2004; Mobbs et al., 2009). Participants were able to perform well despite that extremely valuable rewards were at stake. In fact, under extreme rewards, participants' performance was highest.

Experiment 2

Why did participants perform so well despite the presence of extreme rewards? A potential explanation lies in the fact that, in Experiment 1, participants worked in a sterile, distraction-free environment.

Two lines of research suggest that the presence of physical stimuli that remind people of the extreme rewards at stake, may be a crucial trigger of performance impairments. First, in prior research on choking under pressure, researchers typically used a standardized protocol to induce high motivation (Beilock et al., 2004; Boere et al., 2016; Ramirez & Beilock, 2011). Under this protocol, participants are usually confronted with several cues that remind them that they urgently need to maximize their performance (e.g., a video camera close to the participant; an experimenter delivering scripted reward instructions throughout the session). It seems plausible that these visual aspects of the protocol increase the likelihood of performance impairments. Second, research on *value-driven attention* shows that task-irrelevant stimuli that were previously associated with valuable rewards, are more likely to capture attention, and more likely to disrupt the primary task (Anderson et al., 2011). A meta-analysis of this phenomenon suggests that value-driven attention affects performance on a range of tasks, including cognitive control tasks (Rusz et al., 2020; for an example, see Krebs et al., 2010).

Experiment 2 was similar to Experiment 1b, with the key difference that Experiment 2 introduced a condition in which participants were exposed to reward cues—i.e., to the money that was at stake. In this condition, the coins and banknotes that could be earned was placed on the desk, in view of the participant. We predicted that the drop in performance (from medium to extreme rewards) should be most pronounced when money is on the table.

Method

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We preregistered our hypotheses and analysis plans on aspredicted.org (<https://aspredicted.org/vv6w7.pdf>). Materials, data, and analysis scripts are available at <https://osf.io/5368s/>.

Participants and design

We recruited 80 people (60 females; mean age = 21.6) from the university community to participate in Experiment 2. Participants were randomly assigned to either of the physical-presence-of-money conditions, with the restriction that the distribution of males and females was kept approximately constant between conditions (money on display, $N = 42$, of which 31 females; control, $N = 38$, of

which 29 females). As before, and as preregistered, we excluded trials of which the RT fell outside 3SDs of the participant mean (1.7% of trials).

Experiment 2 was powered to detect drops in performance within-subjects (from medium to extreme reward), separately for both between-subjects conditions. As such, we re-used the results from the power simulation we that did for Experiments 1a and 1b, which suggested that we would need 35 participants per condition to detect ≥ 50 ms increases in RT with 90% power. We aimed for 80 participants in total to consider the possibility of equipment failure and no-shows.

Procedure

Experiment 2 started out in the same way as Experiment 1b. That is, participants were welcomed to the lab, seated in a cubicle, and got familiar with the task by completing 9 practice blocks. However, unlike in Experiment 1b, participants were now told to call the experimenter after they had finished the practice blocks. When they did so, the experimenter entered the cubicle.

Figure 3. Schematic illustration of the setup of Experiment 2. A) Control condition. B) Money-on-display condition.

In the control condition, the experimenter explained to participants that they would start off with €31.50—but that they could lose that money during the experiment. Then, the experimenter sat down next to, and slightly behind, the participant; next, the task began. The experimenter did not do or say anything until the task was finished. At that point, the experimenter paid the participants the money that they did not lose.

In the money-on-display condition, the experimenter placed three €10 bills and three 50c coins on the table, in view of the participant (Figure 3). The experimenter then explained that the money on the table was theirs to take home—but that they could lose that money during the experiment. Then, the experimenter sat down in the same spot as in the control condition; next, the task began.

Whenever participants failed to meet a target during a reward block, the experimenter removed the corresponding amount of money (i.e., one of the €10 bills or one of the 50c coins) from the table. Other than that, the experimenter did not do or say anything until the task was finished. After the experiment, participants were paid the money that was still on the table.

In sum, in both conditions, the experimenter was present in the same cubicle as the participant. The crucial difference was that, in the money-on-display condition, the to-be-earned money was laid out on the table and was being taken away when participants failed to meet their targets on reward blocks.

Analyses

We used the same analytic strategy as in Experiments 1a–b. We fitted a mixed-level linear model with just the main effect of reward, to examine the hypothesized inverted-U across conditions. Then, we added the main effect of physical presence of money and the physical presence of money $\times$ reward interaction. As a secondary analysis, we examined whether the physical presence of money $\times$ reward interaction was different for repeat trials vs. switch trials. All models were maximal models, i.e., models that includes a random intercept and random slopes for all within-subjects predictors (Barr et al., 2013).

Results

RTs

Data from Experiment 2 are summarized in Figure 4. We first estimated the reward–performance relationship across both conditions, using the same analysis we used for Experiment 1—i.e., without taking into account whether the money was on display. In this analysis, the main effect of reward was significant, $\chi^2(2) = 13.49$, $p = .001$. Participants were significantly faster in medium-reward blocks compared to no-reward blocks, $b = -29$, $SE = 12$, $t(78.1) = -2.54$, $p = .013$. However, there was no significant difference in RTs between medium-reward and extreme-reward blocks, $b = -15$, $SE = 12$, $t(76.0) = -1.25$, $p = .216$. The main effect of trial type was significant, $b = -182$, $SE = 11$, $t(78.6) = -16.87$, $p < .001$, indicating that participants were faster on repeat trials than on switch trials.

Figure 4. Reaction times (ms) as a function of reward and trial type. Error bars indicate within-subjects confidence intervals (Cousineau, 2005). Light horizontal bars indicate individual subjects' means. 0 = no reward; \$ = medium reward; \$\$ = extreme reward. A) Control condition; B) Money-on-display condition.

We next tested the prediction that the reward–performance relationship depends on the physical presence of reward cues. To this end, we added the reward $\times$ physical presence of money interaction to the model, which was significant, $\chi^2(2) = 6.76, p = .034$. Specifically, the physical presence of money did not significantly affect the difference between no-reward blocks and medium-reward blocks, $b = 21, SE = 11, t(77.3) = 1.91, p = .060$. However, the physical presence of money did affect the RT difference between medium-reward and extreme-reward blocks, $b = -27, SE = 11, t(75.7) = -2.40, p = .019$. To further interpret this interaction, we inspected the pattern of means (Figure 4). This inspection suggested that the pattern of results was different for switch vs. repeat trials. Thus, we proceeded by testing the effects of reward and physical presence separately for switch trials vs. repeat trials¹:

Among switch trials, there was a main effect of reward, $\chi^2(2) = 9.21, p = 0.010$, showing that participants were faster when more money was at stake (Figure 4, pink lines), but this effect was not moderated by the physical presence of money, $\chi^2(2) = 0.69, p = 0.708$.

¹ An alternative way to test whether the effects of reward value were different for repeat trials and switch trials is to examine the reward $\times$ trial type interaction within each of the physical presence of money conditions. As our preregistration was not specific on this issue (i.e., we planned to examine if the predicted U-shape would be more pronounced on either of the two trial types), we also tried this alternative strategy. To summarize, we found that trial type interacted with reward (medium vs. extreme) in the money-on-display condition, $b = 35, SE = 16, t(52.4) = 2.20, p = 0.032$, but not in the control condition, $b = 5, SE = 13, t(139.5) = 0.36, p = .719$.

Among repeat trials, the main effect of reward, $\chi^2(2) = 10.97$, $p = .004$, was qualified by the reward $\times$ physical presence of money interaction, $\chi^2(2) = 15.13$, $p < .001$. Specifically, when money was *not* physically visible (Figure 4, left panel, orange line), there was no evidence for a RT difference between medium-reward blocks vs. no-reward blocks, $b = -12$, $SE = 18$, $t(40.3) = -0.64$, $p = .524$; and participants were somewhat faster in extreme-reward blocks vs. medium-reward blocks, $b = -37$, $SE = 17$, $t(40.2) = -2.16$, $p = .037$. Thus, if anything, when money was not on the table, on repeat trials, people become faster when more money was at stake. However, when money was physically visible, mean RTs for repeat trials showed a U-shaped pattern (Figure 4, right panel, orange line). That is, participants were faster in medium-reward vs. no-reward blocks, $b = -71$, $SE = 18$, $t(68.4) = -3.97$, $p < .001$; yet, participants were slower in extreme-reward vs. medium-reward blocks, $b = 49$, $SE = 18$, $t(59.7) = 2.68$, $p = .010$.

Accuracy

As in Experiment 1, participants were highly accurate under all conditions ($M = .95$). As we did for RTs, we first estimated the incentive–performance relationship across both treatments, akin to the analysis that we used for Experiment 1. In this analysis, the main effect of reward was not significant, $\chi^2(2) = 1.39$, $p = .499$. The main effect of trial type was significant, $b = -0.4$, $SE = 0.1$, $z = -8.17$, $p < .001$, indicating that participants were more accurate on repeat trials ($M = .97$) than on switch trials ($M = .93$). As we did for RTs, we then added the reward $\times$ physical presence of money interaction to the model, which was not significant, $\chi^2(2) = 1.58$, $p = .454$.

Pooled analysis

We pooled data from all experiments, including two pilot experiments that were nearly identical to Experiments 1a and 1b (see Supplementary Online Material, to provide our best estimate of the dose-response relationship between reward value and cognitive performance (total $N = 254$). We used the same analyses as before, but we now also included five dummy variables to model potential differences between the six independent datasets (i.e., Experiments 1a, 1b, the two between-subjects conditions of Experiment 2, and the two pilot studies; Borenstein et al., 2009, p. 317). This pooled analysis was not pre-registered; p -values should be interpreted with caution.

Results

RTs

Pooled data are summarized in Figure 5. The main effect of reward was significant, $\chi^2(2) = 59.26$, $p < .001$. Specifically, on average, people were faster in medium-reward than in no-reward blocks, $b = -34$, $SE = 6$, $t(246.7) = -5.45$, $p < .001$, and they were faster in extreme-reward blocks than in medium-reward blocks, $b = -15$, $SE = 6$, $t(240.5) = -2.50$, $p = 0.013$. The main effect of trial type was also significant, $b = -174$, $SE = 6$, $t(252.6) = -30.20$, $p < .001$. These main effects were qualified by the reward value $\times$ trial type interaction, $\chi^2(2) = 11.90$, $p = .003$. This interaction was driven by the fact that the decrease in RT between medium-reward and extreme-rewards blocks was somewhat more pronounced on switch trials than on repeat trials, $b = 11$, $SE = 5$, $t(634.5) = 2.27$, $p = 0.023$.

Figure 5. Reaction times (ms) as a function of reward and trial type. Error bars indicate within-subjects confidence intervals (Cousineau, 2005). Light horizontal bars indicate individual subjects' means. 0 = no reward; \$ = medium reward; \$\$ = extreme reward.

Accuracy

We found a significant main effect of reward, $\chi^2(2) = 7.63$, $p = .022$. Participants were slightly more accurate in medium-reward blocks ($M = .96$) and extreme-reward blocks ($M = .96$) than they were in no-reward blocks ($M = .95$). There was an effect of trial type, $b = -0.5$, $SE = 0.0$, $z = -13.23$, $p < .001$, indicating that people were more accurate on repeat trials ($M = .97$) than on switch trials ($M = .94$). The reward value $\times$ trial type interaction was not significant, $\chi^2(2) = 0.64$, $p = .726$.

Discussion

When considering all data together, we find no evidence for an inverted-U shaped relationship between reward value and performance. Instead, people typically performed better when they could earn greater amounts of money, even when this amount was extreme.

General Discussion

Our findings showed that both medium and extreme rewards increased performance. Although unexpected, this finding mirrors previous studies on acute stress, which show that people can often maintain good cognitive performance under high-stress conditions (Plessow et al., 2017). Our studies suggest that, when extreme rewards are at stake, 'choking under pressure' may not be the default outcome—neither on switch trials nor on repeat trials. So, in general, we find no evidence that extreme rewards make people overly rigid or overly flexible during task switching. As an exception to this rule, Experiment 2 showed the anticipated inverted-U shaped relationship—i.e., medium rewards increased, but extreme

rewards decreased, performance. The inverted-U was evident only when the money that could be earned was placed in full view of the participant. Moreover, the inverted-U emerged only on repeat trials.

Besides that it provides a characterization of the dose–response relationship between reward value and cognitive performance, our research contributes to the literature in two ways:

First, our findings suggest that visual reminders of the rewards at stake—here, in the form of the money that can be earned—may be a necessary condition for choking under pressure to occur during cognitive tasks. Though novel, this suggestion may be reconciled with mainstream models of choking under pressure. Specifically, models of choking under pressure suggests that extreme rewards may trigger task-irrelevant thoughts (e.g., “I really need to perform well now, otherwise I miss out on that money”), which take up working memory capacity, which in turn reduces the capacity that is available for carrying out the task (Beilock et al., 2004; Beilock & Carr, 2005; Bijleveld & Veling, 2014). Such *distraction theory*, however, is agnostic regarding how these task-irrelevant thoughts are triggered. Our findings suggest that task-irrelevant thoughts do not appear out of thin air—rather, they may be triggered by visible reminders of what is at stake (Anderson et al., 2011; Bijleveld et al., 2011; Rusz et al., 2020). In addition, our findings suggest that visual reward cues may harm performance through low-level visual processes (e.g., oculomotor capture by reward cues, Watson et al., 2019). This possibility constitutes an important avenue for further research.

The possibility that reward cues trigger choking under pressure affords a new look at the experimental protocol that is often used to induce choking under pressure in the laboratory (Beilock et al., 2004; Beilock & Carr, 2001; Boere et al., 2016; Ramirez & Beilock, 2011). In this protocol, the experimenter explains to participants that they will earn money only if they perform 20% better than they had previously, and that some other participants’ payment also depends on their performance. In addition, the experimenter sets up a video camera, and explains that the recordings will be shown to “some professors and teachers” from the area, “who are interested in understanding the mechanisms behind good performance” (Ramirez & Beilock, 2011). Although this protocol differs from ours, a key feature is that it contains visual reminders of the importance of performing well (e.g., the experimenter being present throughout, the video camera). Our findings suggest that these visual reminders may be a key working ingredient of this previous protocol.

Second, the predicted inverted-U only emerged on repeat trials. If we interpret this finding in terms of meta-control models (Eppinger et al., 2021; Hommel, 2015), extreme rewards seem to have biased people’s control state towards flexibility. Although this bias facilitates performance on switch trials, it also impairs people’s ability to maintain a stable task representation, increasing distractibility and impairing performance on repeat trials. The latter idea resonates with the aforementioned models of choking under pressure that assume a key role for distraction (Beilock et al., 2004).

Limitations

Although we found that participants were generally able to maintain good performance when extreme rewards were at stake, we should note that we explored only a small part of parameter space. It is conceivable that keeping up good

performance under extreme-reward conditions is more difficult to do in different cognitive control tasks, for example, in tasks in which certain trial types occur rarely or unpredictably (Gonthier et al., 2016). Moreover, our sample consisted of college students who are used to performing during high-stakes exams. Such high-stakes practice may have made them relatively resistant to the adverse effects of extreme incentives (Nieuwenhuys & Oudejans, 2011).

Conclusion

Popular science writers often caution against the use of monetary rewards, usually because of their harmful side effects (Kohn, 1993; Pink, 2011). Our research paints a more nuanced and more optimistic picture. We conclude that monetary rewards may trigger choking under pressure, perhaps especially when people are continuously reminded of those monetary rewards. However, this does not happen by default: monetary rewards—even when they are extreme—may well boost, rather than harm, performance on mental tasks.

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