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Case Report

Do people avoid mental effort after facing a highly demanding task?☆

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ABSTRACT

Ego depletion effects are usually examined in a sequential task paradigm in which exerting mental effort in a first task is thought to affect performance on a subsequent self-control task. A so-called ego depletion effect is observed if performance on the second task is impaired for the high demand relative to the low demand group. The present studies take a different approach. Instead of measuring performance in the second task that is equally difficult for all participants, the present studies investigated effects of effortful exertion on the choice to willingly exert effort on a subsequent task. Three pre-registered studies investigated if participants select less effort demanding math problems for upcoming tasks compared to a control group after exerting mental effort in an initial task. Results were mixed. Study 1 ($N = 86$) revealed no significant effect of mental effort exertion on mean choice difficulty. In Study 2 ($N = 269$), the expected effect emerged in an exploratory analysis when controlling for math self-assessment, which was robustly associated with the choice measure. Study 3 ($N = 330$) descriptively, albeit non-significantly replicated this result. An internal random-effects meta-analysis revealed a small overall effect of $g = 0.18$ when accounting for math self-assessment, albeit with large heterogeneity. Exploratory analyses point to the importance of the subjective experience of mental effort in effort-selection paradigms. We discuss the implications of the small overall effect size for future research and the possibility to examine effort choice in everyday life.

1. Introduction

A prominent hypothesis suggests that the initial exertion of self-control impairs subsequent self-control performance in various domains including emotion regulation, resistance to tempting but unhealthy food, or alcohol consumption. As these effects may impact on spheres like aggression, overweight, addiction, and other major threats to personal relationships, health, and wealth, exploring when and why self-control fails is relevant for individuals and society at large. Effects of self-control exertion on subsequent behavior are usually examined using a sequential task paradigm: Participants engage in a task either high or low in self-control demands. Subsequently, self-control performance is measured in a second task. If participants in the high demand group show impaired performance relative to participants in the low demand group, a so-called ego depletion effect is observed (for meta-analyses, see Blázquez, Botella, & Suero, 2017; Dang, 2018; Hagger, Wood, Stiff, & Chatzisarantis, 2010). The present studies explore a somewhat different approach. Rather than assessing self-control performance in the second task, the present studies examined whether facing mental demand influences the self-imposed choice of mental effort. Specifically, we tested the hypothesis that after high demand people would avoid mental effort by choosing less demanding variants of the second task.

Self-control is defined as "…the ability to override or change one's inner responses, as well as to interrupt undesired behavioral tendencies (such as impulses) and refrain from acting on them" (Tangney, Baumeister, & Boone, 2004, p. 274). According to a prominent idea, people who exert self-control in a first task perform poorer on subsequent self-control demanding tasks (Baumeister & Vohs, 2016).

Several hundred studies seemingly support the ego depletion idea. In recent years however, ego depletion research has been heavily criticized based on conceptual and empirical deficiencies (e.g. Carter, Kofler, Forster, & McCullough, 2015; Carter & McCullough, 2014; Gieseler, Loschelder, & Friese, 2019; Hagger et al., 2016; Lurquin et al.,

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2016; Osgood, 2017). These discussions culminated in questioning the very existence of ego depletion effects (for an overview, see Friese, Loschelder, Gieseler, Frankenbach, & Inzlicht, 2019). One possibility to move ego depletion research forward is to think about new ways the psychological processes presumably triggered by exerting mental demand may play out.

Ego depletion effects have mostly been investigated using the so-called sequential task paradigm: Participants engage in a first task requiring a little versus a lot of self-control; the second task measures participants' self-control performance on tasks with fixed difficulty such as interference in a Stroop task or performance on a hand grip task (e.g., Bray, Martin Ginis, Hicks, & Woodgate, 2008; Gieseler, Loschelder, Job, & Friese, in press; Luethi et al., 2016). Using self-control performance in tasks with fixed difficulty as the dependent variable is *one* possible—but perhaps not always optimal—strategy to examine ego depletion effects. For example, ego depletion effects may be masked when participants realize that performance is key and mobilize extra effort to perform well (for an overview on moderators of ego depletion effects, see Loschelder & Friese, 2016).

Furthermore, ego depletion effects may manifest differently than in impaired self-control performance. In daily life, people are often free to choose their next activity or the situation they want to enter after completing a demanding task. They can select from many available alternatives and potentially avoid continued high demands. There may be a difference between what people are able as opposed to willing to show after exerting self-control. This implies that the tendency to selectively seek out versus avoid mentally demanding activities after the exertion of self-control may be an alternative viable and potentially subtler indicator of ego depletion effects.

1.1. Theoretical and empirical grounds for the hypothesis

Several theoretical models support the prediction that after an initial demanding task people will tend to prefer less demanding activities instead. The process model of self-control (Inzlicht & Schmeichel, 2012; Inzlicht, Schmeichel, & Macrae, 2014) assumes that people are less willing to exert effort after initially engaging in demanding tasks. Instead, they seek to do something more pleasurable and rewarding. This suggests that after exerting effort, people will invest less in a subsequent demanding task and consequently perform poorer. It also suggests that, when given the choice, people will choose to not be confronted with further demanding tasks. The opportunity cost model (Kurzban, Duckworth, Kable, & Myers, 2013) proposes that people estimate opportunity costs in terms of possible alternatives to a task at hand. If the opportunity costs for a given task are higher than the relative utility of the next best action, people should disengage and prioritize the alternative task. If given the choice between levels of increasing difficulty, people should choose easier levels if the opportunity costs of the harder levels are high—for instance because of high mental demand of the preceding task and the resulting perception that only a limited amount of is justified for the expected credit.

The labor/leisure tradeoff concept (Kool & Botvinick, 2014) makes a similar assumption: People strive for balance of labor (e.g., cognitive effort) and leisure (e.g., mind-wandering). Thus, participants who have worked on a highly demanding task should favor less demanding variants of following tasks. Finally, the revised version of the strength model of self-control (Baumeister & Vohs, 2016) could account for the same prediction. The model predicts that after engaging in demanding activities, people are inclined to conserve the precious limited self-control resource. One possible way would be to choose easier levels of the subsequent task if given the opportunity.

Apart from the substantive theoretical basis, some empirical research provides suggestive evidence for this idea. In one study, people low (compared to high) in trait self-control chose low (vs. high) demanding task options more often (Kool, McGuire, Wang, & Botvinick, 2013). In another study, participants who had engaged in a demanding task were more likely to rely on heuristics, a means to spare mental effort (Pohl, Erdfelder, Hilbig, Liebke, & Stahlberg, 2013). In a study examining hypothetical effects of exerting effort, participants who *imagined* being depleted after an exhausting day chose less cognitively and emotionally demanding and more funny film alternatives compared to participants who imagined being energetic (Eden, Johnson, & Hartmann, 2018). Finally, one study suggests that self-reported effort avoidance may partly mediate ego depletion effects (Sjåstad & Baumeister, 2018). These studies provide scattered evidence for the hypothesis, even though they are mostly based on fairly small samples and to date none of these findings has been replicated. As of yet, there has been no systematic examination of ego depletion effects on the subsequent selection of demanding versus less demanding tasks presented as such.

1.2. The present research

The present studies examined the hypothesis that engaging in a mentally demanding first task leads to the selection of less effortful subsequent activities. To this end—after the manipulation of mental demand—we provided participants with multiple choices to exert versus avoid mental effort by repeatedly letting them choose the difficulty of upcoming tasks.[1]

We expected self-reported experienced mental demand to be higher in the *high* as compared to the *low mental demand condition*. Furthermore, we expected participants to more frequently select easier alternatives in the *high* as compared to the *low mental demand* condition in a subsequent math effort task.[2] In all three studies, we report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in this manuscript or the online supplementary material (Simmons, Nelson, & Simonsohn, 2012). In the main manuscript, we report only variables relevant for the pre-registered analyses. The online supplementary material also contains additional descriptive and inferential statistics, for instance concerning implicit theories about willpower (Job, Dweck, & Walton, 2010) or trait self-control (Tangney et al., 2004).

2. Study 1

2.1. Method

2.1.1. Pre-registration and sharing

The pre-registration, all materials, data, and code can be accessed at osf.io/f78xa/.

2.1.2. Participants and design

We pre-registered to collect an initial sample of $N = 80$ and to then (a) assess our financial and human resources and (b) compute the Bayes Factor (BF) for the effect of mental demand on effort choice to decide whether or not we would proceed data collection (Bayes Factor Design Analysis, Schönbrodt & Wagenmakers, 2018). The empirical $BF_{01} = 0.52$ indicated that the data were 1.92 times more likely under the null than under our directional hypothesis (Ly, Verhagen, & Wagenmakers, 2016). As our feasibility limit given time and resources was reached, we tested all persons who had already registered and

[1] Initially, ego depletion effects were expected to occur specifically after the exertion of self-control (i.e., the inhibition of dominant response tendencies). Over the years, the range of manipulations used to elicit ego depletion effects broadened to behaviors that more generally can be described as mentally demanding (e.g., working memory tasks, Schmeichel, 2007; Inzlicht et al., 2014). We therefore use the term “mental demand” instead of “self-control”.

[2] Overall, we conducted 4 studies using this dependent variable. One study is not reported here because the self-reported mental effort measures that we used as a manipulation check revealed that the manipulation of mental demand was not successful, precluding a test of the hypothesis (osf.io/5b32j/).

stopped data collection. We did not run any frequentist analyses before terminating data collection.

The final sample consisted of 86 participants (98.85% students, no psychology students, $M_{\text{age}} = 23.69$, $SD_{\text{age}} = 3.62$, 79.07% female). We used a between-participants design with two conditions (*high* vs. *low mental demand*). Sensitivity analyses using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) revealed a statistical power of 1-β = 0.80 (0.70, 0.60) to detect an effect of $d = 0.54$ (0.47, 0.41) or larger (directional hypothesis).

2.1.3. Procedure

Up to four participants were assigned to the same experimental condition. Upon their arrival at the laboratory, they filled in an informed consent explaining that they would work on several tasks on the computer and started the experiment via the experimental software (Inquisit 5, 2016). They then read the general instructions, agreed to participate conscientiously and filled in several questionnaires including the first assessment of mental fatigue. After a short practice phase for the second task (dependent variable), the instructions for the first task (manipulation of mental demand) were given both orally and in writing. Next, we assessed self-reported mental effort that also served as a manipulation check, and mental fatigue. This was followed by the dependent task and questions concerning mental fatigue, subjective effort, and concentration during this task. Finally, participants worked through questionnaires, including self-rated math self-efficacy and ability. Then they were debriefed, paid (5€/35–40 min), and thanked. In addition, the experimenter was there to answer any remaining questions.

2.1.4. Mental demand manipulation

Participants watched funny film clips (11 min, self-created compilation). Participants in the *high mental demand* condition were instructed to suppress all felt and expressed emotions; participants in the *low mental demand* condition were instructed to watch the clips as they would do at the movies (Dang, 2018; Friese, Binder, Luechinger, Boesiger, & Rasch, 2013).[3]

2.1.5. Measured variables

2.1.5.1. Self-reported mental effort. After the emotion suppression task, participants answered the questions "How exhausting did it feel to work through the task?" and "How much did you have to concentrate during the task?" as compared to a 30-min math exam (1 = *much less than in an exam* to 7 = *just like in an exam*; $\rho = 0.83$, Eisinga, te Grotenhuis, & Pelzer, 2013). This measure served as a manipulation check.

2.1.5.2. Math effort task. The math effort task consisted of 60 addition problems. Each problem comprised four numbers displayed one-by-one in the middle of the screen while participants had to update the sum in their head. Each number was presented for 1 s (inter-stimulus interval = 500 ms). When the last number disappeared, participants were given 10.3 s maximum to enter the sum of the presented numbers (time specifications based on Engle-Friedman et al., 2003).

There were five levels of increasing difficulty presenting numbers in the range of 0–2 (Level 1), 2–8, 6–13, 10–25, and 12–35 (Level 5). Participants chose the difficulty level for each upcoming block of 3 problems, respectively, resulting in 20 choices (see Fig. 1). Accuracy feedback was not provided. The primary dependent variable was the mean difficulty-level across the 20 choices.

At the beginning of the study, prior to the mental demand manipulation, participants worked on five practice problems, one of each level, to form an impression of the difficulties. During this practice phase, feedback was provided after each problem ("correct"/"false").

[3] Due to copyright reasons we cannot make the video publicly available. It is available upon request to the first author.

2.1.5.3. Math self-efficacy. Participants indicated their math self-efficacy on two items: "In general, I am confident that I can add several two-digit numbers in my head" and "In general, I'm good at adding several two-digit numbers in my head" (1 = *strongly disagree* to 7 = *strongly agree*; $\rho = 0.88$).

2.1.5.4. Self-rated math ability. Participants rated their math ability on three items (e.g., "I am good at math", 1 = *strongly disagree* to 7 = *strongly agree*, $\alpha = 0.84$).

2.2. Results

2.2.1. Pre-registered confirmatory analyses

As expected, self-reported mental effort was higher in the *high* compared to the *low mental demand* condition ($M_{\text{low}} = 2.19$, $SD = 1.54$, $M_{\text{high}} = 3.58$, $SD = 1.77$; mid-point = 4; $t_{one\text{-}sided}$ [83.29] = −3.89, $p < .001$, $d = -0.84$, 95% CI [$-\infty$, −0.39]).

Against our expectations, participants in the *high mental demand* condition did not select easier levels than participants in the *low mental demand* condition, but even slightly more difficult levels ($M_{\text{low}} = 2.82$, $SD = 0.61$, $M_{\text{high}} = 2.93$, $SD = 0.67$; $d = -0.16$, 95% CI [−0.59, 0.27]).

2.2.2. Non-pre-registered analyses

After excluding two multivariate outliers (studentized residuals > |3|, all others < |2|), there was an interaction between the mental demand condition and math self-efficacy ($b = 0.33$, 95% CI [0.12, 0.54], $t = 3.13$, $p = .002$): Simple slopes analyses revealed that, as expected, the mental demand condition descriptively predicted easier math effort choices for participants 1 *SD* below the mean of math self-efficacy, but the effect was not significant ($b = -0.26$, $SE = 0.15$, $p = .080$). For participants 1 *SD* above the mean of math self-efficacy, stronger mental demand led to *more difficult* choices in the math effort task ($b = 0.40$, $SE = 0.15$, $p = .009$; see Fig. 2 & Table 1).

Choices in the math effort task were robustly correlated with both self-reported math self-efficacy and math ability (see online supplementary material). Thus, these variables may exert an influence on the dependent variable that is not of interest to the present research question. We therefore repeated the main analysis controlling for both math self-efficacy and math ability by first residualizing math effort task choices of these scores. This analysis also revealed no significant difference in effort choices as a function of mental demand ($d = -0.06$, 95% CI [−0.49, 0.37]).

2.3. Discussion

Even though participants in the high mental demand condition rated the emotion suppression task as relatively more mentally demanding than participants in the low demand condition, they nevertheless perceived the task as relatively easy given that, on average, mental demand ratings remained below the mid-point of the scale. This suggests that the mental demand manipulation may not have been strong enough, which could explain why participants in the *high* compared to *low mental demand* condition did not choose easier levels in the math effort task. Exploratory analyses revealed that *high mental demand* led to descriptively, but non-significantly easier choices in the math effort task in participants low in math self-efficacy, but to more difficult choices in participants high in math self-efficacy. We neither expected this interaction nor its specific pattern and the sample size was small. This effect should therefore be interpreted with caution.

Analyses reported in the online supplementary material showed a pronounced tendency to choose the three middle categories, especially the intermediate level. This may have masked an effect of the experimental condition as people generally tend to prefer middle options (Missbach & König, 2016; Simonson, 1989). Providing an even number of difficulty levels and thereby forcing participants to choose between

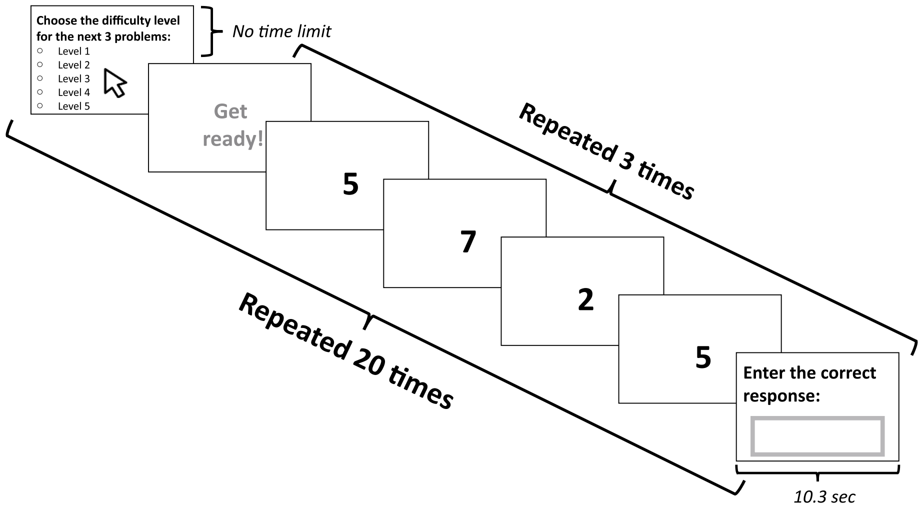

Fig. 1. Flow diagram of the math effort task. Participants chose the difficulty level for each batch of three addition problems. In total, they made 20 decisions, which corresponds to 60 addition problems. The addition problem shown for illustrative purposes corresponds to Level 2: 5 + 7 + 2 + 5 = 19. Numbers were presented for 1 s, inter-stimulus interval = 500 ms.

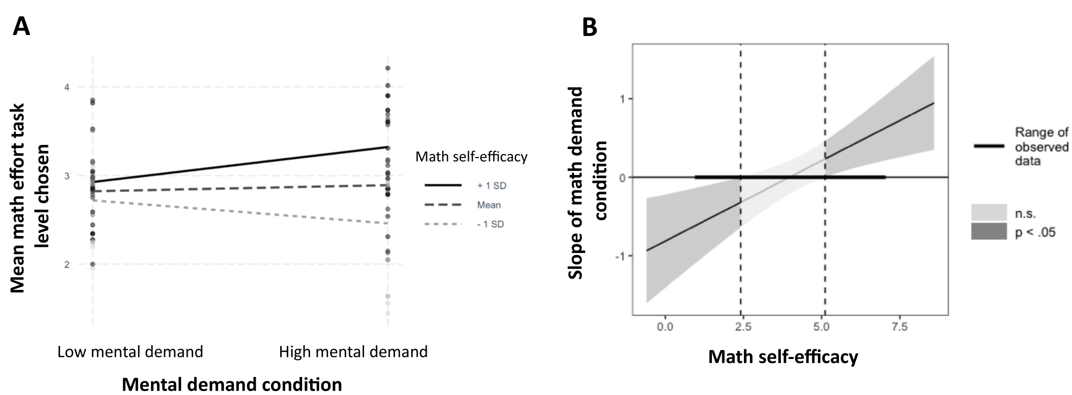

Fig. 2. A) Interaction between the predictor variable mental demand condition and the moderator variable self-reported math self-efficacy on the mean level chosen in the math effort task. High mental demand led to easier math effort choices for participants 1 *SD* below the mean of math self-efficacy, but the effect was non-significant at this value of the moderator variable. For participants 1 *SD* above the mean of math self-efficacy, high mental demand led significantly to more difficult choices in the math effort task. Two multivariate outliers were excluded from the analysis. B) Regions of significance of the effect of mental demand condition on mean level chosen in the math effort task as a function of math self-efficacy (Johnson-Neyman plot). This figure illustrates in greater detail than Fig. 2A for which values of the moderator math self-efficacy the effect of the predictor mental demand condition on the dependent variable mean level chosen in the math effort task is statistically significant. The solid diagonal line represents the regression coefficient of the mental demand condition on the mean level chosen in the math effort task along the math self-efficacy continuum. The grey-shaded confidence bands reflect 95% confidence intervals around the regression coefficient. The effect of the mental demand condition on choices in the math effort task is statistically significant left of the left dashed vertical line and right of the right dashed vertical line (i.e., the confidence bands do not include zero). Within this interval of math self-efficacy values [2.41, 5.11] the effect is not significant (i.e., the confidence bands include zero). Two multivariate outliers were excluded from the analysis.

Table 1
Math self-efficacy: moderation of the effect of mental demand condition on math effort choice in Study 1.

	b	*SE B*	*t*	*p*
Mental demand condition	0.07	0.10	0.65	.516
Math self-efficacy	0.10	0.08	1.34	.184
Mental demand condition × math self-efficacy	0.33	0.11	3.13	.002

Note. N = 84. R^2 = 0.33. Two multivariate outliers excluded: studentized residuals > |3|, all others < |2|. Continuous predictors are mean-centered and scaled by 1 *SD*.

options that are clearly on the more versus less effortful half of options may circumvent this issue.

3. Study 2

Study 2 addressed several issues of Study 1. First, we used an adaptive mental demand manipulation that continuously adjusted the difficulty to each participants' skill level to ensure a strong manipulation for each participant. Second, we sought to explore whether the unexpected interaction between experimental condition and math self-efficacy would replicate. Third, we recruited a much larger sample that allowed for adequate statistical power for smaller effect sizes.

3.1. Method

3.1.1. Pre-registration and sharing

The pre-registration, all materials, data, and code can be accessed at osf.io/sk9e5/.

3.1.2. Participants and design

We pre-registered to collect a sample of 300 participants on Amazon's Mechanical Turk. Participants received $3.60 for their participation. Although we put emphasis on our age restrictions in the study description, 31 participants indicated being older than our pre-registered criterion (18 to 35 years) and had to be excluded. The final sample thus consisted of N = 269 participants (M_{age} = 29.13, SD_{age} = 3.86, 46.47% female). A sensitivity analysis (N_{high} = 144,

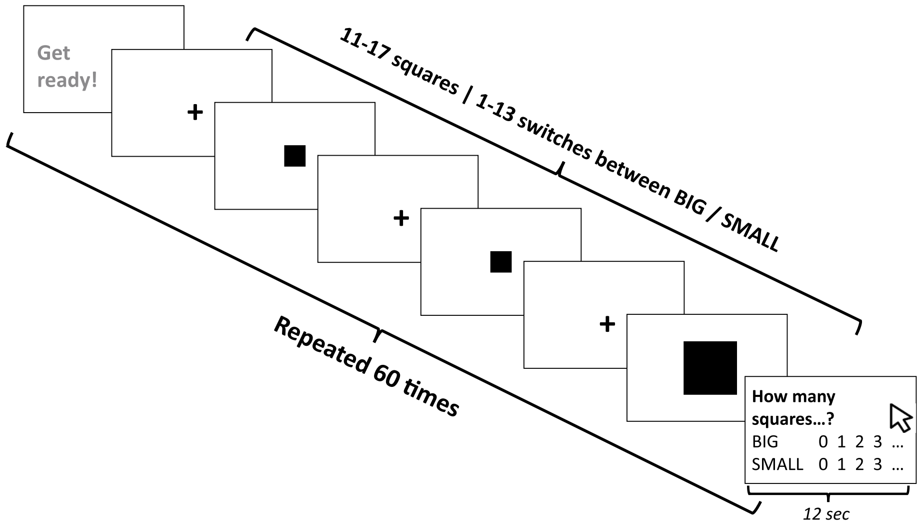

Fig. 3. Flow diagram of the symbol counter task used in Studies 2 and 3. Participants had to keep track of the number of small and big squares presented sequentially on the screen. The difficulty of the task (number of squares presented in a row, switches between big and small squares, length of presentation of each square) was continuously adapted for each participant based on the performance during the task to ensure a task difficulty at the border of what was feasible for the respective participant. Task adapted from Lin et al. (in press).

N_{low} = 125) using G*Power (Faul et al., 2007) revealed a statistical power of 1-β = 0.80 (0.70, 0.60) to detect an effect of d = 0.30 (0.27, 0.23) or larger (directional test).

3.1.3. Procedure

The overall procedure was the same as in Study 1. We made some modifications to address the online environment of the study: We manipulated mental demand using a different task and used slightly different items for self-reported mental effort. The study was run with a web version of the same experimental software as Study 1 (Inquisit 4 Web, 2015).

3.1.4. Mental demand manipulation

We used the symbol counter task to manipulate mental demands (Garavan, 2000). The task requires executive control by prompting participants to simultaneously keep count of two running lists, one list for the number of small and another list for the number of big squares presented in an intermixed sequence on the screen (see Fig. 3 for a schematic illustration). Frequently switching between lists is mentally demanding. We used a modified version of the task to continuously adapt the difficulty for each participant based on performance (Lin, Saunders, Friese, Evans, & Inzlicht, in press). Each trial consisted of a series of small and big squares presented sequentially on the screen. During the first trial, eleven squares were presented one-by-one separated by a fixation cross. Small and big squares were presented in mixed order. During the first trial, there were two switches from *small* to *big* or from *big* to *small* squares. If participants correctly reported the number of small and big squares at the end of a trial, the difficulty for the next trial increased. The total number of squares presented increased by one, square display time decreased by 20 ms, and the number of switches increased. If participants incorrectly reported the number of small and big squares, the parameters were adjusted in the opposite direction. The task lasted 8min.

The *low mental demand* group watched a nature video for 4:30 min. Recent research showed that tasks experienced as boring (e.g. long and easy tasks) might evoke similar subjective states as cognitively demanding tasks (Milyavskaya, Inzlicht, Johnson, & Larson, 2019). Besides, several studies suggested that increasing the duration of the manipulation for the high demand condition evokes stronger effects (Sjåstad & Baumeister, 2018; Vohs, Baumeister, & Schmeichel, 2012). We therefore refrained from matching the control task in terms of duration and task category.

3.1.5. Measured variables

3.1.5.1. Self-reported mental effort. Participants rated mental demand, concentration, mental effort, frustration and mental fatigue using a slider for each item (e.g., “How mentally demanding was the task?”, from “very low demand” to “very demanding”, internally coded 1–70; mean of 5 items; α = 0.91).

3.1.5.2. Math effort task. The math effort task was largely the same as used in Study 1. We added a sixth difficulty level to avoid a middle category. Additionally, we modified the range of numbers for each level to increase the difficulty of the first level and to smoothen the increase in difficulty for the following levels. Participants worked on the task for 7 min, so the number of choices and addition problems varied between participants. Each choice was made for the upcoming 2 addition problems—instead of 3 in Study 1—to increase the overall number of choices made.

3.1.5.3. Math self-assessment. The items used to assess math self-efficacy and math ability were identical to those in Study 1. Similar to the questions on mental effort, we used a slider (e.g., “I am good at math”, 0 = *not good* to 70 = *very good*) instead of a 7-point Likert scale. On recommendation during the review process, we merged both scales into one “math self-assessment” scale (α = 0.85). As we pre-registered separate analyses, we report these in the online supplementary material.

3.2. Results

3.2.1. Pre-registered confirmatory analyses

As expected, participants in the *high mental demand* condition indicated stronger mental effort with a large effect size, which speaks to a successful manipulation (M_{low} = 21.41, SD = 18.21, M_{high} = 49.43, SD = 12.76; mid-point = 35; $t_{one\text{-}sided}$ [217.89] = −14.41, p < .001, d = −1.81, 95% CI [−∞, −1.57]).

Against our predictions and parallel to Study 1, participants did not select easier problems in the *high* compared to the *low mental demand* condition (M_{low} = 2.59, SD = 1.18, M_{high} = 2.51, SD = 1.23; $t_{one\text{-}sided}$ [264.25] = 0.56, p = .434, d = 0.07, 95% CI [−0.17, 0.31]). However, see the additional exploratory analyses for a more nuanced analysis.

3.2.2. Pre-registered exploratory analyses

Contrary to Study 1, math self-efficacy did not moderate the effect of the mental demand manipulation on effort choice (b = 0.07, 95% CI [−0.20, 0.34], t = 0.53, p = .600; see Table 2). Independent of the *mental demand condition*, participants reporting higher math self-efficacy chose more difficult levels in the math effort task.

Table 2
Math self-efficacy: moderation of the effect of mental demand condition on math effort choice in math effort task in Study 2.

	b	*SE B*	*t*	*p*
Mental demand condition	−0.25	0.14	−1.83	.069
Math self-efficacy	0.47	0.10	4.83	< .001
Mental demand condition × math self-efficacy	0.07	0.14	0.53	.600

Note. $N = 269$. $R^2 = 0.16$. Continuous predictors are mean-centered and scaled by 1 *SD*.

3.2.3. Non-pre-registered analyses

Math self-assessment was robustly correlated with math effort task choices ($r = 0.45$, $p < .001$, see online supplementary material). We therefore controlled for this math self-assessment by residualizing math effort task choices of these scores before exploring the potential effect of the *mental demand condition* on effort choice. This analysis revealed the expected effect: Participants in the *high mental demand* condition chose easier levels in the math effort task than those in the *low mental demand* condition ($M_{\text{low}} = 0.17$, $SD = 1.02$, $M_{\text{high}} = -0.15$, $SD = 1.08$; $t_{one\text{-}sided}$ [265.07] = 2.54, $p = .006$, $d = 0.31$, 95% CI [0.11, $+\infty$]).

As reported above, the *mental demand condition* (experimental manipulation) predicted self-reported mental effort during the first task. Higher self-reported mental effort was related to choosing easier math problems, but only for the *high mental demand* condition (see online supplementary material). On an exploratory basis, we ran a moderated mediation model using processR to formally test if the effect of the *mental demand condition* through self-reported mental effort on math effort choice was moderated by the *mental demand condition* (PROCESS model nr. 74, based on Hayes, 2013; R package: Moon, 2020; see Fig. 4A). Math self-assessment was included as covariate. This model revealed an indirect effect of the *mental demand condition* on math effort choices through self-reported mental effort. This mediation was moderated by the *mental demand condition* such that higher reported effort during the symbol counter task was associated with less difficult math effort task choices for participants in the *high*, but not in the *low mental demand* condition (see Fig. 4B, for a depiction of the moderated b-path of the model).

3.3. Discussion

As intended, the demand manipulation led to pronounced effects on self-reported mental demand with the low demand condition falling clearly below and the high demand condition clearly above the midpoint of the scale, suggesting that the adaptation of the demand manipulation was successful. Nevertheless, as in Study 1, there was no effect of mental demand on math effort choice in the pre-registered analysis. However, controlling for math self-assessment (i.e., math self-efficacy and math ability, robustly associated with math effort choices) revealed the predicted effect: Participants in the *high mental demand* condition chose less effort-demanding levels than participants in the *low mental demand* condition. Note that this result emerged from an exploratory analysis that requires replication. The moderation effect of math self-efficacy on effort choice unexpectedly found in Study 1 did not replicate and was possibly a false positive finding in a small sample.

4. Study 3

Study 3 sought to replicate the results of Study 2 with yet a larger sample.

4.1. Method

4.1.1. Pre-registration and sharing

The pre-registration, all materials, data, and code can be accessed at osf.io/u9sj3/. We pre-registered Bayesian analyses in addition to frequentist analyses. Priors are based on the posterior distributions of Study 2 for the respective informed hypotheses.

4.1.2. Participants and design

We pre-registered to collect a sample of 350 participants on Amazon's Mechanical Turk. Twenty participants had to be excluded as they did not meet the age restrictions even though we added an entrance question to exclude participants placing themselves in the wrong age category. Thus, the final sample consisted of 330 participants ($M_{\text{age}} = 29.54$, $SD_{\text{age}} = 3.88$, 41.52% female). They received $3.60 for their participation. A sensitivity analysis for the final sample ($N_{\text{high}} = 162$, $N_{\text{low}} = 168$) using G*Power (Faul et al., 2007) revealed a statistical power of 1-β = 0.80 (0.70, 0.60) to detect an effect of $d = 0.27$ (0.24, 0.21) or larger (directional test).

4.1.3. Procedure

The overall procedure was the same as in Study 2. We made only minor changes: We added an item assessing boredom after the self-reported mental effort items. To further increase the variance in math

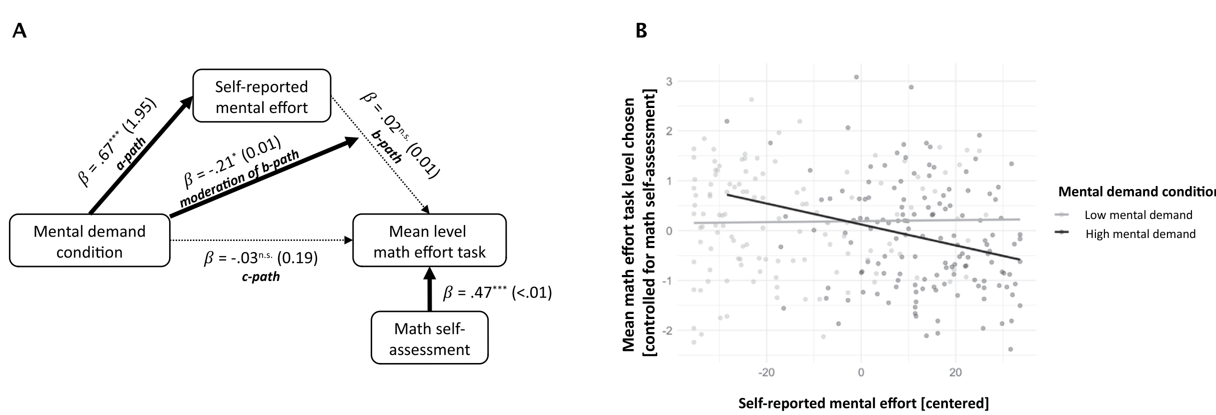

Fig. 4. A) Moderated mediation model: Conceptual diagram. Self-reported mental effort mediated the effect of *mental demand condition* on math effort choice. The path from self-reported mental effort to mean level chosen in the math effort task was moderated by the mental demand condition. β (*SE*). *$p < .05$; ***$p \leq .001$. Bold lines indicate significant paths. Path coefficients are standardized beta regression weights. B) Moderated b-path of the mediation model: Scattered raw data and regression lines. Mental demand predicted self-reported mental effort (a-path). Depicted here, mental demand also moderated the relationship between self-reported mental effort and the mean level chosen in the math effort task, when controlling for math self-assessment. More self-reported mental effort during the first task was associated with easier choices in the math effort task, but only for participants in the high mental demand condition.

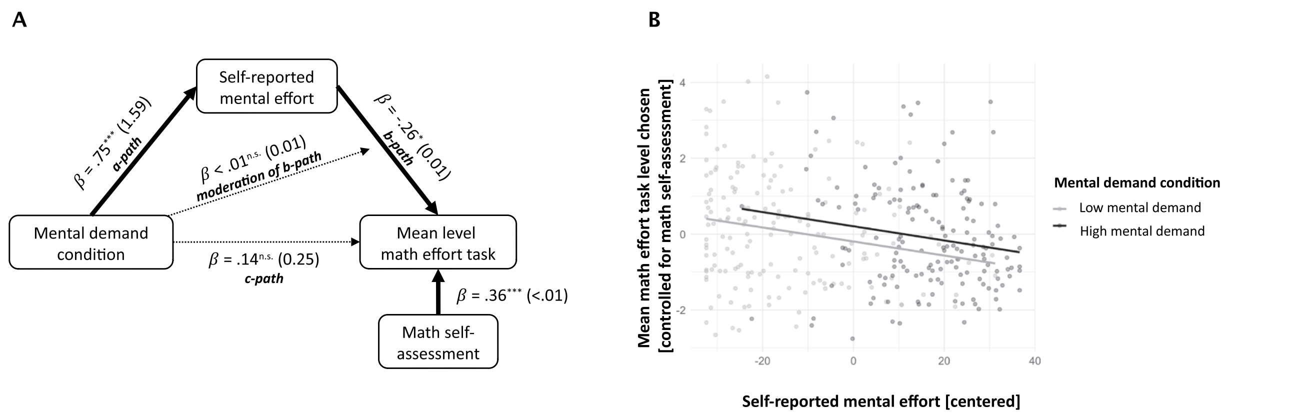

Fig. 5. A) Moderated mediation model: Conceptual diagram. Self-reported mental effort mediated the effect of *mental demand condition* on math effort choice. Bold lines indicate significant paths. Path coefficients are standardized beta regression weights. β (*SE*). *$p < .05$; ***$p \leq .001$. B) Non-moderated b-path of the mediation model: Scattered raw data and regression lines. Mental demand predicted self-reported mental effort. Mental demand did not moderate the relationship between self-reported mental effort and the mean level chosen in the math effort task, when controlling for math self-assessment.

effort choice, we split the first level of the math effort task into two levels. Level 1 was picked most often in Study 2. Besides, we added a question to assess self-rated data quality. For a full list of measured variables, see the online supplementary material.

4.2. Results

4.2.1. Pre-registered confirmatory analyses

As expected, participants in the *high mental demand* condition rated the first task as more demanding than those in the *low mental demand* condition ($M_{\text{low}} = 17.62$, $SD = 15.35$, $M_{\text{high}} = 49.68$, $SD = 12.53$; mid-point = 35; $t_{one\text{-}sided}$ [319.30] $= -20.78$, $p < .001$, $d = -2.29$, 95% CI [$-\infty$, -2.05]; $BF_{10} = 4.21e^{58}$, pre-registered normal prior: $M = -1.77$, $SD = 0.26$).

We first residualized math effort task scores by math self-assessment. Descriptively, participants in the *high mental demand* condition chose less effort-demanding alternatives compared to those in the *low mental demand* condition. However, this effect was not significant and only about half as large as in Study 2 ($M_{\text{low}} = 0.1$, $SD = 1.44$, $M_{high} = -0.1$, $SD = 1.36$; $t_{one\text{-}sided}$ [326.81] $= 1.26$, $p = .104$, $d = 0.14$, 95% CI [-0.08, 0.36]; $BF_{10} = 1.03$, normal prior: $M = 0.26$, $SD = 0.18$).

4.2.2. Pre-registered exploratory analyses

As in Study 2, the (non-significant) effect of the manipulation of mental demand on math effort choice was mediated by the self-reported mental effort. This time, the mediation was not moderated by *mental demand condition*. For both conditions, reporting higher mental effort was associated with choosing easier math problems (see Fig. 5). Math self-assessment was included as a covariate.

5. Internal meta-analytic summary

Multi-study papers presenting partly inconsistent findings profit from reporting internal meta-analyses. Internal meta-analyses strengthen conclusions pertinent to effect sizes, reliability and replicability of the findings—especially when effects are small—as the results are based on a larger sample than the individual studies with overall larger statistical power (Goh, Hall, & Rosenthal, 2016; Maner, 2014). We therefore summarized the findings of the three studies in an internal meta-analysis. We used random effects in which the mean effect size for the effect of mental demand on math effort choice was weighted by sample size. Math effort choices were first residualized by math self-assessment. All effect sizes were converted to Hedge's *g* and we controlled for math self-assessment in math effort choice in all studies. The overall effect of mental demand on math effort choices was significant

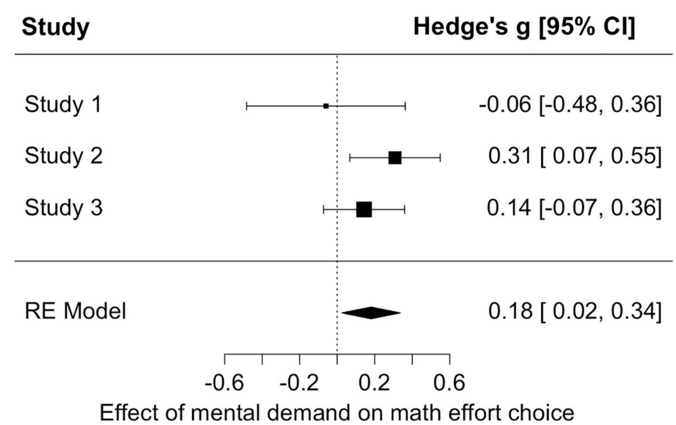

Fig. 6. Internal meta-analysis of all three studies. Small average effect size of $g = 0.18$ with strong (unexplained) heterogeneity across studies.

with a small effect size ($z = 2.27$, $p = .023$, $g = 0.18$, 95% CI [0.02, 0.34][4]; see Fig. 6). Thus, across three studies, after engaging in a highly demanding task, participants selected slightly less effort-demanding math problems when the influence of math self-assessment was controlled for.

6. General discussion

Ego depletion effects have usually been investigated by comparing performance in a self-control task with fixed difficulty for all participants after either facing low or high demands in an initial task. Taking a somewhat different approach, the present studies examined effects of mental demands on the subsequent choice of more or less effort-demanding upcoming tasks. This perspective offers a new way to think about the effects of prior mental demands. This approach may be fruitful for the ongoing debate on ego depletion effects, opening up new ways to investigate ego depletion related phenomena in the laboratory and everyday life.

We expected participants to choose less effort-demanding tasks after engaging in a demanding first task. Overall, results were mixed. In Study 1, there was no significant effect of the mental demand manipulation on the choice of difficulty of upcoming math problems. However, some evidence suggests that the mental demand

[4] The fixed effects model yielded a similar result ($z = 2.37$, $p = .018$, $g = 0.18$, 95% CI [0.03, 0.33]).

manipulation may have been too weak, thus favoring this null effect. Study 2 again found no difference in math effort choices as a function of *mental demand condition*, but when controlling for math self-assessment—robustly associated with the dependent variable but not in the focus of the research question—the expected effect emerged with a small to moderate effect size (albeit with exploratory analyses). Study 3 replicated this effect descriptively, though non-significantly, with a small effect size. An internal meta-analysis of all studies revealed a small average effect size of $g = 0.18$ [0.02, 0.34].

Studies 2 and 3 pointed to the potentially important role of experienced mental effort: In Study 2, participants in the *high mental demand* condition and in Study 3 participants in both conditions who experienced the first task as more demanding chose easier task alternatives later on. These findings—to be interpreted with caution as there may well be alternative mediating variables (Fiedler, Harris, & Schott, 2018)—suggest that subjective experiences of mental demand, effort, and fatigue may play an important role in prompting ego depletion effects and underline the importance of strong manipulations to trigger these subjective experiences (Friese et al., 2019; Wright, Mlynski, & Carbajal, 2019).

6.1. Strengths, limitations, & outlook

Several strengths lend credibility to our findings. First, we followed principles of open science and pre-registered all studies including the respective analysis plans, and provide open materials, data, and code. Second, we employed demand manipulations that were continually adapted to participants' ability limits (Studies 2 and 3) and led to strong effects on the self-reported mental effort questions assessing demand, effort, concentration, and fatigue—a basic requirement that is not reliably met by studies in the field of ego depletion research (Friese et al., 2019; Hagger et al., 2010). The interindividual variability in self-reported mental effort partially accounted for the effect of the mental demand manipulation on the dependent variable. If it turned out that self-reported mental effort mediated ego depletion-type effects in other studies as well, we believe this would be an important step toward a deeper understanding of this (unreliable) phenomenon. Third, Studies 2 and 3 featured relatively large sample sizes. Combining all studies in an internal meta-analysis allowed us to test for even small effects with adequate statistical power.

Despite these strengths, there are obvious limitations. First of all, using a math task has clear advantages as it lends itself to the construction of several levels with steadily increasing difficulty. However, as math anxiety is common in the population (OECD, 2013), the mathematical nature of the effort choice task constitutes a limitation. Second, we cannot be sure if participants saw reason to choose any other than the easiest levels. Personal standards and long-term goals may not have played a role for math effort choice—but the pursuit to bring one's own behavior "into line with standards, such as ideas, values, morals, and social expectations, and to support the pursuit of long-term goals" (Baumeister, Vohs, & Tice, 2007, p. 351) is a basic component of prominent definitions of self-control. From a broader perspective, this issue underlines a partial disconnect between laboratory-based research and people's everyday lives and the need to build empirical bridges between the two. Third, the meta-analytic effect size was small and there was strong (unexplained) heterogeneity across studies. An effect size of this magnitude ($g = 0.18$) is very difficult to study in the laboratory with adequate statistical power.

A sensible next step addressing these limitations would be to investigate effort choice in domains other than math to generalize the present findings. Should the findings generalize, we suggest to examine the same theoretical idea in people's everyday lives, to address concerns regarding personal relevance and the disconnect between laboratory and daily life. Experience sampling methodology would allow to investigate if subjective experiences of high mental demand lead to the choice of less effortful activities in daily life. The investigation of such dynamics within persons would also be conducive to examining potentially small effect sizes with appropriate statistical power. This way it would be possible to compare laboratory and online findings to everyday life settings and to develop an idea about whether the respective statistical effect sizes may practically matter to people's lives.

7. Conclusion

We investigated whether people choose less effort-demanding task alternatives after engaging in mentally demanding tasks. Across three pre-registered studies, we found accumulated evidence that when taking math self-assessment into account, people tend to select easier math problems when exerting mental effort beforehand. An internal meta-analysis revealed a small overall effect of $g = 0.18$, albeit with large heterogeneity between studies. Future research may turn to experience sampling methods to assess the subjective experience of effort, influences on effort choice and their relevance for daily life.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jesp.2020.104008.

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