# The Impact of Cognitive Work Demands on Subsequent Physical Activity Behavior

Sven van As[1], Harm Veling[1], Debby G. J. Beckers[1], Fiona Earle[2], Stefi McMaster[2],

Michiel A. J. Kompier[1] and Sabine A. E. Geurts[1]

[1]Behavioural Science Institute, Radboud University, The Netherlands

[2]Department of Psychology, University of Hull, United Kingdom

## Author Note

Sven van As https://orcid.org/0000-0002-1177-6475

Harm Veling https://orcid.org/0000-0002-5648-2980

Debby G. J. Beckers https://orcid.org/0000-0001-8676-0518

Fiona Earle https://orcid.org/0000-0002-0366-9477

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Correspondence concerning this article should be addressed to Sven van As, Behavioural Science Institute, Radboud University, 6525 HR Nijmegen, The Netherlands.

E-mail: s.vanas@psych.ru.nl

## Abstract

After cognitively demanding work, individuals tend to be less physically active. However, the psychological mechanisms underlying this effect have not been thoroughly tested. The aim of this paper was to experimentally investigate the impact of cognitive work demands on subsequent physical activity behavior. Across two preregistered experiments, participants were exposed to high or low levels of cognitive work demands, operationalized as workload in Experiment 1 and as working memory load in Experiment 2. In a subsequent choice task, participants made binary consequential choices between leisure non-physical activities (e.g., drawing) and effortful physical activities (e.g., cycling). Choice alternatives were matched on attractiveness rankings. Additionally, physical endurance performance was measured using a standardized cycling protocol in Experiment 1. In contast to the hypotheses, after performing work with high cognitive demands, participants were not more likely to choose non-physical over physical activities nor did they perform significantly worse on the physical endurance task. Exploratory analyses suggest that preexisting preferences for either physical or non-physical activities explained physical activity behavior above and beyond exposure to cognitively demanding work. These experiments question the impact of cognitively demanding work on subsequent cognitive fatigue and physical activity behavior. Implications for theory, practice and future directions are discussed.



*Keywords:* physical activity, cognitive demands, fatigue, motivation, decision making


**Public Significance Statement**

In two experimental studies, we found no consistent evidence for causal effects of cognitive work demands on subsequent cognitive fatigue and physical activity behavior. Our exploratory findings highlight the importance of personal preferences for physical activities, which extends contemporary understanding of the motivational processes that underly physical activity participation after work.

**The Impact of Cognitive Work Demands on Subsequent Physical Activity Behavior**

Participation in physical activities is important for health and well-being (Arem et al., 2015; O'Donovan et al., 2017). Physical activity reduces the risk for cancer, Type 2 diabetes, depression, and early mortality (Health Council of the Netherlands, 2017). Global guidelines recommend people to be physically active for at least 150 minutes per week at moderate intensity or 75 minutes at vigorous intensity, or an equivalent combination of the two (World Health Organisation, 2018). However, large proportions of the global population are not sufficiently active (i.e., less than the recommended levels). In high-income western countries, levels of physical inactivity are even rising; from 30.9% in 2001 to 36.8% in 2016 (Guthold et al., 2018). In order to stop this physical inactivity pandemic, it is crucial to investigate barriers for participation in physical activity.

Work has been identified to be an important barrier. In a large meta-analysis combining data of 170,000 participants, Fransson and colleagues (2012) found that unfavorable work-characteristics are related to lower levels of physical activity during leisure time. Especially employees working in jobs with high cognitive work demands (e.g., high time-pressure and workload) and low work control (e.g., low autonomy over task-management) had trouble being sufficiently active during leisure time. Compared to low strain jobs (i.e., low demands, high control), employees in these high strain jobs were 26% more likely to be physically inactive and 21% more likely to become physically inactive in the following year. This implies that high strain work has an unfavorable carry-over-effect to physical (in)activity behavior during leisure time.

Other recent studies have focused specifically on the impact of cognitive work demands (independent of work control) on physical activity behavior. Cognitive work demands are defined here as any type of work stressor that is not physical in nature. This can involve quantitative demands that require individuals to work hard (e.g., workload and time pressure;

Häusser et al., 2010; Van der Doef & Maes, 1999) as well as qualitative demands requiring executive processes such as inhibition, updating or self-control (Brown et al., 2019). Two daily diary studies have shown that on days where cognitive work demands were high, levels of (intended) leisure time physical activity were lower than on days where these cognitive demands were low (Häusser et al., 2018; Payne et al., 2010). This implies that individuals find it difficult to be physically active after demanding days at work. Moreover, a growing body of experimental studies have investigated the impact of cognitively demanding work on subsequent physical performance (for overviews, see Brown et al., 2020; McMorris, Barwood, Hale, Dicks, & Corbett, 2018; van Cutsem et al., 2017) and on spontaneous exercise behavior (Abdel Hadi et al., 2020; Harris & Bray, 2019). While the magnitude and consistency of this effect depend on the study design (e.g., duration of manipulation, between- or within-subjects), physical performance tends to deteriorate after cognitively demanding work. Thus, both field and experimental studies suggest a negative impact of cognitively demanding work on physical activity behavior.

To date, the precise psychological mechanisms underlying this effect remain unclear. Insight into these mechanisms is crucial for designing effective interventions for physical activity enhancement. An emerging approach to understand these mechanisms is behavioral economics, which combines principles from cognitive psychology, economy, decision making, and learning (Epstein, 1998). According to behavioral economics, the decision to engage in behavior is determined by internal cost-benefit analyses (Shenhave et al., 2017; Westbrook & Braver, 2015). Behaviors are only initiated or continued if the predicted benefits outweigh the expected costs in the cost-benefit analysis. Benefits might encompass personal value, enjoyment or monetary rewards while the effort that is required to obtain these rewards is perceived as a cost. In line with this reasoning, a well-documented finding is that individuals are less likely to initiate or continue behavior when the effort requirements increase (i.e., ‘law of least effort’; Hull, 1943; Westbrook, Kester, & Braver, 2013).

Recent insights suggest that fatigue, a psychobiological state resulting from prolonged periods of demanding work (Hockey, 2011; van der Linden, 2011a), increases the weight assigned to effort-costs for subsequent behavior (Kanfer, 2011; Martin et al., 2018; Müller & Apps, 2019). While effort is always perceived as costly, these costs are expected to weigh more heavily in the cost-benefit analyses after having already undertaken demanding work (i.e., in a fatigued state). As a result, motivation for exerting effort is likely to be lower after longer time-periods of demanding work. This reduced motivation for effort is thought to cross domains, such that *cognitive* demands not only reduce motivation for subsequent cognitive effort, but also for *physical* effort and vice versa. In line with early conceptualizations of fatigue, one of its core characteristics seems to be an ‘intolerance of *any* effort’ (Thorndike, 1914). Support for this reasoning comes from neuroimaging studies showing altered activation in overlapping brain areas (i.e., anterior cingulate cortex, anterior insula and dorsolateral prefrontal cortex) after cognitively as well as physically demanding work. Importantly, these areas have repeatedly been linked to effort-based decision-making (Müller & Apps, 2019).

Only two experiments have explicitly addressed the impact of demanding work (and fatigue) on subsequent decision-making regarding physical activity. Iodice and colleagues (2017) investigated the impact of *physical* fatigue (induced by 40 minutes intense cycling) on subsequent physical effort-based decision-making. Following the fatigue and control condition, participants made 360 choices between obtaining a small reward for no effort (i.e., €10 for no cycling), or a varying higher reward for varying levels of effort (i.e., €15-€40 for 10-40 minutes of cycling). In line with predictions from behavioral economics, participants were less likely to choose high effort options as the effort requirement of these options increased (i.e., longer durations of subsequent cycling tasks). Importantly, this effect was more pronounced when participants were physically fatigued.

Similar findings have been reported by Harris and Bray (2019), who tested the impact of a *cognitively* demanding task on the subsequent choice to engage in a 22-minutes cycling task or not. Additionally, the researchers assessed cognitive fatigue and cost-benefit scores regarding physical activity using self-report. The findings indicated that cognitive demands had an indirect, negative impact on the subsequent choice to be physically active, through cognitive fatigue and cost/benefit scores. Thus, both experimental studies suggest that engaging in demanding work affects subsequent decision-making for physical effort by increasing the weight assigned to effort-costs when fatigued.

While these studies provide insight into the impact of demanding work on subsequent physical activity choices, a major caveat is that they both operationalize physical activity exclusively as cycling. This limits the external validity of the reported findings as individuals can choose from a great variety of physical activities in real-life. This variety of activities to choose from could drastically change the pattern of findings. Individuals might still be willing to engage in one type of physical activity after cognitively demanding work, but not in another due to their personal preferences. Support for this reasoning comes from decades of research on physical activity motivation, which has shown that long-term engagement in physical activity is strongly predicted by intrinsic motivation or enjoyment of the activity (for an overview, see Teixeira, Carraça, Markland, Silva, & Ryan, 2012). Depending on personal preferences, the perceived benefits (i.e., enjoyment) of some activities might still outweigh their more heavily weighted effort-costs after demanding work. To obtain more ecologically valid insight into the association between cognitively demanding work and subsequent physical activity decisions, participants should be provided with a range of physical activities to choose from while taking personal enjoyment of these activities into account. This will allow for a more comprehensive exploration of the cost-benefit analysis underlying the decision to engage in physical activities after cognitively demanding work.

In the current study, we therefore investigated the impact of cognitively demanding work on subsequent activity choices. We employed a paradigm in which participants made personalized consequential choices between a variety of physical and non-physical activities. The activities from which participants could choose were always matched on personal liking of those activities (i.e., the best liked physical activity was matched to the best liked non-physical activity, the same for the second best, and so forth). Therefore, findings from this study will provide a more ecologically valid test of the impact of cognitive demands on subsequent physical activity choices. Based on recent experimental studies (Harris & Bray, 2019; Iodice et al., 2017), field studies (Fransson, Heikkilä, et al., 2012; Häusser et al., 2018; Payne et al., 2010), as well as neurocognitive insights (Müller & Apps, 2019), we expected participants to choose physical activities less often after working on more cognitively demanding tasks (i.e., inducing cognitive fatigue). This hypothesis was tested in two experiments in which cognitive work demands were induced by workload (Experiment 1) or working-memory load (Experiment 2).

## Experiment 1

In addition to the overarching goal of this study (testing the impact of cognitively demanding work on subsequent activity choices), Experiment 1 aimed to bridge the discrepancy in the operationalization of cognitive job demands. Within the field of occupational health psychology, cognitive work demands are frequently operationalized as cognitive workload (i.e., work quantity; see Fransson, Nyberg, et al., 2012; Häusser et al., 2011, 2014; Hockey & Earle, 2006), which is the amount of work to finish within a limited timeframe (Fransson et al., 2012). Experimental studies from exercise psychology tend to rely on manipulations of task complexity, requiring demanding executive processes such as inhibition, switching, updating, working memory or self-control (Brown et al., 2019; Martin et al., 2018). In the current experiment, we therefore operationalized cognitive work demands as *cognitive workload* (in line with studies from occupational health psychology) and investigated its impact on *physical activity choices* as well as on physical *performance* (in line with studies from exercise psychology). In this way, the current study provided an experimental test of the relationship between cognitive work demands and physical activity as observed in field studies from occupational health psychology (e.g., Fransson, Heikkilä, et al., 2012; Häusser et al., 2018; Payne et al., 2010). Moreover, it extended experimental studies from exercise psychology that showed a detrimental (indirect) effect of cognitive work demands on physical activity choices and physical performance (Brown et al., 2019; Harris & Bray, 2019). We expected cognitive workload to have a negative impact on subsequent physical activity choices (**hypothesis 1**: Fransson, Heikkilä, et al., 2012; Harris & Bray, 2019; Häusser et al., 2018; Iodice et al., 2017; Müller & Apps, 2019; Payne et al., 2010) and cycling performance (**hypothesis 2**: Brown et al., 2020).

## Method

### *Participants*

Students from the University of Hull were recruited via the University research participation system and through adverts displayed on social media and on campus. We determined our sample size based on previous research using a highly similar methodology to manipulate workload (Hockey & Earle, 2006), which reported a large effect (f = 0.26) of workload on subsequent effortful sedentary task persistence. The a-priori power analysis in G*power (Faul et al., 2007) indicated that 24 participants would be the minimum sample size for detecting a similar effect using an Ancova with main effects and interactions ($\alpha$ = .05, 1-$\beta$ = .80, f = 0.62). Since we investigated different follow-up behavior than in Hockey and Earle's study (2006) and to cover for attrition as well as to enable us to perform exploratory analyses, we preregistered to test 40 to 80 participants and to terminate testing when 80 participants were tested or when the end-date of testing was reached (June 21, 2018: see https://osf.io/uh4wm). Prior to participation, participants filled in a questionnaire to assess demographic information (e.g., age, gender, BMI and exercise habits) and to identify and exclude at-risk individuals (e.g., asthmatic, heart complaints or with current injuries). In total, 47 participants were eligible for participation and were invited to the lab. All participants were instructed to refrain from alcohol on the night before each session, from caffeine in the six hours before each session and from vigorous exercise on the day before each session. Moreover, participants were instructed to wear sports clothes to the lab and to eat sufficiently (but not within 1 hour before session 1) to prevent themselves from getting hungry throughout the tests. Seven participants were excluded because they did not attend ($n$ = 4) or dropped out after session one ($n$ = 3). The final sample of 40 healthy participants (21 females: 52.5%) had an average age of 22.1 ($SD$ = 4.0). Their average BMI was 22.9 ($SD$ = 4.4; healthy range: 18.5 – 24.9), and they exercised at vigorous intensity on average 2.9 times per week ($SD$ = 2.3, range: 0-10) and at moderate intensity 3.2 times per week ($SD$ = 3.6, range = 0-20). Participation was reimbursed with a fixed reward of £20 or course credits and a chance of winning monetary prizes (£50, £75 or £100).

***Procedure and Materials***

An overview of the procedure is presented in Figure 1. Participants visited the lab on two occasions, separated by a 48-hour interval to recover. After providing informed consent in the first visit, participants' maximal cycling output was assessed during an incremental exercise test. Next, their natural working pace was determined in a baseline office session. Also, their baseline endurance performance was assessed in a first time to exhaustion test (TTE1).

In the second visit, participants initially performed a ranking task to assess their liking of different physical and non-physical activities. Next, they worked on simulated office tasks with either a high or low workload for 1.5 hours. Immediately thereafter, participants made 120 rank-matched activity-choices to assess their activity choice behavior. Then, they performed the second time till exhaustion test (TTE2) to assess physical endurance performance. Finally, participants performed one of the activities they chose during the choice-task for ten minutes after which they were debriefed and reimbursed.

All cycling tasks were conducted in a temperature-controlled room with only the experimenter present. The computerized tasks (i.e., ranking, choices and office-work) were performed in a simulated office, consisting of two individual work-stations that were separated by an office divider screen. The testing experimenter sat behind the participant during the simulated office work to record their strategy and to check for adherence to the instructions. Throughout both visits, participants wore a chest-strapped heart rate monitor (Polar H7). These procedures have been reviewed and approved by the ethics committee of the Faculty of Health Sciences at Hull University (REF FHS10). Moreover, the study was pre-registered on the Open Science Framework (https://osf.io/uh4wm).

**Workload Manipulation.** Workload was manipulated using simulated office-work (Hockey & Earle, 2006). Participants were asked to complete five copy-typing tasks in which they had to type information from one document into another. The documents consisted of fake student addresses, timetables, reference lists, meeting minutes and student testimonials.

During a 30-minute baseline session, participants were trained to work on each of the copy-typing tasks. Participants received written instructions for each subtask and could ask for clarifications before working on the subtask for five minutes. Participants were instructed to work at a comfortable pace, as quickly as possible but without feeling rushed. After five minutes, an alarm would indicate the end of a training session for a subtask after which the following subtask was explained and performed.

In the actual work-session, participants worked for 1.5 hours in total on the same tasks as in the previous session, and had 18 minutes to complete each of the five subtasks. Importantly, the amount of work was adapted in such a way that participants would have to work at 120% (high workload) or 80% (low workload) of their own natural pace. These levels of workload were identical to a similar previous study which successfully manipulated workload and evoked fatigue effects on persistence in a voluntary post-work task (Hockey & Earle, 2006). Based on participants' performance during the baseline session, the amount of content each participant had to copy-type varied to represent either high or low workload. To strengthen the manipulation-effect, participants were instructed to work as quickly and accurately as possible. Moreover, participants were informed that their chance to win 50, 75 or 100 pounds depended on the amount of work they had accurately finished. A timer was set at 18 minutes at the start of each subtask and participants were instructed to switch to the next task if the timer had ended. If participants were finished before the timer had ended, they waited for the remaining time.

**Choice Task.** In the first step, right before the workload manipulation, participants' liking of 60 selected activities was assessed with a *ranking task*. In a random order, participants indicated for 30 physical activities (e.g., weightlifting, doing push-ups or juggling) and 30 non-physical activities (e.g., gaming, puzzling or listening to music) to what extent they would like to do the activity at that moment. They indicated their liking on a computerized 100-point VAS scale with only the anchor-points *not at all* and *very much* displayed at each end. Instructions were provided on screen and participants received 8 practice trials to get used to the procedure and to ask for clarifications from the experimenter. For each participant, all physical and non-physical activities were automatically rank-ordered from 1 (liked most) to 30 (liked least).

Two types of trials were constructed based on these rankings. The first type consisted of 30 *between-category* pairs, which were always made up of one physical- and one non-physical activities. Importantly, the activities that made up a between-category pair were always rank-matched. For example, the physical and non-physical activities that a participant liked most (i.e., rank 1) were presented together, as were all subsequent activity pairs (i.e., rank 2 till rank 30). This way, preferences for activity *categories* (physical or non-physical) could be assessed, while taking personal liking of these specific activities into account.

The second type of trials consisted of 30 *within-category* pairs. These pairs were always made up of two activities from the same category (i.e., physical or non-physical), but with either high (i.e., top 15) or low (i.e., lowest 15) rankings. These pairs served to assess the validity of participants' choice behavior. Valid choice behavior is present if people on average prefer high ranked over low ranked activities.

Directly after the workload manipulation, a computerized *choice task* was used to assess participants' actual choice-behavior. Participants were presented with the 60 personalized pairs of activities. All 60 unique pairs were presented twice, with the position of the activities (left or right) counterbalanced to prevent any positioning bias. These 120 trials were divided over two blocks with a short break in between.

Participants were instructed to choose the activity they preferred to do in the last ten minutes of the experiment, and were informed that a selection of the activities was actually present and that their choices were thus consequential. On each trial, participants indicated their choice for the preferred activity by pressing 'z' (left activity) or 'm' (right activity) on a qwerty-keyboard. Participants had 30 seconds to indicate their choice and missed trials were repeated at the end of each block. A yellow rectangle appeared around the selected activity for 500 milliseconds to confirm their choice. Prior to the task, participants received instructions on screen and performed 4 practice trials. After completing all test trials, participants performed 4 additional trials of which one was randomly selected to represent the true choice (i.e., the activity that was chosen on that trial actually had to be performed).

**Physical Endurance Performance.** Two types of cycling tasks were performed to establish i) participants' peak power output and ii) their (baseline) endurance performance. In the first visit, participants' peak power output was determined in a graded exercise test. After 3-minutes of getting used to the bike (20 Watts, 50 revelations per minute (RPM)) and a 3-minutes warmup session (50 Watts, 60-70 RPM), the graded exercise test started. Participants were instructed to keep cycling at 60-70 RPM for as long as possible while the resistance of the bike automatically increased with 25 Watts every 30 seconds. When participants gave up or when pedaling pace was below 60 RPM for more than 5 seconds, the test was terminated. The maximal resistance (Wmax) at termination represented the peak power output of a participant.

In a second cycling task that was performed in both visit 1 and 2, physical endurance performance was assessed during a time to exhaustion (TTE) test. After 3 minutes of warmup cycling at 75 Watts, the resistance of the bike was set at 70% of the participants' Wmax. Again, participants were instructed to keep cycling at 60-70 RPM up to the point where they felt they could not go any further. TTE represented the time in seconds from the moment at which the resistance was increased until the participant gave up or pedaling pace was below 60 RPM for more than 5 seconds. Following the tests, resistance was set at 75 Watts and participants were instructed to keep cycling until their breathing returned to a normal pace.

**Self-report Measures.**

***Perceived Workload.*** Following the simulated office work of 1.5 hours, perceived workload was assessed with a four-item Likert scale (e.g., 'I had to work very fast'; 1 = *Strongly disagree*, 7 = *Strongly agree*). A similar scale has been used in previous work-simulation research (Häusser et al., 2011), and reliability in the current study was very good (Cronbach's $\alpha = .816$).

***Subjective Fatigue***. Before and after work simulation, fatigue was assessed using the four fatigue items of the Brunel Mood Scale (BRUMS; Terry, Lane, Lane, & Keohane, 1999). Participants indicated to what extent each of the depicted feelings described how they felt at that moment (e.g., 'tired' or 'worn out'; 1 = *Not at all*, 5 = *Extremely*). Reliability of the scale was very good to excellent (Cronbach's $\alpha = .908$ before and .873 after the manipulation).

***Exercise Behavior.*** Habitual exercise behavior was assessed in the general questionnaire with the Godin Leisure-Time Exercise Questionnaire (Godin & Shephard, 1985). Participants reported how often they engaged in mild (i.e., minimal effort), moderate (i.e., not exhausting) and strenuous intensity (i.e., heart beats rapidly) exercise bouts of at least 15 minutes per week. The scale has proven to be a valid measure of exercise behavior (Amireault & Godin, 2015; Godin & Shephard, 1985).

### *Validity Checks*

To test the effectiveness of the workload manipulation, we ran an independent t-test with condition (high versus low workload) as the independent variable and experienced workload as the continuous dependent variable.

In order to test the validity of choice-behavior, we ran an intercept-only Generalized Linear Mixed Model (GLMM; Breslow & Clayton, 1993) predicting within-category activity choices (binary: top versus bottom ranking) using the 'glmer' function in the lme4 package (Bates et al., 2015). Valid choice-behavior was indicated by a significant intercept, which meant that top-ranked activities were selected significantly more often than 50%.

### *Main Analyses*

To investigate the impact of workload on activity choices (binary outcome: physical or non-physical), another GLMM was tested. We included a fixed effect for the between-subject factor workload (low = -1, high = +1) as well as fixed effects for the control variables fatigue at T1 (before the manipulation) and general exercise behavior. The model also included a per-participant random adjustment to the fixed intercept (random intercept). Robust p-values were obtained with 200 parametric bootstrap simulations using the 'mixed' function from the package afex (Singmann et al., 2015). Confidence intervals were obtained using the 'confint' function of lme4 (Bates et al., 2015).

We investigated the impact of workload on physical endurance performance (TTE2) with an ANCOVA, including workload as categorical independent variable and the pre-measure of fatigue as covariate[1]. The fatigue variable was log-transformed to normalize its positive within-group skew. As homogeneity of variance and linearity were violated, a robust ANCOVA with 2000 bootstrap simulations was performed using the 'ancboot' function of the WRS package (Wilcox & Schönbrodt, 2019).

***Exploratory Analyses***

In addition to our preregistered analyses, several exploratory analyses were performed in order to better understand the main findings. Following up on our main analysis for choice behavior, we tested whether participants within each experimental group showed a preference for either physical or non-physical activities in the actual choice task. We ran an intercept-only GLMM predicting activity choices (binary: physical versus non-physical). A significant intercept indicated a preference for either physical activities (positive intercept) or non-physical activities (negative intercept).

A Pearson's correlation test was performed to investigate to what extent initial preferences for physical activities (i.e., liking scores of physical activities minus liking scores

[1] Originally, TTE1 was included as covariate. As the assumption of independence of covariate and treatment was violated for TTE1, this variable was not included as covariate in the final analysis.

of non-physical activities) were related to the proportion of physical activities chosen.

As fatigue was expected to underlie the possible impact of workload on subsequent physical activity behavior, we tested whether self-reported fatigue increased more strongly in the high workload condition compared to the low workload condition. We ran an LMM with fixed effects for workload, time (pre vs. post) and a Workload x Time interaction. As the maximal models did not converge, we followed the advice of Barr, Levy, Scheepers, and Tily (2013) to simplify our models. The final model included a per-participant random adjustment to the intercept in addition to the fixed effects.

## Results

### *Validity Checks*

The independent t-test with workload as outcome variable showed that participants in the high workload condition indeed experienced the simulated office work to be more demanding ($M$ = 4.96, $SD$ = 1.07) than people in the low workload condition ($M$ = 2.99, $SD$ = 1.17; $t(36.72) = 5.57$, $p < .001$).

The intercept-only GLMM for within-category choices showed that participants chose top ranked activities more often than bottom ranked activities (on 86% of within-category trials, participants selected the high-ranked activity; 95% CI [84.59, 89.32]). This supports the validity of the task. For a detailed overview of choice behavior with respect to liking-scores, see Appendix Table A1.

### *Main Analyses*

In contrast to hypothesis 1, the likelihood to choose physical over non-physical activities was higher in the high workload condition compared to the low workload condition (OR = 1.58, 95% CI [1.09, 2.32], $p$ = .03). Participants in the high workload condition chose physical activities more often ($M$ = 0.53, $SD$ = 0.27) than participants in the low workload condition ($M$ = 0.35, $SD$ = 0.22; see Appendix, Table A2 and Figure A1 for within-group details). Neither fatigue (*p* = .748) nor exercise behavior (*p* = .501) significantly predicted activity choices.

The ANCOVA showed that the high workload condition did not significantly influence TTE2 ($F(1, 37) = 0.90$, $p = .349$) and neither did the covariate fatigue ($F(1, 37) = 0.93$, $p = .341$). These findings were confirmed in the robust ANCOVA, which is in contrast with our second hypothesis.

***Exploratory Analyses***

Our manipulation check showed that participants experienced the high workload condition to be more demanding than the low workload condition. Given the important role of fatigue within the cost-benefit analysis for physical activity, we additionally tested whether the high workload condition resulted in stronger increases in fatigue. In the exploratory LMM with fatigue as outcome variable, a significant effect for time was found ($b = -0.169$, $SE = 0.06$, $t(40) = -2.841$, $p = .007$). Participants reported to be more fatigued after simulated office work ($M = 2.29$, $SD = 0.98$) than before ($M = 1.95$, $SD = 0.937$). No main effect of workload condition was found ($p = .947$) and also the interaction term of Time x Workload was not significant ($p = .398$). Fatigue did not increase significantly more in the high workload condition compared to the low workload condition.

To better understand the unexpected direction in the difference in activity preferences between the two experimental groups, we conducted an exploratory intercept-only GLMM on the activity choices within each group. The analysis indicated no significant preferences for either physical or non-physical activities in the high workload condition (52.68% physical activities chosen, 95% CI [40.06, 65.76]) while participants in the low workload condition showed a significant preference for non-physical activities (34.56% physical activities chosen, 95% CI [22.15, 42.77]). Thus, the significant difference in choice behavior as found in our main analysis seems to stem from a preference for non-physical activities in the low workload condition.

Close inspection of choice behavior (see Appendix, Figure A2) suggested that within both experimental groups, there were participants with preferences for either physical or non-physical activities. To investigate the origin of this within-group variation, we conducted an exploratory Pearson's correlation test investigating the overall relation between preexisting preferences for physical activities as measured in the ranking task (i.e., individual liking-scores of physical activities minus individual liking-scores of non-physical activities) and the number of physical activities participants chose after the experimental manipulations. The analysis showed that the preexisting preferences strongly correlated with the number of physical activities chosen on the choice task ($r$ = .70, 95%, CI [.50, .83]). Thus, participants who assigned relatively higher liking scores to physical activities compared to non-physical activities on the ranking task were also more likely to choose physical activities more often in the choice task. This shows that initial preferences for physical activities explained a great deal of variation in choice behavior after the experimental manipulations.

Several additional exploratory analyses were performed to further investigate physical performance and choice behavior after the workload manipulations. See supplemental material for detailed descriptions of these analyses and results.

**Discussion**

Experiment 1 does not provide evidence for the hypothesized negative impact of high workload on subsequent physical activity behavior (hypothesis 1 not supported). In fact, our findings show that the likelihood to choose for participation in physical activities was smaller in the low-workload condition compared to the high workload condition. On average, participants in the low workload condition preferred non-physical activities while those in the high workload condition did not show any preference. The expected negative effect of workload on physical performance was also not observed (hypothesis 2 not supported). Participants' endurance performance was not significantly better or worse in the high or low workload condition. These findings do not converge with outcomes of previous experimental studies in which cognitive demands had an (indirect) negative impact on the decision to exercise (Harris & Bray, 2019) and on physical performance (Brown et al., 2019).

Importantly, several elements of the current experimental approach may have contributed to these unexpected findings. First, the small sample size in combination with the between-subjects design may have introduced randomization issues. Although we controlled for idiosyncratic differences in liking of the different activities, it seems plausible that (unmeasured) differences between participants in the two experimental groups underlie the current pattern of findings (e.g., preexisting activity preferences). A within-subject design would decrease error variance and increase statistical power for testing the effect of cognitive demands (Francis et al., 2018).

In addition, the manipulation of workload did not result in a stronger increase in cognitive fatigue in the high workload condition and our exploratory correlational test showed that activity-category preferences (i.e., physical or non-physical) before and after the experimental manipulation were very similar ($r$ = .70). Both findings imply that the manipulation did not elicit an effect of cognitive work demands on subsequent physical activity behavior. On top of that, the unexpected preference for non-physical activities in the low-demands condition may have resulted from under-arousal evoking feelings of boredom, with similar motivational consequences (i.e., increased impulsivity) as cognitive fatigue (Milyavskaya et al., 2019). However, this assumption could not be empirically tested as boredom was not measured in this experiment.

The current operationalization of cognitive work demands as cognitive workload was selected to bridge the gap in its oprerationalization between field studies of occupational health psychology and experimental studies of exercise psychology. Possibly, the effects of workload on cognitive fatigue and physical activity behavior only occur after much longer exposure periods, similar to those in field studies (i.e., an entire working day). To test potential short-term effects of cognitive work demands on subsequent cognitive fatigue and physical activity behavior, it could be more effective to operationalize cognitive work demands as task complexity instead of task quantity, similar to experimental studies from exercise psychology (Brown et al., 2019; McMorris et al., 2018).

In addition to these general design issues, the choice task was limited in two ways. First, the task did not assess predicted effort levels per activity, which is important for obtaining precise insight into effort-allocation following cognitively demanding work. Second, face validity of the task was limited. While the activities were carefully selected, for some activities it was less credible that participants could actually perform these in or around the lab (e.g., taking penalty shots or distance jumping). Therefore, we conducted a replication experiment addressing these issues.

## Experiment 2

In Experiment 2, we directly addressed the potential methodological issues that were identified in Experiment 1 (i.e., the small sample size, between-subjects design, manipulation of cognitive demands and choicetask limitations). First, we increased the sample size and employed a within-subjects design to improve statistical power and prevent randomization issues. This improvement also ruled out the impact of several potential confounding factors such as already existing preferences for physical activities and idiosyncratic variation in sensitivity to the experimental manipulations.

In addition, we manipulated working memory load (WML) instead of quantitative cognitive workload to more effectively evoke possible effects of cognitive demands on subsequent physical behavior. For manipulating WML, we used the n-back task (Kirchner, 1958), which has been used to induce cognitive fatigue in previous experimental research (Hopstaken et al., 2015; Massar et al., 2010). In this way, task complexity instead of task quantity (i.e., workload in Experiment 1) was manipulated.

Finally, the choice task was improved in several ways. The task now included a measure of predicted effort per activity to better understand effort allocation after cognitively demanding work. To enhance face validity of the choice task, eight activities were replaced with activities that were deemed more realistic to be performed on campus. For that same reason, we increased the number of trials from which the computer would select a true choice. As a consequence of these improvements, we expected to obtain more accurate insight into the impact of cognitive work demands on activity choices. Based on converging evidence from experimental studies (Harris & Bray, 2019; Iodice et al., 2017), field studies (Fransson, Heikkilä, et al., 2012; Häusser et al., 2018) and insights from neurocognitive research (Müller & Apps, 2019), we expected individuals to choose physical activities less often after working on a task with high compared to low WML (**hypothesis 3)**.

## Method

### *Participants*

The research participation system of Radboud University was used to recruit participants. We performed an a-priori power simulation in the R package simR (Green & Macleod, 2016) to determine our required sample size. Based on the data of experiment 1, we simulated a similar dataset in which the proportion of physical activities chosen differed on average by 10% ($SD_{within\text{-}group}$ = 25) between the two experimental conditions, which was just above half of the observed difference in experiment 1. We deliberately chose to be conservative for the estimated effect as we switched to a within-subject design and still expected demands to negatively affect activity choices (Hockey & Earle, 2006). Our simulation analysis indicated that 47 participants would be sufficient for detecting our effect of interest (1 - β = .90, α = .05). To cover for exclusion due to testing errors, we preregistered to terminate data collection at 60 full participants (i.e., completing both sessions). Participants had to be 18 years old or above and have at least moderate understanding of English. Participants were instructed to wear sports clothes to the lab, to refrain from alcohol in the 24 hours before testing, from caffeine on the day of testing, and to keep exercise levels (i.e., duration and intensity) on the days before each visit similar. In total, 63 students participated in the study of which 60 took part in both sessions. The sample consisted of 44 women (69.84%), with an average age of 24.08 years (*SD* = 6.89, range = 18-62). Participation was rewarded with a chance of winning monetary prizes (€50, €75 or €100) and all participants received €30 or course credits for participation.

***Procedure and Materials***

Figure 2 provides an overview of the experimental procedure. Participants visited the lab on two occasions, separated by a 48-hours interval in between. Upon arrival on day 1, the experimenter showed participants an activity room, where materials for several physical and non-physical activities were displayed (e.g., stationary bike, weights, juggling balls, puzzles and magazines). Then, the experimenter brought participants to the testing cubicle, where participants received more detailed information on the study and provided informed consent. Following, participants performed the ranking task to assess their liking of different physical and non-physical activities. Moreover, they indicated for each activity how effortful they expected it to be. Then, participants performed either a 2-back or a 0-back task for 45 minutes to manipulate WML. Immediately thereafter, participants made 120 rank-matched activity-choices to assess their activity choice behavior. Finally, participants performed one of the activities they chose during the choice-task for ten minutes and briefly reported their experiences during the task.

In the second visit, participants immediately started with the WML task (i.e., either 2-back or 0-back, counterbalanced) and then followed the exact same steps as in the first visit. Eventually, participants were debriefed and reimbursed.

All computerized tasks were performed in individual testing cubicles. In a larger, neutral room, participants individually performed the selected activity. The experimental procedure has been reviewed and approved by the ethics committee of the Faculty of Social Sciences of Radboud University (ECSW2017-1303-48). In addition, the hypotheses and planned analyses were preregistered on the Open Science Framework (osf.io/thj8q).

**WML Manipulation.** The n-back task was used to manipulate WML. In the n-back task, individual letters appear on screen and participants indicate whether the presented letter is the same as the letter *n* trials before. By increasing *n*, working-memory is more heavily taxed (i.e., more information needs to be remembered), which should lead to stronger increases in fatigue than a lower *n*. In the current experiment, the 2-back task (i.e., indicate match with two letters before the current letter) served as high WML condition, and the 0-back (i.e., indicate match with target letter 'X') as low WML condition. In both versions, letters were presented on screen for 500ms, followed by a 1500ms black screen. All letters ('B', 'C', 'D', 'E', 'G', 'J', 'P', 'T', 'V', and 'W') were presented in white, capitalized Times New Roman. The task consisted of 1320 trials (target rate of 25%) divided over three blocks of 15 minutes. Before and after each block, participants reported their experienced levels of fatigue, boredom and stress on a computerized VAS-scale (i.e., 'How fatigued/bored/stressed do you currently feel'), with only the anchor-points *not at all* and *very much* displayed. Perceived effort during the task was assessed after each block with the single item 'How effortful do you find this task' (*not at all* to *extremely*). Participants had 30 seconds to answer each item to prevent participants from taking long breaks. Similar to previous studies using the N-back to induce fatigue (Hopstaken et al., 2015), performance on the N-back task was operationalized as accuracy, which was calculated as *d* prime (*d*') per 15-minutes block (Macmillan & Creelman, 1990).

**Choice Task.** The ranking- and choice-task of Experiment 1 were slightly adapted for the current experiment to increase credibility of the task. Seven physical activities and one non-physical activity were replaced and the trials from which the true choice was drawn was increased from 4 to 8. In addition, a predicted effort-assessment was added directly after the ranking task to obtain more insight into the allocation of predicted effort. This assessment was similar to the ranking task, but now participants indicated for all 30 physical and non-physical activities how effortful they expected the activity to be on a 100-point VAS-scale (from *not effortful at all* to *very effortful*).

***Validity Checks***

To test whether participants perceived the 2-back task to be more effortful than the 0-back, we tested a Linear Mixed-effects Model (LMM). The model included a fixed intercept and a fixed effect of working memory load (low = -1, high = +1). In addition, a random intercept and a random slope for working memory load were included in the model. Finally, all correlations between random effects were included in the model.

In another LMM, we additionally tested the impact of working memory load on the increase in self-reported fatigue. The model included a fixed intercept and fixed effects for WML (low = -1, high = +1), time (pre = -1, post = +1) and the WML x Time interaction term. Moreover, we included a random intercept as well as random slopes for working memory load, time and the WML x Time interaction term. Again, all correlations between random effects were included in the model.

In a similar model, we explored the impact of working memory load on the increase in self-reported boredom. The model was set up identically to that of self-reported fatigue with only the dependent variable being changed to boredom.

In addition, we performed the same validity check of choice behavior as in Experiment 1. We ran an intercept-only Generalized Linear Mixed Model predicting activity choices (binary: top versus bottom ranking). A significant intercept indicated valid choice behavior, which meant that top-ranked activities were selected significantly more often than 50%.

In an exploratory validation check, we tested whether participants expected the physical activities to be more effortful than the non-physical activities using a LMM. The model included a fixed intercept as well as a fixed effect for activity-category. In addition, we included a random intercept as well as a per-participant random adjustment (i.e., 'random slope') to the activity-category slope. For all validity checks, we used the same functions and R-packages as in previous analyses.

***Main Analysis***

Similar to Experiment 1, we used a GLMM to test the impact of working memory load on physical activity choices. The model included a fixed intercept and a fixed effect for the within-subject factor working memory load (low = -1, high = +1). In addition, we included a per-participant random adjustment to the fixed intercept ('random intercept') as well as a per-participant random adjustment the fixed slope of working memory load ('random slope'). All correlations between the random effects were included. The same R-packages and functions were used as in the analyses for Experiment 1.

To account for potential order effects of the experimental manipulations, we repeated the main analysis while adding session order (high cognitive demand first = -1, low cognitive demand first = +1) and its interaction with working memory load to the original model. In addition to the fixed slopes of working memory load, session order and the interaction term Working Memory Load x Session order, we included the per-participant random adjustments to these slopes ('random slopes') as well as all correlations between the random effects.

***Exploratory Analyses***

Similar to Experiment 1, we ran an intercept-only GLMM predicting activity choices (binary: physical versus non-physical) within each condition. A significant intercept indicated a preference for either physical activities or non-physical activities.

Finally, we investigated to what extent initial preferences for physical activities (i.e., liking scores of physical activities minus liking scores of non-physical activities) related to the proportion of physical activities chosen using a Pearson's correlation test.

**Results**

***Validity Checks***

The LMM testing the effect of WML on experienced effort showed a significant effect of WML ($b$ = -19.01, $SE$ = 2.37, $t$(60.89) = -8.02, $p$ = .001). In line with our expectation, participants experienced the high WML condition to be more effortful ($M$ = 75.51, $SD$ = 27.50) than the low WML condition ($M$ = 37.28, $SD$ = 29.28).

The LMM testing the effect of WML and time on experienced fatigue showed a significant effect of time ($b$ = -18.09, $SE$ = 1.71, $t$(59.09) = -10.56, $p$ < .001). Participants reported to be more fatigued after the manipulation ($M$ = 72.51, $SD$ = 25.74) than before ($M$ = 36.16, $SD$ = 25.55). However, neither the effect of WML nor the interaction between WML and time-on-task were significant ($p$ = 0.069 and $p$ = .152 respectively). Fatigue did not increase significantly more in the high WML condition compared to the low WML condition.

Interestingly, the exploratory LMM testing the effect of WML and time on boredom showed significant effects of time ($b$ = -18.68, $SE$ = 1.53, $t$(61.33) = -12.18 , $p$ = .001), WML ($b$ = 3.24, $SE$ = 1.22, $t$(59.56) = 2.67, $p$ = .006) and also the interaction term Time x WML was significant ($b$ = -2.11, $SE$ = 0.99, $t$(60.27) = -2.13, $p$ = .042). The increase in boredom in the low WML-condition was stronger ($M_{pre}$ = 36.65, $SD$ = 23.43; $M_{post}$ = 78.59, $SD$ = 22.99) than in the high WML-condition ($M_{pre}$ = 33.86, $SD$ = 24.25; $M_{post}$ = 67.10, $SD$ = 30.67).

Thus, the low WML-condition evoked stronger feelings of boredom than the high WML-condition.

Our intercept-only GLMM of choice behavior on within category choices indicated valid choice behavior. Participants chose high ranking activities significantly more often than low ranking activities (on 84.53% of the within-category trials, participants chose the top-ranking activity; 95% CI [83.30, 87.52]). For a detailed overview of choice-behavior with respect to liking-scores, see Appendix Table A1.

To investigate whether participants expected physical activities to be more effortful than non-physical activities, another LMM testing the impact of activity category on predicted effort was performed. This analysis showed a significant effect of activity category ($b$ = 18.53, $SE$ = 0.93, $t$(62) = 19.84, $p$ = .001). Participants expected physical activities to be much more effortful ($M$ = 68.58, $SD$ = 21.66) than non-physical activities ($M$ = 32.51, $SD$ = 29.25).

***Main Analysis***

In contrast to our hypothesis, no significant differences in activity choices were found between the two conditions (OR = 1.08, 95% CI [0.98, 1.20], $p$ = .170). Participants were not significantly more likely to choose physical activities in the low WML condition compared to the high WML condition. See Appendix Table A2 and Figure A2 for more details about choice behavior within the two experimental conditions.

Interestingly, our follow-up analysis in which the interaction between session order and working memory load was added to the original analysis, showed a significant interaction effect (OR = 1.18, 95% CI[1.06, 1.31], $p$ = .004). Post-hoc analyses revealed that, only if participants went through the high WML condition in the first session, participants were more likely to choose physical activities in the high workload condition ($M$ = 0.35, $SD$ = 0.24) than in the low workload condition ($M$ = 0.25, $SD$ = 0.21; $p$ = .002). No significant differences in choice behavior emerged between the two experimental conditions if participants went through the low WML condition first *(*$M_{high\ WML}$ = 0.28, *SD* = 0.21; $M_{low\ WML}$ = 0.29, *SD* = 0.22, *p = .526).* While the means suggest a trend in which participants are less likely to choose physical activities in the low workload condition and in session 2, none of the other cells significantly differed from one another (*p*-values > .05).

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***Exploratory Analyses***

To better understand choice behavior within the two conditions, we performed an exploratory GLMM on within-group preferences. The analysis indicated a significant preference for non-physical activities in the high workload condition (on 31.6% of between-category trials, physical activities were chosen, 95% CI [19.44, 33.32]) and in the low workload condition (on 27.1% of between-category trials, physical activities were chosen, 95% CI [16.79, 27.56]). Thus, in both conditions, participants preferred non-physical over physical activities.

To investigate the origin of within-condition variation in choice-behavior (see Appendix, Figure A2), we conducted an exploratory Pearson's correlation test which showed that initial preferences for physical activities (i.e., liking of physical activities minus liking of non-physical activities) strongly correlated with the number of physical activities chosen (*r* = .72, 95%, CI [.50, .85]).

Several additional exploratory analyses were performed to further investigate choice behavior as well as n-back performance. See supplemental material for detailed descriptions of these analyses and results.

**Discussion**

In Experiment 2, participants experienced the high demanding WML condition as more effortful than the low demanding WML condition. Participants also indicated that they expected physical activities to be more effortful than the non-physical activities, and they again showed valid choice behavior (i.e., participants preferred high-ranked activities). However, in contrast to our hypothesis, participants were not significantly less or more likely to choose physical activities after performing a task with high WML compared to low WML. Exploratory analyses showed that participants in both conditions preferred non-physical activities over physical activities.

These unexpected findings could be explained by several unanticipated effects of our experimental manipulations. While we aimed to specifically induce fatigue in the high WML condition, we actually induced fatigue and boredom in both conditions and even evoked slightly stronger feelings of boredom in the low WML condition than in the high WML condition. Similar findings have been reported in previous research and it seems that prolonged periods of vigilance on a repetitive task (e.g., the n-back task) evoke feelings of both fatigue and boredom (Milyavskaya et al., 2019; Pattyn et al., 2008). Given the overlapping motivational consequences of fatigue and boredom, this could explain why participants in both conditions preferred not to be physically active after either of the experimental conditions.

A different but related issue is the moderating effect of session order we found. Only participants who underwent the high WML condition first were significantly less likely to select physical activities after the low WML condition. While the session order was counterbalanced and several precautions were taken to prevent any carry-over effects (e.g., a 48-hour interval between two sessions), the order of sessions mattered for the experimental effect. One possibility is that familiarity with the experimental procedure caused this moderating effect of session order.

In this light, it is interesting that participants' initial preferences for physical or non-physical activities strongly related to the proportion of physical activities they chose after the experimental manipulations. It seems that, irrespective of the subjective experiences of fatigue and boredom that were evoked by the manipulations, participants chose in line with their already existing preference for either physical or non-physical activities. This suggests that personal preferences for physical or non-physical activities are robust and relatively unaffected by aversive subjective states such as fatigue and boredom.

## General Discussion

In two experiments, we investigated the impact of cognitive work demands on subsequent physical activity behavior. Cognitive work demands were operationalized as workload (i.e., quantity) in Experiment 1 and as working memory load (i.e., task complexity) in Experiment 2. While it was hypothesized that cognitive work demands would negatively affect physical activity choices and physical performance, this was not found in either of the experiments. Therefore, it seems best to conclude that neither Experiment 1 nor Experiment 2 provide evidence for a negative impact of cognitive work demands on subsequent physical activity behavior.

Our findings appear in contrast to a previous study reporting a negative indirect effect of a cognitively demanding task on subsequent activity choices (Harris & Bray, 2019) and a previous meta-analysis reporting a negative effect on physical performance (Brown et al., 2019). A possible explanation for this discrepancy might be that while participants in the current study experienced the conditions with high cognitive demands to be more demanding, this did not result in the assumed elevated increases in subjective fatigue (van der Linden, 2011b). While fatigue increased in both conditions, this increase was not stronger in the more demanding conditions. It is important to note that also Harris and Bray (2019) found no direct effect of cognitive demands on the subsequent decision to exercise but only report an indirect effect through cognitive fatigue and cost-benefit scores. Moreover, while Brown and colleagues (2020) focused on the direct impact of cognitive demands on physical performance, 42 of the 73 included studies measured subjective cognitive fatigue and in 30 of these studies, significant increases in cognitive fatigue were reported. The absence of an effective fatigue manipulation in the present study could therefore explain why the expected impairing effect of cognitive work demands on physical activity behavior was not observed. Within the cost-benefit analyses for engaging in activities, fatigue is thought to increase the weight assigned to effort-costs, resulting in a reduced likelihood to engage in (physically) effortful activities (Müller & Apps, 2019). As fatigue was not effectively manipulated in our experiments, we can neither accept nor reject this cost-benefit assumption. In the absence of different increases in fatigue, our results do not show that individuals prefer less effortful, non-physical activities, over more effortful physical activities, after performing an effortful cognitive task. Rather, they simply choose the activities they like best. This result is noteworthy for several reasons.

First, these findings provide support for the conclusion of Harris and Bray (2019) that the individual experiences of cognitive fatigue, rather than the demanding characteristics of the cognitive task, influence subsequent physical behavior. Similar to Harris and Bray (2019), we found no evidence for a direct effect of cognitive demands on subsequent activity choice behavior while manipulating different types of cognitive demands (i.e., workload and WML instead of inhibition) and while using a more thorough activity choice task (i.e., 60 paired choices instead of one). These insights provide a critical perspective to the conclusions of Brown and colleagues (2020), who stated that cognitive exertion leads to reductions in physical performance. Our findings, together with those of Harris and Bray (2019), suggest it to be more realistic that the studies included in their meta-analysis evoked cognitive fatigue, which then resulted in the reductions in physical performance. While this assumption cannot be tested (only 42 of the 73 studies measured cognitive fatigue), our findings highlight the importance to disentangle the effect of cognitive demands from that of cognitive fatigue on subsequent physical behavior.

Importantly, our study reveals limitations in the conceptualization of cognitive fatigue. Within our experiments, two types of cognitive demands (i.e., workload and WML) were successfully manipulated. However, this did not result in stronger increases of cognitive fatigue in the more demanding conditions. It is hard to pin-point the exact origin of this ineffective fatigue manipulation. The relatively long duration of the manipulations (i.e., 45-90 minutes) could have caused the low demanding condition to be fatiguing as well. At the same time, exploratory analyses suggest that under-arousal in the low demanding condition elicited feelings of boredom, which experiential properties and motivational consequences strongly overlap with those of cognitive fatigue (Milyavskaya et al., 2019). Importantly, this is not the only study where a manipulation in cognitive demands does not elicit the expected changes in self-reported cognitive fatigue (see for example Brown et al., 2019; Massar et al., 2010). This underscores the importance to further refine the current conceptualization of cognitive fatigue as a state resulting from prolonged cognitive effort exertion (Müller & Apps, 2019). The current conceptualization does not describe the precise circumstances under which cognitive effort expenditure results in cognitive fatigue, boredom or a neutral state. Moreover, the definition is not clear with regard to the precise type, duration, and intensity of cognitively demanding tasks that elicit cognitive fatigue. Our findings therefore provide an empirical call for a clearer and more testable conceptualization of cognitive fatigue. This will be crucial for advancing our understanding of the possible carry-over effects of cognitive work demands and cognitive fatigue on subsequent physical behavior.

Second, our findings shed new light on the psychology of physical activity behavior. Our study highlights the importance to consider personal liking of the activities on offer. Our exploratory analyses indicated that liking of activities predicts physical activity behavior above and beyond exposure to cognitively demanding work. Evidently, liking of activities weighs heavily in the cost-benefit analysis underlying the decision to engage in physical activity. This could explain why intrinsic exercise motivation is a strong predictor of physical activity participation in field studies (Teixeira et al., 2012). The experiential properties of engaging in physical activities out of intrinsic reasons (e.g., enjoyment and fun) seem to outweigh many possible costs. This mechanistic account of motivation for physical activity (i.e., cost-benefit) has a strong potential for application in physical activity promotion. It suggests that personal barriers (e.g., effort) and facilitators (e.g., enjoyment) of physical activity should never be considered in isolation but always relative to each other.

Strengths of the present work are the controlled experimental procedures including several validation checks. Moreover, the combination of two experiments allowed us to both identify and address potential shortcomings such as the quality of the manipulation. At the same time, several limitations provide interesting opportunities for future research. First of all, our study has shown that more cognitively demanding work does not necessarily lead to stronger increases in subjective cognitive fatigue. Manipulating cognitive fatigue will be important for better understanding the impact of cognitive fatigue on subsequent physical activity behavior. To successfully do so, the fatigue inducing effects of the experimental and control condition should differentiate more strongly. This may be obtained by selecting more fatiguing tasks for the experimental condition (for examples, see Lin, Saunders, Friese, Evans, & Inzlicht, 2020; O'Keeffe, Hodder, & Lloyd, 2020; Smith, Chai, Nguyen, Marcora, & Coutts, 2019), by limiting the fatiguing effects of the control condition (e.g., performing leisure activities such as watching a documentary), or by a combination of the two. Such study designs will enable researchers to disentangle the impact of cognitively demanding work from the impact of cognitive fatigue on physical activity behavior. Second, insight into activity choice behavior could be advanced by matching activities based on their absolute liking instead of their within-category rankings. Moreover, the (predicted) effort levels of each activity (i.e., costs) should be incorporated in the choice task. The current choice paradigm was a step forward towards valid activity-choice assessment since it was the first to explicitly take personal liking of activities into account. However, our findings imply that for accurately capturing activity category preferences (i.e., physical or non-physical) from a cost-benefit perspective, the activities to choose from should be matched on their absolute liking scores while controlling for the effort requirements of each activity. Combining an improved fatigue manipulation with an improved choice-task will advance our understanding of the cost-benefit analyses underlying physical activity choice behavior. Specifically, it will allow researchers to unravel the possible interactions between fatigue, effort and liking of activities as well as the way they feed into the cost-benefit analyses.

To conclude, this study improves our understanding of physical activity behavior. Our study questions the effect of cognitively demanding tasks on subsequent feelings of cognitive fatigue and physical behavior. Furthermore, findings from exploratory analyses highlight the robustness of individuals' preferences for activities, even after periods of cognitively demanding work. This stresses the importance of taking personal liking of activities into account when investigating and promoting physical activities. Importantly, these latter findings need to be replicated in future studies. Theoretically, the cost-benefit approach has high potential to improve our understanding of the motivation for physical activity. While its predictions with respect to physical activity behavior demand further testing, the mechanistic approach towards physical activity motivation is promising. The approach requires specificity in prediction and precision in measurement, which will be crucial for advancing our understanding of physical activity motivation. In this respect, researchers and healthcare providers are advised to disentangle how exactly liking, effort requirements and fatigue feed into the decision to engage in physical activities. Such insights will be crucial for improving the effectiveness of global physical activity promotion.

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## Appendix

Table A1.

*Choice behavior and liking scores of activities per group and per activity-category.*

| Variable[a] | Experiment 1 ($N = 40$) High workload | Experiment 1 ($N = 40$) Low workload | Experiment 1 ($N = 40$) Significance[b] | Experiment 2 ($N = 63$) High WML | Experiment 2 ($N = 63$) Low WML | Experiment 2 ($N = 63$) Significance[b] |
|---|---|---|---|---|---|---|
| % Physical activities chosen | 52.86 (26.76) | 34.56 (22.04) | * | 31.58 (46.49) | 27.12 (44.47) | n.s. |
| % High ranked activities chosen | 86.03 (8.30) | 86.14 (6.33) | n.s. | 84.84 (7.09) | 84.22 (7.77) | n.s. |
| Liking of physical activities | 50.62 (27.12) | 46.23 (30.59) | n.s. | 44.55 (27.92) | | ** |
| Liking of non-physical activities | 49.96 (28.87) | 49.09 (31.87) | n.s. | 52.96 (30.97) | | |

*Note.* WML = Working Memory Load

[a]Theoretical range for all variables was 0-100. [b]All tests of significance were performed using (parametric) bootstrapping.

*$p < .05$, **$p < .01$

Table A2.

*Liking Difference Scores per Condition and per Chosen Category.*

| | | Experiment 1 | | Experiment 2 | |
|---|---|---|---|---|---|
| Trialtype | | | | | |
| *Between-category* | Chosen activity | High Workload | Low Workload | High WML | Low WML |
| | Physical activity | | | | |
| | Mean(SD) | 9.17(18.54) | 6.86(17.94) | 3.93(19.71) | 4.63(19.94) |
| | Range | -47.48 – 49.91 | -71.96 – 49.22 | -57.47 – 73.27 | -81.25 – 73.27 |
| | Non-physical activity | | | | |
| | Mean(SD) | 8.87(17.73) | 8.00(21.34) | 12.55(20.48) | 10.77(21.58) |
| | Range | -43.75 – 48.96 | -49.22 – 80.12 | -74.83 – 65.97 | -74.83 – 85.42 |
| *Within-category* | | | | | |
| | Physical activity | | | | |
| | Mean(SD) | 21.71(28.51) | 29.76(32.50) | 27.57(30.96) | 25.36(32.24) |
| | Range | -83.77 – 87.68 | -78.65 – 99.91 | -79.34 – 100 | -93.14 – 100 |
| | Non-physical activity | | | | |
| | Mean(SD) | 33.42(32.55) | 37.23(35.78) | 34.91(35.87) | 34.92(36.27) |
| | Range | -74.39 - 100 | -80.99 – 92.97 | -100 – 100 | -100 – 100 |

*Note*. Liking difference scores were calculated as: VAS liking score of chosen activity – VAS liking score of unchosen activity. Scores that are closer to zero represent a stronger match on absolute liking-scores. Moreover, a positive score indicates that participants chose activities they liked better while a negative score indicates the opposite.