The effect of opportunity costs on mental fatigue in labor/leisure tradeoffs

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Author Note

The authors have complied with the APA ethical principles regarding research with human participants in the conduct of the research presented in this manuscript. Link to data and materials: https://osf.io/t4afr/?view_only=945cbc60b4764b618deb6c2dfb5a3fb7.

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Abstract

Most people experience the feeling of mental fatigue on a daily basis. Previous research shows that mental fatigue impacts information processing and decision making. However, the proximal causes of mental fatigue are not yet well understood. In this research, we test the opportunity cost model of mental fatigue, which proposes that people become more fatigued when the next-best alternative to the current task is higher in value. In four preregistered experiments (total N = 430), participants repeatedly reported their current level of fatigue and chose to perform a paid labor task vs an unpaid leisure task. In Study 1, all participants were offered the same labor/leisure choice. In Studies 2 and 3, we manipulated the opportunity costs of a labor task by varying the value of an alternative leisure task. In Study 4, we manipulated the opportunity costs of a labor task by varying the value of that labor task. In all studies, we found that people were more likely to choose for leisure as they became more fatigued. In Studies 2–4, we did not find that the manipulated leisure value influenced the amount of fatigue participants experienced nor the likelihood to choose for leisure. However, in exploratory analyses, in all studies, we found that participants who reported to value the leisure task more, got more fatigued during labor and less fatigued during leisure. Collectively, these results provide cautious support for the opportunity cost model, but they also show that cost-benefit analyses relating to labor and leisure tasks are fleeting.

Keywords: opportunity costs, mental fatigue, motivation, labor/leisure, decision-making

For most people, most of the time, prolonged cognitive activity results in an aversive subjective experience called *mental fatigue*. Although scientists are still struggling to agree on a definition of mental fatigue, there is consensus that mental fatigue involves a feeling of tiredness and a reduced willingness to invest further effort (Hockey, 2013). Also, there is consensus that fatigue, as it increases with time on task, is accompanied by impaired performance, at least during laboratory tasks (Kato, Endo, & Kizuka, 2009). In line with this consensus, research shows that the feeling of fatigue impacts human information processing and decision making (Hopstaken, van der Linden, Bakker, & Kompier, 2015b) and that fatigue is a risk factor for workplace accidents (Swaen, Van Amelsvoort, Bültmann, & Kant, 2003) and errors (Baker, Olson, & Morisseau, 1994). Given that fatigue is experienced by so many people on a daily basis, and given its consequences for cognition and behavior, it is worthwhile to study fatigue. Yet, despite more than 100 years of research on the subject (Dodge, 1917), we still have no good answers to several basic questions surrounding fatigue. For example, what are the proximal causes of the feeling of fatigue? And, how is it possible that people can sometimes work hard for hours and *not* feel fatigued?

In the past decades, mental fatigue has usually been conceptualized as a negative consequence of investing mental effort that arises when some limited *resource* gets depleted (Kahneman, 1973; Muraven, Tice, & Baumeister, 1998; Wickens, 2002). In other words, fatigue was often thought to be a signal that indicates that a metaphorical mental battery is being drained. Although these models have been important for the field (they inspired a large body of empirical work), they have been less well-regarded recently for at least three reasons. First, they are circular (Hockey, 2011; Lurquin & Miyake, 2017). That is, they claim that people become fatigued due to a depleted resource, while fatigue is seen as an indicator of depletion. Second, several findings emerged that are seemingly incompatible with the depletion model (e.g., the effect can be reversed by increasing task motivation, Hopstaken, van der Linden, Bakker, Kompier, & Leung, 2016; Muraven & Slessareva, 2003; by meta-cognitive beliefs, Job, Dweck, & Walton, 2010; and by perceiving oneself as vital, Clarkson, Hirt, Jia, & Alexnander, 2010). Third, attempts to pinpoint the resource that is being depleted when people start to feel fatigue have been unsuccessful (Kurzban, 2010; Orquin & Kurzban, 2016).

As it thus became clear that a critical theoretical revision was needed, in the past decade, several researchers proposed motivational models that conceptualize fatigue as an *adaptive signal* that reflects the costs of performing the current activity (Boksem & Tops, 2008; Hockey, 2011; Inzlicht, Schmeichel, & Macrae, 2014; Kurzban et al., 2013). According to these models, changes in motivation lead to changes in how resources are *deployed* rather than depleted. These motivational accounts have in common that they view fatigue as a functional experience that supports goal pursuit. In particular, when people have the choice to pursue multiple goals, fatigue can be thought of as a ‘stop emotion’ (Meijman, 1997; van der Linden, 2011) that triggers a reconsideration of priorities. In other words, fatigue may function as a signal to disengage from the currently-selected activity, in order to switch to doing something else.

One of these motivational models, the *opportunity cost model* (Kurzban et al., 2013), proposes a specific mechanism that explains the occurrence of fatigue. The opportunity cost model starts out from the observation that the human mind is capable of pursuing multiple goals but that it can usually only work towards one goal at a time (Shenhav et al., 2017). Thus, people need to continuously prioritize one activity over a set of alternative activities (Kurzban et al., 2013). As carrying out an activity makes it more difficult to do other things at the same time, activities carry *opportunity costs*. According to the opportunity cost model, these costs equal the utility of the next-best activity that is currently *not* carried out. In the model, the utility of an activity is thought to be the rewards relative to the costs associated with the activity. The experience of fatigue, then, is the output of a cost-benefit analysis that weighs the utility of the current activity against the utility of the next-best alternative(s).

The opportunity cost model suggests that fatigue functions as a conscious signal that tells people that it is time to switch activities, as alternative activities likely have higher utility than the current one. For example, while writing a paper, a student would get fatigued faster if the alternative in the environment (e.g., texting a friend) would have higher utility in that moment. Following from this, the model predicts that as long as the currently-selected activity carries the most favorable cost-benefit ratio, one would not become fatigued, or only very slowly so. On the other hand, as soon as the relative utility of the next-best alternative is higher than the utility of the currently-selected activity, fatigue should emerge.

A decision context that often involves fatigue pertains to decisions between *cognitive labor* (i.e., investing effort to obtain a reward) and *cognitive leisure* (i.e., performing a non-demanding, relieving activity; Inzlicht, Schmeichel, & Macrae, 2014; Kool & Botvinick, 2014). Previous research shows that people gradually disengage from a mentally demanding task when they are fatigued (Hopstaken, van der Linden, Bakker, & Kompier, 2015a; Warm, Parasuraman, & Matthews, 2008). For example, a student studying in the library can choose to continue to study (mental labor) or to disengage from studying to play with her smartphone (mental leisure). Following the model (and assuming that the student values playing with her smartphone), the student should become fatigued faster if she brought her phone with her (versus not). After all, not bringing her phone to the library should remove a high-value alternative activity. As the student becomes fatigued faster when she brought her phone, she should also disengage from her labor task earlier to switch to the highest-valued alternative task that is currently available.

In this paper, we try to understand the origin of fatigue through the lens of the *opportunity cost model* of mental fatigue (Kurzban et al., 2013). In four studies, we test three basic hypotheses derived from the model. First, we hypothesize that people are more likely to decide to perform leisure (vs labor) tasks when they are more fatigued (Kurzban et al., 2013, see also Inzlicht et al., 2014; Study 1). Second, we hypothesize that during labor the feeling of fatigue *increases* with the relative utility of available leisure activities, while during leisure the feeling of fatigue *decreases* with the relative utility of the same leisure activities (Studies 2 – 4). Third, we hypothesize that people are more likely to decide to perform leisure (vs labor) tasks when the utility of the leisure task relative to the labor task is higher (Studies 2 – 4). Within these studies, we test how people make decisions between cognitive labor (e.g., performing a 2-back task) and cognitive leisure (e.g., interacting with one's smartphone).

In all studies, participants repeatedly (a) reported their current level of fatigue, (b) chose between a paid *labor* task vs an unpaid *leisure* task, and then (c) executed their choice. Our task contained a key difference compared to previous work on the tradeoff between cognitive labor and cognitive leisure (Kool & Botvinick, 2014; Rom, Katzir, Diel, & Hofmann, 2019). Whereas in previous work leisure was often operationalized as an easier version of the labor task, we offered participants the choice between two qualitatively different alternatives. We chose to do this in order to more closely model decisions in real life, where choices between labor and leisure tend to be less similar than a high- and low-demanding alternative of the same task (Algermissen, Bijleveld, Jostmann, & Holland, 2019). Hence, we combine the experimental control of the laboratory with the ecological validity of real-world leisure activities. For instance, recent work suggests that many students (Orben & Przybylski, 2019) and office workers (Dora, van Hooff, Geurts, Hooftman, & Kompier, 2019) interrupt their work flow many times a day in order to interact with their smartphone. Given the qualitative difference between labor (effortful, gainful activity) and leisure (non-effortful, relieving activity), we will test the model offering participants to interact with their own smartphone and similar real-life leisure activities.

Study 1

Study 1 tested the prediction that fatigue relates to subsequent choice, such that participants are more likely to choose to carry out a leisure task when they are more fatigued. Secondary, in line with the basic idea that leisure tasks help people recover (Inzlicht et al., 2014; Kurzban et al., 2013), we predicted that change in fatigue after performing a leisure task is less positive than after performing a labor task. Following this formulation, we expected fatigue to *increase* during labor and to *decrease* during leisure. We chose to test this additional prediction to ensure that our choice task worked as intended, with participants getting increasingly more fatigued during labor and recovering during leisure. This is an important feature of the task for the predictions we tested in Studies 2 and 3.

We developed a choice task similar to previous work on labor/leisure tradeoffs (Algermissen et al., 2019; Kool & Botvinick, 2014). Participants first rated their current level of fatigue; then, they chose to do either a paid labor task (in this case, a 2-back task) or an unpaid leisure task (in this case, interacting with their smartphone); then, they carried out the task of their choice for two minutes. This sequence of events was repeated 40 times, such that the total duration of task performance (80 minutes) was sufficiently long to reasonably expect fatigue to increase over time.

Method

Preregistration and data availability

We preregistered design, hypotheses, sample size, and statistical analyses. Our preregistration, experimental materials, data, power simulation and analysis scripts are available on the Open Science Framework project of this article (https://osf.io/t4afr/).

Sample size rationale

A set of power simulations (N = 1000) based on data from a small pilot study revealed that we would achieve power = .90 with N = 22 participants for the observed 16-point difference in change in fatigue after labor and leisure respectively[1]. Due to the limitations of powering to the effect found in a small sample, we decided to collect data from 40 participants to be on the safe side.

Participants, procedure, and design

40 university students (M_{age} = 22.38; 32 females) participated in exchange for either 10€ or partial course credit and an extra cash payment of up to 6€, depending on how often they chose for the 2-back task. Participants had to be between 18 and 30 years of age and own a smartphone. Upon arrival in the lab, the experimenter made sure that the participants brought their smartphone, that it was sufficiently charged, and put to silent mode. The participants were then seated in a dimly-lit cubicle, putting their smartphone face-down on a marked position on the table. After informed consent was obtained, participants reported demographics (age and gender), received instructions, and practiced the 2-back task for two blocks (first at 50% speed, then at 100% speed). Participants next completed 40 blocks of the choice task, which is described below. These 40 blocks took approximately 85 minutes to complete. After they were done, participants were debriefed and received their compensation. The study as well as the

[1] We discovered a small mistake in our power script after the data was collected. Fixing this mistake revealed that we would have reached power = .90 with N = 19 under the same assumptions.

subsequent studies reported in this paper were approved by the local ethics review board. We employed a correlational within-subjects design with repeated measures of fatigue and choice.

Choice task

The task was created using PsychoPy (Peirce, 2007). Within one block, participants first rated their current level of fatigue on a 100-point Visual Analogue Scale (ranging from ‘not at all’ to ‘extremely’). Next, participants chose whether they would like to work on the 2-back task (described in further detail below), for which they would earn an additional 0.15€, or whether they would rather like to engage in an unpaid interaction with their smartphone. Participants were instructed that the extra cash payment would only be paid out if accuracy on the 2-back task remained above 80%. We chose this threshold in order to ensure that participants continuously worked hard on the 2-back task throughout the session. We instructed the participants to interact with their smartphone and not do anything else when they chose for the leisure task. Participants then engaged with either the labor task or leisure task (depending on their choice) for 2 minutes, after which the next block would start. The choice task is visualized in Figure 1.

2-back task. We used a visual letter variant of the 2-back task, which is a cognitively demanding task that has been used previously to induce fatigue (e.g, Hopstaken et al., 2016; Massar, Wester, Volkerts, & Kenemans, 2010). Participants had to decide whether a letter presented on the screen was a target or a non-target, and in case of a target, press a corresponding button on the keyboard. Targets were trials where the letter presented was the same as the letter presented before the previous one. The stimuli were presented for 500ms in the center of the screen, followed by an intertrial interval of 1500ms. The target rate was 25%.

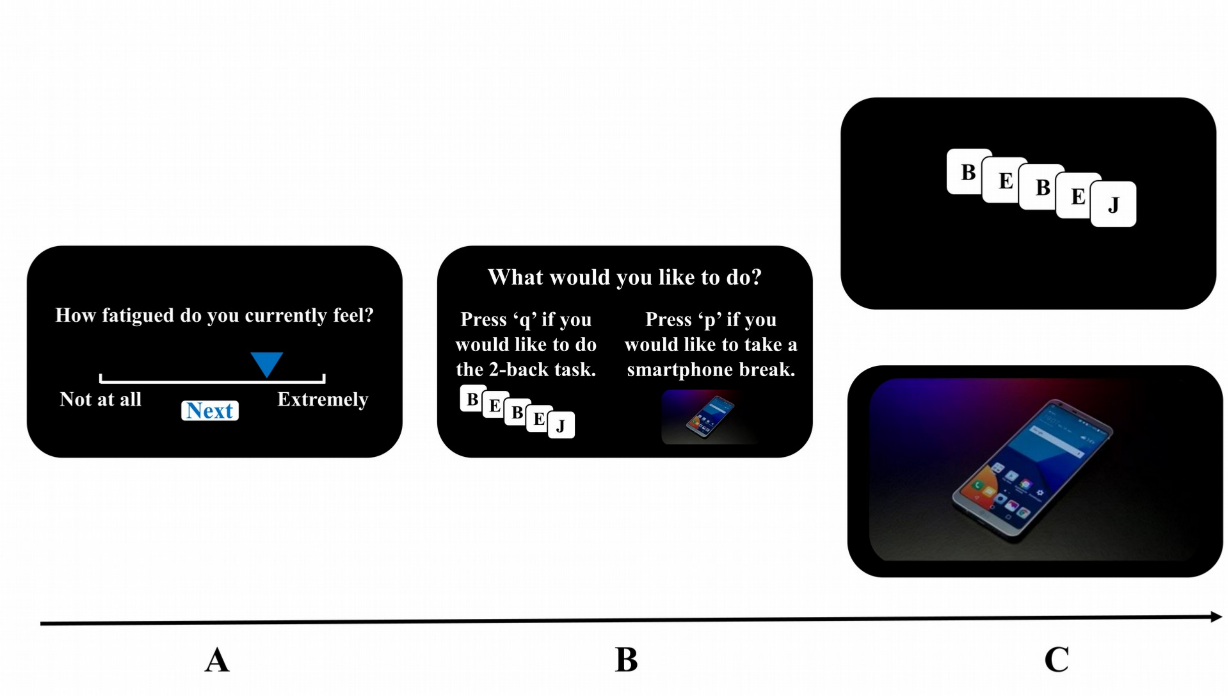

Figure 1. Sequence of events in the choice task. (A) Self-report of current fatigue. (B) Labor/leisure choice. (C) Execution of labor or leisure depending on choice.

Data analysis

We conducted all of our analyses in R (version 3.6.0; R Core Team, 2019). In line with our preregistration, we tested our hypotheses using a (generalized) linear mixed-effects modeling approach using the *(g)lmer* function (*lme4* package; version 1.1.21; Bates, Martin, Bolker, & Walker, 2015). In all analyses, the block was the unit of analysis. Continuous predictors were standardized on a sample level, because this was most favorable for model convergence. We aimed for 'maximal' random effects structures in our two models as advocated by Barr, Levy, Scheepers, and Tily (2013) to avoid inflated Type-1 errors. Accordingly, in our two models, we included a random intercept in order to take into account that participants naturally differ in their general experience of fatigue, as well as their general tendency to choose for labor or leisure. We also included random slopes for all within-participant predictors. We did this in order to take into account that the effect of fatigue on labor/leisure choice as well as of labor/leisure choice on change in fatigue may be stronger in some participants than in others. This resulted in the following R syntax: labor/leisure choice ~ 1 + fatigue + (1 + fatigue | participant); change in fatigue ~ 1 + labor/leisure choice + (1 + labor/leisure choice | participant). Change in fatigue was computed by subtracting the fatigue score of the previous block from the fatigue score of the current block. To determine p-values, we computed Type III bootstrapped Likelihood Ratio tests (two-tailed; $\alpha = .05$) using the *mixed* function (*afex* package; version 0.23.0; Singmann, Bolker, & Westfall, 2015).

Results

Preregistered analyses

Across all blocks from all participants, mean fatigue was 60 points ($SD = 22$). Participants chose for the 2-back task on 78% of the blocks. The main effect of fatigue on labor/leisure choice was significant, estimate = -1.12, $SE = 0.17$, 95% CI [-1.44, - 0.79], $OR_{leisure} = 3.06$, $p < .001$. In line with our hypothesis, with an increase of one standard deviation in fatigue, participants were more than three times as likely to choose for the leisure task compared to the labor task. The effect of labor/leisure choice on change in fatigue was also significant, estimate = -6.63, $SE = 1.02$, 95% CI [-8.61, -4.57], $p < .001$. In line with our hypothesis, participants were more fatigued after choosing and executing the labor task (compared to before the labor task; $M = 3.82$) and less fatigued after choosing and executing the leisure task (compared to before the leisure task; $M = -9.29$)[2]. Thus, on average, during one two-minute leisure block participants' decreased experience of fatigue roughly equated the increase in fatigue during two two-minute labor blocks.

[2] We repeated this analysis, as well as all subsequent analyses predicting change in fatigue, controlling for baseline fatigue level. Unless otherwise noted, none of our results changed when (not) controlling for baseline fatigue.

Secondary analysis

Due to our correlational design, at this point we could not be sure that participants *used* their perception of fatigue to guide their labor/leisure choice. An alternative explanation is that participants *inferred* their level of fatigue from the choice they just made ('I just chose labor, so I am probably not that tired.'; for a similar effect, see Khan & Dhar, 2006). In order to tentatively rule out this explanation, we tested whether fatigue mediates the relationship between time on task (operationalized as block number) and labor/leisure choice. Due to the temporal order of the sequence of events in study, finding this mediation would be more consistent with our proposed explanation. That is, if participants got more fatigued over time and in turn more likely to choose for leisure over labor, this speaks more to participants using their experience of fatigue for the decision what to do next than vice versa.

We tested this idea with the *mediate()* command (*mediation* package; version 4.4.7; Tingley, Yamamoto, Hirose, Keele, & Imai, 2014), which decomposes the total effect of time on task on labor/leisure choice into a direct effect and an indirect effect through fatigue. This analysis indicated that the indirect effect of time on task on labor/leisure choice through fatigue was significant, estimate = -0.13, 95% CI [-0.20, -0.08], $p < .001$. This means that over time, participants got more fatigued, and in turn more likely to choose for leisure over labor. The direct effect of time on task on choice was significant and positive, estimate = 0.11, 95% CI [0.06, 0.16], $p < .001$, while the total effect was not significant, estimate = -0.03, 95% CI [-0.11, 0.04}, $p = .40$. Thus, this result is more in line with participants using their feeling of fatigue in order to make a labor/leisure choice than with them inferring their fatigue level from their previously made choice.

The positive direct effect of time on task on choice may be explained post-hoc from participants' desire to balance labor and leisure (Kool & Botvinick, 2014). Specifically, as people chose more leisure later in the experiment, due to increases in fatigue, they may have tried to offset this behavioral tendency by also increasing their general (fatigue-independent) tendency to choose labor. The latter tendency may have caused the positive direct effect of time on task on choice.

Discussion

Study 1 supported our prediction that fatigue is associated with a greater likelihood to choose leisure over labor. Also, Study 1 showed that people get more fatigued during labor and less fatigued during leisure. These results are in line with the basic tenets of the opportunity cost model, but they are also in line with a range of other theoretical accounts of mental fatigue (Boksem & Tops, 2008; Hockey, 2011; Muraven et al., 1998). Thus, in Study 2, we wanted to test the central and unique assumption of the opportunity cost model, namely that the experience of fatigue does not only depend on the current task but also on the utility of the alternative in one's immediate environment. To do so, we attempted to manipulate the opportunity costs of the labor task by manipulating the utility of the leisure task (high-value leisure activity vs low-value leisure activity).

A brief note on terminology: While the *utility* is thought to be a characteristic of the task (Kurzban et al., 2013), the subjective *value* is thought to be a representation of this utility in the participant's mind (Berkman, Hutcherson, Livingston, Kahn, & Inzlicht, 2017). Hence, going forward we will refer to the participants' perception of a task's utility as *value*.

Study 2

We examined the opportunity cost model by testing three specific predictions.[3] First, we predicted that while people perform mental labor, the increase in fatigue is stronger if the opportunity costs of the labor task (i.e., the value of mental leisure) are higher. Evidence for this prediction would suggest that the feeling of fatigue stems from a cost-benefit analysis. Second, we predicted that increases in fatigue (due to opportunity costs) are associated with a greater likelihood of choosing for mental leisure over mental labor. Evidence for this prediction would suggest that fatigue functions as a signal to switch activities. Third, we predicted that while performing mental leisure, the decrease in fatigue is stronger if the opportunity costs of the labor task (i.e., the value of mental leisure) are higher. Evidence for this prediction would again suggest that the feeling of fatigue stems from a cost-benefit analysis.

In Study 2, we added a between-participant manipulation of the opportunity costs of the labor task to the setup of Study 1. More specifically, we manipulated the utility of the leisure task. Given that the leisure task was the only viable alternative that people have in our paradigm, the value of this leisure task should impact the opportunity costs of the labor task. We operationalized the high-value leisure task again as the smartphone interaction. For the low-value leisure task, we offered the participants to read in a magazine we assumed to be of low value to our sample of university students ('How to retire in style', 2018 edition). We chose this magazine for two main reasons. First, reading a magazine is another leisure task high in

[3] The wording of the hypotheses in the preregistration differed slightly. Because this was our first time adding a between-participant manipulation, we preregistered some additional hypotheses for our own understanding unrelated to the opportunity cost model. Additionally, we preregistered two tests of the first prediction and adjusted our α level accordingly. Since then, we lost confidence in one of these tests (see preregistration Study 3). For clarity reasons, here we report the analyses that we also preregistered for Study 3 and moved the additional analyses to the Open Science Framework project page. None of the results omitted from the manuscript change our conclusions in any way.

ecological validity. Second, we assumed that reading in a magazine requires similar information processing (i.e., mainly processing of text and pictures) to the use of one's smartphone.

Method

Preregistration and data availability

We preregistered design, hypotheses, sample size, and statistical analyses. Our preregistration, experimental materials, data, power simulation and analysis scripts are available on the Open Science Framework project of this article (https://osf.io/t4afr/).

Sample size rationale

We ran a set of power simulations (N = 1000) using the simr package (version 1.0.3; Green & MacLeod, 2016) in R. As input to the simulations we used the data from Study 1. As there was no between-participant treatment in Study 1, we a priori assumed that a raw estimate of -0.2 would represent a meaningful effect for the test of the leisure value manipulation on the increase in fatigue. According to these simulations, we would achieve power = .90 with N = 130.

Participants, procedure, and design

130 university students (65 per treatment; M_{age} = 22.03; 96 females) participated in exchange for the same compensation as in Study 1, and were assigned to either the high leisure value (smartphone) or low leisure value (magazine) treatment as they entered the lab in an alternating fashion. Participants again had to be between 18 and 30 years of age and own a smartphone. The procedure in the high leisure value treatment was identical to that in Study 1. In the low leisure value treatment, the magazine took the place of the smartphone on the table. After the experimental blocks were completed, participants additionally reported how much they enjoyed the leisure task during the experiment. This was done as a manipulation check to measure how much participants valued the leisure task in both treatments. We employed a

between-subjects design (high leisure value vs low leisure value) with repeated measures of fatigue and choice.

Choice task

The choice task was identical to the one employed in Study 1. The only difference was that participants in the low leisure value treatment were asked to choose between paid execution of the 2-back task (labor) or an unpaid interaction with the provided retirement magazine (leisure). We asked participants in the low leisure value treatment to silence their smartphone. We did not give them any other information or instructions regarding their smartphone when they entered the lab in order to prevent the smartphone from being an additional salient alternative to the labor task.

Data analysis

We used similar analyses to the ones reported in Study 1. Again, continuous predictors were standardized on the sample level. In order to achieve maximal models, all models included a per-participant random intercept to account for the repeated-measures nature of the data. Wherever possible, fixed effects were additionally modeled as random slopes varying across participants (i.e., those predictors that were nested in participants; e.g. fatigue and labor/leisure choice, but not treatment). In order to test whether the increase in fatigue while performing labor was stronger when opportunity costs where higher, we tested the effect of treatment (high leisure value vs low leisure value) on change in fatigue in those blocks where participants chose the labor task. In order to test whether this increase in fatigue translated into a higher likelihood to choose the leisure task, we tested the mediation reported in Study 1 (time on task → fatigue → labor/leisure choice) in both treatments separately. Since the moderated mediation implemented in the mediation package does not calculate an exact p-value, we preregistered to reject the null hypothesis if the 95% CIs of the indirect effect in both treatments do not overlap. To test whether the decrease in fatigue while performing leisure was stronger when the opportunity costs were higher, we tested the effect of treatment on change in fatigue in those blocks where participants chose for the leisure task.

Results

Preregistered analyses

Across all blocks from all participants, mean fatigue was 62 points (*SD* = 23). Participants chose for the 2-back task on 74% of the blocks. Participants in the high leisure value treatment rated the leisure task as more enjoyable (*M* = 61.38, *SD* = 26.11) than participants in the low leisure value treatment (*M* = 47.03, *SD* = 27.94), *d* = 0.53 (see Figure 2).

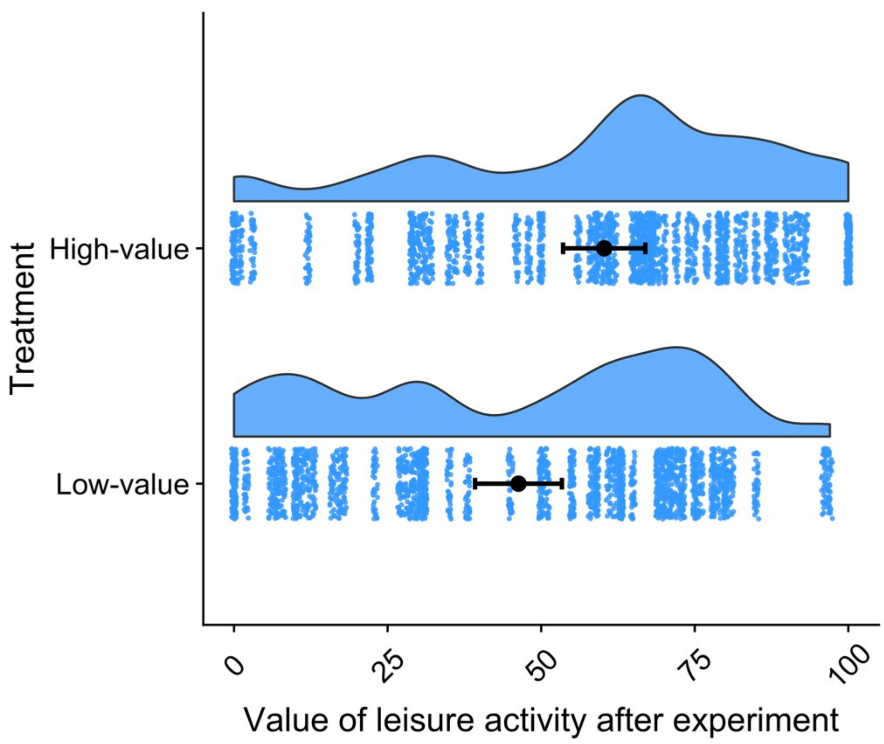

Figure 2. Raincloud plot of reported enjoyment of leisure activity after experiment in both treatments. Error bars reflect between-participant 95% confidence intervals.

We proceeded by testing our main predictions. First, the effect of treatment on change in fatigue was not significant in those blocks where participants chose for labor, estimate = -0.26, *SE* = 0.31, 95% CI [-0.91, 0.36], *p* = .40. Hence, we did not find evidence that participants became more fatigued in the high leisure value treatment while working on the cognitively demanding labor task. The data associated with this analysis are visualized in Figure 3.

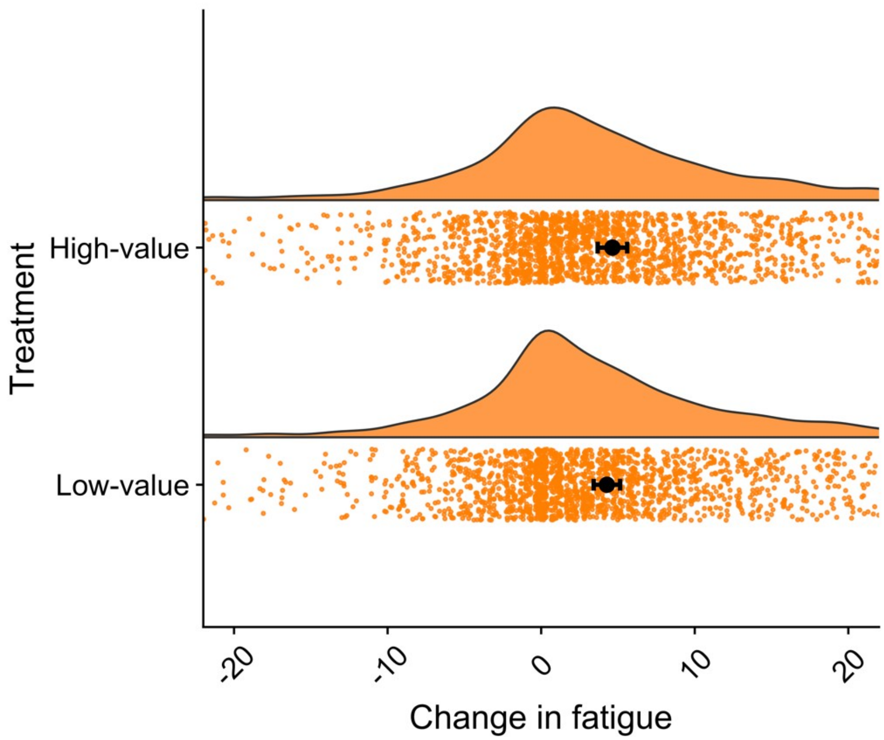

Figure 3. Raincloud plot of change in fatigue after performing the labor task in both treatments. Error bars represent within-participant 95% confidence intervals. Positive (negative) scores reflect an increase (decrease) in fatigue during labor.

Second, the indirect effect of time on task on labor/leisure choice through fatigue was significant in both treatments, indicating that participants got more fatigued over time and in turn more likely to choose for leisure. However, this effect did not differ significantly between the two treatments. The 95% CIs for the indirect effect in both treatments overlapped, $\text{estimate}_{\text{low leisure value}}$ = -0.16, 95% CI [-0.21, -0.11]; $\text{estimate}_{\text{high leisure value}}$ = -0.12, 95% CI [-0.17, -0.09] (see Figure 4). This result is unsurprising given that the previous model revealed that participants did not get more fatigued in the high leisure value treatment (and hence this non-existent increase in fatigue was unlikely to lead to an increased probability to choose for the leisure task). The direct effect of time on task on labor/leisure choice was positive in both treatments, $\text{estimate}_{\text{low leisure value}}$ = 0.07, 95% CI [0.03, 0.10]; $\text{estimate}_{\text{high leisure value}}$ = 0.06, 95% CI [0.03, 0.09], while the total effect was negative in both treatments, $\text{estimate}_{\text{low leisure value}}$ = -0.09, 95% CI [-0.14, -0.05]; $\text{estimate}_{\text{high leisure value}}$ = -0.07, 95% CI [-0.12, -0.03].

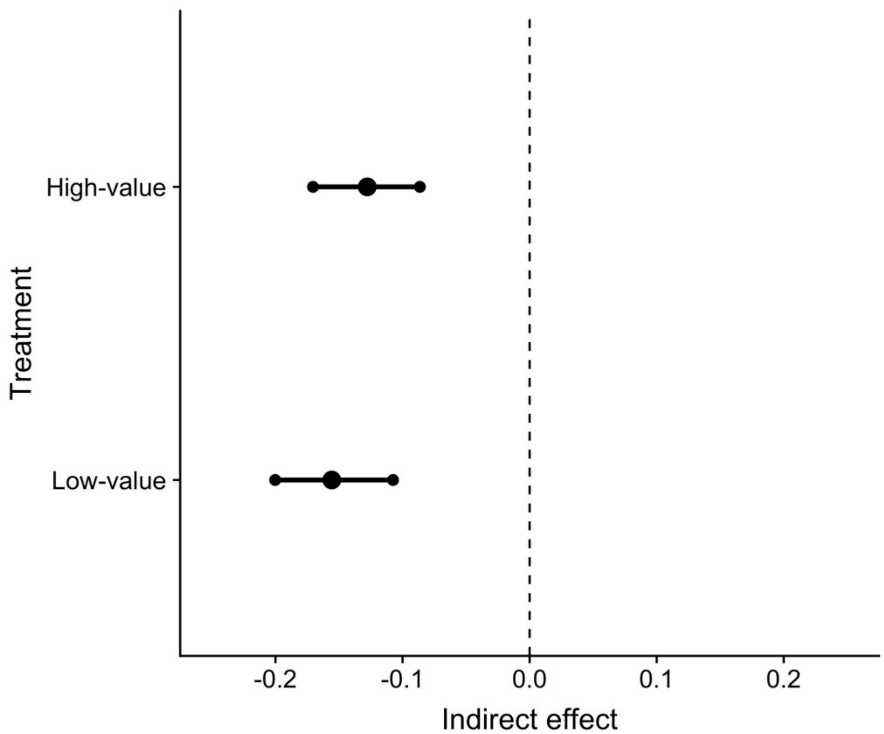

Figure 4. Indirect effect of time on task on labor/leisure choice through fatigue in both treatments. Error bars reflect between-participant 95% confidence intervals.

Third, the effect of treatment on change in fatigue was significant in the leisure blocks, estimate = 2.49, *SE* = 1.11, 95% CI [0.37, 4.52], *p* = .03[4]. The change in fatigue was more negative in the high leisure value treatment (*M* = -10.03) than in the low leisure value treatment (*M* = -7.03) after the leisure blocks. The data associated with this analysis is visualized in Figure 5.

Exploratory analysis

The manipulation of the opportunity costs revealed that participants in the high leisure value treatment did not unanimously enjoy the smartphone interaction while participants in the low leisure value treatment did not unanimously dislike reading in the retirement magazine. In the low leisure value treatment, 27 out of 65 participants reported the magazine interaction to be

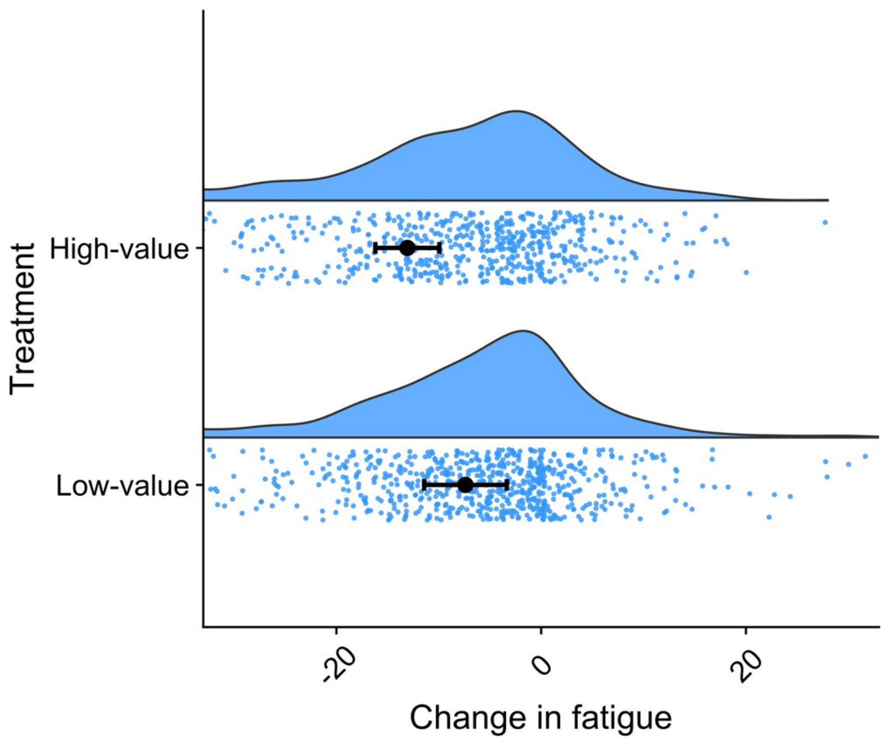

Figure 5. Raincloud plot of change in fatigue after performing the leisure task in both treatments. Error bars represent within-participant 95% confidence intervals. Positive (negative) scores reflect an increase (decrease) in fatigue during leisure.

[4] This effect was non-significant (p = .06) when controlling for baseline fatigue level.

more enjoyable than the average in the high leisure value treatment, while 17 out of 65 participants in the high leisure value treatment reported the smartphone interaction to be less enjoyable than the average in the low leisure value treatment. Given that the difference in reported enjoyment of the leisure task between both treatments was small, we were curious to test the effect of said self-reported enjoyment on change in fatigue. Under the assumption that this self-reported enjoyment captures the value of the leisure task, this exploratory analysis would strengthen our confidence in the null findings if enjoyment shows no effect. However, if the effect shows when we replace the treatment with the reported enjoyment, this could imply that our manipulation of the opportunity costs was simply not strong enough (as some participants in the low leisure value treatment actually did value the leisure task highly and vice versa). This analysis revealed that as enjoyment increased by one standard deviation, change in fatigue increased by 0.95 points in the labor blocks and decreased by 2.76 points in the leisure blocks. A visualization of this effect can be found in Figure 6. Thus, the results from this exploratory analysis appear to be in line with the opportunity cost model.

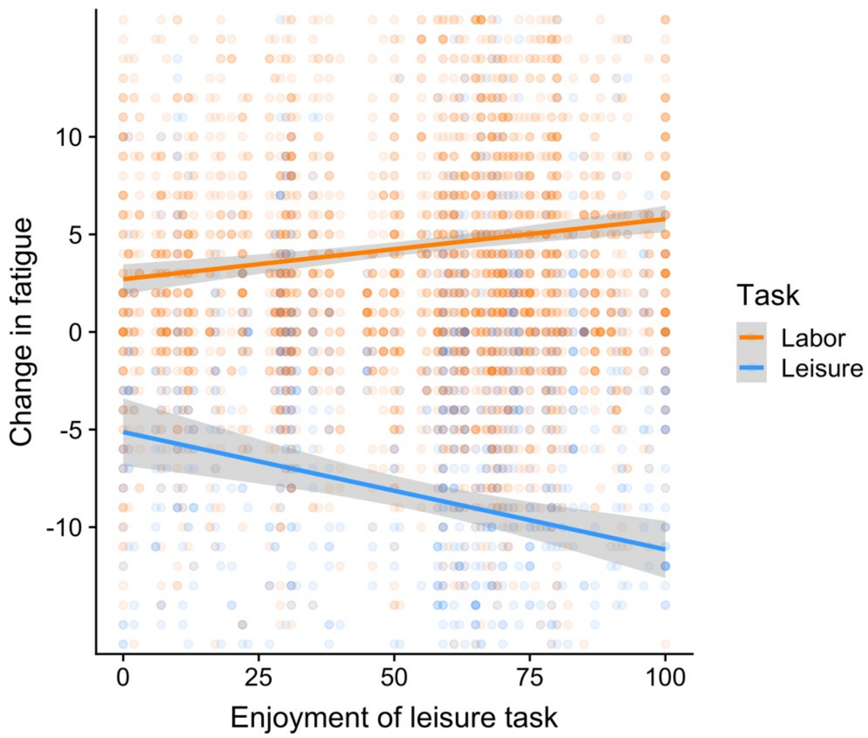

Figure 6. The effect of self-reported enjoyment of the leisure task on change in fatigue after performing labor and leisure. Positive (negative) scores reflect an increase (decrease) in fatigue during labor and leisure respectively. Grey areas reflect 95% confidence intervals.

Discussion

Overall, we did not find evidence for the predictions made by the opportunity cost model in our confirmatory analyses. However, we were surprised by participants' self-reported enjoyment of the leisure task. The manipulation check revealed that our manipulation did not create two separate treatments, one in which the opportunity costs were high, and one in which the opportunity costs were low. Intriguingly, our exploratory analysis suggests that participants who valued the leisure task higher – irrespective of treatment – did get more fatigued while performing labor and less fatigued while performing leisure. In order to resolve the contradiction between the preregistered and exploratory analyses, we attempted to strengthen the manipulation of opportunity costs in the next study. Because there seemed to be a lot of variation between participants with regard to how they valued both leisure tasks we used in Study 2, we decided to tailor the leisure task to each participant in Study 3.

Study 3

We set out to test the same three predictions as in Study 2. In order to create a stronger manipulation of the opportunity costs, we measured the value of different leisure tasks before the experiment. We then tried to use this knowledge to offer participants a leisure task they value highly in the high leisure value treatment (lowly in the low leisure value treatment). As before, we operationalized labor as a 2-back task. In the high leisure value treatment, we operationalized leisure as the leisure task that participants wanted to engage with the most out of a set of six leisure tasks prior to the experiment. Accordingly, in the low leisure value treatment we operationalized leisure as the leisure task that participant wanted to engage with the least prior to the experiment.

Method

Preregistration and data availability

We preregistered design, hypotheses, sample size, and statistical analyses. Our preregistration, experimental materials, data, power simulation and analysis scripts are available on the Open Science Framework (https://osf.io/t4afr/).

Sample size rationale

We again ran a set of power simulations (N = 1000) using the simr package (Green & MacLeod, 2016). As input to the simulations we used the data from Study 2. To simulate a stronger manipulation of opportunity costs, we excluded all participants in the low leisure value treatment that reported the enjoyment of the leisure task to be 30 or higher, and all participants in the high leisure value treatment that rated the enjoyment of the leisure task to be 70 or lower. We then simulated power based on this subsample for the observed 2.5-point difference between treatments in change in fatigue in the labor blocks. According to this simulation, we would have achieved power = .90 with N = 90. Because we wanted to make sure to have sufficient power even if the manipulation would be slightly weaker, we decided to once again sample 130 participants, 65 per treatment.

Participants, procedure, and design

130 university students (65 per treatment; M_{age} = 22.42; 91 females) participated in exchange for the same compensation as in Studies 1 and 2, and were assigned to either the high leisure value or low leisure value treatment as they entered the lab in an alternating fashion. Participants again had to be between 18 and 30 years of age and own a smartphone. The procedure in both treatments was largely identical to that in Study 2. At the start of the experiment, all participants rated a set of six leisure tasks (described below) on how much they would like to engage with them. The program then assigned participants in the high leisure value treatment the leisure task they rated highest, and participants in the low leisure value treatment the leisure task they rated lowest (in case of a tie, a random task from the tied list was assigned). The assigned leisure task then took the place of the smartphone/magazine (Study 2) on the table. At the end of the experiment, participants once again reported how much they enjoyed the leisure task during the choice task. We employed a between-subjects design (high leisure value vs low leisure value) with repeated measures of fatigue and choice.

Choice task

The choice task was identical to the one employed in Study 1 and Study 2. The only difference was that the assigned leisure task depended on the participant's pre-experiment ratings in both treatments. Before we carried out Study 3, we asked an independent sample of attendees of an undergraduate lecture (N = 166) to provide enjoyment ratings of a set of 13 leisure activities[5]. We included leisure activities that are (at least somewhat) common and that require (at least some) information processing (e.g., interacting with one's own smartphone, writing a diary entry, solving a crossword puzzle). Based on this pilot study, we selected a combination of six leisure tasks that maximized the probability that each participant rated at least one task low in terms of enjoyment (≤ 20) and one task high in terms of enjoyment (≥ 80). The resulting six leisure activities offered to the participant were (1) interacting with one's own smartphone ($N_{\text{high-leisure value}}$ = 28, $N_{\text{low-leisure value}}$ = 2), (2) coloring in mandalas ($N_{\text{high-leisure value}}$ = 18, $N_{\text{low-leisure value}}$ = 3), (3) solving a jigsaw puzzle ($N_{\text{high-leisure value}}$ = 12, $N_{\text{low-leisure value}}$ = 3), (4) writing a story about one's best friend ($N_{\text{high-leisure value}}$ = 3, $N_{\text{low-leisure value}}$ = 8), (5) solving a Rubik's cube ($N_{\text{high-leisure value}}$ = 3, $N_{\text{low-leisure value}}$ = 18), and (6) reading a car magazine ($N_{\text{high-leisure value}}$ = 1, $N_{\text{low-leisure value}}$ = 31). None of our subsequently reported results differed as a function of the specific leisure activity assigned.

Data analysis

We used the same analyses as in Study 2.

Results

Preregistered analyses

Across all blocks from all participants, mean fatigue was 56 points (*SD* = 25). Participants chose for the 2-back task on 61% of the blocks. Prior to the experiment, participants in the high leisure value treatment reported to feel more like engaging in the assigned leisure task (*M* = 82.86, *SD* = 14.78) than participants in the low leisure value treatment (*M* = 11.00, *SD* = 11.51), d = 5.42 (see Figure 7a). After the experiment, participants in the high leisure value treatment rated the leisure task as more enjoyable (*M* = 76.25, *SD* = 14.91) than participants in the low leisure value treatment (*M* = 40.86, *SD* = 27.87), *d* = 1.59 (see Figure 7b).

[5] These data are available on the OSF project page related to this paper.

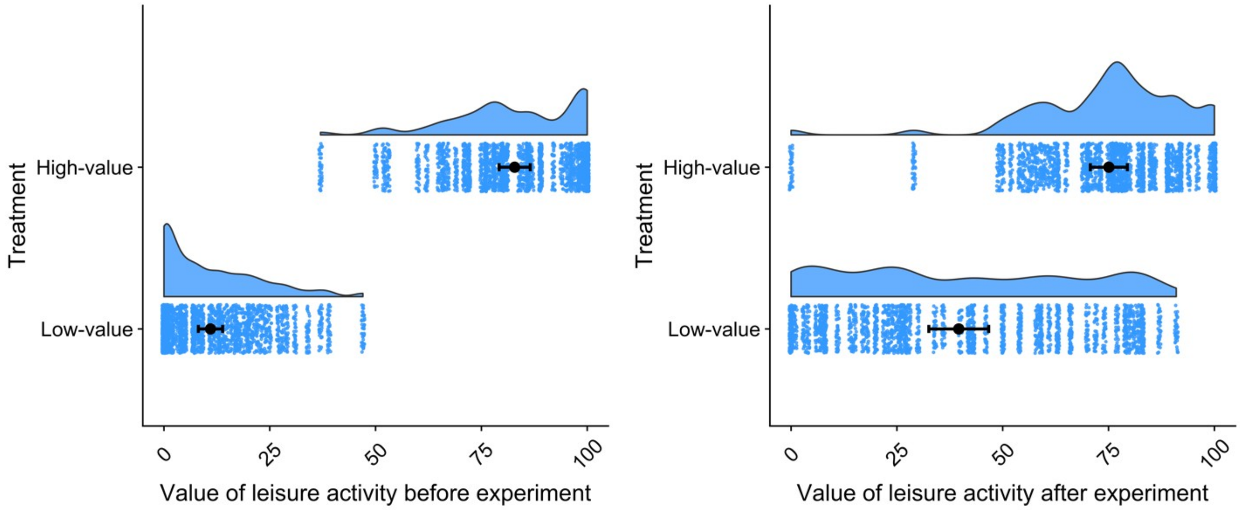

Figure 7a & 7b. Raincloud plots of ratings of the extent to which participants wanted to engage with the assigned leisure task on the left and ratings of enjoyment of the leisure task after the experiment on the right. Error bars reflect between-participant 95% confidence intervals.

We proceeded by testing our main predictions. First, the effect of treatment on change in fatigue during mental labor was not significant, estimate = -0.36, *SE* = 0.48, 95% CI [-1.29, 0.54], $p = .45$. Hence, we once again did not find evidence that participants became more fatigued in the high leisure value treatment while working on the cognitively demanding labor task. The data associated with this analysis are visualized in Figure 8.

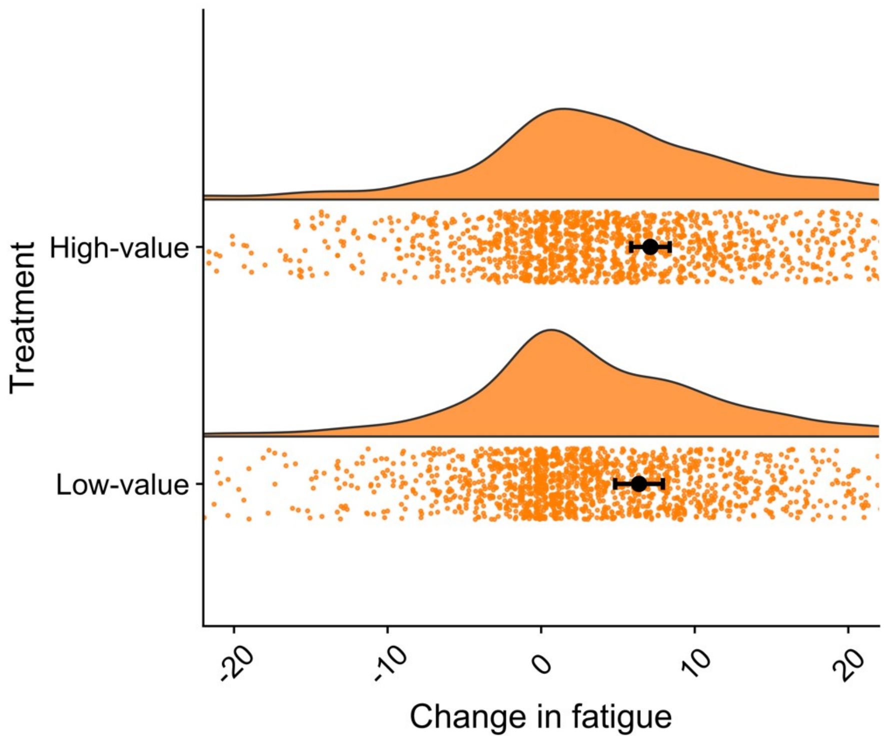

Figure 8. Raincloud plot of change in fatigue after performing the labor task in both treatments. Error bars represent within-participant 95% confidence intervals. Positive (negative) scores reflect an increase (decrease) in fatigue during labor.

Second, in line with the results from Study 1 and Study 2, the indirect effect of time on task on labor/leisure choice through fatigue was significant. However, this effect once again did not differ significantly between the two treatments. The 95% CIs for the mediation in both treatments overlapped, $\text{estimate}_{\text{low leisure value}}$ = -0.17, 95% CI [-0.21, -0.13]; $\text{estimate}_{\text{high leisure value}}$ = -0.13, 95% CI [-0.16, -0.09] (see Figure 9). This result is unsurprising given that the previous model revealed that participants did not get more fatigued in the high leisure value treatment (and hence this non-existent increase in fatigue was unlikely to lead to an increased probability to choose for the leisure task). The direct effect of time on task on labor/leisure choice was positive in both treatments, $\text{estimate}_{\text{low leisure value}}$ = 0.05, 95% CI [0.01, 0.09]; $\text{estimate}_{\text{high leisure value}}$ =

0.05, 95% CI [0.01, 0,09], while the total effect was negative in both treatments, $\text{estimate}_{\text{low leisure value}}$ = -0.12, 95% CI [-0.18, -0.06]; $\text{estimate}_{\text{high leisure value}}$ = -0.08, 95% CI [-0.12, -0.03].

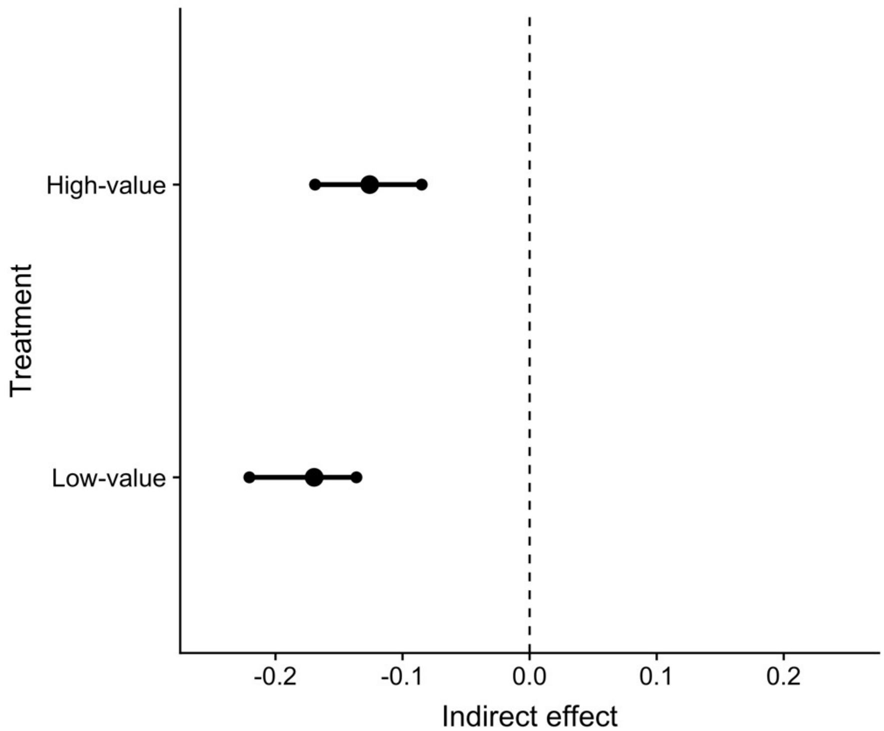

Figure 9. Indirect effect of time on task on labor/leisure choice through fatigue in both treatments. Error bars reflect between-participant 95% confidence intervals.

Third, the effect of treatment on change in fatigue during mental leisure was not significant, estimate = 0.98, *SE* = 0.62, 95% CI [-0.28, 2.13], *p* = .11[6]. We thus did not replicate the finding from Study 2 that participants in the high leisure value treatment show a stronger decrease in fatigue while engaging with the leisure task. The data associated with this analysis are visualized in Figure 10.

[6] The effect becomes barely significant when the participant with the largest Cook’s distance value is excluded.

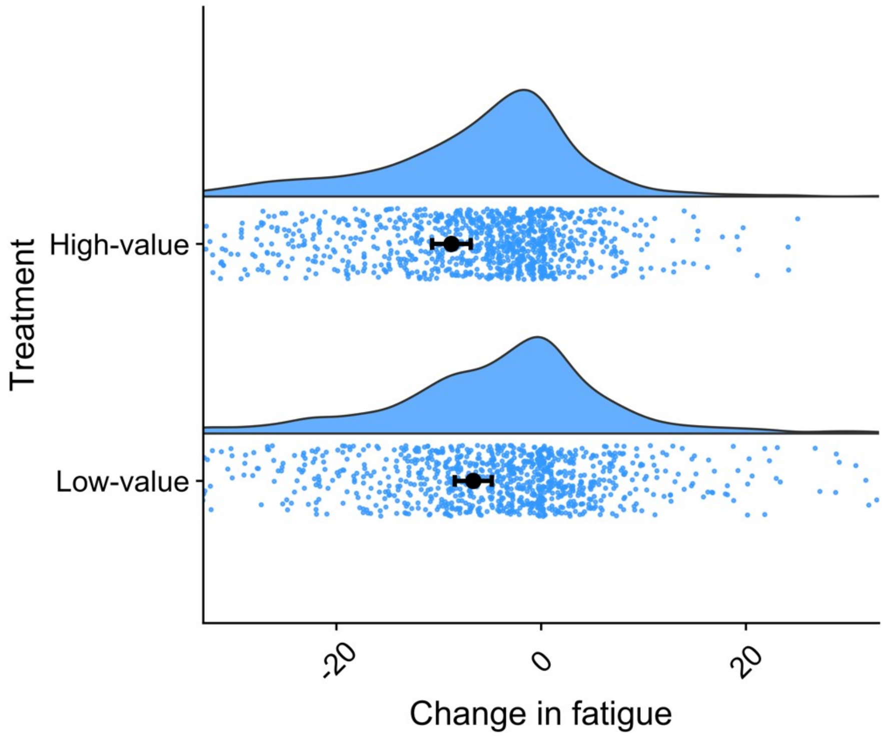

Figure 10. Raincloud plot of change in fatigue after performing the leisure task in both treatments. Error bars represent within-participant 95% confidence intervals. Positive (negative) scores reflect an increase (decrease) in fatigue during leisure.

Exploratory analysis

The difference in reported enjoyment of the leisure task between both treatments was three times as large as in Study 2. However, the difference was much smaller after the experiment than before the experiment. This suggests that a substantial subset of people value leisure over labor, no matter how mundane a leisure task is projected to be in advance. As a result, similar to Study 2, participants in our two treatments ended up partially overlapping in the extent to which they valued the available leisure task. For this reason, we once again tested the effect of self-reported enjoyment of the leisure task on change in fatigue. This analysis revealed that as enjoyment increased by one standard deviation, change in fatigue increased by 1.41 points in the labor blocks and decreased by 2.14 points in the leisure blocks. A visualization of this effect can be found in Figure 11. Thus, the results from this exploratory analysis again appear to be in line with the opportunity cost model.

To gain further confidence in this exploratory analysis, we repeated the preregistered analyses in a subsample in which we excluded participants from the low leisure value treatment that reported an enjoyment value of 50 points or more. The results of this analysis are in line with the previously reported exploratory analysis. Excluding participants in the low leisure value treatment that did value the leisure task highly, participants in the high leisure value treatment got more fatigued during mental labor ($M_{\text{high leisure value}}$ = 6.03 vs $M_{\text{low leisure value}}$ = 4.00) and less fatigued during mental leisure ($M_{\text{high leisure value}}$ = -7.05 vs $M_{\text{low leisure value}}$ = -3.74).

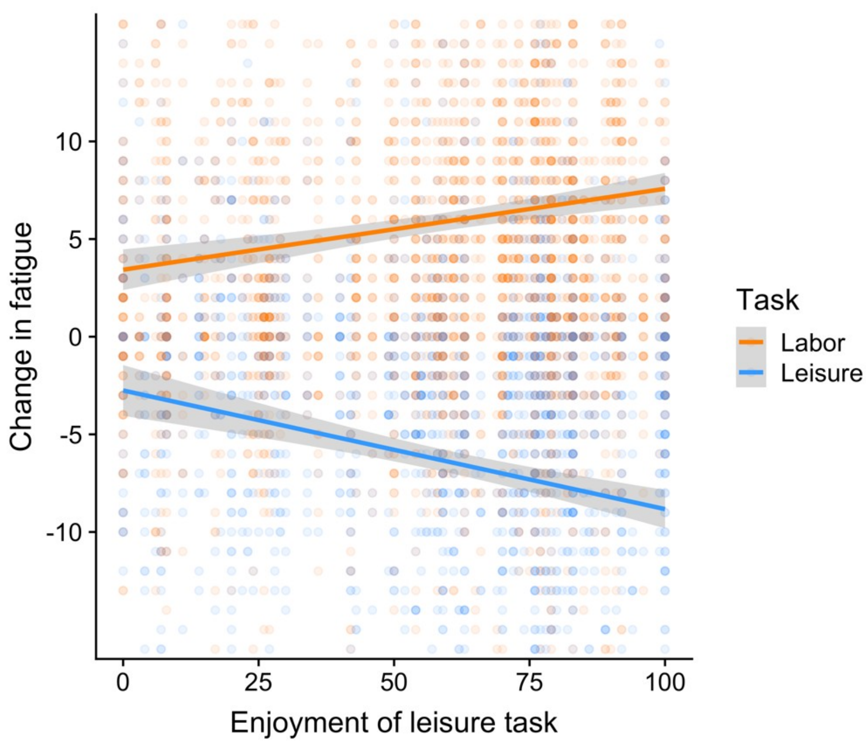

Figure 11. The effect of self-reported enjoyment of the leisure task on change in fatigue after performing labor and leisure. Positive (negative) scores reflect an increase (decrease) in fatigue during labor and leisure respectively. Grey areas reflect 95% confidence intervals.

Discussion

In Study 3, we found that the value participants assign to a certain leisure activity (and thus, also the activity’s utility) dynamically changes over time, at least if it is paired with a labor task. While basing the leisure task offered to participants on information gathered by the participants themselves did result in a stronger manipulation compared to Study 2, there were still numerous participants who assigned high value to the leisure task in the low leisure value treatment. This indicates that a subset of people value leisure over labor even if they assign very low value to the specific leisure task initially. The exploratory analysis again indicated that participants who reported higher enjoyment of the leisure task got more fatigued during labor and less fatigued during leisure. In order to further explore the apparent contradiction between the preregistered and exploratory analyses in Studies 2 and 3, we decided to make two adaptations to our paradigm in Study 4.

Study 4

We set out to test the same predictions as in Studies 2 and 3. In order to account for the differences between participants’ valuation of labor relative to leisure (see Study 2), and for the changes of these perceptions over time (see Study 3), we adapted our paradigm to a within-subjects design. Moreover, in Study 4 we chose to manipulated the value of labor rather than the value of leisure to manipulate the opportunity costs of the task.

We should point out that, by manipulating the value of labor (while keeping the value of leisure constant), we are not testing a prediction that is unique to the opportunity cost model, as we did in Studies 2 and 3. That is, alternative motivational theories of fatigue (e.g., Hockey, 2011) also predict that the value of labor (irrelevant of the value of leisure/opportunity costs) affects the amount of fatigue that people experience. We nevertheless chose to manipulate the value of labor in Study 4, so that we could achieve a relatively objective manipulation of opportunity costs, by systematically varying the payment that people received for working on the 2-back task.

In Study 4, participants first completed a discounting task (Westbrook, Kester, & Braver, 2013), in which they made repeated choices between performing labor (2-back task) for a varying amount of money and leisure (interacting with their own smartphone) for no compensation. They were told that one of these choices would be presented to them in the subsequent choice task to give meaning to each choice. Through this procedure, we established a *point of indifference*, i.e., we estimated the level of payment for labor that resulted in the participant valuing labor and leisure about equally. By determining the point of indifference separately for each participant, we took individual differences in the perception of value into account. In order to in- vs. decrease the opportunity costs, we de- vs. increased the compensation for labor during the experiment, based on participants' point of indifference. Next, participants performed the choice task, in which they were presented with the choice between labor for the amount of money determined by the discounting task and leisure.

Participants underwent the sequence described in the previous paragraph twice. That is, all participants underwent both the high labor value and the low labor value treatment, in counterbalanced order.

Method

Preregistration and data availability

We preregistered design, hypotheses, sample size, and statistical analyses. Our preregistration, data, power simulation and analysis scripts are available on the Open Science Framework (https://osf.io/t4afr/).

Sample size rationale

We again ran a set of power simulations (N = 1000) using the simr package (Green & MacLeod, 2016). As input to the simulations, we used the data from Study 3. We assumed that in the present study, participants would choose for the labor task eight (out of 12) times in each treatment on average. We further decided that a 2.5-point difference (in the increase in fatigue during labor; on a 100-point scale) would be the smallest effect size of interest. According to this simulation, we would have achieved power = .90 with N = 88. In order to conservatively account for the assumptions made in this power simulation, we again recruited 130 participants.

Participants, procedure, and design

130 university students (M_{age} = 22.11; 47 females) participated via Prolific (Palan & Schitter, 2018) for a base payment of £5 and an extra cash payment, which depended on their choices in the discounting task and the choice task (see below). As in Studies 1-3, participants had to be between 18 and 30 years of age and had to own a smartphone. After giving informed consent, participants reported demographics (age and gender), received instructions (including the request to silence their smartphone and to put it face down on the table next to them), and practiced the 2-back task for two blocks (first at 50% speed, then at 100% speed). Participants were assigned to either first complete the low labor value treatment, or the high labor value treatment (order was counterbalanced). In both treatments, participants first completed a

discounting task (see below), followed by 12 blocks of the choice task (see below). In total, the experiment took approximately 60 minutes to complete. We employed a within-subjects design (low labor value vs. high labor value) with repeated measures of fatigue and choice.

We preregistered two exclusion criteria to account for the fact that we collected data online. First, we incorporated two attention checks in the study, which no participant failed. Second, we preregistered to exclude participants whose accuracy during the 2-back task was below 80%. This cut-off was based on our results in the lab. However, because participants' performance was homogeneous (*M* = 75.27%, *SD* = 0.28%) and because the data otherwise resembled our lab datasets on a descriptive level, we decided to not exclude any participants from our analyses. We made this decision before analyzing our data.

Discounting task

We used an adapted version of a discounting procedure developed by Westbrook et al. (2013). In this procedure, participants made six repeated choices between labor (working on the 2-back task for a varying amount of money) vs. leisure (interacting with their own smartphone for no money). If participants chose labor, the amount of money offered for labor was diminished for the next choice; if participants chose leisure, the amount of money for labor was increased for the next choice. For the first choice, the offer was an hourly bonus payment of £5 for performing labor. At each subsequent choice, the adjustment (increase or decrease) in our offer was half as much as on the prior adjustment (i.e., we started out by increasing or decreasing the offer with £2.5; then £1.25; then £0.63; and so forth). We took the offer that was displayed after six choices as participants' point of indifference. We told participants that one of these offers would be selected later on, i.e., in the choice task, in order to ensure that participants took these choices seriously.

The final offer we made to participants—i.e., the offer to which participants were repeatedly exposed to in the choice task—was determined by taking participants' point of indifference and then increasing (vs. decreasing) that point by 50% in the high labor value treatment (vs. low labor value treatment). For example, a point of indifference of £3.36 would be adjusted to £5.04 (£3.36 + 0.5*£3.36) in the high labor value treatment, and to £1.68 (£3.36 – 0.5*£3.36) in the low value treatment.

Choice task

The task was created using Gorilla (Anwyl-Irvine, Massonnie, Flitton, Kirkham, & Evershed, 2020), a platform for administering computer tasks online. The task was otherwise identical to the one employed in Study 1. Thus, all participants were asked repeatedly to choose between performing the 2-back task (labor) or interacting with their own smartphone (leisure).

Data analysis

We used the same analyses as in Study 3. As we made use of a within-subjects design, we controlled for treatment order (low labor value first vs. high labor value first) in all analyses. In order to get our models to converge, we had to remove random slopes in all analyses.

Results

Preregistered analyses

The average point of indifference for participants was a bonus payment of £1.69/hour (*SD* = 1.71) for performing labor. On average, the point of indifference almost doubled in the second half of the experiment (point of $\text{indifference}_{\text{first-half}}$ = £1.22/hour, point of $\text{indifference}_{\text{second-half}}$ = £2.17/hour), indicating that the relative value of leisure increased over time. Across all blocks from all participants, mean fatigue was 60 points (*SD* = 28). Prior to the experiment, participants overall reported to feel like interacting with their own smartphone (*M* = 77.19, *SD* =

22.05). Participants chose for the 2-back task on 63% of the blocks. Participants reported higher motivation for labor during the high labor value treatment (*M* = 57.66, *SD* = 31.43) compared to the low labor value treatment (*M* = 40.72, *SD* = 35.39), *d* = 0.47 (see Figure 12a). Participants reported the leisure task as similarly enjoyable in the high labor value treatment (*M* = 60.95, *SD* = 33.85) compared to the low labor value treatment (*M* = 61.66, *SD* = 34.54), *d* = 0.02 (see Figure 12b).

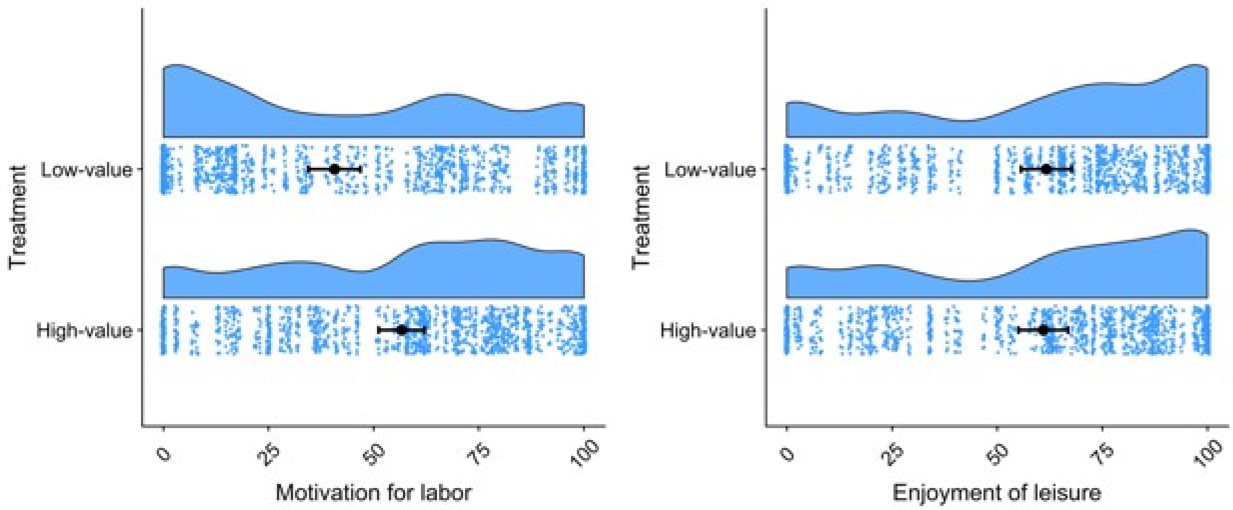

Figure 12a & 12b. Raincloud plots of ratings of the extent to which participants were motivated to perform the labor task on the left and ratings of enjoyment of the leisure task on the right. Error bars reflect between-participant 95% confidence intervals.

We proceeded by testing our main predictions. First, the effect of treatment on change in fatigue during mental labor was not significant, estimate = -0.64, *SE* = 0.33, 95% CI [-1.28, 0.00], *p* = .055. Hence, like before, we did not find evidence that participants became more fatigued when the opportunity costs were high while they worked on the 2-back task. The data associated with this analysis are visualized in Figure 13.

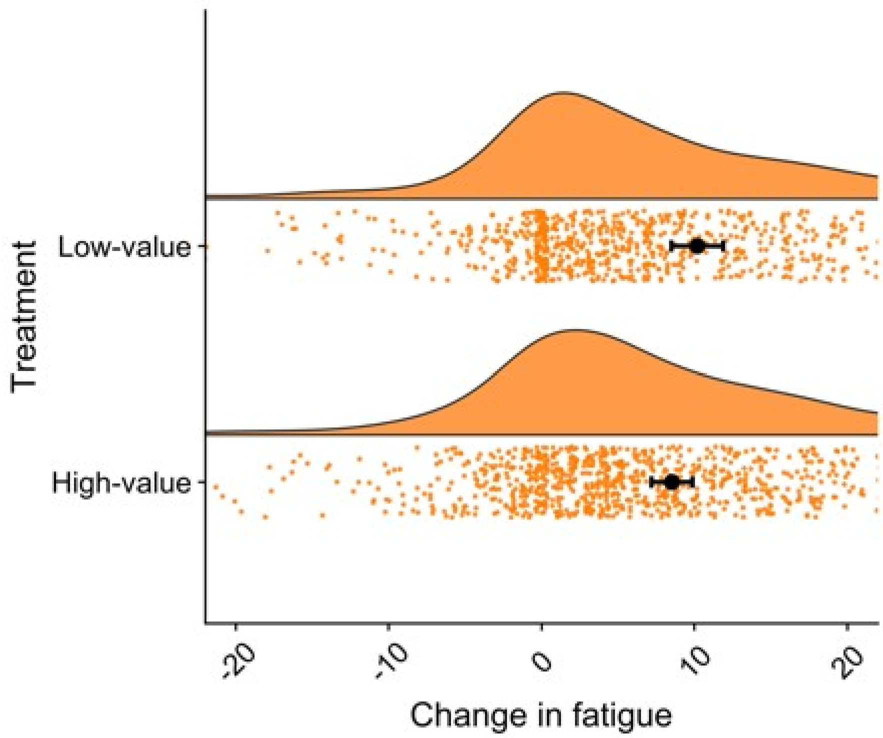

Figure 13. Raincloud plot of change in fatigue after performing the labor task in both treatments. Error bars represent within-participant 95% confidence intervals. Positive (negative) scores reflect an increase (decrease) in fatigue during labor.

Second, in line with the results from Studies 1–3, the indirect effect of time on task on labor/leisure choice through fatigue was significant, indicating that participants got more fatigued over time and, in turn, more likely to choose for leisure. Like before, this effect did not differ significantly between the two treatments. The 95% CIs for the mediation in both treatments overlapped, $\text{estimate}_{\text{low labor value}}$ = -0.048, 95% CI [-0.062, -0.035]; $\text{estimate}_{\text{high labor value}}$ = -0.077, 95% CI [-0.094, -0.061] (see Figure 14). Both the direct effect of time on task on labor/leisure choice, $\text{estimate}_{\text{low labor value}}$ = -0.07, 95% CI [-0.10, -0.04]; $\text{estimate}_{\text{high labor value}}$ = -0.06, 95% CI [-0.09, -0.04], and the total effect, $\text{estimate}_{\text{low labor value}}$ = -0.12, 95% CI [-0.15, -0.09]; $\text{estimate}_{\text{high labor value}}$ = -0.14, 95% CI [-0.17, -0.11], were negative in both treatments.

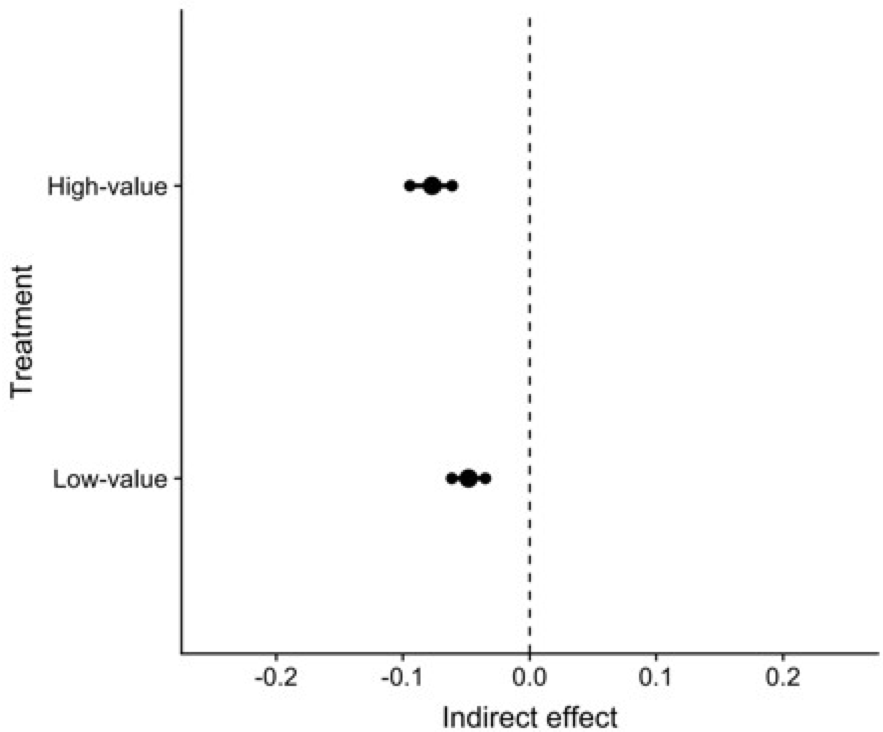

Figure 14. Indirect effect of time on task on labor/leisure choice through fatigue in both treatments. Error bars reflect between-participant 95% confidence intervals.

Third, the effect of treatment on change in fatigue during mental leisure was not significant, estimate = -0.17, *SE* = 0.43, 95% CI [-1.01, 0.71], *p* = .698. Thus, the significant finding from Study 2 that participants showed a stronger decrease in fatigue while engaging with the leisure task when the labor task's opportunity costs were high, did not replicate for a second time. The data associated with this analysis are visualized in Figure 15.

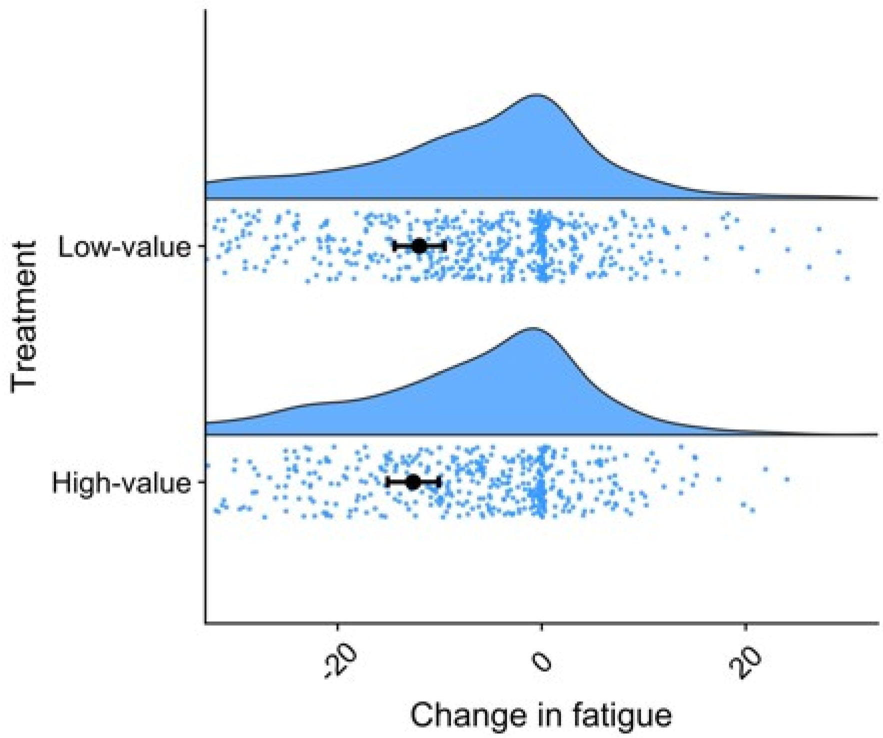

Figure 15. Raincloud plot of change in fatigue after performing the leisure task in both treatments. Error bars represent within-participant 95% confidence intervals. Positive (negative) scores reflect an increase (decrease) in fatigue during leisure.

Exploratory analysis

In an attempt to replicate the finding from Studies 2 and 3, we tested the effect of self-reported enjoyment of the leisure task on change in fatigue. This analysis revealed that as enjoyment increased by one standard deviation, change in fatigue increased by 2.04 points in the labor blocks and decreased by 1.15 points in the leisure blocks. A visualization of this effect can be found in Figure 16. Thus, in this exploratory analysis, even though we did not manipulate the value of leisure in Study 4, we again found support for the predictions made by the opportunity cost model. Although our data do not experimentally support the role of opportunity costs in the development of fatigue, the consistent association between the value of leisure and increases in fatigue makes it implausible that characteristics of the labor task (e.g., its difficulty and its value) are solely responsible for the amount of fatigue people experience.

Next, we further explored the non-significant effect of treatment on change in fatigue during labor. Even though participants generally reported higher motivation for labor in the high labor value treatment, a substantial subset of 45 participants reported equal or higher motivation for labor when they could earn less money. Exploration of our data revealed that, when we excluded these 45 participants, there was a substantial difference in change in fatigue between the low labor value treatment (M = 9.92) and high labor value treatment (M = 8.04; 95% $CI_{difference}$ = [-1.91, -0.36]).This finding may indicate that people's susceptibility to opportunity costs in labor/leisure tradeoffs, depends on the extent to which they are externally motivated by the rewards tied to labor

Finally, we explored the effects of the order in which participants were subjected to the two treatments. We found that order seemed to interact with the effect of treatment on change in fatigue during the labor blocks. Specifically, among those participants who first went through the low labor value treatment, there was a substantial difference in change in fatigue between the low labor value treatment (M = 9.73) and high labor value treatment (M = 7.87; 95% $CI_{difference}$ = [-2.12, -0.09]). In contrast, among those participants who first went through the high labor value treatment, there was little difference ($M_{low\ labor\ value}$ = 8.12 vs $M_{high\ labor\ value}$ = 8.09; 95% $CI_{difference}$ = [-1.14, 0.68]). This finding might indicate that people's susceptibility to opportunity costs is higher when people just start a task, as they have not yet made progress towards some income target (see Camerer, Babcock, Loewenstein, & Thaler, 1997). We return to this interpretation in the Discussion.

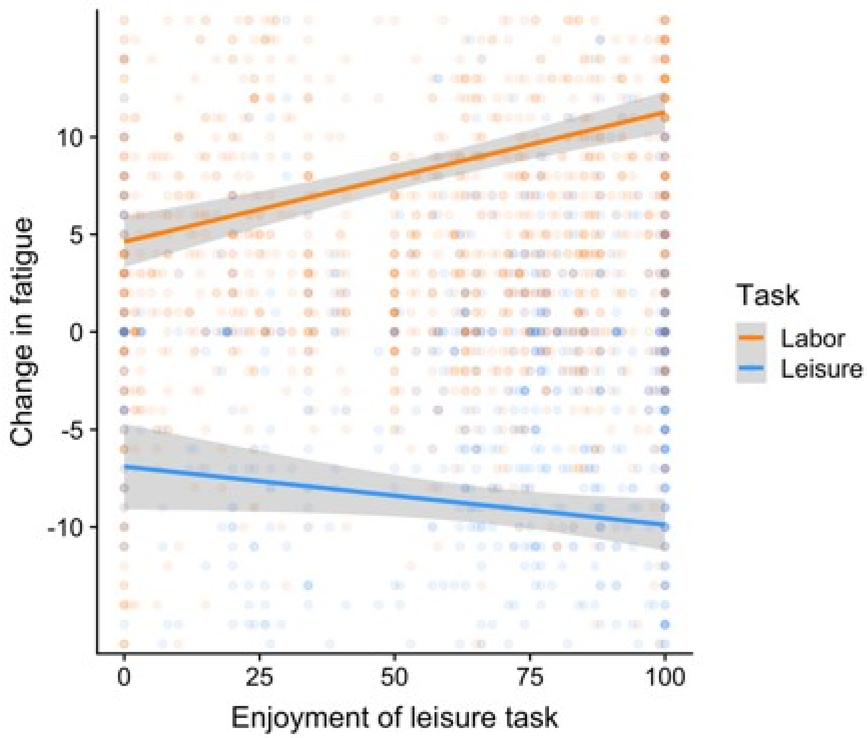

Figure 16. The effect of self-reported enjoyment of the leisure task on change in fatigue after performing labor and leisure. Positive (negative) scores reflect an increase (decrease) in fatigue during labor and leisure respectively. Grey areas reflect 95% confidence intervals.

Discussion

In Study 4, we made two critical changes to our paradigm. First, we manipulated the opportunity costs through the value of labor, rather than the value of leisure. Second, we manipulated the opportunity costs within rather than between participants. Overall, the results from Study 4 mirror and extend the results from Studies 2 and 3. As in Studies 2 and 3, we did not find evidence for the predictions made by the opportunity cost model in our confirmatory analyses. However, as in Studies 1–3, and in line with the opportunity cost model, exploratory analyses indicated that the naturally fluctuating value of leisure correlates with steeper increases (decreases) during labor (leisure).

In line with Studies 2 and 3, further exploratory analyses again suggested that the perception of opportunity costs differs considerably between people and over time. First, we found that a considerable subset of participants did not report higher motivation for labor, when the monetary rewards tied to labor were increased. If we excluded those participants, who arguably did not respond strongly to monetary rewards, we found that participants did get less fatigued during labor when they could earn more money. This finding is in line with the opportunity cost model.

Second, the interaction between our manipulation and the manipulation order suggests that people are more susceptible to high opportunity costs, initially, when they are just starting a new task. A post-hoc explanation for this order effect is that participants may have intuitively set an income target at the beginning of our experiment (for a similar idea, see Camerer et al., 1997). Speculatively, participants who underwent the low labor value treatment first, may have experienced higher opportunity costs during the low labor value treatment because they were making little progress towards their income target early on, Potentially, this slow start in earnings may have caused these participants to become dismayed about meeting the income target that had set. This initial discouragement may have further increased opportunity costs specifically among this group of participants. Together and in the context of Studies 2 and 3, these exploratory results provide further cautious evidence for the idea that opportunity costs influence people's experience of fatigue.

General discussion

In the current set of studies, we aimed to understand the nature of mental fatigue by testing the key predictions from the opportunity cost model of fatigue (Kurzban et al., 2013). In Studies 1–4, as predicted, we found that fatigue predicts subsequent choices between labor and leisure. That is, the more fatigued people became, the more likely they were to disengage from labor, and to switch to leisure (Boksem & Tops, 2008; Hockey, 2011; Inzlicht et al., 2014; Kurzban et al., 2013; van der Linden, 2011). This finding extends previous work that showed that people tend to gradually disengage from cognitively demanding tasks when they are fatigued (Hopstaken et al., 2015a, 2015b).

In Studies 2 – 4, in a preregistered set of analyses, we found no evidence for the unique prediction of the opportunity cost model that the opportunity costs influence the amount of fatigue experienced, nor that they influence labor/leisure choices through fatigue. These null findings may have been due to the fact that the value, and hence the utility, associated with different leisure tasks (relative to the same labor task) as well as an external reward tied to labor differed strongly between people and that this value changed over time. To further examine whether opportunity costs impact the experience of fatigue, an exploratory analysis—in which we operationalized the opportunity costs as the self-reported enjoyment of the leisure task—supported the idea that people become more fatigued during labor when they value the leisure alternative more in all three studies. We will now discuss these findings in greater detail.

Several modern theories of fatigue converge on the idea that the experience of fatigue functions as a signal to switch activities (Boksem & Tops, 2008; Hockey, 2011; Inzlicht et al., 2014; Kurzban et al., 2013; van der Linden, 2011). We found strong evidence for this notion in all studies. Our findings indicate that fatigued people are much more likely to switch to alternative, relieving leisure tasks, if given the opportunity. In our studies, participants were willing to forego a monetary incentive to carry out a leisure task. So, our results are consistent with the idea that fatigue plays an adaptive role in goal selection and goal pursuit.

Regarding the causal role of opportunity costs on the feeling of fatigue, our findings are less straightforward. In our preregistered analyses, we found no evidence for the idea that people get more fatigued when the opportunity costs are higher. In Studies 2 and 3, we tried to manipulate opportunity costs (of a labor task) by giving people an alternative task, of which we varied the value. Yet, not all participants experienced our low-value leisure tasks to be actually of low value; similarly, not all participants perceived our high-value leisure tasks to be of high value. At the same time, the experienced value of the leisure tasks clearly changed throughout the 80-minute session: for many people, the low-value leisure tasks often turned out to be nicer than expected. Similarly, for a substantial subset of participants in Study 4 the value of labor did not seem to increase when the external rewards tied to labor were increased. Based on these intriguing findings, we argue that our results do not provide strong evidence *against* the opportunity cost model. We thus proceeded to examine the data in greater detail, from which we learned two important things:

First, utilities associated with labor and leisure tasks are idiosyncratic (they vary between people) and fleeting (they change over time). Not all participants enjoyed using their smartphone, while some participants enjoyed reading in a retirement magazine (Study 2). Additionally, a substantial subset of participants ended up valuing a leisure task while comparing it to a labor task when they did not expect to value it (Study 3). And there seemed to be considerable variation in the extent to which participants were motivated by in vs decreases in external rewards tied to labor (Study 4). These findings have at least two important implications. First, for research that offers participants two behavioral options that are assumed to differ in value (e.g., Algermissen et al., 2019; Apps, Grima, Manohar, & Husain, 2015; Kool & Botvinick, 2014; Westbrook, Kester, & Braver, 2013), the volatility of this relative value needs to be carefully studied and taken into account. It should be ensured that the difference in value between the two options (a) is roughly constant between participants and (b) does not markedly change with time on task. Second, regardless of whether opportunity costs affect the feeling of fatigue, this finding reinforces one of the basic assumptions of the opportunity cost model (Kurzban et al., 2013), namely that utilities are relative. People differ in what they value; and, how much people value behavioral options depends on alternatives in the environment, and on what they just did before.

Second, when considering the characteristics of utility described above, an exploratory analysis supported the idea that opportunity costs are related to mental fatigue. In Study 2, we found that participants who valued the leisure alternative to a labor task higher (regardless of treatment), became more fatigued while performing the labor task. We replicated this result in Studies 3 and 4. Our exploratory analyses further suggest that participants who valued the leisure task more, became less fatigued while performing the leisure task. Thus, our results also shed light on how recovery from accumulated fatigue might work, in that they suggest that recovery is, at least in part, a motivational process. This suggestion fits well with a recent proposal by Inzlicht et al. (2014), who argued that people have an intrinsic need to balance mental labor and mental leisure. According to this proposal, people can regain motivation to carry out mental labor by avoiding another cognitive task after having invested mental effort. In terms of the opportunity cost model, this would mean that, during mental leisure, the utility of labor should steadily increase—which should then allow to again perform labor while feeling less fatigued. Taken together, the pattern of findings from Studies 2 – 4 supports, rather than contradicts, the opportunity costs models' assumption that fatigue stems from a cost-benefit analysis. However, to gain confidence in this conclusion, we would like to see a similar result in a preregistered analysis involving an experimental manipulation of the opportunity costs.

Practical implications

Taken at face value, the results of our exploratory analysis have several important implications for everyday life. For example, the possibility that people's smartphone is (partially) responsible for low academic achievement and work performance has received a lot of attention in the public media. So far, this smartphone–cognition literature primarily focused on the long-term effects of smartphone use on attention and memory (for a review, see Wilmer, Sherman, & Chein, 2017). However, our findings suggest that the smartphone influences people's productivity without having a lasting effect on the mind (contrary to what has been hypothesized previously; e.g., Clayton, Leshner, & Almond, 2015; Ward, Duke, Gneezy, & Bos, 2017), by simply being a highly-valued alternative in the environment. Our results further suggest that the smartphone is not unique in its potential to increase the opportunity costs. Rather, different activities carry different utilities at different times. This seems to depend on the individual, characteristics of the current task and alternatives, and the balance of labor and leisure in the short-term past. In general, our exploratory analyses suggest that exposure to valued alternative leisure tasks increases opportunity costs, and hence the amount of fatigue experienced, during labor. To minimize fatigue, it should help people to eliminate valued alternatives from their environment.

Limitations

Besides that the manipulation of opportunity cost did not work exactly as planned (as discussed above), there are several limitations that should be highlighted. First, the leisure tasks we offered to participants in Studies 2 and 3 did not differ exclusively in the value participants assigned to them – it is reasonable to assume that they differed on other dimensions such as information processing, affective reactions, and familiarity. Furthermore, participants might have engaged with these leisure tasks in different ways (e.g., one participant might have watched videos on his smartphone, while another participant might have texted with a friend). These limitations are unavoidable when one wants to offer participants real-world leisure tasks and might have contributed to the substantial inter-individual variance in value associated with the offered leisure tasks. Ultimately, we do not believe these limitations to be highly problematic for three reasons. First, the opportunity cost model predicts that it is the value of the alternative that should have an influence on phenomenology, not other task characteristics. Second, in Study 3, across the whole sample, people became about equally fatigued regardless of what specific leisure task they were assigned to. Third, our ultimate goal was to understand when and why people experience fatigue in the real world. In order to achieve this goal, we believe that the present design, which combined a controlled laboratory environment with real-world leisure options, was appropriate.

With regard to understanding how opportunity costs and fatigue relate to the choice between labor and leisure, a limitation of our study design was that participants could not choose freely when to switch tasks. The fact that participants had to decide which task to engage with at fixed time points (i.e., every two minutes) made this choice a bit artificial. We designed the study like this to consistently pair fatigue self-reports with choices. Alternatively, one could probe fatigue at fixed time intervals (say, every two minutes) but give the participant free control over when to switch tasks. We chose against using this alternative design, as it would hamper our ability to make inferences (e.g., different amounts of time would have passed between the report of fatigue and the choice to switch; probes would sometimes interrupt labor and sometimes interrupt leisure, potentially affecting the self-report measurement).

Conclusion

In conclusion, the present research advances the scientific literature on mental fatigue in several ways. We found strong evidence for the idea that mental fatigue functions as a signal to switch activities. We also found that the utility associated with labor and leisure tasks differs between people and changes over time. Against the background that the energy metaphor (i.e., the idea that the feeling of fatigue indicates that some metaphorical mental battery is almost depleted) is increasingly being questioned (e.g., Hagger et al., 2016; Kurzban, 2016; Shenhav et al., 2017), our studies cautiously support modern views of fatigue that propose that fatigue and related phenomenology (e.g., effort, Bijleveld, 2018; boredom, Westgate & Wilson, 2018) reflect the non-energetic costs of engaging with the current activity (Hockey, 2011; Johnston et al., 2018; Kurzban, 2016; Shenhav et al., 2017). In future research, it may well be useful to continue to think of fatigue as a motivational phenomenon.

Context

This research was motivated by a lack of empirical evidence for modern theoretical accounts of mental fatigue. Fatigue causes people to disengage from productive tasks, and so a better understanding of fatigue may eventually help people to perform productive but effortful tasks for longer without feeling fatigue and other related aversive experiences (e.g., effort, boredom). We believe that investigating the role of motivation related to the experience of fatigue may help us to eventually understand why people sometimes get fatigued very quickly and other times do not.

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Competing interests

The authors have no competing interests to declare.

Data accessibility statement

All experimental materials, data, and analysis code are available on the Open Science Framework (https://osf.io/t4afr/?view_only=945cbc60b4764b618deb6c2dfb5a3fb7).