Cortex
A journal devoted to the study of the nervous system and behavior

Relationship between reward-related brain activity and opportunities to sit

Juliana O. Parma[1,†], Mariane F. B. Bacelar[2,†], Daniel A. R. Cabral[1], Robyn S. Recker[1], Dan Orsholits[3,4], Olivier Renaud[5], David Sander[6,7], Olav E. Krigolson[8], Matthew W. Miller[1,9,††,*], Boris Cheval[10,11,††,*], Matthieu P. Boisgontier[12,13,††,*]

Cite this article:
Parma JO, Bacelar MFB, Cabral DAR, Recker RS, Orsholits D, Renaud O, Sander D, Krigolson OE, Miller MW, Cheval B, Boisgontier MP.
Relationship between reward-related brain activity and opportunities to sit.
Cortex 2023, In press.

Preregistration:
https://osf.io/tcr7f

Data, code, & materials:
https://doi.org/10.5281/zenodo.8011562

Key words
Exercise; Physical activity; Sedentary behaviors; Reward; Electroencephalography; Reinforcement learning

[1]Swiss 1School of Kinesiology, Auburn University, AL, USA; [2]Department of Kinesiology, Boise State University, ID, USA; [3]Centre for the Interdisciplinary Study of Gerontology and Vulnerability, University of Geneva, Switzerland; [4]Swiss National Centre of Competence in Research LIVES—Overcoming Vulnerability: Life Course Perspectives, Lausanne and Geneva, Switzerland; [5]Methodology and Data Analysis, Department of Psychology, University of Geneva, Geneva, Switzerland; [6]Swiss Center for Affective Sciences, University of Geneva, Switzerland; [7]Laboratory for the Study of Emotion Elicitation and Expression (E3Lab), Department of Psychology, University of Geneva, Switzerland; [8]Centre for Biomedical Research, University of Victoria, Canada; [9]Center for Neuroscience, Auburn University, USA; [10]Department of Sport Sciences and Physical Education, Ecole Normale Supérieure Rennes, Bruz, France; [11]Laboratory VIPS2, University of Rennes, Rennes, France; [12]School of Rehabilitation Sciences, Faculty of Health Sciences, University of Ottawa, Ottawa, Canada; [13]Bruyère Research Institute, Ottawa, Canada; *Corresponding authors: mwm0024@auburn.edu (Matthew W. Miller); boris.cheval@unige.ch (Boris Cheval); matthieu.boisgontier@uOttawa.ca (Matthieu P. Boisgontier); [†]JOP and MFBB contributed equally to this work; [††]MWM, BC, MPB contributed equally to this work.

Abstract

The present study tested whether energy-minimizing behaviors evoke reward-related brain activity that promotes the repetition of these behaviors via reinforcement learning processes. Fifty-eight healthy young adults in a standing position performed a task where they could earn a reward either by sitting down or squatting while undergoing electroencephalographic (EEG) recording. Reward-prediction errors were quantified as the amplitude of the EEG-derived reward positivity. Results showed that reward positivity was larger on reward versus no reward trials, confirming the validity of our paradigm to measure evoked reward-related brain activity. However, results showed no evidence that sitting (vs. standing and squatting) trials led to larger reward positivity. Moreover, we found no evidence suggesting that this effect was moderated by typical physical activity, physical activity on the day of the study, or energy expenditure during the experiment. However, at the behavioral level, results showed that the probability of choosing the stimulus more likely to lead to sitting than standing increased as the number of trials increased. In addition, results revealed that the probability of changing the selected stimulus was higher when the previous trial was a stand trial relative to a sit trial. In sum, neural results showed no evidence supporting the theory that opportunities to minimize energy expenditure are rewarding. However, behavioral findings suggested participants tend to choose the less effortful behavioral alternative and were therefore consistent with the theory of effort minimization (TEMPA).

Imagine your supervisor calls you to their office to give you a bonus check. Upon learning that you earned the reward, would its value change if you knew

you had to walk several flights of stairs as opposed to being able to take an elevator ride, equal in time, to retrieve it? The answer to this question has implications for one's level of physical activity. Most individuals are now cognizant of the positive effects of regular physical activity and have the intention to be active (Martin, Morrow, Jackson, & Dunn, 2000; Canadian Fitness and Lifestyle Research Institute, 2008). Yet, this intention is often not sufficient to engage in physical activity (Rhodes & Dickau, 2012). A recent study involving 1.9 million participants showed that more than a quarter of all adults are physically inactive, which extrapolates to more than 1.4 billion adults when considering the world population (Guthold, Stevens, Riley, & Bull, 2018). Some other results are even more concerning, especially in the United States, where more than 95% of adults fail to accumulate the recommended 30 minutes of moderate-to-vigorous physical activity on at least 5 days per week (Troiano et al., 2008). This high prevalence is concerning because physical inactivity involves higher risks of cardiovascular disease (Wahid et al., 2016), hypertension (Liu et al., 2017), diabetes (Aune, Norat, Leitzmann, Tonstad, & Vatten, 2015), cancer (Moore et al., 2016), depression (Schuch et al., 2017; Boisgontier et al., 2020), obesity (Bleich, Vercammen, Zatz, Frelier, Ebbeling, & Peeters, 2018), and mortality (Ekelund et al., 2019) with 6 to 10% of all deaths from non-communicable diseases worldwide attributed to physical inactivity (Lee et al., 2012).

It has been speculated that this failure to be physically active may be explained by automatic reactions toward stimuli that are related to physical activity behaviors (Conroy and Berry, 2017). These automatic reactions may disrupt the implementation of behavioral goals grounded in reflective motivation (Strack & Deutsch, 2004). Experimental studies testing these automatic reactions show that stimuli related to physical activity automatically attract attention (Berry, 2006; Berry, Spence, & Stolp, 2011; Calitri, Lowe, Eves, & Bennett, 2011; Cheval et al., 2020c), and trigger automatic affective reactions (Bluemke, Brand, Schweizer, & Kahlert, 2010; Conroy, Hyde, Doerksen, & Ribeiro, 2010; Rebar, Ram, & Conroy, 2015) as well as approach tendencies (Cheval, Sarrazin, & Pelletier, 2014; Cheval, Sarrazin, Isoard-Gautheur, Radel, & Friese, 2015; Cheval, Sarrazin, Boisgontier, & Radel, 2017; Cheval et al., 2018b; Farajzadeh et al., 2023). These effects are stronger in active individuals, but inactive individuals generally demonstrate similar positive automatic reactions toward physical activity. Taken together, these results suggest that automatic reactions can support physical activity behaviors in both active and inactive individuals, which contrasts with the current pandemic of physical inactivity (Kohl 3rd et al., 2012). These results also suggest that automatic reactions toward physical activity can hardly explain this pandemic.

The recent theory of effort minimization in physical activity (TEMPA) suggests that an automatic attraction toward behaviors minimizing energetic cost, which may be inherently rewarding, could explain the inability to transform intentions to be physically active into actions (Cheval et al., 2018a; Cheval & Boisgontier, 2021). The repeated failure in counteracting this automatic attraction may partly explain the pandemic of physical inactivity (Boisgontier & Iversen, 2020). A positive bias toward lower energy expenditure has been evidenced in decision-making and learning tasks (Klein-Flügge, Kennerley, Friston, & Bestmann, 2016; Palidis & Gribble, 2020; Prévost, Pessiglione, Météreau, Cléry-Melin, & Dreher, 2010; Skvortsova, Palminteri, & Pessiglione, 2014). In the study by Klein-Flügge et al. (2016), participants were asked to make a series of choices between two options, which independently varied in required grip force and reward magnitude. The monetary reward ranged from 10 to 40 pence and required effort ranged from 20% to 80% of maximum grip force. Similarly, Skvortsova et al. (2014) used a probabilistic instrumental learning task with binary choices (left or right) and four possible outcomes: two reward levels (20¢ or 10¢) times two effort levels (80% and 20% of maximal force). Participants were encouraged to accumulate as much money as possible and to avoid making unnecessary effort. In the study by Palidis and Gribble (2020), participants made binary choices that probabilistically affected whether they were asked to accurately produce a low or high level of quadriceps activation to earn a reward. Electroencephalographic (EEG) activity time-locked to feedback about whether they earned the reward for accurate force production was assessed. Results showed participants were more likely to change their response from the previous trial if it led to high effort. Results also showed that reward-related brain activity was greater when participants received reward feedback on high effort trials. These results are consistent with findings showing individuals learn to make decisions to avoid high physical effort but, paradoxically, value rewards obtained with high effort more than those obtained with low effort (Inzlicht, Shenhav, & Olivola, 2018). In the study by Prévost et al. (2010), participants decided whether it was worth investing in a stronger effort using a hand grip to see an erotic picture clearly for 3 s or to invest in a small effort to see the picture for 1 s. These four studies showed that during choices involving monetary or erotic reward and physical effort the brain serves as a choice comparator for effort-reward trade-offs (Klein-Flügge et al., 2016) with behaviors associated with higher physical effort being avoided (Paladis & Gribble, 2020) and devalued (Prévost et

al., 2010; Skvortsova et al., 2014). In line with the theory of effort minimization, experimental results suggest that a high tendency to approach stimuli related to sedentary behaviors can contribute to explain the gap between intentions to be physically active and actual physical activity (Cheval et al., 2015). Other results suggest sedentary stimuli require more inhibitory control to avoid relative to physical activity stimuli (Cheval et al., 2020a) and that avoiding sedentary stimuli requires higher brain activity linked to inhibitory control and conflict monitoring than approaching sedentary stimuli (Cheval et al., 2018b). These results are consistent with the notion that such stimuli are attractive and, thus, difficult to avoid. Finally, epidemiological research shows that declines in cognitive functioning, which may be necessary to avoid sedentary stimuli, precede declines in physical activity (Cheval et al., 2020c).

An untested corollary from the theory of effort minimization is that energy-minimizing behaviors elicit reward-related brain activity that promotes the repetition of such behaviors via reinforcement learning processes (Rescorla & Wagner, 1972; Sutton & Barto, 1998). One of the crucial processes underlying reinforcement learning is the brain's computation of positive and negative reward-prediction errors, which represent the degrees to which actual outcomes are better or worse than expected, respectively. Positive reward-prediction errors act as signals within the brain to increase the value of decisions and actions that led to the errors, thus 'stamping in' such decisions and actions. Conversely, negative reward-prediction errors act as signals within the brain to decrease the value of decisions and actions that led to the errors, thus 'stamping out' such decisions and actions. Reward-prediction errors in humans can be quantified using the reward positivity component of the event-related potential (ERP) derived from the EEG (Krigolson, 2018; Proudfit, 2015; Sambrook & Goslin, 2015). The reward positivity manifests as a positive deflection in the ERP 250 – 350 ms following rewarding feedback and is maximal at midline frontocentral electrode sites. Based on the theory of effort minimization and reinforcement learning theory, experiencing a positive reward-prediction error from taking the elevator or a negative reward-prediction error from taking the stairs should reinforce behaviors that optimize opportunities to take the former, such as choosing to enter a building through a specific door known to have easy access to an elevator.

In the present research, we tested hypotheses consistent with the theory of effort minimization in physical activity (Cheval et al., 2018a; Cheval & Boisgontier, 2021) and reinforcement learning theory (Rescorla & Wagner, 1972; Sutton & Barto, 1998). Specifically, participants performed a doors task inspired by Hassall, Hajcak, and Krigolson (2019) and crossed with a movement-incentive delay task (Cheval, Boisgontier, Bacelar, Feiss, & Miller, 2019), both of which have been used to study reinforcement learning brain activity (i.e., reward positivity). On each trial, participants in a standing position chose one of two stimuli ("doors") on the screen. Following this choice, they were first informed whether they had to sit down and squat, should they earn a reward on the trial. Next, participants were informed whether they earned the reward or not. If they earned the reward, they had to retrieve it by implementing the behavior indicated in the first step (i.e., sitting down or squatting and returning to the standing position). Unbeknownst to participants, both doors were equally likely to lead to a reward, but one door was programmed to lead to an opportunity to sit 3.5 times more often than the other door. As such, since choices were unrelated to the probability of receiving a reward, we could test whether participants learned to make choices based on the likelihood of sitting.

Our primary hypothesis was that opportunities to sit lead to more positive reward-prediction errors, as expressed by a larger reward positivity (H1). To test this hypothesis, we examined whether the opportunity to sit versus stand (Trial Type) and the presence of absence of reward (Reward) was associated with reward positivity amplitude and whether these variables interacted with each other (Trial Type x Reward). This hypothesis followed directly from the theory of effort minimization's prediction that opportunities to minimize energy expenditure are rewarding. We also investigated whether the effect of opportunities to sit tested in H1 was moderated by factors related to energy expenditure. Specifically, we hypothesized that the effect was larger in participants who were typically less physically active (H2.1), in participants who were physically active on the day of the experiment prior to the experiment (H2.2), and after energetically demanding behavior (i.e., squatting) during the experiment (H2.3). These predictions followed from the theory of effort minimization's contention that opportunities to minimize energy expenditure are particularly rewarding for individuals who are typically physically inactive, and that the reward of effort minimization increases when an individual spends energy. A third hypothesis was that the probability of choosing the stimulus more likely to lead to sitting than standing increased together with the increase in trials (H3). This followed from the theory of effort minimization's claim that opportunities to minimize energy expenditure are rewarding, and reinforcement learning theory's claim that decisions that lead to rewards are repeated. Finally, our fourth hypothesis was that reward positivity predicted subsequent decisions about whether one chooses the same or a different stimulus. Consistent

with reinforcement learning theory, we hypothesized that a large positive reward-prediction error reinforced the decision that led to it (i.e., the participant should choose the same stimulus) (H4). This experiment was conducted as a registered report, and the approved protocol (stage 1 of the registered report) can be found at https://osf.io/tcr7f (Miller et al., 2021).

Methods

Population

Adults 19 to 40 years of age were recruited from the College of Education Research Participant Pool at Auburn University (USA) and by word-of-mouth to participate in the study in exchange for course credit, if applicable. This demographic was convenient to the investigators and had been used in similar studies (e.g., Cheval et al., 2019). To be included in the study, participants had to report an absence of physical impairment and disabilities that would make repeatedly standing and sitting difficult (yes vs. no), an absence of skin allergies or sensitivity to lotions or cosmetics, and an absence of neurological impairment.

Sample Size Calculation

To estimate the sample size required for sufficient power (90%) with an alpha level lowered to 2%, we focused on the linear mixed-effects model (MEM) used to test H1, our primary hypothesis. In general, sample size calculation is difficult and sensitive since it depends on the values of all (fixed and random) parameters. However, in a fully balanced case, such as the current design (40 trials per trial type/reward combination [condition]), repeated-measures ANOVA and linear MEM will be nearly identical. For repeated-measures ANOVA, we know the main effects and interaction tests will be independent; the distribution under the alternative hypothesis is a non-central F with non-centrality parameter:

$$\lambda = \frac{n\sum_{j=1}^{2}\sum_{k=1}^{2}\beta_{jk;\text{interest}}^{2}}{\frac{1}{R}\sigma_{\varepsilon}^{2} + 2\sigma_{interest}^{2}}$$

where "interest" corresponds either to the main effect of trial type and, thus, β_1 and σ_1^2, to the main effect of reward and, thus, β_2 and σ_2^2, or to the Trial Type x Reward interaction and, thus, β_3 and σ_3^2. R is the number of repetitions per participant and per condition. Based on H1, our primary hypothesis, our effect of interest is the Trial Type × Reward interaction. Our pilot data results showed a Cohen's f = .516 (see 3.2 Pilot Results). However, we decided to use a more conservative f = .25, representing a medium effect size (Cohen, 1962), because pilot study results are unlikely to yield accurate estimates of effect sizes (Albers & Lakens, 2018). An f = .25, where $f = \sqrt{\lambda/n}$, implies that β should be equal to 0.25 times the squared root of the denominator in the definition of λ. To take realistic values, we based our values on the pilot study and used R = 34, $\sigma_{\varepsilon}^2 = 108$, and $\sigma_{interest}^2 = 2.5$. This implies a value for βs of .715. To ensure this approach was also valid for linear MEM for our design, we ran simulation studies that showed, as in repeated-measures ANOVA, that the main effects and the interaction tests would be independent and, for example, the power for β_1 depends only on σ_1^2 (the variance of u_{1j}) and σ_{ε}^2. The values of σ_2^2 and σ_3^2 have almost no influence on this power. The power is guided by λ, as defined above. To evaluate the power for different sample sizes, we ran a MEM Monte Carlo simulation based on the model planned to address H1 with 500 samples of each size and with the above values. It was accomplished with the lmer R functions and simulated from the lme4 package. With these settings, for all effects, with α = .02, the number of participants needed to detect a medium effect size was ≥ 56. Based on the pilot study where 1 of 9 participants had a poor EEG recording, we expected poor EEG recordings from 11.11% of participants. Therefore, we recruited 64 participants but ensured that we had quality data in a sufficient number of trials (n ≥ 20 condition; Marco-Pallares, Cucurell, Münte, Strien, & Rodriguez-Fornells, 2011) from at least 56 participants.

For the first secondary analysis (H2), the same reasoning and computations as the ones used for H1 was made for all effects and, with α = .02, the number of participants needed to detect a medium effect size was also ≥ 56. Power calculation for secondary analyses addressing H3 and H4 was attempted but not completed because the calculations failed to yield reliable results, possibly due to the increased complexity of the models.

Experimental setup

Each trial of the task began with the participant standing and facing a table upon which was a computer monitor, approximately eye level to the participant (Figure 1). There was a blue container holding plastic coins next to the monitor and approximately arm-level with the participant when standing. A foldup butterfly chair was positioned immediately behind the participant. Another blue container holding plastic coins and an empty red (collection) container were positioned next to the chair and

approximately arm-level with the participant when seated. A recording device (e.g., iPAD) was positioned on the ground facing the participant's legs. Participants were told their lower body movements was recorded to confirm that they were standing as still as possible, which they were instructed to do to facilitate EEG recording. The participant held a wireless game controller throughout the experiment.

Figure 1. Experimental Setup. The participants used a game controller to respond to stimuli on a computer monitor. They had the opportunity to win plastic coins from the blue container at arm-level while standing or the blue container at arm-level while seated, based on probabilistic learning and chance. The participant deposited the coins won in the red container.

Experimental setup

Each Data were collected at a single testing site. Participants' height and weight was measured with a stadiometer and scale. They were asked to rate how fatigued they felt using the Multidimensional Fatigue Inventory (Smets, Garssen, Bonke, & De Haes, 1995) and three custom items (see Appendix B) prior to starting the task. Participants began each trial standing and were prompted to hit a game controller button to start the trial (Figure 2). Next the participant saw two squares (or "doors") appear on the computer monitor, one to the left and one to the right. One of the squares was burnt orange (RGB: 205, 85, 0) and one was navy blue (RGB: 0, 0, 128). The color of the square appearing on the left or right varied randomly with equal probability. Participants were instructed to select one of the squares by pressing the game controller button corresponding with the side of the monitor containing their square of choice (i.e., the left button if the square they choose is on the left side, and the right button if the square they choose is on the right side). After a choice was made, a fixation cross appeared for 300 – 500 ms followed by a stimulus depicting two lines, an upper line and a lower line, with a container depicted upon one of the lines. If the container was upon the upper line (stand trial), it indicated that, if the participant earned a reward on the trial, it would result in them retrieving coins from the upper blue container that was arm-level when standing. If the container was upon the lower line (sit trial), it indicated that, if the participant earned a reward on the trial, it would result in them retrieving coins from the lower blue container that was arm-level when sitting. The lines and container stimuli remained on the monitor for 2000 ms and were followed by a fixation cross for 300 – 500 ms. Next, participants saw a feedback stimulus informing them whether they earned the reward or not. They either saw a "$" sign for 1000 ms indicating that they earned a reward, or a "0" for 1000 ms if they did not. Then, participants saw the word "WAIT" appear on the monitor for 3000 ms. Then, on stand reward trials, participants heard a tone indicating that they should take a coin from the upper container, squat to touch their butt to the chair while placing the coin in the red collection container, then return to a standing position. This process was repeated after a 6000 ms interval before the next tone, until a total of 5 coins had been retrieved. On sit reward trials, participants sat down in the chair upon hearing the tone and took a coin from the lower container, then placed the coin in the red collection container. The participant remained seated until the next tone, at which time they retrieved another coin from the lower container by simply reaching into the container. This process was repeated until the participant retrieved five coins in total. Participants were told to remain seated after retrieving the fifth coin until prompted to start the next trial.

On no-reward trials ("0" sign), participants remained standing for 30 s, irrespective of the information provided to them in the first step (i.e., sit vs. stand trial). Thus, participants should have set expectations about whether they would sit or squat to retrieve coins in the first step, then compute a reward-prediction error based on the feedback stimulus ("$" vs. "0") in the second step, which informed them whether they indeed sat or squatted to retrieve coins.

Prior to starting the task, participants were told that each coin represents a raffle ticket to win $10 [USD]; the more coins they earned, the more likely they were to win $10; on each trial, a certain color square gave them a certain probability of winning, so they should focus on choosing a square based on color; and there was no strategy for selecting a color square to win. Please see Appendix A for complete instructions that were given to the participants. Unbeknownst to participants, each color square had a 50% probability of resulting in a reward on each trial, but one square had a 70% chance of resulting in a sit trial, whereas the other square had a 20% chance of resulting in a sit trial. This procedure allowed to test whether participants began to choose the square more likely to minimize effort (H3) while avoiding having them choose a square based on its likelihood of resulting in a reward (coins). Through

preliminary pilot testing, we established that these probabilities should lead to at least n = 25 of each trial type (sit reward, sit no-reward, stand reward, stand no-reward), which past research has revealed leads to a reliable reward positivity (Marco-Pallares et al., 2011). The median and minimum number of trials per condition and dependability (reliability) are reported for both the pilot and main study (Table 1). Reliability was obtained using generalizability theory (Carbine, Clayson, Baldwin, LeCheminant, & Larson, 2021; Clayson & Miller, 2017b), and using the ERP reliability analysis toolbox implemented in Matlab software (Clayson & Miller, 2017a, 2017b). We used reliability to contextualize results from our primary experiment (reliability is associated with standard error of measurement and effect size; Clayson & Miller, 2017) and inform future research (e.g., how many trials per condition researchers should try to obtain).

The color square with the higher probability of resulting in a sit trial varied randomly between participants. Participants completed a total of 160 trials, which took about 110 min. Participants were given breaks approximately every 22 min and remained standing during the breaks.

Figure 2. Experimental protocol and stimuli. There were four types of trials, each of which began with the participant standing. For each participant, one of the colored squares had a 70% chance of resulting in a sit trial and the other square had a 20% chance of resulting in a sit trial. Each square and each type of trial had a 50% chance of resulting in a reward, which determined whether the behavior had to be performed or not.

After finishing the task, participants completed questionnaires. The Borg scale (Borg, 1982) was used to rate the perceived level of exertion they typically experienced when retrieving coins and waiting for the next trial from the sitting vs. standing position. Participants were asked whether they preferred to retrieve coins by sitting or standing. The custom fatigue questions were asked again (Appendix B). The International Physical Activity Questionnaire (IPAQ) (Craig et al., 2003) was used to assess the level of energy expenditure during a typical week and on the current day. Dependence on exercise was assessed with the Exercise Dependence Scale-21 (Hausenblas & Symons Downs, 2002) and their affective attitudes toward exercise were also assessed (Courneya & Bobick, 2000). Participants provided information related to handedness (Oldfield, 1971). Finally, participants were informed that one of the squares was more likely to result in stand trials and asked to rate their awareness of this manipulation of likelihood on a 0 ("not aware at all") to 10 ("fully aware") scale.

EEG recording and signal processing

Scalp EEG was collected from a BrainVision actiCAP system (Brain Products GmbH, Munich, Germany) labeled in accord with an extended international 10-20 system (Oostenveld & Praamstra, 2001) and sampled at 250 Hz. Data were collected from the following electrodes: FP1, FP2, F3, Fz, F4, FC3, FCz, FC4, C3, Cz, C4, CP3, CPz, CP4, P3, Pz, and P4. EEG data were referenced online to the left earlobe and a common ground was employed at the FPz electrode site. Electrode impedances were maintained below 25 kΩ throughout the study and a high-pass filter was set at 0.016 Hz. The EEG signal was transmitted via the BrainVision wireless MOVE add-on (Brain Products GmbH) to a BrainAmp DC amplifier (Brain Products GmbH) that amplified and digitized the signal. The amplifier was linked to a computer running BrainVision Recorder software (Brain Products GmbH) that recorded the signal. EEG data processing was conducted with BrainVision Analyzer 2.2 software. Data was visually inspected to determine whether any electrode needed to be interpolated, for example due to recording failure (e.g., 1-s or longer periods of voltage changing by less than 0.5 μV) and/or electrical noise (e.g., sharp changes in voltage of more than 200 μV). Next, data were re-referenced to an average ears montage. Then, data were prepared for independent component analysis (ICA) cleaning. First, a 1 – 40 Hz band-pass filter with 4th order roll-offs and a 60 Hz notch filter was applied. Next, data were visually inspected and non-stereotypical artifacts were marked. Then, an ICA was conducted to identify stereotypical artifacts, such as blinks and saccades. We identified stereotypical artifacts, such as blinks and saccades, by looking for components that exhibited relatively sharp changes in frontopolar voltage (e.g., more than 200 μV) that decreased in amplitude from anterior to posterior electrode sites (blinks), or exhibited broad frontopolar changes in voltage (e.g., more than 200 μV) that were larger in a hemisphere than in the other hemisphere and decreased in amplitude from anterior to posterior electrode sites (saccades). This ICA was applied to the unfiltered data to remove identified artifacts. This cleaned

data was band-passed filtered between 0.1 and 30 Hz with 4th order roll-offs, and a 60 Hz notch filter was applied.

Measures

Reward-prediction errors: "Reward Positivity"

The reward positivity was extracted from an epoch beginning 200 ms prior to the onset of the feedback stimulus, indicating whether the participant earned the reward or not, and ending 800 ms after this stimulus. Then, the epoch was baseline corrected with respect to the pre-stimulus interval (-200 – 0 ms). Next, epochs containing a change of more than 50 μV from one data point to the next, a change of 100 μV within a moving 200-ms window, or a change of less than 0.5 μV within a moving 200-ms window in any of the midline electrodes (Fz, FCz, Cz, CPz, and Pz) were excluded from subsequent analysis. Next, we determined the time window for reward positivity quantification. Specifically, epochs time-locked to reward feedback were averaged separately for reward and no-reward trials. Then, the average of the no-reward feedback epochs was subtracted from the average of the reward feedback epochs to create a difference wave for each participant. In our pilot data, difference waves exhibited substantial interindividual variability in reward positivity peak latency (the positive peak 230 – 350 ms after feedback onset). Thus, we adaptively centered each participant's reward positivity time window (length = 40 ms) on their reward positivity peak latency at the electrode at which it peaked (Fz, FCz, or Cz) (Clayson, Baldwin, & Larson, 2013). We also confirmed that this window included a negative deflection in the no-reward feedback waveforms (Krigolson, 2018). If it did not, we centered the window on the maximal negativity between 230 and 350 ms in the no-reward feedback waveforms. Of note, we originally planned to identify each participant's reward positivity between 250 and 350 ms, but, after collecting data from 9 participants, we noticed that the reward positivity was peaking as early as 230 ms. Thus, we consulted the editorial team and were advised to adjust our reward positivity window to 230 – 350 ms and conduct sensitivity analyses with the original time window. Then, we computed mean amplitude in each participant's time window at Fz, FCz, and Cz for each epoch (i.e., the non-averaged data) and then averaged across these electrodes. That is, the mean amplitude, pooled across Fz, FCz, and Cz, in each participant's reward positivity time window for each trial served as the reward positivity. If one of the electrodes malfunctioned during recording, it was not included in the average. Finally, since the reward positivity exhibited an unexpected posterior scalp distribution (i.e., maximal voltage at electrode CPz or Pz), we quantified the component by averaging across electrodes Cz, CPz, and Pz, and submitted this reward positivity to a sensitivity analysis.

Energy expenditure

The typical level of energy expenditure was assessed using the IPAQ (Craig et al., 2003) assessing moderate-to-vigorous physical activity undertaken during a typical week ("typical MVPA"). Typical MVPA was computed using the Metabolic Equivalent of Task (MET) associated with moderate (6 METs) and vigorous physical activity (8 METs) (IPAQ Research Committee, 2005). Specifically, based on the IPAQ protocol, the formula we used was: typical MVPA in MET minutes per week = 4.0 x minutes of moderate physical activity per week + 8.0 x minutes of vigorous physical activity per week (IPAQ Research Committee, 2005). The level of energy expenditure prior to the experiment on the day of the experiment ("today MVPA") was also assessed using the IPAQ assessing moderate-vigorous physical activity in MET-minutes. Finally, the level of energy expenditure during the experiment ("study energy expenditure") was computed by summing the METs spent on each trial up to the current trial. To compute the energy expended on each trial, we considered the actions performed during the trial and the time spent performing these actions. Specifically, participants spent 28 s standing on sit/stand no-reward trials; 26 s sitting down and 2 s squatting (sitting down to retrieve coins and standing up to begin the next trial) on sit reward trials; and 12 s squatting and 16 s standing on stand reward trials. 1.50 MET was assigned for sitting; 1.75 MET was assigned for standing; and 4 METs was assigned for squatting, which we consider moderate-intensity exercise (Mansoubi et al., 2015). After converting METs from min to s, the trial types were determined to have the following energy expenditure: sit reward trial = 1.30 MET; sit/stand no-reward trial = 1.36 MET; and stand reward trial = 2.11 METs.

Behavioral measures

The first behavioral measure was the stimulus participants chose on each trial ("**stimulus chosen**"), which was either the stimulus with the higher or lower probability of resulting in a sit trial. The second behavioral measure was whether a participant changed their response (what stimulus they chose) from the previous trial ("**changed response**").

Statistics

The first Factors, designs, and formal tests used to investigate the hypotheses are summarized in Supplemental Table 1. If a variable was not normally distributed, as tested

by the Shapiro-Wilk normality test, the variable was normalized using the Box–Cox transformation (Box and Cox 1964), which represents a family of power transformations that incorporates and extends the traditional methods (e.g., square root, log, inverse) to find the optimal normalizing transformation for each variable. As such, Box-Cox represents a potential best practice to normalize data (Osborne, 2010).

MEMs were used to test the hypotheses. The mixed-effect approach provides a type I error rate that corresponds to its expected level (Boisgontier & Cheval, 2016; Lachaud & Renaud, 2011) and is useful when modeling effects predicted to change over time (e.g., H3; Lohse, Shen, & Kozlowski, 2020). In several research fields, the use of MEM is promoted as a better alternative than traditional statistical models (Boisgontier & Cheval, 2016). Unlike traditional approaches (e.g., ANOVA), which require averaging trials within each condition, MEM preserve all the information (i.e., for each participant, these models keep the variability of the responses within each condition). Therefore, the number of data points in the model increases, which contains type I error rate without compromising the power (Judd, Westfall, & Kenny, 2012). The MEMs were built and fit by maximum likelihood in R using the lme4 and lmerTest packages and p-values were approximated using the Satterthwaite's method (Bates, Mächler, Bolker, & Walker, 2015; Kuznetsova, Brockhoff, & Christensen, 2016; R Core Team, 2019). An estimate of the effect size of the fixed effects was reported using the marginal pseudo R2 computed with the MuMIn package (Barton, 2018). Statistical assumptions associated with MEMs (normality of the residuals, homogeneity of variance, linearity, multicollinearity exclusion, and control of undue influence) were checked for all models. If some observations exerted undue influence on the model estimation (i.e., outliers), the models were tested with and without them to ensure results' robustness. Alpha was set to .02 for all analyses. To interpret significant interactions, simple-effect analyses were conducted.

Primary Analyses

H1 was tested with the following linear MEM:

$$\begin{aligned}&\boldsymbol{Reward\ Positivity_{ij}} = \\ &(\boldsymbol{\beta_0} + \boldsymbol{u_{0j}}) \\ &+ (\boldsymbol{\beta_1} + \boldsymbol{u_{1j}})\boldsymbol{Trial\ Type\ (stand\ vs.sit)_{ij}} + (\boldsymbol{\beta_2} \\ &+ \boldsymbol{u_{2j}})\boldsymbol{Reward\ (no\ reward\ vs.reward)_{ij}} \\ &+ \boldsymbol{\beta_3\ Trial\ Type_{ij} \times Reward_{ij}} + \boldsymbol{\epsilon_{ij}}\end{aligned} \quad \textbf{(1)}$$

where $Reward\ Positivity_{ij}$ is the participant's reward positivity in condition i, β_0 to β_3 are the fixed effect coefficients, u_{0j} to u_{2j} are the random effects for participant j (random intercepts and slopes), ϵ_{ij} is the error term, u_{1j}, u_{2j} and ϵ_{ij} are Gaussian and independent.

To test H1, we checked and ensured that reward positivity was larger on reward versus no reward trials as this condition must be satisfied to demonstrate the presence of a reward positivity that could potentially be moderated by other factors, such as trial type.

Sensitivity Analyses

As mentioned in section 2.6.1, a sensitivity analysis was conducted with the window centered on the maximal negativity between 250 and 350 ms in the no-reward feedback waveforms. In addition, a sensitivity analysis was conducted with reward positivity averaged across electrodes Cz, CPz, and Pz (and centered on a peak between 230 and 350 ms).

Secondary Analyses

H2.1, H2.2, and H2.3 were tested with the following linear MEM:

$$\begin{aligned}&\boldsymbol{Reward\ Positivity_{ij}} = (\boldsymbol{\beta_0} + \boldsymbol{u_{0j}}) + \\ &(\boldsymbol{\beta_1} + \boldsymbol{u_{1j}})\boldsymbol{Trial\ Type\ (stand\ vs.sit)_{ij}} + \\ &(\boldsymbol{\beta_2} + \\ &\boldsymbol{u_{2j}})\boldsymbol{Reward\ (no\ reward\ vs.reward)_{ij}} + \\ &(\boldsymbol{\beta_3} + \boldsymbol{u_{3j}})\boldsymbol{Energy\ Expenditure_{ij}} + \\ &\boldsymbol{\beta_4 Trial\ Type_{ij} \times Reward_{ij}} + \\ &\boldsymbol{\beta_5 Trial\ Type_{ij}} \times \\ &\boldsymbol{Energy\ Expenditure_{ij}} + \boldsymbol{\beta_6 Reward_{ij}} \times \\ &\boldsymbol{Energy\ Expenditure_{ij}} + \\ &\boldsymbol{\beta_7 Trial\ Type_{ij} \times Reward_{ij}} \times \\ &\boldsymbol{Energy\ Expenditure_{ij}} + \boldsymbol{\epsilon_{ij}}\end{aligned} \quad \textbf{(2)}$$

where $Reward\ Positivity_{ij}$ is the participant's reward positivity in condition i, β_0 to β_7 are the fixed effect coefficients, u_{0j} to u_{3j} are the random effects for participant j (random intercepts and slopes), ϵ_{ij} is the error term, u_{1j}, u_{2j}, u_{3j}, and ϵ_{ij} are Gaussian and independent, *Energy Expenditure* is the score on typical MVPA, today MVPA, and study energy expenditure for model 2.1, 2.2, and 2.3, respectively.

H3 was tested with the following logistic MEM:

$$\begin{aligned}&\boldsymbol{logit}(\boldsymbol{E_j}(\boldsymbol{Stimulus\ Chosen_{ij}})) \\ &= \boldsymbol{\beta_0} + (\boldsymbol{\beta_1} \\ &+ \boldsymbol{u_{1j}})\ \boldsymbol{Trial\ Number_{ij}} + \boldsymbol{u_{0j}}\end{aligned} \quad \textbf{(3)}$$

where *Stimulus Chosen* is the stimulus chosen by the j^{th} participant on trial i, E_j is the conditional expectation, β_0 and β_1 are the fixed effect coefficients, u_{0j} and u_{1j} are the random intercepts and slopes for the j^{th} participant and are Gaussian and independent.

H4 was tested with the following logistic MEM:

$$\boldsymbol{logit}(\boldsymbol{E_j}(\boldsymbol{Changed\ Response_{ij}})) = \boldsymbol{\beta_0} + (\boldsymbol{\beta_1} + \boldsymbol{u_{1j}})\boldsymbol{Reward\ Positivity_{i-1j}} + \boldsymbol{u_{0j}} \quad \textbf{(4)}$$

where *Changed Response* is whether the j^{th} participant changed their response from trial i -1 to trial i, β_0 and β_1 are the fixed effect coefficients, u_{0j} and u_{1j} are the random intercepts for the j^{th} participant and are Gaussian and independent.

Several variables were added to determine if they explained residual variance. For *models 1 and 2*, the outcome variable, reward positivity, is sensitive to whether a reward is predicted on a trial. Although each trial (1, 2, 3, etc.), each stimulus chosen (burnt-orange square vs. navy-blue square), and each type of trial (sit vs. stand) was programmed to have 50% chances of resulting in a reward, it was possible that rewards occurred more or less frequently at times. Thus, we added variables reflecting the probability of receiving a reward on the current trial given how frequently (1) a reward had been received up to the current trial ("**reward probability**"); (2) a reward had been received when choosing a certain stimulus up to the current trial ("**stimulus reward probability**"); and (3) a reward had been received on a certain trial type up to the current trial ("**trial type reward probability**"). We also added interaction terms between these variables and those in the primary models.

For *model 3*, the choice of the stimulus should also be sensitive to reward probability based on the stimuli chosen up to the current trial. Therefore, we added stimulus reward probability in this model. Stimulus chosen should also be sensitive to trial type given the stimulus chosen. Although one stimulus was programmed to lead to sit trials 70% of the time and the other stimulus only 20%, the actual difference may have departed from 50% at times. Thus, we added a variable reflecting the probability that one stimulus led to a sit trial relative to the probability that the other stimulus led to a sit trial, up to the current trial ("**stimulus trial type probability**"). We also added interaction terms between these variables and those in the primary models.

For *model 4*, trial number may have predicted changed response, with participants changing their responses less often across trials as they learned the stimuli-trial type relationship (e.g., Lohse, Miller, Daou, Valerius, & Jones, 2020). Additionally, trial type (sit vs. stand) on the prior trial ("**previous trial type**") and reward (reward vs. no-reward) on the prior trial ("**previous reward**") may have predicted changed response. We also added interaction terms between these variables and those in the primary models.

Non-Registered Analyses

Non-registered analyses using data from questionnaire responses were conducted to determine whether independent variables that have been shown, or could reasonably be expected, to be related to physical activity or sedentary behavior could contribute to explaining the variability in the following dependent variables: (i) reward positivity, (ii) the probability of choosing the stimulus with a higher probability of sitting, and (iii) the probability of changing the chosen stimulus compared to the previous trial. The independent variables examined in these exploratory analyses were age (Cheval et al., 2018c), gender (Chalabaev et al., 2022), body mass index (BMI; computed from height and weight) (Cheval et al., 2018c; Klimentidis et al., 2018), typical sitting time (Craig et al., 2003), exercise dependence (Hausenblas & Symons Downs, 2002), affective attitudes toward exercise (Farajzadeh et al., 2023; Rhodes & Kates, 2015), instrumental attitudes toward exercise (Rollo, Gaston, & Prapavessis, 2016), fatigue (Multidimensional Fatigue Inventory [Smets et al., 1995] as well as pre- and post-task custom questions), IPAQ scores ranked by quartiles (Sagelv et al., 2020), rating of perceived exertion associated with retrieving coins on sit reward trials and stand reward trials, preference for the sit vs. stand trials, and awareness about the fact that one stimulus led to a higher probability of stand (vs. sit) trials relative to the other stimulus.

When estimating the effect on reward positivity (i), we tested the interaction between reward, type of stimulus, and each independent variable in models that accounted for the random effect of trial type and reward (reward vs. no reward) at the participant level. When estimating the effect on the probability of choosing the stimulus with the higher probability of sitting (ii), we tested the interaction between trial number and each independent variable in models that accounted for the random effect of trial at the participant level. When estimating the effect on the probability of changing chosen stimulus (iii), we tested the interaction between reward positivity and each independent variable in models that accounted for the random effect of reward positivity at the participant level.

Pilot Study

After conducting several preliminary pilot studies aiming to refine the paradigm (e.g., number of trials, probabilities that each stimulus leads to a sit trial), we conducted our main pilot study with two objectives. First, we sought to determine whether we could observe a reward positivity in our data that could potentially be moderated by trial type. Such effect would be observed if there was a frontocentral positive deflection in the ERP time-locked to feedback onset for reward trials in comparison to no-reward trials. Second, we sought to determine whether the rating of perceived exertion (Borg, 1982) was lower for trials in which participants sat to retrieve rewards versus squatted to retrieve rewards. No persistent movement artifact was observed in the segments of pilot EEG data from which the reward positivity was extracted (i.e., the data time-locked to feedback presentation). This was expected because participants were motionless when feedback was presented. Additionally, despite participants squatting, no sweat artifact was observed in the pilot EEG data, which was expected because the testing room temperature was kept at 20°C. The pilot data informed the sample size calculation, which was conducted with a simulation informed by the data (see 2.2 Sample Size Calculation). Regarding the number of trials for each condition, the medians were as follows: sit reward: 36.5 (minimum = 24), sit no-reward: 32.5 (minimum = 26), stand reward: 39 (minimum = 30), and stand no-reward: 39 (minimum = 29).

Pilot Population

We recruited nine participants from the College of Education Research Participant Pool at Auburn University (USA) (5 males; age = 21.2 ± 1.2 years, BMI = 24.7 ± 4.8 kg/m2, mean ± SD). We determined seven participants were required to detect a main effect of reward, based on an effect size observed in our past research (Meadows, Gable, Lohse, & Miller, 2016), but chose to recruit at least eight participants in case of data loss due to poor EEG recording, which did occur for one participant.

Pilot Results

ERP waveforms and scalp topographies for the pilot data are depicted in Supplemental Figure 1. The figure suggested that we were able to obtain clean data, which was further evidenced by the fact that we lost only 11.4% (SD = 10.8%) of trials per participant due to artifacts in the EEG. As expected, a 2 (Trial Type: Sit vs. Stand) x 2 (Reward: Reward vs. No-Reward) repeated-measures ANOVA revealed a main effect of reward, $F(1, 7) = 16.2$, $p = .005$, $f = 1.52$, such that reward positivity was larger for reward trials ($M = 11.8$ μV, $SD = 8.48$ μV) than no-reward trials ($M = 5.51$ μV, $SD = 5.86$ μV). The Trial Type x Reward interaction was $F(1, 7) = 1.86$, $p = .215$, $f = .516$, and the main effect of trial type was $F(1, 7) = 0.851$, $p = .387$, $f = .348$. Regarding the second objective of the pilot data, as expected, a paired-sample t-test revealed that rating of perceived exertion was lower when retrieving rewards on sit trials ($M = 7.33$, $SD = 1.41$) than stand trials ($M = 11.1$, $SD = 2.20$), $t(8) = 4.09$, $p = .004$, $d = 1.36$. The primary statistical models were also tested with the pilot study data and results shown in Supplemental Table 2, 3, and 4.

	n	Mean	SD	
Age (years)	58	20.5	1.1	
BMI (kg/m^2)	58	25.6	3.9	
Typical MVPA (MET minutes per week)	54	4396.6	2831.9	
Today MVPA (MET minutes)	57	314.3	420.2	
Study-related energy expenditure (METs)	58	122.3	3.2	
Perceived Exertion for the sit trial (range 6-20)	58	7.4	1.3	
Perceived Exertion for the stand trial (range 6-20)	58	12.5	1.8	
Reward Positivity (μV)				
Average	56	6.8	4.6	
Reward trials	56	9.2	5.5	
No-reward trials	56	4.6	4.6	
Probability to choose the sit vs. stand stimulus (%)	58	58	15	
Change of chosen stimulus (vs. previous trial) (%)	58	38	14	
Typical sitting time on a weekday (min/day)	54	389.2	209.3	
Fatigue				
Multidimensional Fatigue Inventory (range 1-5)	58	3.9	0.5	
Pre-task custom score (range 0-10)	58	1.8	1.6	
Post-task custom score (range 0-10)	58	4.7	2.0	
Exercise dependence (range 1-6)	58	2.7	0.8	
Affective attitudes toward exercise (range 1-9)	58	7.0	1.5	
Instrumental attitudes toward exercise (range 1-9)	58	8.5	0.7	
Awareness that a stimulus led more to sit than stand trials (range 0-10)	58	6.3	3.4	
Number of trials per participant and EEG reliability		**Median**	**Min.**	**Reliability [95% CI]**
Sit reward trials	56	37	23	.86 [.81, .91]
Sit no-reward trials	56	40.5	21	.78 [.68, .86]
Stand reward trials	56	40	24	.84 [.78, .90]
Stand no-reward trials	56	37	21	.85 [.78, .90]

Table 1. Sample description. Note. BMI = body mass index: 95% CI = 95% confidence intervals. Reliability estimates were

computed using the ERP Reliability Analysis (ERA) Toolbox (v0.5.2; 1000 iterations), which uses generalizability theory (Clayson & Miller, 2017a).

Results

All the models can be tested using the data and R code available in a public repository (Parma et al., 2023). In lieu of a laboratory log, readers can note the data of each data collection by viewing the log files at this repository. MEM do not require Gaussianity of the dependent and independent variables, but of the residuals and of the random effects, which can be checked only after a model has been fitted. Accordingly, results in the main text reflect the initial results, except in the few cases where results changed with transformed variables. In these cases, the main text shows results based on transformed variables. For transparency, complete results based on non-transformed variables can be found in Table 2 and those based on transformed variables can be found in Supplementary Table 5.

Since outliers have an influence on the choice of the best transformation made by the traditional Box-Cox likelihood-based transformation, this method may not always provide the correct transformation. Therefore, when the Box-Cox transformation did not visually improve the distribution of the variable, other transformations were tested.

All independent variables treated as continuous (i.e., trial, typical MVPA, today MVPA, study energy expenditure, reward probability, stimulus reward probability, trial type reward probability, typical sitting time, exercise dependence, affective attitudes, instrumental attitudes, fatigue, rating of perceived exertion, awareness) were standardized to facilitate interpretation and to simplify the random structure. Standardization was conducted using the scale() function in the R base package (R Core Team, 2021). Thus, all the continuous independent variables included in the models have a mean of zero and a standard deviation of one.

Since the dependent variables were not standardized, the b-values reported in the results can be interpreted as follows: If the b-value is positive, then for each one-standard-deviation increase in the independent variable, the dependent variable increases by the value of the b coefficient. This strategy was chosen to facilitate comparison of the effects of the independent variables, to reduce potential multicollinearity problems, and to improve model convergence.

Descriptive Statistics

Table 1 shows the characteristics of the participants. Sixty-four participants began the study, but the final sample included 58 participants (30 women; mean age 20.5 ± 1.1 years; mean body mass index 25.6 ± 3.9 kg/m2), two of whom had their EEG data discarded due to excessive artifact. Six participants did not complete the study due to experiment equipment failure or not meeting the minimum age criterion. The typical level of moderate-to-vigorous physical activity was 4396.6 ± 2831.9 MET minutes per week, which is above the threshold for a high level of physical activity (3000 MET-mins per week) (IPAQ Research Committee, 2005). This result is likely due to our sample consisting of young adults who were enrolled in Auburn University College of Education courses, many of which are about exercise science and physical activity. It should also be noted that the IPAQ is prone to overestimating actual levels of physical activity (e.g., Dinger, Behrens, & Han, 2006; Lee, Macfarlane, Lam, & Stewart, 2011). The level of moderate to vigorous physical activity during the day of the study was 314.4 ± 420.2 MET minutes, and the energy expenditure during the study was 122.3 ± 3.2 METs. The mean rating of perceived exertion was 7.4 (± 1.3) for sit trials and 12.5 (± 1.8) for stand trials. The mean reward positivity amplitude was of 6.8 μV (± 4.6), the mean reward positivity amplitude in the no reward condition was of 4.6 μV (± 4.6), and the mean reward positivity amplitude in the reward condition was of 9.1 μV (± 15.1). On average, participants chose the stimulus with the higher probability to sit rather than to stand 58% (± 15%) of the trials. Finally, participants changed the stimulus chosen in 38% (± 14%) of the trials. The median number of trials per condition were as follows: sit reward = 37 (minimum = 23), sit no-reward = 40.5 (minimum = 21), stand reward = 40 (minimum = 24), and stand no-reward = 37 (minimum = 21). Other variables that were used for exploratory analyses are described in Table 1.

Reward Positivity

Table 2 and Figure 3 show the results for reward positivity as a function of the reward and the type of trial. Results showed that reward positivity was larger on reward versus no reward trials (b = 2.29; 95% confidence interval [95CI] = [1.74; 2.84]; p = 2.0 × 10-11). This result demonstrated the presence of a reward positivity that could potentially be moderated by other factors, such as trial type. Contrary to H1, results showed no evidence of a two-way interaction between reward (reward vs. no reward) and the type of trial (sit vs stand), suggesting that the effect of reward on reward positivity did not significantly vary with the type of trial (b = 0.10; 95CI = [-0.18; 0.40]; p = 0.482). Contrary to H2.1, H2.2, and H2.3, results showed no

evidence suggesting that typical MVPA (b = 0.14; 95CI = [-0.15; 0.45]; p = 0.338) or the energy expended across the task (b = -0.07; 95CI = [-0.37; 0.21]; p = 0.604) moderated the interaction effect of reward x type of trial on reward

Reward positivity	**Without MVPA (n = 56)**		**With typical MVPA (n = 52)**		**With today MVPA (n = 55)**		**With study energy expenditure (n = 56)**	
	b (CI)	*p*	b (CI)	*p*	b (CI)	*p*	b (CI)	*p*
Fixed Effects								
Intercept	6.94 (5.71;8.16)	5.0×10^{-16}	7.09 (5.78;8.39)	5.7×10^{-15}	7.02 (5.79;8.25)	4.1×10^{-16}	6.95 (5.72;8.18)	4.9×10^{-16}
Reward (ref. no reward)								
Reward	2.29 (1.74;2.84)	2.0×10^{-11}	2.35 (1.78;2.93)	5.7×10^{-11}	0.19 (1.73;2.85)	4.1×10^{-11}	2.28 (1.74;2.83)	1.9×10^{-11}
Type of trial (ref. sit)								
Stand	-0.19 (-0.24;0.63)	.388	0.20 (-0.25;0.66)	.384	1.91 (-0.25;0.64)	.398	0.22 (-0.21;0.67)	.307
Reward x Type of trial	0.10 (-0.18;0.40)	.482	0.11 (-0.19;0.43)	.449	0.08 (-0.21;0.38)	.573	0.09 (-0.20;0.39)	.531
Typical level of physical activity								
Typical MVPA			0.33 (-0.95;1.62)	.607				
Typical MVPA x Reward			0.41 (-0.15;0.98)	.151				
Typical MVPA x Type of trials			-0.36 (-0.81;0.09)	.119				
Typical MVPA x Reward x Type of trial			0.14 (-0.15;0.45)	.338				
Today level of physical activity								
Today MVPA					0.56 (-0.65;1.77)	.361		
Today MVPA x Reward					0.21 (-0.34;0.76)	.448		
Today MVPA x Type of trials					-0.12 (-0.56;0.32)	.591		
Today MVPA x Reward x Type of trial					0.38 (0.08;0.68)	.012		
Study energy expenditure								
Study energy expenditure							0.80 (0.51;1.10)	7.1×10^{-8}
Study energy expenditure x Reward							-0.11 (-0.40;0.17)	.445
Study energy expenditure x Type of trial							0.03 (-0.25;0.33)	.797
Study energy expenditure x Reward x Type of trial							-0.07 (-0.37;0.21)	.604
Random Effects								
Participants								
Intercept	15.559		16.481		15.066		15.599	
Reward for subject	5.955		6.019		6.076		5.902	
Type of trial for subject	2.924		2.899		3.003		2.974	
Residual	191.342		195.568		193.195		190.664	

Table 2. Results of the mixed-effects models predicting reward positivity. *Notes*. CI = confidence interval at 95%; MVPA = moderate-to-vigorous physical activity.

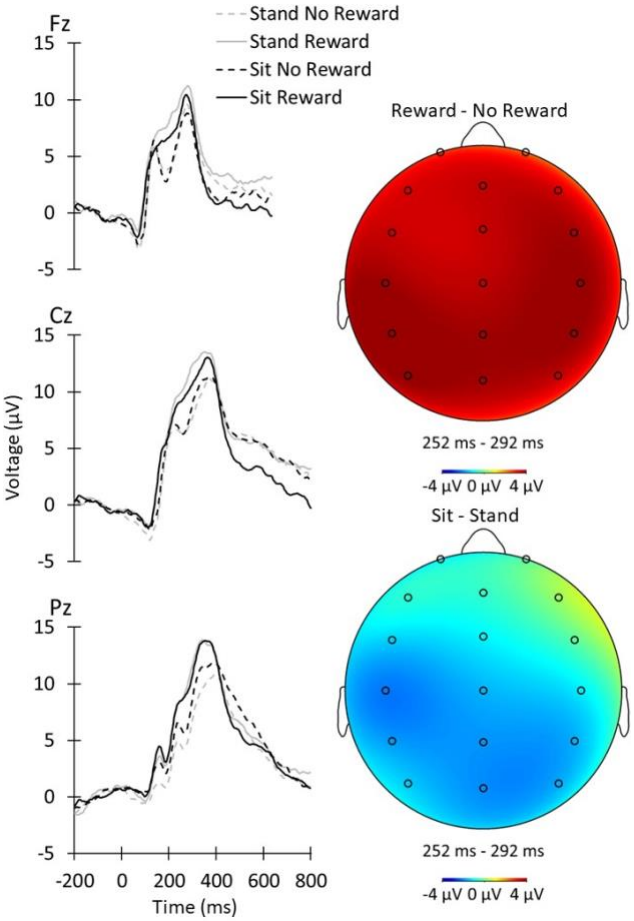


Figure 3. ERP waveforms and difference wave scalp topographies. Left panel: Grand average waveforms by trial type and reward. Right panel: Scalp topographies for reward minus no reward difference wave (top) and sit minus stand difference wave (bottom). Topographies are shown for a window that spanned 252 to 292 ms after feedback onset, as this was the average timing of the window in which reward positivity was analyzed.

positivity. However, in line with H2.2, today MVPA moderated this interaction effect of reward x type of trial on reward positivity (b = 0.38; 95CI = [0.08; 0.683], p = 0.012). Simple analyses further showed that when today MVPA was high (+ 1SD), the two-way interaction between reward (reward vs. no reward) and the type of trial (sit vs. stand) was in a different direction (b = 0.47; 95CI = [0.047; 0.839], p = 0.029) than when today MVPA was low (-1 SD) (b = -0.29; 95CI = [-0.723; 0.127], p = 0.170). Specifically, when today MVPA was high, the effect of reward in the seated trial was lower than in the stand trial (b = 2.03; 95CI = [1.135; 2.932], p = 1.97 × 10-5 vs. b = 2.97; 95CI = [2.098; 3.854], p = 1.6 × 10-9 for sit and standing trials, respectively). In contrast, when today MVPA was low, the effect of reward in the sit trial was higher than in the stand trial (b = 2.37; 95CI = [1.135; 2.932], p = 8.94 × 10-7 vs. b = 1.78; 95CI = [2.098; 3.854], p = 1.4 × 10-4 for sit and standing trials, respectively). Of note, when today MVPA was transformed using the Box Cox transformation, the moderation did not stand (b = 0.28; 95CI = [-0.01; 0.58]; p = 0.061), but it did when a log1000 transformation that provided a better distribution of today MVPA was conducted (b = 0.37; 95CI = [0.07; 0.67]; p = 0.014). Since both the analysis with non-transformed today MVPA and the analysis with transformed MVPA with the better distribution (log1000) were significant with a p-value

below 0.02 (p = 0.012 and p = 0.014) and a b-value above 0.36 (b = 0.38 and b= 0.37), we considered this moderation effect in the discussion. However, this result should be treated with caution, as the third analysis using another, yet less optimal, transformation (Box Cox) showed no significant effect (p = 0.061), although the b-value was similar and in the same direction (b = 0.28).

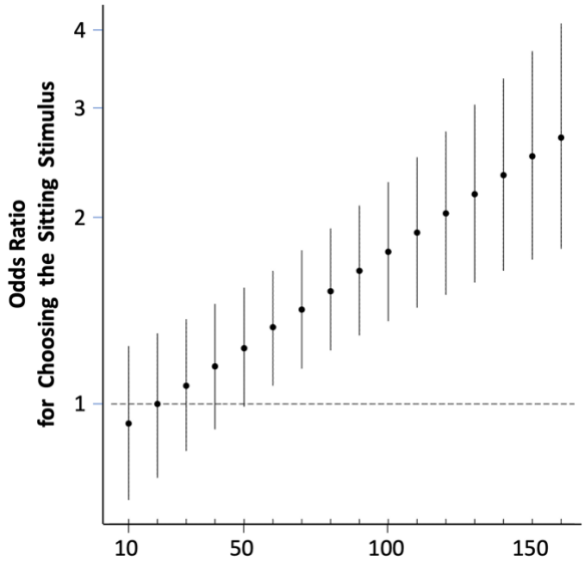


Figure 4. Odds Ratio for choosing the stimulus that was more likely to lead to sitting (vs. standing) as a function of trial number. *Notes.* Errors bars = confidence interval at 95%. Figure shown with uncentered Trial Number.

Probability of choosing the "sit" stimulus	**(n = 58)**	
	OR (95 CI)	*p*
Fixed Effects		
Intercept	0.42 (0.20;0.65)	1.7×10^{-4}
Trial number	0.32 (0.16;0.49)	1.0×10^{-4}
Random Effects		
Participants		
Intercept	0.710	
Trials number	0.371	
Corr. (Intercept, trial number)	0.30	

Table 3. Results of the mixed effects models predicting the probability of choosing the stimulus with the higher sitting likelihood. *Notes.* OR = odds ratio. 95 CI = confidence interval at 95%. Trial number was centered at the middle (i.e., 80th trial) of the task.

Probability of changing of stimulus	**(n = 56)**	
	b (95CI)	*p*
Fixed Effects		
Intercept	-0.51 (-0.70;-0.31)	1.4×10^{-7}
Reward positivity preceding trial	-0.001 (-0.005;0.001)	.301
Random Effects		
Participants		
Intercept	0.490	
Reward positivity preceding trial	2.9×10^{-5}	
Corr. (Intercept, trial number)	-0.47	

Table 4. Results of the mixed effects models predicting the influence of reward positivity on the subsequent decision to choose the same (vs. different) stimulus. *Notes.* 95 CI = confidence interval at 95%.

Probability of choosing the stimulus with the higher sitting likelihood

Table 3 and Figure 4 show the results for the probability of choosing the stimulus that was more likely to lead to sitting (vs. standing). Consistent with H3, results showed that the probability of choosing the stimulus more likely to lead to sitting increased as the number of trials increased (OR = 0.32; 95CI = [0.16; 0.49], p = 1.0 × 10-4). For example, at the 20th trial of the task, participants odds of choosing the stimulus more likely to lead to sitting than standing was not significant (OR = 0.99; 95CI = [0.76; 1.30], p = 0.990), this odd was higher and significant in the 140th trial of the task (OR = 2.33; 95CI = [1.64; 3.35], p = 2.0 × 10-6). An exploratory analysis showed no evidence of a quadratic effect of trial number (OR = -0.006; 95CI = [-0.05; 0.04], p = 0.813).

Influence of reward positivity on the subsequent decision to choose the same (vs. different) stimulus

Table 4 shows the results for influence of reward positivity on the subsequent decision about whether a participant chose the same or different stimulus. Contrary to H4, MEM results showed no evidence that the reward positivity in a given trial predicted subsequent decision to change (vs. keep) the selected stimulus in the subsequent trial.

Sensitivity analyses related to reward positivity

Overall, results of the sensitivity analyses were consistent with those of the main analyses. Specifically, for the reward positivity centered on a peak between 250 and 350 ms, results showed that reward positivity was larger in reward than no reward trials (b = 2.25; 95CI = [1.71; 2.79]; p = 2.3 × 10-11), but this effect was not significantly moderated by the type of trial (b = 0.19; 95CI = [-0.10; 0.49]; p = 0.198). Results showed that reward positivity averaged across electrodes Cz, CPz, and Pz (and centered on a peak between 230 and 350 ms) was larger in reward than no reward trials (b = 2.29; 95CI = [1.68; 2.90]; p = 5.1 × 10-10). Moreover, as the significance threshold was set to .02, the type of trials did not significantly moderate the main effect of reward (b = 0.28; 95CI = [0.01; 0.56], p = 0.039). As the p-value was significant under a less stringent threshold (0.05), we explored the simple effects, which confirmed the absence of a meaningful moderation pattern as they showed no evidence of a difference between stand and sit trials, be it in the reward (b = 0.20, 95CI = [-0.28; 0.69], p = 0.411) or no reward condition (b = -0.36, 95CI = [-0.85; 0.11], p = 0.137). Thus, in line with the main analyses, the effect of reward was not significantly more pronounced in the sitting vs. standing trials.

Secondary analyses

Reward Positivity

As registered, we tested whether the frequency a reward had been received (1) up to the current trial, (2) when choosing a certain stimulus up to the current trial, and (3) on a certain trial type up to the current trial explained residual variance. For the frequency related to the type of stimulus or the type of trial, we built two indicators. The indicator related to the type of stimulus contrasted the probability of obtaining a reward when choosing the stimulus with the higher probability to sit minus the probability of obtaining a reward when choosing the stimulus with the higher probability to stand. A higher value indicates a higher reward probability for the sit relative to the stand stimulus. Likewise, for the frequency related to the type of trial, we built a variable contrasting the probability of obtaining a reward following sit trials minus the probability of obtaining a reward following stand trials. A higher value indicates a higher reward probability for the sit relative to the stand trials.

Results testing each indicator separately showed no evidence that the indicator related to reward probability (b = -0.20; 95CI = [-0.50; 0.08]; p = 0.172), reward frequency associated to the type of stimulus (b = -0.001; 95CI = [-0.30; 0.29]; p = 0.992), or reward frequency associated to the type of trial (b = 0.09; 95CI = [-0.20; 0.39]; p = 0.526) moderated the two-way interaction between reward and the type of trial.

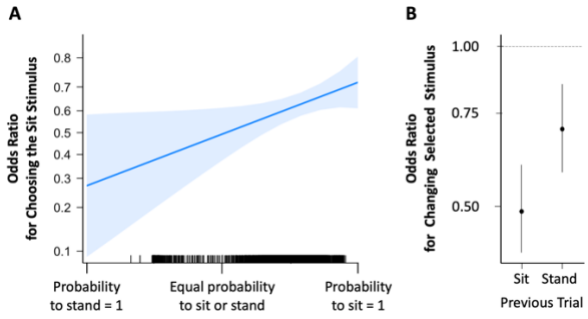


Figure 5. Odds for choosing the sit stimulus as a function of the probability that the stimulus leads to a stand or a sit trial (A) and odds for changing of stimulus as a function of choice on the previous trial (B). *Notes.* Error bars and blue area = confidence interval at 95%. The results illustrated in Figure 5A should be considered with caution as the p value (p = 0.029) was above the alpha level of the study (0.02).

Reward Positivity

As registered, for the model testing the probability of choosing the stimulus more likely to lead to sitting than standing, we built a variable reflecting the probability that the stimulus with the higher sit probability led to a sit trial relative to the probability that the other stimulus, with the higher stand probability, led to a sit trial, up to the current trial. Specifically, this variable (stimulus trial type probability) as well as its interaction with the number of trials were included in the model. Consistent with the main analyses, results showed that the probability of choosing the stimulus more likely to lead to sitting than standing increased as the number of trials increased (OR = 0.30; 95CI = [0.15; 0.46], p = 6.3 × 10-5). However, and based on a stringent alpha level (i.e., .02), we found no statistically significant evidence that the actual probability to sit affected the probability of choosing the sit stimulus relative to the stand stimulus (OR = 0.18; 95CI = [0.01; 0.34], p = 0.029) or interacted with the number of trials (OR = 0.08; 95CI = [-0.03; 0.19], p = 0.152). Because a less stringent statistical threshold (0.05) would have suggested a positive relationship between the probability to sit and the probability of choosing the sit stimulus, this relationship is illustrated in Figure 5A.

Influence of the reward positivity and the subsequent stimulus choice

As registered, for the model testing the influence of reward positivity on the subsequent decision about whether a participant chose the same or different stimulus, we added in separate models the previous trial type and the probability of reward up to the current trial, as well as their interactions with the number of trials. In the model adjusting for the previous trial type, results showed that the probability of changing of stimulus was higher when the previous trial was a stand trial relative to a sit trial (OR = 0.35; 95CI = [0.26; 0.44], p = 4.8 × 10-14) (Figure 5B). However, results showed no evidence of an association between reward positivity and the probability of changing stimulus (OR = -0.07; 95CI = [-0.14; 0.001], p = 0.052). The two-way interaction between previous reward positivity and previous trial type was not significant (OR = 0.07; 95CI = [-0.01; 0.16], p = 0.122). In the model adjusting for the probability of reward up to

the current trial, no main or interactive effects were observed (ps > 0.196).

Non-Registered Analyses

None of the exploratory analyses showed significant main or interactive effects on reward positivity. The main effect of typical physical activity ranked by quartiles (OR = -0.22; 95CI = [-0.41; -0.03], p = 0.019) and the interaction effect between trial and awareness of the experimental manipulation (OR = 0.25; 95CI = [0.10; 0.40], p = 7.4 × 10-4) were the only significant effects on the probability of choosing the stimulus with the higher probability of sitting. Importantly, in the latter model, the main effect of trial remained significant (OR = 0.32; 95CI = [0.17; 0.47], p = 1.9 × 10-5). The main effect of preference for the sit vs. stand trials (OR = -1.70; 95CI = [-3.13; -0.28], p = 0.017) and awareness (OR = -0.21; 95CI = [-0.39; -0.03], p = 0.017) as well as the interaction effect between reward positivity and typical physical activity ranked by quartiles (OR = -0.05; 95CI = [-0.10; -0.01], p = 0.009) were the only significant effects on the change in chosen stimulus. The simple effects of the latter 2-way interaction showed that higher reward positivity was significantly associated with a lower probability of changing the stimulus chosen but only among individuals in the highest quartile (Q4: OR = 0.88; 95CI = [0.81; 0.96], p = 0.004). In the lower quartiles, the effect of reward positivity on the probability of changing the stimulus chosen was not significant (for Q1: OR = 1.05; 95CI = [0.96; 1.29], p = 0.215; for Q2: OR = 0.99; 95CI = [0.94; 1.05], p = 0.855; for Q3: OR = 0.93; 95CI = [0.88; 0.99], p = 0.025).

Discussion

The theory of effort minimization in physical activity (TEMPA) suggests that sedentary behaviors are rewarding (Cheval & Boisgontier, 2021; Cheval et al., 2018a). However, direct evidence supporting its rewarding value is lacking. Here, the objective of this registered report was to test whether sedentary behaviors (i.e., retrieving a reward while sitting down) evoke reward-related brain activity (reward positivity), and whether this effect is moderated by factors related to energy expenditure (typical physical activity, physical activity on the day of the study, physical activity during the experiment). Moreover, based on reinforcement learning theory (Sutton & Barto, 2018), we tested whether decisions leading to sedentary behaviors are "learned" (i.e., participants learned to choose a stimulus likely to lead to sitting down), and whether reward positivity is linked to subsequent decisions (i.e., whether reward positivity associated with sitting down after choosing a stimulus increased the likelihood of choosing the same stimulus).

At the neural level, results showed that reward positivity was larger on reward versus no-reward trials, thereby confirming the validity of the experimental procedure we used to evoke reward-related brain activity. However, contrary to our main hypothesis, we found no evidence that this reward positivity effect was significantly moderated by the type of trial (sit vs. stand). At the behavioral level, results showed that the probability of choosing the stimulus more likely to lead to sitting than standing and squatting increased when the number of trials increased. In addition, participants were more likely to change the selected stimulus if the stimulus they chose on the previous trial led to a stand (vs. a sit) trial. Hence, in line with the theory of effort minimization in physical activity, and consistent with sitting serving as a reward in reinforcement learning, our study confirms that people choose the options associated with the least effort. Yet, our results showed no evidence suggesting this behavioral pattern could be explained by the reward positivity. Likewise, we found no evidence suggesting that typical physical activity, physical activity on the day of the study, or physical activity during the experiment influenced reward positivity.

Several factors can explain why sitting reward trials did not lead to larger reward positivity than standing reward trials. First, our paradigm crossing a doors task (Hassall et al., 2019) with a movement-incentive delay task (Cheval et al., 2019) may not be suitable for measuring the rewarding value of sedentary behaviors. In particular, a process of justification of effort, "a form of cognitive dissonance in which one gives greater value to outcomes that require greater effort to obtain, to justify the greater effort" (Aronson &

Mills, 1959), may explain why trials associated with standing (vs. sitting) were not processed as less rewarding in our paradigm. Indeed, in our task, participants already knew that they would have to expend energy (i.e., to stand and squat) if they earned a reward (see Figure 2, column 4) before finding out whether they indeed received the reward (see Figure 2, column 6). Accordingly, after learning that they would have to expend energy to retrieve the reward, participants may have raised the rewarding value of the energy expenditure, midtrial, through a process of justification of effort (Alessandri, Darcheville, & Zentall, 2008) before finding out whether they would have to actually expend energy to retrieve the reward, which was when the reward positivity was measured.

At the theoretical level, an evolutionary account of human behavior can largely explain this process of effort justification. Specifically, since people minimize unnecessary energy expenditure, investing effort into a given behavior should be justified by a reward that is worth the investment. As such, through a rationalization mechanism aiming to reduce the risk for cognitive dissonance, a conflict that occurs when beliefs do not line up with behaviors, people may increase the value of a reward associated with a behavior as soon as they engage in this behavior. Of note, this mechanism is not unique to physical effort and can be extended to other costs, such as the money invested in an object (e.g., wine) (Schmidt, Skvortsova, Kullen, Weber, & Plassmann, 2017).

Noteworthy, for physical effort at least, this reasoning highlights the need to dissociate the mechanisms associated with the anticipation phase (i.e., the incentive value of a given potential reward) from those associated with the consummatory phase (i.e., the rewarding activity while the reward is obtained) (Novak & Foti, 2015). In other words, the effect of physical effort intensity on the reward associated with this effort during the anticipation phase (i.e., negative relationship) could be different from its effect during the consummatory phase (i.e., positive relationship). While people typically behave in a way that minimizes effort (Klein-Flügge et al., 2016; Prévost, et al., 2010; Skvortsova et al., 2014) – which confirms that effort is essentially processed as a cost and as an aversive experience to avoid –, once they engage in an effortful behavior, the subjective value of the behavior becomes higher through this effort justification to reduce cognitive dissonance ("I have engaged a lot of effort in this behavior, but it is not worth the effort" vs. "I have engaged a lot of effort in this behavior, and it was worthwhile"). For example, in the study by Palidis and Gribble (2020), reward-related brain activity was greater when participants received reward feedback on high-effort trials, an observation aligned with other studies showing that individuals value rewards obtained during high effort more those obtained during low effort (Inzlicht et al., 2018). In sum, the more a behavior involves effort, the less people are likely to engage in it, but, paradoxically, once people are committed to the effort, the more this effortful behavior is valued. Thus, physical effort can be avoided (anticipation phase) or valued (consummatory phase), depending on the behavior phase. The observation that the effect of reward in the stand trials (vs. sit trials) was higher when today MVPA was high was consistent with this reasoning. Indeed, when people already engaged in physical activity on the day of the study, the standing trials may be perceived as more effortful, thereby potentially explaining the higher rewarding value of such trials via the effort justification process.

Second, EEG primarily records cortical activity (Krishnaswamy, Obregon-Henao, Ahveninen, et al., 2017). Yet, it is possible that the brain regions underpinning the rewarding value of sedentary behaviors are subcortical and not accessible by EEG. For example, regions typically involved in reward processing, such as amygdala, nucleus accumbens, and the ventral striatum (Corbit & Balleine, 2011; Gottfried, O'Doherty, & Dolan 2003; Knutson, Adams, Fong, & Hommer, 2001; Prévost, Liljeholm, Tyszka, & O'Doherty, 2012; Roesch & Olson, 2004; Schultz, Tremblay, & Hollerman, 2000), may not be reflected in EEG. However, it is important to note that combined ERP-functional magnetic resonance imagining (fMRI) research has shown that the blood-oxygen-level-dependent signal in the ventral striatum is correlated with the amplitude of the reward positivity, and EEG source localization analysis suggests the striatum may be the neural generator of the reward positivity (Carlson et al., 2011; Foti et al., 2011). Thus, variations in reward positivity amplitude may correspond with changes in the

activation of subcortical regions associated with reward processing, providing indirect measures of subcortical activities involved in reward processing. Nonetheless, future studies using fMRI, possibility in conjunction with EEG, could be useful to measure the subcortical regions that may process the rewarding value of sedentary behaviors. Another avenue for future research may involve examining the role of ERP components other than the reward positivity in processing the rewarding value of sedentary behaviors and influencing the likelihood of choosing stimuli associated with such behaviors. For example, Meadows et al. (2016) found the P3b ERP component was sensitive to reward value, and Fischer and Ullsperger (2013) observed the P3b predicted future choices in an experimental task. Notably, in the present study, the P3b seems sensitive to reward feedback, with reward trials exhibiting higher amplitude over parietal cortex than no reward trials (Figure 3).

At the behavioral level, results showing that the probability of choosing the stimulus more likely to lead to sitting than standing increased as the number of trials increased was consistent with existing literature, the theory of effort minimization in physical activity, and the corollary that decisions leading to sedentary behaviors are reinforced (Cheval et al., 2018a; Cheval & Boisgontier, 2021). Experimental works have shown that humans favor lower rather than higher effort, everything else being equal (Prévost et al., 2010; Skvortsova et al., 2014; Klein-Flügge et al., 2016; Palidis & Gribble, 2020). For example, findings have robustly confirmed that humans process physical effort as a cost in decision-making tasks and minimize the physical effort required to obtain a specific reward (Prévost et al., 2010; Skvortsova et al., 2014; Klein-Flügge et al., 2016; Bernacer et al., 2019). Morevoer, from an health psychology perspective, our current behavioral findings are consistent with the observation that sedentary-related stimuli act as temptations (Cheval et al., 2017), and that not engaging in such behaviors require higher inhibitory and cognitive function (Cheval et al., 2020a; Cheval et al., 2020c). In sum, the current study provides additional behavioral evidence, based a whole-body exercise task, that individuals favor the behavioral alternative associated with the least effort.

Regarding the secondary analyses, tests focusing on the neural outcomes showed no evidence that the frequency at which a reward has been received 1) up to the current trial, 2) when choosing a certain stimulus up to the current trial, or 3) on a certain trial type up to the current trial were related to the reward positivity or moderated the effect of reward depending on the type of trial. Analyses focusing on behavioral outcomes showed that the probability of changing the selected stimulus was higher when the previous trial was a stand trial relative to a sit trial. This finding was consistent with some empirical studies (Palidis & Gribble, 2020). For example, in the study by Palidis and Gribble (2020), results showed participants were more likely to change their response from the previous trial if it led to high effort. Morevoer, although not significant based on the stringent alpha level required by the current journal (i.e., $p < .02$), participants were more likely to choose the sit stimulus when the actual probability of this stimulus leading to a sit trial was relatively high ($p = 0.029$). If this finding would have been considered significant, it would have provided additional evidence that people tend to behave in a way that maximizes the probability to conserve energy.

Regarding the non-registered analyses, if our alpha level would have been less stringent (e.g., 0.05), our results would have suggested that stronger affective attitudes toward physical activity reduced the probability of choosing the sit (vs. stand) stimulus ($p= 0.044$), and that higher perceived exertion associated with the stand trials (i.e., higher pecevied effort for the squats) was associated with an increased probability of choosing the sit (vs. stand) stimulus ($p = 0.033$). Although not planned and above the stringent significance threshold, these findings are consistent with the existing literature – improved affective experience associated with physical activity should favor engagement in physically active behaviors (Maltagliati, Sarrazin, Fessler, Lebreton, & Cheval, 2022). Finally, results revealed that the increased probability of choosing the stimulus more likely to lead to sitting than standing as a function of trial number was more pronounced in people who were aware that one stimulus led to more sit than stand trials compared to the other stimulus. Notably, the main effect of trial number was significant even after accounting for this awareness. Thus, this effect

was observed even in people who were unaware that their decisions were influencing their energy expenditure. That is, the selection of the behavioral option minimizing effort can also take place at a rather automatic, unconscious level.

Limitations & Strengths

The present study has some limitations. First, as explained above, the used paradigm may have confounded the potential devaluation of the reward by the physical effort to obtain it because of a process of effort justification. To reduce the risk of this potential confounding, future studies need to disentangle the effect of effort at different stages of the decision process: before (i.e., effort avoidance), during (i.e., effort minimization), and after (i.e., effort justification) physical activity behavior. Such a design may allow for disentangling the differential effects of effort across stages of behavioral regulation, thus allowing for a more nuanced and accurate assessment of the effects of effort and reward processing. Second, while EEG provides an advantage over other brain imaging techniques in terms of temporal resolution, which was essential in our study, the use of this technique may have precluded accurate assessment of subcortical brain regions that may process the rewarding value of sedentary behaviors as EEG primarily records cortical activity (Krishnaswamy et al., 2017). Studies based on another non-invasive brain imaging technique, magnetic resonance imaging (MRI), can overcome this limitation and provide images with higher spatial resolution, but lower temporal resolution. Third, typical levels of physical activity were assessed using a self-report questionnaire, which may not accurately capture the actual levels of physical activity, as correlations between self-report and direct measures of physical activity are low to moderate (Lee et al., 2011; Prince et al., 2008). Assessment of usual physical activity using device-based measures, such as accelerometers, would have provided more reliable and valid information, as they have shown greater validity and reliability than self-report measures (Dowd et al., 2018). Fourth, the sample was young, healthy, and physically active, which may have biased the current results as this population is likely to be less attracted toward effort minimization than adults who are older, more sedentary adults, or adults with a health condition, as the latter populations' perception of the same level of effort is likely higher than the former population's due to greater fatigability (LaSorda et al., 2020) or chronical pain (Shupler, Kramer, Cragg, Jutzeler, &Whitehurst, 2019). Therefore, energy-minimizing behaviors are more likely to elicit reward-related brain activity in older, more sedentary, and/or less-healthy adults.

Conclusion

This registered report showed evidence that people behave in the way that minimizes the effort to invest in the task to obtain the reward, consistent with the theory that opportunities to minimize energy expenditure are rewarding. However, we found no evidence that reward-related brain activity underlies these behavioral manifestations. Future studies using other EEG paradigms or relying on other methodologies (e.g., magnetic resonance imaging) are warranted to better capture the neural mechanisms at works.

Additional Information

Data & Code Availability

The data, materials and code are available at: https://doi.org/10.5281/zenodo.8011562 (Parma et al., 2023).

CRediT Authorship Contribution Statement

- **Juliana O. Parma**: Investigation; Methodology; Project Administration; Writing – Review & Editing
- **Mariane F. B. Bacelar**: Investigation; Methodology; Project administration; Writing – Review & Editing
- **Daniel A. R. Cabral**: Writing – Review & Editing
- **Robyn S. Recker**: Investigation; Writing – Review & Editing
- **Dan Orsholits**: Formal Analysis (supporting); Writing – Review & Editing

- **Olivier Renaud**: Formal Analysis (supporting); Writing – Review & Editing
- **David Sander**: Writing- review & Editing
- **Olav E. Krigolson**: Methodology (EEG); Writing – Review & Editing
- **Matthew W. Miller**: Conceptualization; Methodology; Formal analysis (EEG data); Resources; Writing – Original Draft; Writing – Review & Editing; Visualization; Supervision
- **Boris Cheval**: Conceptualization; Methodology; Formal Analysis; Writing – Original Draft; Writing – Review & Editing; Visualization; Supervision
- **Matthieu P. Boisgontier**: Conceptualization; Methodology; Formal Analysis; Data Curation; Writing – Original Draft; Writing – Review & Editing; Visualization; Supervision

Funding

Boris Cheval is supported by an Ambizione grant (PZ00P1_180040) from the Swiss National Science Foundation (SNSF). Matthieu P. Boisgontier is supported by the Natural Sciences and Engineering Research Council of Canada (NSERC; RGPIN-2021-03153), the Canada Foundation for Innovation (CFI), Mitacs, and the Banting Research Foundation.

Conflict of Interest Disclosure

The authors declare they have no conflict of interest relating to the content of this article.

References

Aarts H, Dijksterhuis A, Vries P. On the psychology of drinking: being thirsty and perceptually ready. British J Psychol. 2001;92:631-642. https://doi.org/10.1348/000712601162383

Albers C, Lakens, D. When power analyses based on pilot data are biased: Inaccurate effect size estimators and follow-up bias. J Exp Soc Psychol, 2018;74:187-195. https://doi.org/10.1016/j.jesp.2017.09.004

Alessandri J, Darcheville JC, Zentall TR. Cognitive dissonance in children: justification of effort or contrast? Psychon Bull Rev. 2008;15(3):673-677. https://doi.org/10.3758/pbr.15.3.673

Aronson E., Mills J. The effect of severity of initiation on liking for a group. J Abnor Soc Psychol. 1959;59(2):177-181. https://doi.org/10.1037/h0047195

Aune D, Norat T, Leitzmann M, Tonstad S, Vatten LJ. Physical activity and the risk of type 2 diabetes: a systematic review and dose-response meta-analysis. Eur J Epidemiol. 2015;30(7):529-542. https://doi.org/10.1007/s10654-015-0056-z

Althoff T, Sosič R, Hicks JL, King AC, Delp SL, Leskovec J. Large-scale physical activity data reveal worldwide activity inequality. Nature. 2017;547(7663):336-339. https://doi.org/10.1038/nature23018

Baayen RH, Davidson DJ, Bates DM. Mixed-effects modeling with crossed random effects for subjects and items. J Mem Lang. 2008;59:390-412. https://doi.org/10.1016/j.jml.2007.12.005

Barton, K. (2018). MuMIn: multi-model inference [R package]. Version 1.42.1.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. Journal of Statistical Software, 67, 1-48. https://doi.org/10.18637/jss.v067.i01

Bernacer J, Martinez-Valbuena I, Martinez M, Pujol N, Luis EO, Ramirez-Castillo D, Pastor MA. An amygdala-cingulate network underpins changes in effort-based decision making after a fit- ness program. Neuroimage. 2019;203:116181. https://doi.org/10.1016/j.neuroimage.2019.116181

Berridge KC. Food reward: brain substrates of wanting and liking. Neurosci Biobehav Rev. 1996;20:1-25. https://doi.org/10.1016/0149-7634(95)00033-b

Berry TR. Who's even interested in the exercise message? Attentional bias for exercise and sedentary-lifestyle related words. J Sport Exerc Psychol. 2006;28:4-17. https://doi.org/10.1123/jsep.28.1.4

Berry TR, Spence JC, Stolp SM. Attentional bias for exercise-related images. Res Q Exerc Sport. 2011;82:302-309. https://doi.org/10.1080/02701367.2011.10599758

Bleich SN, Vercammen KA, Zatz LY, Frelier JM, Ebbeling CB, Peeters A. Interventions to prevent global childhood overweight and obesity: a systematic review. Lancet Diabetes Endocrinol. 2018;6(4):332-346. https://doi.org/10.1016/S2213-8587(17)30358-3

Bluemke M, Brand R, Schweizer G, Kahlert D. Exercise might be good for me, but I don't feel good about it: do automatic associations predict exercise behavior? J Sport Exerc Psychol. 2010;32:137-153. https://doi.org/10.1123/jsep.32.2.137

Boisgontier MP. Research integrity requires to be aware of good and questionable research practices. Eur Rehabil J. 2022;2(1):1-3. https://doi.org/10.52057/erj.v2i1.24

Boisgontier MP, Cheval B. The anova to mixed model transition. Neurosci Biobehav Rev. 2016;68:1004-1005. https://doi.org/10.1016/j.neubiorev.2016.05.034

Boisgontier MP, Iversen MD. Physical inactivity: a behavioral disorder in the physical therapist's scope of practice. Phys Ther. 2020;100:743-746. https://doi.org/10.1093/ptj/pzaa011

Boisgontier MP, Orsholits D, von Arx M, Sieber S, Miller MW, Courvoisier DS, Iversen MD, Cullati S, Cheval B. Adverse childhood experiences, depressive symptoms, functional dependence, and physical activity: a moderated mediation model. J Phys Act Health. 2020;17:790-799. https://doi.org/10.1123/jpah.2019-0133

Bollen KA, Harden JJ, Ray S, Zavisca J. BIC and Alternative Bayesian Information Criteria in the Selection of Structural Equation Models. Struct Equ Modeling. 2014;21(1):1-19. https://doi.org/10.1080/10705511.2014.856691

Borg GA. Psychophysical bases of perceived exertion. Med Sci Sports Exerc. 1982;14:377-381.

Box G, Cox D (1964) An analysis of transformations. J R Stat Soc Ser B Stat Methodol 26:211–252.

Brand R, Schweizer G. Going to the gym or to the movies?: situated decisions as a functional link connecting automatic and reflective evaluations of exercise with exercising behavior. J Sport Exerc Psychol. 2015;37(1):63-73. https://doi.org/10.1123/jsep.2014-0018

Caldwell AR, Vigotsky AD, Tenan MS, et al. Moving sport and exercise science forward: a call for the adoption of more transparent research practices. Sports Med. 2020;50(3):449-459. https://doi.org/10.1007/s40279-019-01227-1

Calitri R, Lowe R, Eves FF, Bennett P. Associations between visual attention, implicit and explicit attitude and behaviour for physical activity. Psychol Health. 2009;24:1105-1123. https://doi.org/10.1080/08870440802245306

Canadian Fitness and Lifestyle Research Institute. Physical activity monitor: facts and figures. 2008. http://www.cflri.ca/sites/default/files/node/95/files/PAM2008FactsFigures_Bulletin14_Intention_to_be_activeEN.pdf. Accessed January 2023.

Carbine KA, Clayson PE, Baldwin SA, LeCheminant JD, Larson MJ. Using generalizability theory and the ERP Reliability Analysis (ERA) Toolbox for assessing test-retest reliability of ERP scores Part 2: Application to food-based tasks and stimuli. Int J Psychophysiol. 2021;166:188-198. https://doi.org/10.1016/j.ijpsycho.2021.02.015

Carlson JM, Foti D, Mujica-Parodi, LR, Harmon-Jones, E, Hajcak, G. Ventral striatal and medial prefrontal BOLD activation is correlated with reward-related electrocortical activity : a combined ERP and fMRI study. Neuroimage. 2011 ; 57(4) :1608-1616. https://doi.org/10.1016/j.neuroimage.2011.05.037

Chalabaev A, Sieber S, Sander D, Cullati S, Maltagliati S, Sarrazin P, Boisgontier MP, Cheval B. Early-life socioeconomic circumstances and physical activity in older age: women pay the price. Psychol Sci. 2022;33(2):212-223. https://doi.org/10.1177/09567976211036061

Cheval B, Boisgontier MP. The theory of effort minimization in physical activity (TEMPA). Exerc Sport Sci Rev. 2021;49(3):168-178. https://doi.org/10.1249/JES.0000000000000252

Cheval B, Boisgontier MP, Bacelar MFB, Feiss R, Miller MW. Opportunities to sit and stand trigger equivalent reward-related brain activity. Int J Psychophysiol. 2019;141:9-17. https://doi.org/10.1016/j.ijpsycho.2019.04.009

Cheval B, Daou M, Cabral DAR, Bacelar, MFB, Parma, JO, Forestier, C, Orsholits, D, Sander D, Boisgontier MP, Miller MW. Higher inhibitory control is required to escape the innate attraction to effort minimization. Psychol Sport Exerc. 2020a;51:101768. https://doi.org/10.1016/j.psychsport.2020.101781

Cheval B, Miller WM, Orsholits D, Berry T, Sander D, Boisgontier MP. Physically active individuals look for more: an eye tracking study of attentional bias. Psychophysiol. 2020b;57:e13582. https://doi.org/10.1111/psyp.13582

Cheval B, Orsholits D, Sieber S, Courvoisier DS, Cullati S, Boisgontier MP. Relationship between decline in cognitive resources and physical activity. Health Psychol. 2020c;39(6):519-528. https://doi.org/10.1037/hea0000857

Cheval B, Radel R, Neva JL, Boyd LA, Swinnen SP, Sander D, Boisgontier MP. Behavioral and neural evidence of the rewarding value of exercise behaviors: a systematic review. Sports Med. 2018a;48(6):1389-1404. https://doi.org/10.1007/s40279-018-0898-0

Cheval B, Sarrazin P, Boisgontier MP, Radel R. Temptations toward behaviors minimizing energetic costs (BMEC) automatically activate physical activity goals in successful exercisers. Psychol Sport Exerc. 2017;30:110-117. https://doi.org/10.1016/j.psychsport.2017.02.006

Cheval B, Sarrazin P, Isoard-Gautheur S, Radel R, Friese M. Reflective and impulsive processes explain (in)effectiveness of messages promoting physical activity: a randomized controlled trial. Health Psychol. 2015;34:10-19. https://doi.org/10.1037/hea0000102

Cheval B, Sarrazin P, Pelletier L. Impulsive approach tendencies towards physical activity and sedentary behaviors, but not reflective intentions, prospectively predict non-exercise activity thermogenesis. PLoS One. 2014;9:e115238. https://doi.org/10.1371/journal.pone.0115238

Cheval B, Sieber S, Guessous I, Orsholits D, Courvoisier DS, Kliegel M, Stringhini S, Swinnen SP, Burton-Jeangros C, Cullati S, Boisgontier MP. Effect of Early- and Adult-Life Socioeconomic Circumstances on Physical Inactivity. Med Sci Sports Exerc. 2018c;50(3):476-485. https://doi.org/10.1249/MSS.0000000000001472

Cheval B, Tipura E, Burra N, Frossard J, Chanal J, Orsholits D, Radel R, Boisgontier MP. Avoiding sedentary behaviors requires more cortical resources than avoiding physical activity: an EEG study. Neuropsychologia. 2018b;119:68-80. https://doi.org/10.1016/j.neuropsychologia.2018.07.029

Chodzko-Zajko WJ. The World Health Organization issues guidelines for promoting physical activity among older persons. J Aging Phys Act. 1997;5:1-8. https://doi.org/10.1123/japa.5.1.1

Clayson PE, Baldwin SA, Larson MJ. How does noise affect amplitude and latency measurement of event-related potentials (ERPs)? A methodological critique and simulation study. Psychophysiol. 2013;50:174-186. https://doi.org/10.1111/psyp.12001

Clayson, PE, & Miller, GA. ERP Reliability Analysis (ERA) Toolbox: An open-source toolbox for analyzing the reliability of event-related brain potentials. Int J Psychophysiol. 2017a; 111:68-79. https://doi.org/10.1016/j.ijpsycho.2016.10.012

Clayson, PE, & Miller, GA. Psychometric considerations in the measurement of event-related brain potentials: Guidelines for measurement and reporting. Int J Psychophysiol. 2017b; 111:57-67. https://doi.org/10.1016/j.ijpsycho.2016.09.005

Cohen J. The statistical power of abnormal–social psychological research. J Abnorm Soc Psych. 1962; 65: 145-153. https://doi.org/10.1037/h0045186

Conroy DE, Berry TR. Automatic Affective Evaluations of Physical Activity. Exerc Sport Sci Rev. 2017;45:230-237. https://doi.org/10.1249/JES.0000000000000120

Conroy DE, Hyde AL, Doerksen SE, Ribeiro NF. Implicit attitudes and explicit motivation prospectively predict physical activity. Ann Behav Med. 2010;39:112-118. https://doi.org/10.1007/s12160-010-9161-0

Corbit LH, Balleine BW. The general and outcome-specific forms of Pavlovian-instrumental transfer are differentially mediated by the nucleus accumbens core and shell. J Neurosci. 2011;31(33):11786-11794. https://doi.org/10.1523/JNEUROSCI.2711-11.2011

Courneya, KS, Bobick, TB. Integrating the theory of planned behavior with the processes and stages of change in the exercise domain. Psychol Sport and Exerc. 2000;1(1):41-56. https://doi.org/0.1016/S1469-0292(00)00006-6

Craig CL, Marshall AL, Sjöström M, Bauman AE, Booth ML, Ainsworth BE, Pratt M, Ekelund U, Yngve A, Sallis JF, Oja P. International physical activity questionnaire: 12-country reliability and validity. Med Sci Sports Exerc. 2003;35:1381-1395. https://doi.org/10.1249/01.MSS.0000078924.61453.FB

Dinger MK, Behrens TK, Han JL. Validity and reliability of the International Physical Activity Questionnaire in college students. Am J Health Educ. 2006;37:337-343. https://doi.org/10.1080/19325037.2006.10598924

Dowd KP, Szeklicki R, Minetto MA, Murphy MH, Polito A, Ghigo E, van der Ploeg H, Ekelund U, Maciaszek J, Stemplewski R, Tomczak M, Donnelly AE. A systematic literature review of reviews on techniques for physical activity measurement in adults: a DEDIPAC study. Int J Behav Nutr Phys Act. 2018;15(1):15. https://doi.org/10.1186/s12966-017-0636-2

Ekelund U, Tarp J, Steene-Johannessen J, Hansen BH, Jefferis B, Fagerland MW, Whincup P, Diaz KM, Hooker SP, Chernofsky A, Larson MG, Spartano N, Vasan RS, Dohrn IM, Hagströmer M, Edwardson C, Yates T, Shiroma E, Anderssen SA, Lee IM. Dose-response associations between accelerometry measured physical activity and sedentary time and all cause mortality: systematic review and harmonised meta-analysis. BMJ. 2019;366:l4570. https://doi.org/10.1136/bmj.l4570

Farajzadeh A, Goubran M, Beehler A, Cherkaoui N, Morrison P, de Chanaleilles M, Maltagliati S, Cheval B, Miller MW, Sheehy L, Bilodeau M, Orsholits D, Boisgontier MP. Automatic approach-avoidance tendency toward physical activity, sedentary, and neutral stimuli as a function of age, explicit affective attitude, and intention to be active. Peer Community J. 2023;3:e21. https://doi.org/10.24072/pcjournal.246

Faul F, Erdfelder E, Buchner A, Lang A. Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses. Behav Res Methods. 2009;41:1149-1160. https://doi.org/10.3758/BRM.41.4.1149

Fischer A G, Ullsperger M. Real and fictive outcomes are processed differently but converge on a common adaptive mechanism. Neuron. 2013;79(6):1243-1255. https://doi.org/10.1016/j.neuron.2013.07.006

Forestier C, Sarrazin P, Allenet B, Gauchet A, Heuzé JP, Chalabaev A. “Are you in full possession of your capacity?”. A mechanistic self-control approach at trait and state levels to predict different health behaviors. Pers Individ Dif. 2018;134:214-221. https://doi.org/10.1016/j.paid.2018.05.044

Foti D, Weinberg A, Dien J, Hajcak G. Event-related potential activity in the basal ganglia differentiates rewards from nonrewards: temporospatial principal components analysis and source localization of the feedback negativity. Hum. Brain Mapp. 2011;32:2207-2216. https://doi.org/10.1002/hbm.21182

Gottfried JA, O'Doherty J, Dolan RJ. Encoding predictive reward value in human amygdala and orbitofrontal cortex. Science.

2003;301(5636):1104-1107. https://doi.org/10.1126/science.1087919

Guthold R, Stevens GA, Riley LM, Bull FC. Worldwide trends in insufficient physical activity from 2001 to 2016: a pooled analysis of 358 population-based surveys with 1·9 million participants. Lancet Glob Health. 2018;6(10):e1077-e1086. https://doi.org/10.1016/S2214-109X(18)30357-7

Hassall CD, Hajcak G, Krigolson OE. The importance of agency in human reward processing. Cogn Affect Behav Neurosci. 2019;19:1458-1466. https://doi.org/10.3758/s13415-019-00730-2

Hausenblas HA, Symons Downs D. The Exercise Dependence Scale manual. Unpublished manuscript. 2002. https://www.personal.psu.edu/dsd11/EDS/EDS21Manual.pdf

Inzlicht M, Shenhav A, Olivola CY. The effort paradox: Effort is both costly and valued. Trends Cogn Sci. 2018;22:337-349. https://doi.org/10.1016/j.tics.2018.01.007

IPAQ Research Committee. Guidelines for data processing and analysis of the International Physical Activity Questionnaire (IPAQ) - short and long forms. 2005. https://sites.google.com/view/ipaq/score (Accessed June 8, 2023)

Judd CM, Westfall J, Kenny DA. Treating stimuli as a random factor in social psychology: a new and comprehensive solution to a pervasive but largely ignored problem. J Pers Soc Psychol. 2012;103:54-69. https://doi.org/10.1037/a0028347

Klein-Flügge MC, Kennerley SW, Friston K, Bestmann S. Neural signatures of value comparison in human cingulate cortex during decisions requiring an effort-reward trade-off. J Neurosci. 2016;36(39)10002-10015. https://doi.org/10.1523/JNEUROSCI.0292-16.2016

Klimentidis YC, Raichlen DA, Bea J, Garcia DO, Wineinger NE, Mandarino LJ, Alexander GE, Chen Z, Going SB. Genome-wide association study of habitual physical activity in over 377,000 UK Biobank participants identifies multiple variants including CADM2 and APOE. Int J Obes (Lond). 2018;42(6):1161-1176. https://doi.org/10.1038/s41366-018-0120-3

Knutson B, Adams CM, Fong GW, Hommer D. Anticipation of increasing monetary reward selectively recruits nucleus accumbens. J Neurosci. 2001;21(16):RC159. https://doi.org/10.1523/JNEUROSCI.21-16-j0002.2001

Kohl 3rd HW, Craig CL, Lambert EV, Inoue S, Alkandari JR, Leetongin G, Kahlmeier S, Lancet Physical Activity Series Working Group. The pandemic of physical inactivity: global action for public health. Lancet. 2012;380(9838):294-305. https://doi.org/10.1016/S0140-6736(12)60898-8

Krigolson OE. Event-related brain potentials and the study of reward processing: methodological considerations. 2018;132(B):175-183. https://doi.org/10.1016/j.ijpsycho.2017.11.007

Krishnaswamy P, Obregon-Henao G, Ahveninen J, Khan S, Babadi B, Iglesias JE, Hämäläinen MS, Purdon PL. Sparsity enables estimation of both subcortical and cortical activity from MEG and EEG. Proc Natl Acad Sci U S A. 2017;114(48):E10465-E10474. https://doi.org/10.1073/pnas.1705414114

Kuznetsova A, Brockhoff, PB, Christensen, RHB. (2016). lmerTest: tests in linear mixed effects models [R package]. Version 2.0-33.

Lachaud CM, Renaud O. A tutorial for analyzing human reaction times: How to filter data, manage missing values, and choose a statistical model. Appl. Psycholinguistics. 2011;32:389-416. https://doi.org/10.1017/S0142716410000457

LaSorda KR, Gmelin T, Kuipers AL, Boudreau RM, Santanasto AJ, Christensen K, Renner SW, Wojczynski MK, Andersen SL, Cosentino S, Glynn NW. Epidemiology of perceived physical ratigability in older adults: The Long Life Family Study. J Gerontol A Biol Sci Med Sci. 2020;75(9):e81-e88. https://doi.org/10.1093/gerona/glz288

Lee PH, Macfarlane DJ, Lam TH, Stewart SM. Validity of the International Physical Activity Questionnaire Short Form (IPAQ-SF): a systematic review. Int J Behav Nutr Phys Act.

2011;8:115. https://doi.org/10.1186/1479-5868-8-115

Lee IM, Shiroma EJ, Lobelo F, Puska P, Blair SN, Katzmarzyk PT, Lancet Physical Activity Series Working Group. Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy. Lancet. 2012;380(9838):219-229. https://doi.org/10.1016/S0140-6736(12)61031-9

Liu X, Zhang D, Liu Y, Sun X, Han C, Wang B, Ren Y, Zhou J, Zhao Y, Shi Y, Hu D, Zhang M. Dose-response association between physical activity and incident hypertension: a systematic review and meta-analysis of cohort studies. Hypertension. 2017;69(5):813-820. https://doi.org/10.1161/HYPERTENSIONAHA.116.08994

Lohse KR, Miller MW, Daou M, Valerius W, Jones M. Dissociating the contributions of reward-prediction errors to trial-level adaptation and long-term learning. Biol Psychol. 2020;149:107775. https://doi.org/10.1016/j.biopsycho.2019.107775

Lohse KR, Shen, J, Kozlowski, AJ. Modeling longitudinal outcomes: a contrast of two methods. J Motor Learn Dev. 2020;8(1):145-165. https://doi.org/10.1123/jmld.2019-0007

Maltagliati S, Sarrazin P, Fessler L, Lebreton M, Cheval B. Why people should run after positive affective experiences instead of health benefits. J Sport Health Sci. In press. https://doi.org/10.1016/j.jshs.2022.10.005

Mansoubi M, Pearson N, Clemes SA, Biddle SJH, Bodicoat DH, Tolfrey K, Edwardson CL, Yates T. Energy expenditure during common sitting and standing tasks: examining the 1.5 MET definition of sedentary behaviour. BMC Pub Health. 2015;15:516. https://doi.org/10.1186/s12889-015-1851-x

Martin SB, Morrow JR Jr, Jackson AW, Dunn AL. Variables related to meeting the CDC/ACSM physical activity guidelines. Med Sci Sports Exerc. 2000;32(12):2087-2092. https://doi.org/10.1097/00005768-200012000-00019

Marco-Pallares J, Cucurell D, Münte TF, Strien N, Rodriguez-Fornells A. On the number of trials needed for a stable feedback-related negativity. Psychophysiol. 2011;48:852-860. https://doi.org/10.1111/j.1469-8986.2010.01152.x

Meadows CC, Gable PA, Lohse KR, Miller MW. The effects of reward magnitude on reward processing: an averaged and single-trial event-related potential study. Biol Psychol. 2016;118:154-160. https://doi.org/10.1016/j.biopsycho.2016.06.002

Meng L, Ma Q. Live as we choose: The role of autonomy support in facilitating intrinsic motivation. Int J Psychophysiol. 2015;98(3 Pt 1):441-447. https://doi.org/10.1016/j.ijpsycho.2015.08.009

Miller MW, Cheval B, Bacelar MFB, Cabral DAR, Parma JO, Sander D, Krigolson OE, Boisgontier MP (2022, August 18). Relationship between reward-related brain activity and opportunities to sit [Preregistration]. https://doi.org/10.17605/OSF.IO/TCR7F

Moore SC, Lee IM, Weiderpass E, Campbell PT, Sampson JN, Kitahara CM, Keadle SK, Arem H, Berrington de Gonzalez A, Hartge P, Adami HO, Blair CK, Borch KB, Boyd E, Check DP, Fournier A, Freedman ND, Gunter M, Johannson M, Khaw KT, Linet MS, Orsini N, Park Y, Riboli E, Robien K, Schairer C, Sesso H, Spriggs M, Van Dusen R, Wolk A, Matthews CE, Patel AV. Association of leisure-time physical activity with risk of 26 types of cancer in 1.44 million adults. JAMA Intern Med. 2016;176(6):816-825. https://doi.org/10.1001/jamainternmed.2016.1548

Novak KD, Foti D. Teasing apart the anticipatory and consummatory processing of monetary incentives: An event-related potential study of reward dynamics. Psychophysiology. 2015;52(11):1470-1482. https://doi.org/10.1111/psyp.12504

Oldfield RC. The assessment and analysis of handedness: the Edinburgh inventory. Neuropsychologia. 1971;9(1):97-113. https://doi.org/10.1016/0028-3932(71)90067-4

Oostenveld R, Praamstra P. The five percent electrode system for high-resolution EEG and

ERP measurements. Clin Neurophysiol. 2001;112:713-719. https://doi.org/10.1016/S1388-2457(00)00527-7
Osborne J. Improving your data transformation: applying the Box-Cox transformation. Pr Assess Res Eval. 2010; 15:1-9.
Palidis DJ, Gribble PL. EEG correlates of physical effort and reward processing during reinforcement learning. J Neurophysiol. 2020;124:610-622. https://doi.org/10.1152/jn.00370.2020
Parma JO, Bacelar MFB, Cabral DAR, Recker RS, Orsholits D, Renaud O, Sander D, Krigolson OE, Miller MW, Cheval B, Boisgontier MP. Relationship between reward-related brain activity and opportunities to sit (v1.0). Zenodo [Data set] 2023. https://doi.org/10.5281/zenodo.8011562
Pool ER, Pauli WM, Kress CS, O'Doherty JP. Behavioural evidence for parallel outcome-sensitive and outcome-insensitive Pavlovian learning systems in humans. Nature Human Behav. 2019;3:284-296. https://doi.org/10.1038/s41562-018-0527-9
Prévost C, Liljeholm M, Tyszka JM, O'Doherty JP. Neural correlates of specific and general Pavlovian-to-Instrumental Transfer within human amygdalar subregions: a high-resolution fMRI study. J Neurosci. 2012;32(24):8383-8390. https://doi.org/10.1523/JNEUROSCI.6237-11.2012
Prévost C, Pessiglione M, Météreau E, Cléry-Melin ML, Dreher JC. Separate valuation subsystems for delay and effort decision costs. J Neurosci. 2010;30(42):14080-14090. https://doi.org/10.1523/JNEUROSCI.2752-10.2010
Prince SA, Adamo KB, Hamel ME, Hardt J, Connor Gorber S, Tremblay M. A comparison of direct versus self-report measures for assessing physical activity in adults: a systematic review. Int J Behav Nutr Phys Act. 2008;5:56. https://doi.org/10.1186/1479-5868-5-56
Proudfit GH. The reward-positivity: from basic research on reward to a biomarker for depression. Psychophysiol. 2015;52(4):449-459. https://doi.org/10.1111/psyp.12370
R Core Team. (2019). R: a language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria.
R Core Team (2021). The R base package [R package]. Version 4.0.4. https://www.rdocumentation.org/packages/base/versions/3.6.2/topics/scale
Radel R, Clément-Guillotin C. Evidence of motivational influences in early visual perception: hunger modulates conscious access. Psychol Sci. 2012;23:232-234. https://doi.org/10.1177/0956797611427920
Rebar AL, Ram N, Conroy DE. Using the EZ-diffusion model to score a single-category implicit association test of physical activity. Psychol Sport Exerc. 2015;16:96-105. https://doi.org/10.1016/j.psychsport.2014.09.008
Rescorla R, Wagner A. A theory of Pavlovian conditioning: variations in the effectiveness of reinforcement and nonreinforcement. Classical conditioning II: current research and theory. 1972;2:64-99.
Rhodes RE, Dickau L. Experimental evidence for the intention-behavior relationship in the physical activity domain: a meta-analysis. Health Psychol. 2012;31(6):724-727. https://doi.org/10.1037/a0027290
Rhodes RE, Kates A. Can the affective response to exercise predict future motives and physical activity behavior? a systematic review of published evidence. Ann Behav Med. 2015;49(5):715-31. https://doi.org/10.1007/s12160-015-9704-5
Robinson MJ, Berridge KC. Instant transformation of learned repulsion into motivational "wanting". Current Biol. 2013;23:282-289. https://doi.org/10.1016/j.cub.2013.01.016
Roesch MR, Olson CR. Neuronal activity related to reward value and motivation in primate frontal cortex. Science. 2004;304(5668):307-310. https://doi.org/10.1126/science.1093223
Rollo S, Gaston A, Prapavessis H. Cognitive and motivational factors associated with sedentary behavior: a systematic review. AIMS Public Health. 2016;3(4):956-984. https://doi.org/10.3934/publichealth.2016.4.956
Sagelv EH, Hopstock LA, Johansson J, Hansen BH, Brage S, Horsch A, Ekelund U, Morseth

B. Criterion validity of two physical activity and one sedentary time questionnaire against accelerometry in a large cohort of adults and older adults. BMJ Open Sport Exerc Med. 2020;6(1):e000661. https://doi.org/10.1136/bmjsem-2019-000661

Sambrook TD, Goslin J. A neural reward prediction error revealed by a meta-analysis of ERPs using great grand averages. Psychol Bull. 2015;141(1):213-235. https://doi.org/10.1037/bul0000006

Schmidt L, Skvortsova V, Kullen C, Weber B, Plassmann H. How context alters value: the brain's valuation and affective regulation system link price cues to experienced taste pleasantness. Sci Rep. 2017;7(1):8098. https://doi.org/10.1038/s41598-017-08080-0

Schuch F, Vancampfort D, Firth J, Rosenbaum S, Ward P, Reichert T, Bagatini NC, Bgeginski R, Stubbs B. Physical activity and sedentary behavior in people with major depressive disorder: a systematic review and meta-analysis. J Affect Disord. 2017;210:139-150. https://doi.org/10.1016/j.jad.2016.10.050

Schultz W, Tremblay L, Hollerman JR. Reward processing in primate orbitofrontal cortex and basal ganglia. Cereb Cortex. 2000;10(3):272-284. https://doi.org/10.1093/cercor/10.3.272

Seibt B, Häfner M, Deutsch R. Prepared to eat: how immediate affective and motivational responses to food cues are influenced by food deprivation. Eur J Soc Psychol. 2007;37:359-379.

Shupler MS, Kramer JK, Cragg JJ, Jutzeler CR, Whitehurst DGT. Pan-Canadian estimates of chronic pain prevalence from 2000 to 2014: a repeated cross-sectional survey analysis. J Pain. 2019 May;20(5):557-565. https://doi.org/10.1016/j.jpain.2018.10.010

Skvortsova V, Palminteri S, Pessiglione M. Learning to minimize efforts versus maximizing rewards: computational principles and neural correlates. J Neurosci. 2014;34(47):15621-15630. https://doi.org/10.1523/JNEUROSCI.1350-14.2014

Smets EMA, Garssen B, Bonke B, De Haes J. The multidimensional fatigue inventory (MFI) psychometric qualities of an instrument to assess fatigue. J Psychosom Res. 1995;39(5):315-325. https://doi.org/10.1016/0022-3999(94)00125-O

Sutton RS, Barto AG. Introduction to Reinforcement Learning. Cambridge, MA: MIT Press. https://doi.org/10.1.1.32.7692

Troiano RP, Berrigan D, Dodd KW, Mâsse LC, Tilert T, McDowell M. Physical activity in the United States measured by accelerometer. Med Sci Sports Exerc. 2008;40(1):181-188. https://doi.org/10.1249/mss.0b013e31815a51b3

Wahid A, Manek N, Nichols M, Kelly P, Foster C, Webster P, Kaur A, Friedemann Smith C, Wilkins E, Rayner M, Roberts N, Scarborough P. Quantifying the association between physical activity and cardiovascular disease and diabetes: a systematic review and meta-analysis. J Am Heart Assoc. 2016;5(9):e002495. https://doi.org/10.1161/JAHA.115.002495

Zhang J, Berridge KC, Tindell AJ, Smith KS, Aldridge JW. A neural computational model of incentive salience. PLoS Comput Biol. 2009;5:e1000437. https://doi.org/10.1371/journal.pcbi.1000437

Appendix A: Task instructions read to participants

"To start each trial, press the bottom (A) button. Each trial begins with a burnt-orange and a navy-blue square. Select which color square you want to choose by pressing the left (X) button or the right (B) button. So, on this trial, if you choose the burnt-orange square, you would press the ____ button. If you choose the navy-blue square, you would press the _____ button. YOU SHOULD FOCUS ON SELECTING A SQUARE BASED ON COLOR, NOT BASED ON LOCATION. In other words, select a square because it is burnt-orange or navy-blue, not because it is on the left or right. After making your selection, you will see a stimulus indicating whether you will retrieve your reward from the upper or lower container, if you win a reward. If you see a stimulus with the container on the upper line, then you will be retrieving your reward from the upper container. If you see a stimulus with the container on the lower line, then you will be retrieving your reward from the lower container. Next, you will see if you actually won a reward or not. If you see a dollar sign, then you won a reward. If you see a zero, then you did not win a reward. If you win a reward from the upper container, then you will wait until you hear a tone. When you hear a tone, you will take a coin from the upper container, touch your butt to the chair, then place the coin in the upper collection container. You will repeat this sequence four more times when prompted by a tone. If you win a reward from the lower container, then you will wait until you hear a tone. When you hear a tone, you will sit down in the chair and take a coin from the lower container, then place the coin in the lower collection container. You will remain seated and reach into the lower container to retrieve a coin each time you hear a tone (you will hear four more tones). When you are prompted to start the next trial, return to a standing position. If you get feedback that indicates a zero instead of a dollar sign, then simply remain standing. Each coin represents a raffle ticket to win $10, so the more coins you earn, the more likely you are to win $10. On each trial, a certain color square will give you a certain probability of winning, so, again, FOCUS ON CHOOSING A SQUARE BASED ON COLOR. However, there is no strategy for selecting a color square in order to win. In other words, there is no pattern as to which color square will give you the best chance at winning from trial to trial."

Appendix B: Fatigue Questions

1. Right now, how fatigued are you?

0	1	2	3	4	5	6	7	8	9	10
Not At All										Very Much

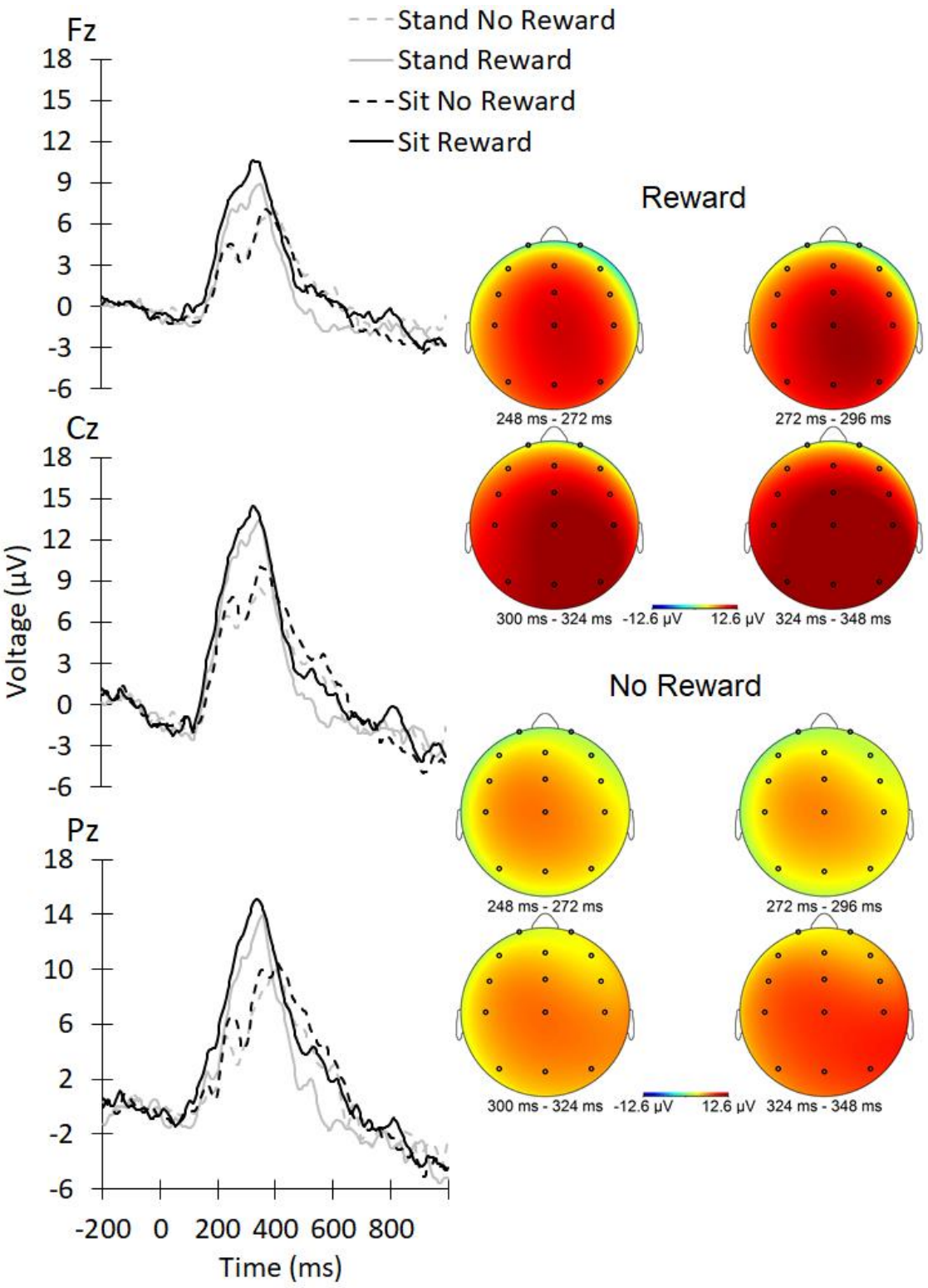
2. Right now, I have no energy

0	1	2	3	4	5	6	7	8	9	10
Completely Disagree										Completely Agree

3. Right now, I feel physically exhausted

0	1	2	3	4	5	6	7	8	9	10
Completely Disagree										Completely Agree

Supplementary Figure 1. ERP waveforms and scalp topographies for the pilot data



Notes. Left panel: Grand average waveforms by trial type and reward from pilot study. Right panel: Scalp topographies for reward and no reward trials, both averaged across trial type.

Supplementary Table 1.

	Factors	Design	Formal test
Primary Hypothesis			
H1: Larger reward positivity for opportunities to sit	Within: Trial Type (stand vs. sit) Within: Reward (no reward vs reward)	Within-subjects	Significant interaction between the within factors
Secondary Hypotheses			
H2.1: The larger reward positivity for opportunities to sit is more pronounced in participants who are typically less physically active.	Within: Trial Type (stand vs. sit) Within: Reward (no reward vs reward) Between: Energy expenditure (typical MVPA; continuous)	Mixed-subjects	Significant 3-way within-between interaction
H2.2: The larger reward positivity for opportunities to sit is more pronounced in participants who are more active on the day of the experiment.	Within: Trial Type (stand vs. sit) Within: Reward (no reward vs reward) Between: Energy expenditure (today MVPA; continuous)	Mixed-subjects	Significant 3-way within-between interaction
H2.3: The larger reward positivity for opportunities to sit is more pronounced after energetically demanding behavior during the experiment (i.e., squatting).	Within: Trial Type (stand vs. sit) Within: Reward (no reward vs reward) Between: Energy expenditure (study energy expenditure; continuous)	Mixed-subjects	Significant 3-way within-between interaction
H3: The probability of choosing the stimulus more likely to lead to sitting than standing increases as the number of trials increases.	Within: Trial number (continuous)	Within-subjects	Significant main effect of trial number on the chosen stimulus
H4: Reward positivity predicts subsequent decision about whether a participant chooses the same or different stimulus.	Within: reward positivity values (continuous)	Within-subjects	Significant main effect of reward positivity on the changed response

Notes. MVPA = Moderate to vigorous physical activity

Supplementary Table 2. Pilot estimates of the effects of opportunities to sit on reward positivity and the moderation by energy expenditure

	Opportunities to sit (Model 1, 1083 obs.)				**Typical MVPA** (Model 2.1, 1083 obs.)				**Today MVPA** (Model 2.2, 1083 obs.)				**Study energy expenditure** (Model 2.3, 1079 obs.)			
Fixed Effects	b	SE	p		b	SE	p		b	SE	p		b	SE	p	
Intercept	5.378	2.379	0.050	.	5.485	1.964	0.020		5.245	2.353	0.053		5.368	2.376	0.050	
Reward	5.703	0.893	2.5×10^{-10}	***	5.542	0.886	5.9×10^{-10}	***	5.787	0.891	1.3×10^{-10}	***	5.728	0.895	2.3×10^{-10}	***
Type	0.127	0.922	0.890		0.451	0.919	0.623		0.058	0.922	0.949		0.152	0.926	0.869	
Energy					-3.091	1.859	0.129		2.132	2.276	0.373		0.466	0.648	0.472	
Reward × Type	1.693	1.292	0.190		1.352	1.285	0.293		1.710	1.290	0.185		1.679	1.296	0.195	
Reward × Energy					-1.708	0.884	0.053		-1.461	0.867	0.092	.	-0.353	0.921	0.701	
Type × Energy					2.120	0.926	0.022		-0.173	0.917	0.850		-0.647	0.897	0.470	
Reward × Type × Energy					-2.540	1.305	0.051		-0.605	1.300	0.641		0.070	1.294	0.956	
Random Effect	σ^2				σ^2				σ^2				σ^2			
Participant (intercept)	42.15				27.75				40.89				42.00			
Residual	111.81				109.34				110.98				112.00			

Notes. SE = standard error; obs. = observations; MVPA = Moderate-to-vigorous physical activity. No Reward is coded 0 and Reward is coded 1. Type is coded 0 for stand trials and 1 for sit trials. Here, due to the low sample size of this pilot study, the analyses could not follow the models defined above, some random effects are missing as the analyses only included the random intercept of subject. In Stage 2 of the Registered Report, the random intercepts of all factors will be included. In the final manuscript, we will make sure to have exactly the same number of observations across models to be able to compare them using BIC.

Supplementary Table 3. Pilot estimates of the effect of trial number on the probability of choosing the stimulus more likely to lead to sitting than standing.

	Opportunities to sit (Model 1, 1083 obs.)		
Fixed Effects	b	SE	p
Intercept	0.150	0.128	0.241
Trial	0.112	0.066	0.091
Random Effects	σ^2		
Participant (intercept)	0.114		
Trial	0.059		

Note. SE = standard error; obs. = observations; Choosing the stimulus more likely to lead to standing and sitting are coded 0 and 1, respectively.

Supplementary Table 4. Pilot estimate of the effect of previous trial's reward positivity on whether participant changed response from previous trial (0 = did not change; 1 = changed)

	Opportunities to sit (Model 1, 980 obs.)		
Fixed Effects	b	SE	p
Intercept	-0.011	0.061	0.855
Reward Positivity on previous trial	0.042	0.061	0.486
Random Effects	σ^2		
Participant (intercept)	1×10^{-14}		
Reward Positivity on previous trial	0.007		

Note. SE = standard error; obs. = observations; an absence of change and a change of response from previous are coded 0 and 1, respectively.

Supplemental Table 5. Results of the mixed-effects models predicting reward positivity based on Box-Cox transformed typical moderate-to-vigorous physical activity, Box-Cox transformed study-related energy expenditure, and log_{1000} transformed today moderate-to-vigorous physical activity.

Reward positivity	**Without MVPA (n = 56)**		**With Box-Cox typical MVPA (n = 52)**		**With log_{1000} Today MVPA (n = 55)**		**With Box-Cox Energy expenditure (n = 56)**	
	b (CI)	*p*	b (CI)	*p*	b (CI)	*p*	b (CI)	*p*
Fixed Effects								
Intercept	6.94 (5.71;8.16)	5.0×10^{-16}	7.08 (5.78;8.39)	6.4×10^{-15}	7.02 (5.79;8.25)	4.2×10^{-16}	6.95 (5.72;8.18)	4.9×10^{-16}
Reward (ref. no reward)								
Reward	2.29 (1.74;2.84)	2.0×10^{-11}	2.35 (1.78;2.93)	6.1×10^{-11}	2.29 (1.73;2.84)	3.5×10^{-11}	2.29 (1.74;2.83)	1.9×10^{-11}
Type of trial (ref. sit)								
Stand	-0.19 (-0.24;0.63)	.388	0.20 (-0.25;0.65)	.386	0.19 (-0.25;0.64)	.399	0.23 (-0.21;0.67)	.304
Reward x Type of trial	0.10 (-0.18;0.40)	.482	0.12 (-0.18;0.43)	.437	0.08 (-0.21;0.38)	.575	0.09 (-0.20;0.38)	.535
Typical level of physical activity								
Typical MVPA			0.11 (-1.17;1.41)	.856				
Typical MVPA x Reward			0.41 (-0.15;0.97)	.152				
Typical MVPA x Type of trials			-0.40 (-0.85;0.04)	.081				
Typical MVPA x Reward x Type of trial			0.24 (-0.06;0.54)	.117				
Today level of physical activity								
Today MVPA					0.56 (-0.65;1.78)	.363		
Today MVPA x Reward					0.28 (-0.26;0.83)	.311		
Today MVPA x Type of trials					-0.08 (-0.53;0.36)	.717		
Today MVPA x Reward x Type of trial					0.37 (0.07;0.67)	.014		
Study energy expenditure								
Study energy expenditure							0.86 (0.57;1.16)	7.3×10^{-9}
Study energy expenditure x Reward							-0.09 (-0.39;0.19)	.505
Study energy expenditure x Type of trial							0.01 (-0.27;0.31)	.895
Study energy expenditure x Reward x Type of trial							-0.08 (-0.37;0.21)	.582
Random Effects								
Participants								
Intercept	15.559		16.632		15.251		15.596	
Reward for subject	5.955		6.029		5.803		5.893	
Type of trial for subject	2.924		2.826		3.002		2.985	
Residual	191.342		195.530		193.270		190.567	

Notes. CI = confidence interval at 95%; MVPA = moderate-to-vigorous physical activity.