Relationship between reward-related brain activity and opportunities to sit

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Abstract

The present study will test whether energy-minimizing behaviors evoke reward-related brain activity that promotes the repetition of such behaviors via reinforcement learning processes. Participants in a standing position will perform a task where they can earn a reward either by sitting down or squatting while undergoing electroencephalographic (EEG) recording. Reward-prediction errors will be quantified as the amplitude of the EEG-derived reward positivity. Our primary hypothesis is that reward associated with sitting leads to larger reward positivity (H1). Secondarily, we hypothesize that this effect is moderated by typical physical activity, physical activity on the day of the study, and during the study (H2); the probability of choosing the stimulus more likely to lead to sitting than standing increases as the number of trials increases (H3); and reward positivity predicts subsequent decisions about whether one chooses the same or different stimulus (H4).

Keywords

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

1. INTRODUCTION

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 not always 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 min 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., 2020a), 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., 2018). 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 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., 2018; 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 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., 2020) and that avoiding sedentary stimuli requires higher brain activity linked to inhibitory control and conflict monitoring than approaching sedentary stimuli (Cheval et al., 2018). 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., 2020b).

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 will test hypotheses consistent with the theory of effort minimization in physical activity (Cheval et al., 2018; Cheval & Boisgontier, 2021) and reinforcement learning theory (Rescorla & Wagner, 1972; Sutton & Barto, 1998). Specifically, participants will perform a doors task inspired by Hassall, Hajcak, and Krigolson (2019) and crossed with a movement-incentive delay task (Cheval, Boisgontier, Bacelar, Feiss, and 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 will choose one of two stimuli ("doors") on the screen. Following this choice, they will first be informed whether they will have to sit down and squat, should they earn a reward on the trial. Next, participants will be informed whether they earned the reward or not. If they earn the reward, they will have 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 are equally likely to lead

to a reward, but one door is programmed to lead to an opportunity to sit 3.5 times more often than the other door. As such, since choices are unrelated to the probability of receiving a reward, we can test whether participants learn to make choices based on the likelihood of sitting.

Our primary hypothesis is that opportunities to sit lead to more positive reward-prediction errors, as expressed by a larger reward positivity (H1). To test this hypothesis, we will examine whether the opportunity to sit versus stand (trial type) and being rewarded or not (reward) is associated with reward positivity amplitude and whether these variables interact with each other (Trial Type x Reward). This hypothesis follows directly from the theory of effort minimization's prediction that opportunities to minimize energy expenditure are rewarding. We will also explore whether the effect of opportunities to sit observed in H1 is moderated by factors related to energy expenditure. Specifically, we hypothesize that the effect is larger in participants who are typically less physically active (H2.1), in participants who are 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 follow 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 is that the probability of choosing the stimulus more likely to lead to sitting than standing will increase as the number of trials increases (H3). This follows 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 is that reward positivity predicts subsequent decisions about whether one chooses the same or a different stimulus. Consistent with reinforcement learning theory, we hypothesize that a large positive reward-prediction error reinforces the decision that led to it (i.e., the participant should choose the same stimulus) (H4).

2. METHODS

2.1. Population

Sixty-four men and women between the ages of 19 and 40 years will be 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 is convenient to the investigators and has been used in similar studies (e.g., Cheval, Boisgontier et al., 2019). To be included in the study, participants should 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.

2.2. 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 is 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 will be independent and, for example, the power for β_1 depends only on σ_1^2 (the variance of $u_{1\mathrm{j}}$) 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 is ≥ 56. Based on the pilot study where 1 of 9 participants had a poor EEG recording, we expect poor EEG recordings from 11.11% of participants. Therefore, we plan to recruit 64 participants but will ensure that we have 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 exploratory analysis (H2), the same reasoning and computations as the ones used for H1 can be made for all effects, and with α = .02, the number of participants needed to detect a medium effect size is also ≥ 56. Power calculation for exploratory 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.

2.3. Experimental setup

Each trial of the task will begin with the participant standing and facing a table upon which will be a computer monitor, approximately eye level to the participant (Figure 1). There will be a blue container holding plastic coins next to the monitor and approximately arm-level with the participant when standing. A foldup butterfly chair will be positioned immediately behind the participant. Another blue container holding plastic coins and an empty red (collection) container will be positioned next to the chair and approximately arm-level with the participant when seated. A recording device (e.g., iPAD) will be positioned on the ground facing the participant's legs. Participants will be told their lower body movements will be recorded to confirm that they are standing as still as possible, which they will be instructed to do to facilitate EEG recording. The participant will hold a wireless game controller throughout the experiment.

Figure 1. Experimental Setup. The participants will use a game controller to respond to stimuli on a computer monitor. They will have 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 will deposit the coins won in the red container.

2.4. Experimental protocol

Data will be collected at a single testing site. Participants' height and weight will be measured with a stadiometer and scale. They will be asked to rate how fatigued they feel using the Multidimensional

Fatigue Inventory (Smets, Garssen, Bonke, & De Haes, 1995) and three custom items (see Appendix B) prior to starting the task. Participants will begin each trial standing and be prompted to hit a game controller button to start the trial (Figure 2). Next the participant will see two squares (or "doors") appear on the computer monitor, one to the left and one to the right. One of the squares will be burnt orange (RGB: 205, 85, 0) and one will be navy blue (RGB: 0, 0, 128). The color of the square appearing on the left or right will vary randomly with equal probability. Participants will be 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 is made, a fixation cross will appear 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 is upon the upper line (stand trial), it indicates that, if the participant earns a reward on the trial, it will result in them retrieving coins from the upper blue container that is arm-level when standing. If the container is upon the lower line (sit trial), it indicates that, if the participant earns a reward on the trial, it will result in them retrieving coins from the lower blue container that is arm-level when sitting. The lines and container stimuli will remain on the monitor for 2000 ms and will be followed by a fixation cross for 300 – 500 ms. Next, participants will see a feedback stimulus informing them whether they earned the reward or not. They will either see a "$" sign for 1000 ms indicating that they earned a reward, or a "0" for 1000 ms if they did not. Then, participants will see the word "WAIT" appear on the monitor for 3000 ms. Then, on stand reward trials, participants will hear 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 will be repeated after a 6000 ms interval before the next tone, until a total of 5 coins have been retrieved. On sit reward trials, participants will sit down in the chair upon hearing the tone and take a coin from the lower container, then place the coin in the red collection container. The participant will remain seated

until the next tone, at which time the participant will retrieve another coin from the lower container by simply reaching into the container. This process will be repeated until the participant retrieves five coins in total. Participants will be told to remain seated after retrieving the fifth coin until prompted to start the next trial.

On no-reward trials ("0" sign), participants will remain standing for 30 s, irrespective of the information provided to them in the first step (i.e., sit vs. stand trial). Thus, participants should set expectations about whether they will 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 will inform them whether they will indeed sit or squat to retrieve coins.

Prior to starting the task, participants will be told that: each coin represents a raffle ticket to win $10 [USD]; the more coins they earn, the more likely they are to win $10; on each trial, a certain color square will give them a certain probability of winning, so they should focus on choosing a square based on color; and there is no strategy for selecting a color square to win. Please see Appendix A for complete instructions that will be given to the participants. Unbeknownst to participants, each color square will have a 50% probability of resulting in a reward on each trial, but one square will have a 70% chance of resulting in a sit trial, whereas the other square will have a 20% chance of resulting in a sit trial. This procedure allows to test whether participants begin 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 from the pilot study are reported, and these numbers will be reported for the main study, too, as will dependability (reliability). Reliability will be obtained using generalizability theory (Carbine et al., in press; Clayson & Miller, 2017b), and using the ERP reliability analysis toolbox

implemented in Matlab software (Clayson & Miller, 2017a, 2017b). We will use 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 will vary randomly between participants. Participants will complete a total of 160 trials, which will take about 110 min. Participants will be given breaks approximately every 22 min and will remain standing during the breaks.

After finishing the task, participants will complete questionnaires. The Borg scale (Borg, 1982) will be 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 will be asked whether they preferred to retrieve coins by sitting or standing. The custom fatigue questions will be asked again (Appendix B). The International Physical Activity Questionnaire (IPAQ) (Craig et al., 2003) will be used to assess the level of energy expenditure during a typical week and the current day. Dependence on exercise will be assessed with the Exercise Dependence Scale-21 (Hausenblas & Symons Downs, 2002) and their affective attitudes toward exercise will also be assessed (Courneya & Bobick, 2000). Participants will provide information related to handedness (Oldfield, 1971). Finally, participants will be 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.

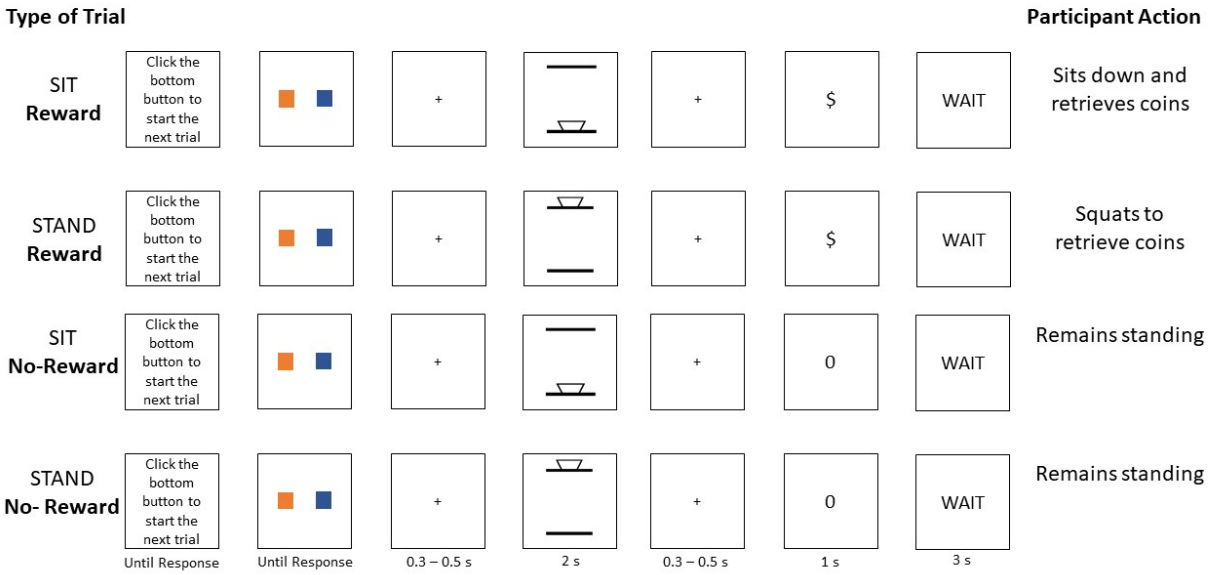

Figure 2. Experimental protocol and stimuli. There are four types of trials, each of which begins with the participant standing. For each participant, one of the colored squares has a 70% chance of resulting in a sit trial and the other square has a 20% chance of resulting in a sit trial. Each square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

2.5. EEG recording and signal processing

Scalp EEG will be 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 will be 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 will be referenced online to the left earlobe and a common ground will be employed at the FPz electrode site. Electrode impedances will be maintained below 25 kΩ throughout the study and a high-pass filter will be set at 0.016 Hz. The EEG signal will be transmitted via the BrainVision wireless MOVE add-on (Brain Products GmbH) to a BrainAmp DC amplifier (Brain Products GmbH) that will amplify and digitize the signal. The amplifier will be linked to a computer

running BrainVision Recorder software (Brain Products GmbH) that will record the signal. EEG data processing will be conducted with BrainVision Analyzer 2.2 software. Data will be visually inspected to determine whether any electrode needs 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 will be re-referenced to an average ears montage. Then, data will be prepared for independent component analysis (ICA) cleaning. First, a 1 – 40 Hz band-pass filter with 4^{th} order roll-offs and a 60 Hz notch filter will be applied. Next, data will be visually inspected and non-stereotypical artifacts will be marked. Then, an ICA will be conducted to identify stereotypical artifacts, such as blinks and saccades. We will identify stereotypical artifacts, such as blinks and saccades, by looking for components that exhibit relatively sharp changes in frontopolar voltage (e.g., more than 200 μV) that decrease in amplitude from anterior to posterior electrode sites (blinks), or exhibit broad frontopolar changes in voltage (e.g., more than 200 μV) that are larger in a hemisphere than in the other hemisphere and decrease in amplitude from anterior to posterior electrode sites (saccades). This ICA will be applied to the unfiltered data to remove identified artifacts. This cleaned data will be band-passed filtered between 0.1 and 30 Hz with 4^{th} order roll-offs and a 60 Hz notch filter.

2.6. Measures

2.6.1. Reward-prediction errors: "Reward Positivity"

The reward positivity will be 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 will be 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) will be excluded from subsequent analysis. Next,

we will determine the time window for reward positivity quantification. Specifically, epochs time-locked to reward feedback will be averaged separately for reward and no-reward trials. Then, the average of the no-reward feedback epochs will be 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 250 – 350 ms after feedback onset). Thus, we will adaptively center each participant's reward positivity time window (length = 40 ms) on their reward positivity peak latency at the electrode at which it peaks (Fz, FCz, or Cz) (Clayson, Baldwin, & Larson, 2013). We will also confirm that this window includes a negative deflection in the no-reward feedback waveforms (Krigolson, 2018). If it does not, we will center the window on the maximal negativity between 250 and 350 ms in the no-reward feedback waveforms. Then, we will compute mean amplitude in each participant's time window at Fz, FCz, and Cz for *each epoch* (i.e., the non-averaged data) and then average across these electrodes. If one of the electrodes malfunctions during recording, it will not be included in the average. Finally, if the reward positivity exhibits an unexpected posterior scalp distribution (i.e., maximal voltage at electrode CPz or Pz), we will quantify the component by averaging across electrodes Cz, CPz, and Pz, and submit this reward positivity to a sensitivity analysis.

2.6.2. Energy expenditure

The typical level of energy expenditure will be assessed using the IPAQ (Craig et al., 2003) assessing moderate-to-vigorous physical activity undertaken during a typical week ("**typical MVPA**"). The level of energy expenditure prior to the experiment on the day of the experiment will also be assessed using the IPAQ assessing moderate-vigorous physical activity ("**today MVPA**"). Finally, the level of energy expenditure during the experiment will be assessed. This variable ("**study energy expenditure**") will be computed by summing the metabolic equivalents (METs) spent on each trial up to the current trial. To compute the METs spent on each trial, we will consider the actions performed during the trial and the

time spent performing these actions. Specifically, participants will spend 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 METs will be assigned for sitting; 1.75 METs will be assigned for standing; and 4 METs will be assigned for squatting, which we consider moderate intensity exercise (Mansoubi et al., 2015). After converting METs from min to s, the trial types will be determined to have the following METs: sit reward = 1.30 METs; sit/stand no-reward = 1.36 METs; and stand reward = 2.11 METs.

2.6.3. Behavioral measures

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

2.7. Statistics

Factors, designs, and formal tests used to investigate the hypotheses are summarized in Supplemental Table 1. If a variable is not normally distributed, as tested by the Shapiro-Wilk normality test, the variable will be 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 will be used to test hypotheses. The mixed-effect approach provides a type I error rate that corresponds to its expected level (Boisgontier & Cheval, 2016) 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 MEM will be built and fit by maximum likelihood in R using the lme4 and lmerTest packages and *p*-values will be 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 will be 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) will be checked for all models. If some observations exert undue influence on the model estimation (i.e., outliers), the models will be tested with and without them to ensure results' robustness. Alpha will be set to .02 for all analyses. For exploratory analyses (see sections 2.6.2 and 2.6.3), factors that increase the fit of the models will be tested on the basis of the Bayesian Information Criterion (BIC), -2-log-likehood (-2LL), and *p*-values (Bollen et al., 2014). To interpret significant interactions, simple-effect analyses will be conducted.

2.7.1. Primary statistical model

H1 will be tested with the following linear MEM:

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

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

ϵ_{ij} is the error term, $u_{1\mathrm{j}}$, $u_{2\mathrm{j}}$ and ϵ_{ij} are independent, σ_1^2 is the variance of $u_{1\mathrm{j}}$, σ_2^2 is the variance of $u_{2\mathrm{j}}$ and σ_ε^2 is the variance of ϵ_{ij}.

2.7.2. Neutral outcome analysis

We will use the model for H1 to ensure that reward positivity is larger on reward versus no reward trials, a condition that must be satisfied to demonstrate the presence of a reward positivity that could potentially be moderated by other factors, such as trial type.

2.7.3. Exploratory analyses

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

$$Reward\ Positivity_{ij} = (\beta_0 + u_{0\mathrm{j}}) + (\beta_1 + u_{1\mathrm{j}})Trial\ Type\ (stand\ vs.sit)_{ij} + (\beta_2 + u_{2\mathrm{j}})Reward\ (no\ reward\ vs.reward)_{ij} + (\beta_3 + u_{3\mathrm{j}})Energy\ Expenditure_{ij} + \beta_4 Trial\ Type_{ij} \times Reward_{ij} + \beta_5 Trial\ Type_{ij} \times Energy\ Expenditure_{ij} + \beta_6 Reward_{ij} \times Energy\ Expenditure_{ij} + \beta_7 Trial\ Type_{ij} \times Reward_{ij} \times Energy\ Expenditure_{ij} + \epsilon_{ij} \quad (2.1 - 2.3)$$

where $Reward\ Positivity_{ij}$ is the participant's reward positivity in condition i, β_0 to β_7 are the fixed effect coefficients, $u_{0\mathrm{j}}$ to $u_{3\mathrm{j}}$ are the random effects for participant j (random intercepts and slopes), ϵ_{ij} is the error term, $u_{1\mathrm{j}}$, $u_{2\mathrm{j}}$, $u_{3\mathrm{j}}$, and ϵ_{ij} are independent, σ_1^2 is the variance of $u_{1\mathrm{j}}$, σ_2^2 is the variance of $u_{2\mathrm{j}}$, σ_3^2 is the variance of $u_{3\mathrm{j}}$ and σ_ε^2 is the variance of ϵ_{ij}, *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 will be tested with the following logistic MEM:

$$logit(E_j(Stimulus\ Chosen_{ij})) = \beta_0 + (\beta_1 + u_{1\mathrm{j}})Trial\ Number_{ij} + u_{0\mathrm{j}} \quad (3)$$

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, $u_{0\mathrm{j}}$ and $u_{1\mathrm{j}}$ are the random intercepts and slopes for the *j*th participant.

H4 will be tested with the following logistic MEM:

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

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, $u_{0\mathrm{j}}$ and $u_{1\mathrm{j}}$ are the random intercepts for the *j*th participant.

Secondary analyses

There are several variables that we plan to add to the primary models to determine if they explain 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) will be programmed to have 50% chances of resulting in a reward, it is possible that rewards will occur more or less frequently at times. Thus, we will add variables reflecting the probability of receiving a reward on the current trial given how frequently (1) a reward has been received up to the current trial ("**reward probability**"); (2) a reward has been received when choosing a certain stimulus up to the current trial ("**stimulus reward probability**"); and (3) a reward has been received on a certain trial type up to the current trial ("**trial type reward probability**"). We may also add 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 will add stimulus reward probability in this model. Stimulus chosen should also be sensitive to trial type given the stimulus chosen. Although one stimulus will be programmed to lead to sit trials 70% of the time and the other stimulus only 20%, the actual difference may depart from 50% at times. Thus, we will add a variable reflecting the probability that one stimulus leads to a sit trial relative to the probability that the other stimulus leads to a sit trial, up to the current trial ("**stimulus trial type probability**"). We may also add interaction terms between these variables and those in the primary models.

For *model 4*, trial number may predict changed response, with participants changing their responses less often across trials as they learn 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 predict changed response. We may also add interaction terms between these variables and those in the primary models.

We will also conduct exploratory analyses with data from questionnaire responses, such as sitting time, age, gender, body mass index (BMI; computed from height and weight), exercise dependence, affective attitudes toward exercise, fatigue, and rating of perceived exertion associated with retrieving coins on stand reward and sit reward trials. Additionally, we may conduct sensitivity analyses using ranked IPAQ scores (Sagelv et al., 2020).

3. 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 are motionless when feedback is presented. Additionally, despite participants squatting, no sweat artifact was observed in the pilot EEG data, which was expected because the testing room temperature is kept at 20°C. The pilot data to inform 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, sit reward: median = 36.5, min = 24; sit no-reward: median = 32.5, min = 26; stand reward: median = 39, min = 30, and stand no-reward: median = 39, min = 29.

3.1. 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/m^2, 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.

3.2. Pilot results

ERP waveforms and scalp topographies for the pilot data are depicted in Supplemental Figure 1. The figure suggests that we were able to obtain clean data, which is 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 are shown in Supplemental Table 2, 3, and 4.

Acknowledgements

Boris Cheval is supported by an Ambizione grant (PZ00P1_180040) from the Swiss National Science Foundation (SNSF).

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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

748 order to win. In other words, there is no pattern as to which color square will give you the best chance at

749 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

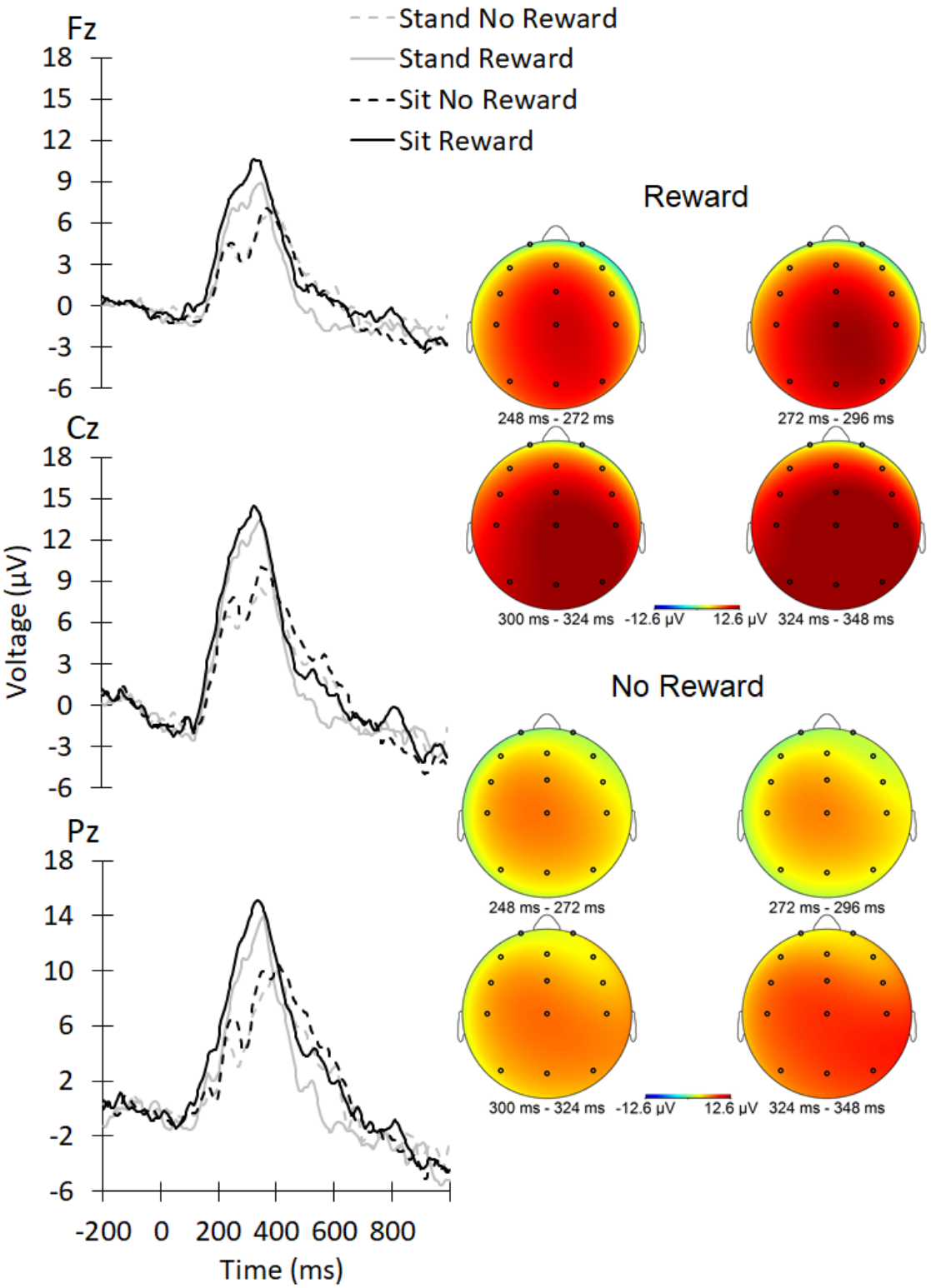
Completely Disagree Completely Agree

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
Exploratory 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.