RUNNING HEAD: COST-BENEFIT ANALYSIS IN PHYSICAL EFFORT EXPENDITURE

Cost-benefit analysis in physical effort expenditure: An electrophysiological registered report

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Abstract

Navigating through everyday life requires us to make series of choices involving effort: *Is it worth the effort for what I want to accomplish?* Effort-based decision making depends on evaluating the value of effort-related costs against potential rewards, and only when the rewards outweigh their effort costs do effortful behaviors tend to get carried out. Despite a surge of research on this topic, what effortful control and reward processes are involved in such decisions and whether electrophysiological measures of control and reward processes could better elucidate these processes remain unclear. Here, we will parametrically manipulate effort and reward levels to investigate their effects on different decision processes (i.e., choice evaluation, choice itself, subsequent physical effort production, reward feedback valuation). To assess these decision processes, we will examine two electrophysiological indices: frontal midline theta power and reward positivity amplitude; further, we will investigate whether these indices track cost-benefit integration, which will be reflected in subjective values derived from behavioral modelling of choices. Our goal is to understand how effort and reward affect different aspects of decision making and effort production, and how the electrophysiological and behavioral measures of these processes relate to each other.

Keywords: physical effort; cognitive control; reward process; reward positivity; frontal-midline theta

Many choices we make in life involve evaluating whether or not it is worth exerting effort for the outcome we desire: Should I study for an exam on a Friday night or go to a party with friends? Should I take the stairs instead of the elevator for health? Both anecdotes and experiments indicate that effort -- whether in the cognitive or physical domain -- is inherently aversive with people tending to avoid it (e.g., Westbrook & Braver, 2015), yet reward is known to counteract this effect. Effort-based decision making thus depends on weighing the value of effort costs (e.g., studying for an exam on a Friday night) against the potential reward outcomes (e.g., getting an A on the exam). Notably, effort de-values the subjective appeal of reward, such that the same reward appears less rewarding once effort is required to obtain it, and that larger rewards are needed to compensate for the increasing effort demands both in humans and other animals (e.g., Chong et al., 2017; Westbrook & Braver, 2015).

Although research on effort- and reward-based decision making has increased in recent years, many questions remain: What effortful control and reward processes are involved? Can electrophysiological measures help us better elucidate these processes? Here, we will investigate the effects of effort and reward on decision making and effort production by measuring two known electrophysiological correlates of control and reward processes (frontal midline theta power and reward positivity amplitude) using electroencephalography (EEG). Specifically, we will examine how these correlates of control and reward processes are associated with different aspects of decision making; namely, processes related to choice evaluation, choice itself, effort production, and reward feedback valuation in a task involving physical effort. Our goal is to better understand whether and how effort and reward influence different aspects of decision making and effort production by examining their electrophysiological correlates.

Effort- and reward-based processes supported by anterior cingulate cortex

Substantial evidence from animal (Floresco, Onge, Ghods-Sharifi, & Winstanley, 2008; Walton, Bannerman, & Rushworth, 2002; Salamone, Correa, Farrar, & Mingote, 2007; Walton et al., 2009) and human neuroimaging (e.g., Bonnelle, Manohar, Behrens, & Husain, 2016; Chong et al., 2017; Croxson, Walton, O'Reilly, Behrens, & Rushworth, 2009; Klein-Flugge et al., 2016; Skvortsova, Palminteri, & Pessiglione, 2014) studies have revealed brain regions that are critical in value-based decision making requiring physical effort, including the striatum and anterior cingulate cortex (ACC) among others. The dorsal part of ACC (dACC), in particular, has been indicated as a key neural hub that integrates effort-related costs and reward (e.g., Holroyd & Umemoto, 2016; Krebs, Boehler, Roberts, Song, & Woldorff, 2011; Rushworth & Behrens 2008; Shenhav, Botvinick, & Cohen, 2013; Verguts, Vassena, & Silvetti, 2015; Walton, Kennerley, Bannerman, Phillips, & Rushworth, 2006), with computational models more recently focusing on the ACC's role in control process requiring effort (Holroyd & McClure, 2015; Shenhav, Botvinick, & Cohen, 2013; Shenhav et al., 2017; Silvetti, Vassen, Abrahamse, & Verguts, 2018; Vassena, Deraeve, & Alexander, 2017; Verguts et al., 2015; see Vassena, Holroyd, & Alexander, 2017 for review).

For example, the ACC is thought to calculate the value of applying effortful control when it is deemed profitable, which in turn biases behaviors (Shenhav et al., 2013; Verguts et al., 2015), or to motivate behavior by overcoming effort costs based on reward input (Holroyd & McClure, 2015). Although the specifics of what precisely ACC does is still debated (Vassena et al., 2017) and elucidating ACC's precise function is beyond the scope of this paper, existing theoretical models appear to agree that ACC supports effort-related behaviors. The ACC appears critical in motivating goal-directed behavior (Le Heron, Holroyd, Salamone, & Husain, 2018), and lesions to the ACC lead to pathological apathy in humans (Devinsky, Morrell, & Vogt, 1995;

Levy & Dubois 2006; Holroyd & Yeung 2012; Holroyd & Umemoto, 2016) and other animals (e.g., Walton, Bannerman, Alterescu, & Rushworth, 2003; Walton, et al., 2002; 2006). Consistent with this evidence, neuroimaging studies have suggested that increased dACC activity may be related to increased willingness to engage in future effort that is rewarding (Krebs et al., 2011; Vassena et al. 2014). Nevertheless, further research can provide insights into what effort and reward processes are involved in effort- and reward-based decision making, and how electrophysiological correlates of ACC function are associated with these processes.

We have previously suggested that electrophysiological correlates of cognitive control and reward, believed to reflect ACC function, could shed light on this question (Holroyd & Umemoto, 2016, Umemoto, Inzlicht, & Holroyd, 2018). Here, by using a task that independently manipulates levels of effort and reward, our goal is to investigate how these electrophysiological measures are associated with different aspects of decision making and physical effort production. EEG's high temporal resolution allows us to examine how these processes evolve over a short period of time (e.g., Gheza, Paul, & Pourtois, 2018), from choice evaluation to reward feedback valuation. For example, by examining different electrophysiological measures, Schevernels and colleagues (2014) reported that effort and reward related processes have temporally differential effects during task preparation. Consistent with this, we suggest that EEG will provide further insights into the precise functional processes involved in different aspects of decision making and effort production, which in turn will help complement existing neuroimaging research examining effort- and reward-based decision making. Thus, the current work has the potential to offer converging evidence across modalities such as neuroimaging, computational modeling, and EEG.

We will model behavioral choices using computational models previously used in this task to estimate the subjective value of each effort and reward combination (e.g., Lockwood et al., 2017). Previous work on tasks requiring physical effort production found that subjective values covary with dACC activity (Chong et al., 2017; see also Croxson et al., 2009; Klein-Flugge, 2016; Silvetti et al., 2018), suggesting that this brain region integrates effort and reward information. Thus, the electrophysiological correlates of control and reward processes might reflect such subjective values.

EEG correlates: frontal midline theta power, reward positivity amplitude, and delta power

Effortful control and reward processes have been extensively studied in the electrophysiological literature, yet they are often examined in isolation (Holroyd & Umemoto, 2016; Umemoto et al., 2018). Here we focus on two electrophysiological correlates believed to reflect effortful control and reward processes. First, we will focus on 4 to 8 Hz oscillations measured by EEG, observed at the frontal midline area of the scalp, known as frontal midline theta (FMT). FMT power is believed to originate in the ACC, and appears to reflect (at least in part) cognitive control processes requiring effort (e.g., Cavanagh & Frank, 2014; Holroyd & Umemoto, 2016). While fast, phasic bursts in FMT power have often been studied in cognitive processes involving error commissions, response conflicts, and negative performance feedback (e.g., Bernat, Nelson, & Baskin-Sommers, 2015; Cavanagh & Frank, 2014; Foti et al., 2015; Luu & Tucker, 2001), FMT power is also observed during economic decision making (Lin, Saunders, Hutcherson, & Inzlicht, 2018), and is positively associated with memory and cognitive demands (e.g., Holroyd & Umemoto, 2016, for review). Similarly, ongoing, (more tonic) FMT power is observed during cognitive effort exertion (e.g., Mussel, Ulrich, Allen, Osinsky, & Hewig, 2016; Umemoto et al., 2018, Wascher et al., 2014).

Second, we will examine the reward positivity (RewP) component of the event-related brain potential (ERP), also known as the feedback-related negativity (Miltner, Braun, & Coles, 1997). It is sensitive to the negative and positive valence of feedback stimuli and appears to be modulated more by reward than error outcomes, hence renamed as such (Holroyd, Pakzad-Vaezi, & Krigolson, 2008; Proudfit, 2015). Influential work by Holroyd & Coles (2002) proposed that RewP indexes fast, phasic midbrain dopamine's reward prediction error signals carried to the ACC for the purpose of regulating behaviors. This proposal has been supported by a wealth of studies (Sambrook & Goslin, 2015; Walsh & Anderson, 2012; but see Janssen, Poljac, & Bekkering, 2016), and ACC appears to be the neural source of the RewP (e.g., Miltner et al., 1997; Becker, Nitsch, Miltner, & Straube, 2014; but see Proudfit, 2015). A growing number of studies indicates that RewP amplitude may index individuals' subjective reward valuation signals (Holroyd & Umemoto, 2016 for review), with a higher reward sensitivity reflected by a larger RewP amplitude (Bress & Hajcak, 2013, Umemoto & Holroyd, 2017) and a lower reward sensitivity reflected by a smaller RewP amplitude, as seen in depression (e.g.,Proudfit, 2015; Umemoto & Holroyd, 2017; see also Paul & Pourtois, 2017). Hence RewP amplitude may serve as a promising index for examining the impact of reward on decision making.

A few studies report that the reward-related ERP comprising RewP is characterized in part by fluctuations in delta frequency band of 1-3 Hz when RewP is decomposed in the time-frequency domain (Bernat, Nelson, Holroyd, Gehring, & Patrick, 2008; Bernat, Nelson, Steele, Ghering, & Patrick, 2011; Foti, Weinberg, Bernat, & Proudfit, 2015; Gheza et al., 2018). Consistent with the aforementioned finding between RewP and reward insensitivity in depression, reduced reward-related delta power was associated with internalizing psychopathology symptoms, including depression (Foti et al., 2015). Therefore, delta power may provide additional information about the effect of reward on decision making.

We suggest that FMT power and RewP amplitude will offer insights into what and how control and reward processes are involved in different aspects of decision making and effort production, as specified below (see Hypotheses). This in turn will also shed light on which aspects of effortful control and reward processes FMT power and RewP amplitude are related to, which will help us advance the knowledge of what these electrophysiological measures specifically represent regarding control and reward valuation processes. In line with this, Gheza and colleagues (2018) have recently investigated electrophysiological correlates of reward processing with effort cost anticipation, focusing on feedback processing by RewP amplitude and spectral activities (i.e., delta, theta, and beta-gamma). They found the effect of effort cost anticipation on RewP amplitude and delta power, but no such effect on FMT power. Our study will advance this study by further elucidating the role of these electrophysiological correlates during decision making, as well as reward feedback valuation following effort production. Moreover, as we describe below, the use of computational modeling and parametric variations in effort and reward levels in our study will additionally better illuminate the role of FMT power and RewP in effortful control and reward processing.

Current Study

Across various contexts both in everyday examples and laboratory experiments, more effort production tends to be associated with more rewarding outcomes (e.g., the more one exercises, the more one loses weight). However, to illuminate the mechanisms underlying effort and reward processes, it is necessary to examine both their independent effects and interactions on behavior. To do this, we will employ a commonly-used task paradigm that independently and linearly manipulates physical effort and reward levels (Apps, Grima, Manohar, & Husain 2015; Chong et al., 2017; Lockwood et al., 2017). On each trial, participants will be asked to select one of two effort choices: a fixed low-effort/low-reward "baseline" choice and a variable high-effort/high-reward "offer" (Figure 1, 2nd panel, "Choice Evaluation"). The baseline choice is always associated with minimal effort and reward (i.e., slightly squeezing a hand-dynamometer for 5 cents), whereas the alternative effort offer will vary on the effort required and reward offered (e.g., squeezing a hand-dynamometer strongly for 8 cents; squeezing it very strongly for 12 cents, etc.). There will be five levels of effort and four levels of reward[1], with the only caveat being that the effort and reward on offer are higher than the baseline choice, which is low in both effort and reward. Upon selecting either the baseline choice or the effort offer (Figure 1, 3rd panel, "Choice"), participants will then actually execute the task (i.e., squeeze a hand-dynamometer for a given effort level) for a chance to earn a reward (Figure 1, 5th panel, "Effort Production"). Finally, participants will receive reward feedback (Figure 1 ,7th panel, "Reward Feedback Valuation"). This design will allow us to investigate each participants' effort and reward sensitivity, behaviorally and electrophysiologically, as a function of parametrically increasing effort and reward levels.

Hypotheses

1. Choice behavior will vary as a function of effort and reward.

It has been consistently observed in the literature that effort de-values potential reward outcomes, whereas increasing reward levels counteracts this devaluation effect. We expect to

[1] We chose this unbalanced 5 x 4 design to maximize the effort and reward levels that we can reliably fit discounting functions for within a given time frame of the experiment (i.e., to keep the actual task length to within 1 hour and minimize muscle fatigue).

replicate past findings: Participants will choose the high effort offer more frequently when reward levels increase, but choose it less frequently when effort levels increase.

2. Which effort processes do FMT power relate to?

2a. FMT power will increase during choice evaluation as a function of effort and reward levels.

FMT power, as well as ACC activity which FMT is believed to originate from, has been observed during decision making paradigms (Lin et al., 2018; Shenhav, Straccia, Cohen, & Botvinick, 2014). We predict that FMT power will linearly increase as a function of increasing effort levels during choice evaluation. We also expect FMT power to linearly increase as a function of increasing reward levels during choice evaluation (i.e., participants should be willing to exert more effort when reward levels are high). These two predictions (one for effort level and one for reward level) will be tested within the same statistical model (see Model 2a in the **Statistical Analyses**).

2b. FMT power will increase during effort production as a function of effort and reward levels.

Past studies reported increased FMT power associated with increased cognitive and memory demands – yet it is unclear whether this was related to effort production per se or to other aspects such as conflict and task difficulty (Hsieh & Ranganath, 2014; Jensen & Tesche, 2002; Mussel et al., 2016; Zakrzewska & Brzezicka, 2014). Similar to Hypothesis 2a above, we will examine whether FMT power will linearly increase as a function of increasing effort and reward levels during effort production. As in Hypothesis 2a, these two predictions (one for effort level and one for reward level) will be tested within the same statistical model (see Model 2b in the **Statistical Analyses**).

3. RewP amplitude will vary as a function of effort and reward levels.

3a. RewP amplitude will increase as a function of increasing effort levels.

An interesting question that has not been investigated in the EEG literature is whether effort modulates reward feedback valuation as measured in RewP amplitude. A number of studies, particularly in social psychology, have reported that effort can increase the value of outcomes (i.e., the so-called effort paradox; see Inzlicht et al., 2018, for a review). To our knowledge, only a few electrophysiological studies have investigated a similar question. Ma and colleagues (2014) had participants perform a cognitive task differing in effort levels and found that increased effort production led to increased RewP amplitudes. In contrast, Gheza and colleagues (2018) found an enhanced RewP amplitude on trials when participants succeeded in avoiding physical effort production, which was accompanied by feelings of pleasure and relief. We will replicate and expand upon this effect (i.e., effort influencing reward feedback valuation) using physical effort, and predict that RewP amplitudes will increase as a function of increasing effort levels, indicating that participants perceive the same reward feedback to be more rewarding when they exerted effort to obtain them. Nevertheless, we will also conduct exploratory analysis on the possibility that the effect of effort on RewP amplitude is due to an additional factor, such as reduced expectation to succeed in the task on high effort trials which makes reward feedback unexpected (Schouppe et al., 2015; Silvetti, Seurinck, & Verguts, 2011; see also Vassena et al., 2017).

3b. RewP amplitude will increase as a function of increasing reward levels.

Although the past work has suggested that RewP amplitude reflects a binary valence effect, indicating whether an event was better or worse than expected (e.g., Hajcak, Moser, Holroyd, & Simons, 2006), a recent meta-analysis indicates that reward size modulates RewP amplitude (Sambrook & Goslin, 2015). Using a parametric modulation of reward levels in our task, we predict that RewP amplitude will linearly increase as a function of increasing reward levels.

4. Subjective value will be associated with trial-by-trial variations in FMT power, RewP amplitude (or delta power), and/or the FMT-RewP (or -delta) interactions (single-trial analysis).

We will model behavioral choices using computational models (see Materials and Methods section) to estimate the subjective value of each effort and reward combination relative to the baseline choice for each subject (e.g., Lockwood et al., 2017). This subjective value estimate reflects how much a reward is discounted by the effort required to obtain that reward. Given findings that ACC activation varies with subjective values (e.g., Chong et al., 2017; Croxson et al., 2009; Klein-Flugge, 2016; Silvetti et al., 2018; see also Westbrook, Lamichhane, & Braver, 2019), we will test whether trial-by-trial subjective value is related to FMT power during choice evaluation, RewP amplitude (or delta power), or the interactions of FMT power and RewP amplitude (or delta power).

Materials and methods

Participants and Power

We conducted a sensitivity analysis using the G*power software program (Erdfelder et al., 1996) to determine the smallest effect size we could detect with our design and sample size. We submitted a 5 (effort level) by 4 (reward level) within-subjects, repeated analysis of variance design (i.e., 4*5 = 20 conditions total) with 0.02 alpha-level and 0.9 power[2]. This analysis reveals that with 65 participants[3] we will be able to detect an effect size of at least f = 0.108 (d = .22) or larger for all of the proposed analyses (see Statistical Analyses). Because this is an EEG study, and we expect that 10-15% of participants may need to be excluded based on hardware problems, excessive movement artefacts (e.g., artifacts of more than 30% of the data), or not producing the required effort on more than 90% of the trials, we will aim to recruit up to 75 participants total. If the number of usable participants' data fall below 65, we will collect additional data so that the power is maintained at 90%.

Undergraduate students will be recruited from the University of Toronto Scarborough Department of Psychology subject pool to fulfill a course requirement or earn bonus credits. All participants will be required to have normal or corrected-to-normal vision, and aged between 18 and 40. Each participant will also receive a monetary bonus in addition to the credits, the amount of which will depend on their task performance (see below). All subjects will be required to provide informed consent as approved by the local research ethics committee. The experiment will be conducted in accordance with the ethical standards prescribed in the 1964 Declaration of

[2] Because we plan to fit multilevel models (linear mixed models) on all of our data (which G*power is not well developed for) rather than analysis of variance (which G*power is relevant) we also ran simulations with mixed models to determine the smallest effect size we could detect with a similar sample size (see results at https://git.io/fhSPq). The simulation results suggest that with 60 participants we could detect a minimum effect size of f = 0.111 with approximately 92% power. This result is consistent with the sensitivity analysis above using G*power. Note that we will have more power to detect even smaller effects for the single-trial analyses (i.e., Hypotheses/Statistics 1 (i.e., logistic regression on choice behavior) and 4).

[3] We conducted the sensitivity analysis on this sample size based on our previous study (Umemoto, Inzlicht, & Holroyd, 2019), which recruited 65 participants for a completely within-subjects design (as in the current study), performed multilevel modeling analyses, and found a significant behavioral-electrophysiological association that was of a similar small effect size.

Helsinki. At the beginning of data collection, we will recruit up to 5 participants as pilot participants to ensure that participants are able to perform the task with high success rates (above 90%)[4], and the task and the analyses are error-free.

Grip force calibration

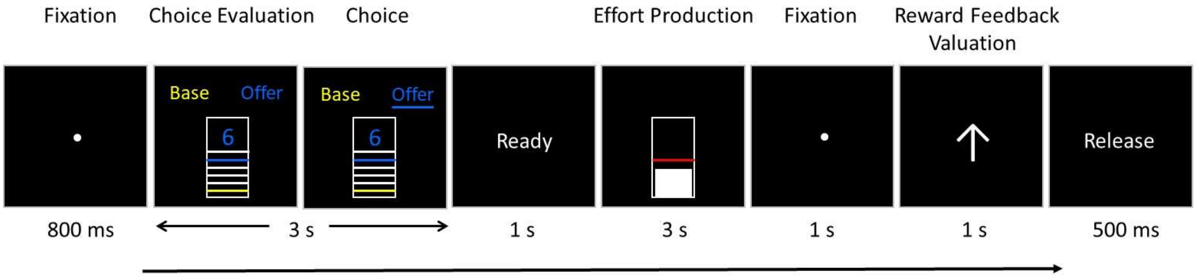
Physical effort will be measured using a hand-dynamometer (Neulog, U.S.). First, each participant's maximum grip force will be measured. The hand-dynamometer will be affixed to the table in a straight-up position in front of the computer screen (approximately 35 cm from the participants and 50 cm from the computer screen). Participants will be asked to exert their maximum grip force for 2 seconds, 3 times for both their right hand and left hand. We will use the largest force produced by each hand as the maximum grip force for that hand. Participants will alternate between their right and left hand for each block of trials to minimize fatigue (see Procedure, below).

Task Design

Each trial will require participants to choose between two effort choices: a fixed low-effort/low-reward "baseline" choice or a variable high-effort/high-reward "offer". The baseline choice will require participants to squeeze a hand-dynamometer with approximately 5% of their maximum force and to maintain it for 1.5 seconds out of 3 seconds, whereas the high effort choice will require participants to squeeze the device with 15%, 25%, 35%, 45%, or 55% of their maximum force and to maintain it for 1.5 seconds out of 3 seconds. The reward offered for the

[4] Based on our unpublished data using a similar effort discounting design, we believe the majority of participants, if not all, will be able to achieve at least 90% success rates without difficulty. Moreover, if participants are unable to successfully perform the higher effort option, they can always choose the baseline option, which requires only 5% of their maximum grip force.

baseline choice will always be 5 cents, whereas it will vary for the effort offer among 6, 8, 10, and 12 cents. Both the level of high effort and its associated reward will be randomly generated on each trial, with a constraint that each reward level will be about equally likely to occur for each effort level. Each trial will begin with a fixation screen for 800 ms (Figure 1, 1st panel). On the following choice evaluation screen (Figure 1, 2nd panel) participants will be presented with a white bar in which six lines are overlaid on top of it, indicating each effort level. The bottom line, highlighted in yellow, will indicate the baseline choice, and the other five lines placed above it indicates the possible effort offer from low to high effort level (i.e., from the 15% effort level to the 55% effort level at the top). The effort offer on a given trial will be shown in blue (Figure 1, 2nd & 3rd panel). The potential reward for the effort offer on a given trial will also be shown inside the white bar in blue (Figure 1, 2nd & 3rd panel). Participants will be given 3 seconds to select between the baseline choice and the effort offer using the left or the right arrow key (Figure 1, 2nd & 3rd panels). The mapping between the response keys and effort choices will be reversed for half of the participants (i.e., in Figure 1, 2nd & 3rd panels, the word “Base” will be placed on the right and “Offer” on the left for these participants). After participants make a choice, the chosen option will be underlined for the remaining duration within the 3-second choice deadline (i.e., if a participant made a choice after 1 second, his/her option will be underlined for the remaining 2 seconds) (Figure 1, 3rd panel). A message “Ready” will then be presented for 1 second (Figure 1, 4th panel). Then a white rectangular bar with a red horizontal line will be shown, corresponding to the selected effort choice, upon which participants will start squeezing the device (Figure 1, 5th panel). A message “Respond faster!” will be presented for 500 ms if participants does not make a choice within the choice deadline, in which case the same trial will be repeated. The height of the white rectangular bar will correspond to each participant's maximum grip force for his/her responding hand. As participants squeeze the dynamometer, a visual feedback of their applied force will be given online (Figure 1, 5th panel). Participants will be given 3 s to produce and maintain their grip force for at least 1.5 s, after which the image will be replaced with a fixation dot at the center of the screen for 1 second and participants will be told to release their grip (Figure 1, 6th panel). Reward feedback will then be presented for 1 second. An up-arrow image will indicate a receipt of reward and a down-arrow image will indicate a receipt of a no-reward (Figure 1, 7th panel). Participants will receive a reward with a 50% reward probability[5] only if the applied force exceeds the effort requirement and is maintained for at least 1.5 s (i.e., successfully executed a chosen effort). If this is not achieved, participants will receive a no-reward feedback. Note that this reward probability is 50% whether participants select the baseline choice or the effort offer, hence equating the probability manipulation between effort choices. Finally, the word "Release" will be presented for 500 ms, indicating to participants that their grip should be relaxed in preparation for the next trial (Figure 1, last panel).



[5] This is necessary to measure RewP, because its amplitude is sensitive to the expectation of reward and no-reward feedback.

Figure 1. An example trial sequence of the task. On each trial participants will be presented with two choices to choose from (2nd panel from the left). Baseline choice ("Base") is always associated with the minimal effort level and a reward amount of 5 cents, whereas the alternative effort offer ("Offer") is associated with one of five effort levels and one of four reward levels (both of which are higher than the baseline choice). During the choice evaluation period (2nd panel), all possible effort levels will be indicated by 6 lines overlaid on top of a white bar: the bottom, yellow line indicates the baseline choice level. The other 5 lines placed above the yellow line indicate, linearly from the bottom to the top, each effort offer. The effort offer on a given trial will be highlighted in blue (the 2nd most effortful offer in this example), with a reward at stake also shown in blue inside the white bar (6 cents in this example). Participants will be given 3 seconds (s) to choose between the two choices, and their choice, once made, will be highlighted by an underline underneath the word "Base" or "Offer" corresponding to their choice (3rd panel). Following their choice participants will execute the effort of their choice within a given 3 seconds time-limit (5th panel). Upon completion of effort production and following a fixation period, participants will receive a reward feedback. An up-arrow indicates a receipt of reward (7th panel), and a down-arrow indicates a receipt of no-reward (not shown in this figure). The next trial will begin following a fixation screen.

Procedure

Participants will be seated comfortably in front of a computer monitor (1024 by 1280 pixels) at a distance of about 85 cm in a dimly lit room. The task will be programmed in MATLAB (MathWorks, Natick, MA, USA) using the Psychophysics Toolbox extension (Brainard, 1997; Pelli, 1997). Participants will receive a task instruction both verbally and in a written format on a computer screen. They will be told that they will be using a hand-dynamometer to perform a task and will have a chance to win monetary rewards. Each participant's maximum hand-grip strength is then calibrated (see Grip force calibration, above).

Practice: Participants will first practice the task, which will be conducted in two steps. The first step will be similar to the actual task, except 1) information regarding the potential reward associated with each effort choice will not be included. 2) Reward feedback will consist of the words "Good job!" at the center of the screen for successful effort production, and "Squeeze harder" for unsuccessful effort production (1 s). 3) No choice deadline will be imposed for selecting between the two effort choices during the entire practice session. Participants will practice executing the baseline choice and each of the effort offers once each for each hand, for a total of 12 trials. The location of the effort choices (left or right side of the screen) will be counterbalanced across participants but will be maintained throughout the experiment for each participant.

The second step will introduce participants to the potential reward with reward probability. Participants will be instructed that the baseline choice will always provide a chance to earn a 5 cents reward, whereas the effort offer will provide a chance to earn among 6, 8, 10, and 12 cents reward, given successful effort production. No-reward will be given following unsuccessful effort production. Participants will be told, following effort production, an up-arrow image will indicate a receipt of reward and a down-arrow image will indicate a receipt of a no-reward. Moreover, the probability of obtaining the reward will always be 50% (regardless of whether the baseline choice or the effort offer is selected). Participants will practice the task with this additional information as described above (Task Design) for a total of 4 trials (2 trials with each hand).

Task: The actual experiment will begin following the task practice. The task proper (Figure 1) will be identical to the practice session except that 1) each trial will begin with a fixation dot presented at the center of the screen (800ms; Figure 1, 1st panel from left), and 2) a choice deadline of 3 s will be imposed for selecting between effort choices (Figure 1, 2nd & 3rd panels). Participants will complete 10 blocks of 30 trials each, with a minimum 30 seconds and up to 1 minute rest in between blocks, and the entire experiment will last approximately 1 h and 20 minutes (including grip calibration, practice trials, and self-report questions (below)). Participants will be told that the goal of the study will be to perform the task as best as they can.

At the beginning of each block of trials a computer screen will show which hand they should use to grip the device for the upcoming block (the first hand will be determined randomly for each participant). To minimize muscle fatigue, the hand to use will alternate in each block (Note that the maximum grip strength will be calibrated for each hand separately, as described in Grip force calibration). Feedback about the sum total of participants' accumulated earnings for each block will be presented at the end of each block. The total amount of reward they earn will be presented upon completion of the task, which are estimated to be up to approximately $13. At the end of the experiment each participant's hand-grip strength will be re-calibrated twice for each hand.

Self-report questions

On randomly selected trials (approximately every 5 trials), participants will answer one of three questions on a 1-7 Likert scale: 1) "How much do you want the reward offered?", 2) "How much did you like the feedback you just received?" (This applies whether reward or no-reward feedback is received), and 3) "How motivated are you to exert the effort you just selected?". Question #1 and #3 will be asked immediately after participants selected one of the two effort choices (i.e., after Figure 1, 3rd panel, but before effort production), whereas question #2 will be asked following a receipt of reward or no-reward feedback (i.e., after Figure 1, 7th panel). Because we do not have clear predictions, we will conduct exploratory analyses to investigate the relation between these self-report measures and RewP amplitude and FMT power.

EEG Data Acquisition and Pre-processing

The EEG will be recorded from 32 tin sintered electrodes embedded in a stretch-lycra cap arranged according to the international 10-20 system. Vertical electrooculography (VEOG) will be recorded using a supra- to sub-orbital bipolar montage surrounding the right eye, and horizontal electrooculography (HEOG) will be recorded from electrodes placed on the left and right outer canthi (all approximately 1 cm from the pupil). Impedances will be maintained at or less than 5 KΩ for all the electrodes except the VEOG and HEOG channels, which will be kept at or less than 10 KΩ during recording. The EEG signal will be digitized at 512 Hz using ASA acquisition hardware (Advanced Neuro Technology, Enschede, the Netherlands).

Data Analysis

Model fitting for Hypothesis 4. Following previous work using similar physical effort discounting paradigms, we will fit and compare four discounting functions. For the linear, hyperbolic, and parabolic functions, *k* is the only free parameter to be estimated (Chong et al., 2017), with higher *k* values reflecting steeper discounting (*SV* = subjective value; *t* = trial number).

Linear: $SV_t = Reward_t \cdot (1 - k \cdot Effort_t)$

Hyperbolic: $SV_t = Reward_t \cdot \frac{1}{(1+k \cdot Effort_t)}$

Parabolic: $SV_t = Reward_t - k \cdot Effort_t^2$

In the sigmoidal function, two parameters, *k* and *p*, will be estimated, with *k* reflecting the slope of the sigmoid function and *p* the turning point (Klein-Flügge, Kennerley, Saraiva, Penny, & Bestmann, 2015; Klein-Flügge et al., 2016).

Sigmoidal: $SV_t = Reward_t \cdot (1 - (\frac{1}{1+e^{-k(Effort_t - p)}} - \frac{1}{1+e^{kp}}) \cdot (1 + \frac{1}{e^{kp}}))$

In general, these discounting functions assume that the subjective value (*SV*) of the offer on trial *t* will be determined by the effort and reward levels on that trial and the subject-specific discounting parameter k (and the turning point, p, in the sigmoidal function). These four functions will be fitted to participants' choices using a softmax function and maximum likelihood estimation using the ucminf function from the ucminf package in R. The softmax function, which transforms subjective values into choice probabilities, was defined as:

$$P_{t,i} = \frac{e^{\beta \cdot SV_{t,i}}}{e^{\beta * 1} + e^{\beta * SV_{t,i}}}$$

Where $P_{i,t}$ is the probability of choosing option *i* on trial *t* that has a subjective value of $SV_{i,t}$, and β is the noise parameter that determines the randomness or noisiness of participants' choices. Note that the baseline choice will be fixed at 5 cents.

For each participant and each model, we will fit the model 50 times with different random starting values each time and will choose the set of parameters associated with the smallest negative log-likelihood. We will compare and select the winning model by choosing the model with the lowest Bayesian Information Criteria (BIC), which penalizes models for the number of free parameters that are estimated to ensure that models with more parameters (sigmoidal function) are not overfitted.

Electrophysiology. Analysis and data visualization will be performed on MATLAB using the EEGLAB (Delorme & Makeig, 2004), ERPLAB (Lopez-Calderon & Luck, 2014), and fieldtrip (Oostenveld, Fries, Maris, & Schoffelen, 2011) toolboxes. The digitized signals will be filtered using a second-order digital Butterworth filter with a high pass at 0.10 Hz. Ocular artifacts (eye blinks and movements) will be removed using independent component analysis (ICA) on continuous EEG. The EEG data will be re-referenced to the average of two electrodes placed on earlobes.

Time-frequency analysis will be performed using fieldtrip toolbox to compute FMT power during both the decision phase and the effort production phase, and delta power during the time of feedback outcome. We will use complex Morlet wavelets to compute power values for frequencies between 1 and 40 Hz, with the width (or cycles) of each frequency band increasing from 3 to 12 cycles between 1 and 40 Hz. We will then average the single-trial power for every participant. To avoid potential time-frequency decomposition edge artifacts, EEG data will be segmented into long epochs of 6500 ms (Decision making: −2500 to 4000 ms relative to onset of choice evaluation and choice itself, separately; Effort production: -2500 to 4000 ms relative to onset of effort production (i.e., hand-grip execution); Reward feedback: −2500 to 4000 ms relative to onset of reward and no-reward feedback). Muscular and other artifacts will be excluded according to the following criteria as implemented in EEGLAB (for detail see Delorme, Sejnowski, & Makeig, 2007): 1) Linear trends with a maximum slope exceeding 100µV, 2) Data improbability exceeding 5 standard deviations (SD) based on the joint probability for each epoch at each electrode, 3) Spectral pattern that deviated from baseline by +/- 50 dB in the 0–2 Hz frequency window for detecting eye movements, and +/- 100 dB in the 20–40 Hz frequency window for detecting muscle activity. FMT power and delta power will be measured, respectively, between 4 and 8 Hz and between 1 and 3 Hz at channel FCz, where they generally reach maximum power (e.g., Bernat et al., 2008; Foti et al., 2015; Umemoto et al., 2018). A time-window of interest will be determined based on a collapsed localizer approach separately for FMT and delta power (i.e., based on the average across all of the conditions across all participants) (Luck & Gaspelin, 2017). To measure fast, phasic burst of FMT power (i.e., phasic FMT power) during decisions and delta power during feedback, data will be decibel-normalized using a -500 to -300 ms period preceding event onset, and average FMT power and average delta power will be calculated within the determined time-windows above. To measure ongoing FMT power (i.e., tonic FMT power), average FMT power will be calculated across the entire 3 seconds decision period, and 3 seconds of effort production period without applying decibel-normalization.

For the analysis of RewP amplitude, the data will be segmented for an 800 ms epoch extending from 200 ms prior to 600 ms following presentation of reward and no-reward feedback. Data will be baseline corrected by subtracting from each sample for each channel the mean voltage associated with that electrode during the 200 ms interval preceding feedback onset. The same artifact rejection procedure as for the time frequency analysis will be applied. However, to be consistent with the literature, we will also separately apply a standard artifact rejection procedure to ensure that results for RewP are consistent across different artifact rejection procedures. For the standard procedure, we will apply the following criteria: Trials with muscular and other artifacts will be excluded according to a 150 μV Max-Min voltage difference, a ±150 μV level threshold, a ±35 μV step threshold, and a 0.1 μV lowest-allowed activity level as rejection criteria. ERPs will then be created for each electrode and participant by averaging the single-trial EEG according to the reward and no-reward feedback type. These ERPs will then be filtered with a low pass at 20 Hz using a second-order digital Butterworth filter.

The RewP amplitude will be measured at channel FCz, where it generally reaches maximum amplitude. A difference wave will be calculated that isolates the RewP from overlapping ERP components such as the P300 (Holroyd & Krigolson, 2007; Sambrook &

Goslin, 2015); for each participant the ERP to no-reward feedback stimuli will be subtracted from the ERP to reward feedback stimuli. RewP amplitude will be then determined by averaging the mean amplitude in the difference wave within a time-window that will be determined using a collapsed localizer approach (i.e., based on the average across all of the conditions and participants) (Luck & Gaspelin, 2017).

We will also conduct single-trial time-frequency analysis on FMT power, RewP amplitude, and delta power. We will apply the same time-windows of interest as calculated above for each of these measures to single trials in order to extract power from each trial.

Data Removal Summary

Participant exclusions, artifact removal, and data organization for statistical tests occurred in the following ordered steps:

1. Participant data will be excluded based on the success rates of effort production (i.e., squeezing the hand-dynamometer that reaches a given effort level for a given period of time). If participants fail to produce the required effort successfully on more than 10% of the trials, their data will be excluded from analyses entirely. High success rates of effort production in the task is important; to measure RewP amplitude, both reward and no-reward feedback need to occur approximately with similar frequency (because expectation of feedback occurrence modulates RewP amplitude).

2. If a participant selects the baseline choice or the effort offer on more than 90% or less than 10% of the trials, we plan to exclude data from these participants entirely from all analyses.

3. The entire dataset of a participant will be removed based on EEG artifact rejection criteria (which includes excessive motor artifacts). If more than 30% of the trials contain artifacts overall across conditions, data of this participant will be excluded entirely from the analyses. As

noted in the Participants and Power section, if the number of eligible participants fall below 65 (as per our power analysis) because of this exclusion criterion, we will additionally collect more data.

4. For RewP amplitude, the minimum number of trials for average will be 15 in both the reward and no-reward feedback conditions for each effort and reward level. For FMT power, the minimum number of trials for average will be 15 for each effort and reward level. If these criteria are not met, participants' RewP and FMT data will be excluded.

Statistical Analyses

We will use linear mixed models (i.e., multi-level or hierarchical models) for analyses where there are repeated measures per participant (i.e., measures nested within participants). To fit the models, we will use a restricted maximum likelihood method and unstructured covariance matrix with random intercepts implemented in the lme4 package in R. All continuous regressors will be participant mean-centered. Two-tailed probability values and degrees of freedom associated with each statistic will be determined using the Satterthwaite approximation. Data will be aggregated for each effort and reward level for all the analyses, except when we conduct single-trial analyses (i.e., Hypothesis 1 (i.e., logistic regression) and 4). Trial number will be included for these single-trial analyses to account for growing fatigue over time.

Hypothesis 1: Choice Behavior (single-trial analysis with logistic regression).

We will fit generalized linear mixed effects (logistic regression) to participants' choice behavior.

Model 1: Binary choice on each trial ~ effort +reward + trial number

R syntax: glmer(choice ~ effort + reward + trial_number + (1|participant), family = binomial())

In model 1 we will test whether participants' effort choice will vary as a function of effort and reward levels. We expect to replicate previous finding in which participants will choose the high effort offer more frequently when reward levels increase, but choose it less frequently when effort levels increase.

Hypothesis 2: Which effort processes do FMT power relate to?

Model 2a: FMT power (during choice evaluation) ~ effort + reward

R syntax: lmer(fmtPow ~ effort + reward + (1 | participant))

In model 2a we will test whether FMT power will linearly increase as a function of increasing effort and reward levels during choice evaluation.

Model 2b: FMT power (during effort production) ~ effort + reward

R syntax: lmer(fmtPow ~ effort + reward + (1 | participant))

Similar to model 2a, model 2b will test whether FMT power will linearly increase as a function of increasing effort and reward levels during effort production.

Hypothesis 3: RewP amplitude will vary as a function of effort and reward levels.

Model 3a/3b: RewP amplitude ~ effort + reward

R syntax: lmer(RewP ~ effort + reward + (1 | participant))

In model 3 we will test whether RewP amplitude will increase as a function of increasing effort and/or reward levels. Hypothesis 3a and 3b will be tested within the same statistical model.

Hypothesis 4: Subjective value will be associated with trial-by-trial variations in FMT power, RewP amplitude (or delta power), and/or the FMT-RewP (or -delta) interactions (single-trial analysis).

Model 4: Single-trial subjective value of high effort offer ~ single-trial FMT power + single-trial RewP amplitude (or delta power) + single-trial FMT power * RewP amplitude (or *delta power) interaction + trial number

R syntax: lmer(subjective_value ~ fmtPow * RewP + trial number + (1 | participant))

In model 4 we will test whether trial-by-trial subjective value of effort offer (relative to the baseline choice) will vary as a function of trial-by-trial FMT power during choice evaluation, RewP amplitude (or delta power), and the interaction of FMT power and RewP amplitude (or delta power). We will examine whether a particular electrophysiological measure more strongly relate to variations in subjective values than another electrophysiological measure.

Timeline

If the initial submission is accepted, data collection will begin immediately. We anticipate that data collection will continue up to one academic year (approximately 8 months), followed by 6 to 10 months of data analyses and writing of the final manuscript. This will be approximately 1.5 years in total from the initial acceptance of the research proposal to the submission of a completed manuscript.

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