BEHAVIORAL AND NEURAL EFFECTS OF SELF-DETERMINED CHOICE ON GOAL PURSUIT

by

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DISSERTATION ABSTRACT

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A wealth of research has documented the positive associations between autonomy and health and well-being. Acting in autonomous, self-determined ways promotes intrinsic motivation and has been linked to more successful goal pursuit in numerous domains. However, it is unclear how motivation might affect the ability or tendency to use self-regulatory strategies. If such strategies are the building blocks that enable successful goal pursuit, then investigating how motivation affects strategy implementation might help elucidate the mechanisms underlying the relationship between motivation and goal pursuit.

The goal of this dissertation was to assess whether and how motivation impacts goal pursuit during a novel appetitive self-regulation task in which participants use cognitive reappraisal to control their cravings for personally-desired foods. Since choice is a primary method for supporting autonomy, and autonomy is associated with greater intrinsic motivation and more successful goal pursuit, we expected that manipulating motivation via choice would result in enhanced goal pursuit during this task. Across three experiments, we showed that autonomous and controlled goal pursuit were dissociable neurally, and that autonomous goal pursuit was perceived as less difficult across task goals. Furthermore, we demonstrated that the degree to which choice helps or hinders

goal pursuit is dependent on how self-determined and autonomously motivated choice feels. Together, these results help refine neurobiological and social psychological theories of motivation, self-regulation, and goal pursuit.

This dissertation includes previously published co-authored material.

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CHAPTER I

INTRODUCTION

Whether your goal is to start running, eat more healthfully, or simply to better manage your emotional experience, how successful you are at achieving your goal will have major implications for your health and well-being (Carver & Scheier, 1999; Deci & Ryan, 2000; Sheldon & Elliot, 1999). As universal as goal striving is, so too is the experience of failure and frustration. Why is it that some people are better at achieving their goals than others? What strategies do they use to help them regulate their behavior in goal-congruent ways? And why is it that goals you're passionate about seem easier to accomplish? How does motivation influence goal pursuit? Inspired by these questions, this dissertation will explore how choice, motivation, and difficulty impact goal pursuit in the context of an appetitive self-regulation task with the goal of identifying mechanisms underlying the relationship between motivation and goal pursuit.

Goal pursuit, motivation, and self-regulation

Some goals are large and take years to accomplish, while others might be ticked off a to-do list in the space of an afternoon. In general, a goal can be defined as a mental representation of a desired state or outcome (Braver et al., 2014). Goals are hierarchically organized with lower-level, more concrete goals (e.g., prepare a salad) subserving higher-order, more abstract goals (e.g., live healthfully; Carver & Scheier, 1999). Lower-order goals tend to be more closely connected to the "how" of goal pursuit, whereas higher-order goals tend to be connected to the "why" (Vallacher & Wegner, 1989). Within this framework, the higher a goal is in the hierarchy, the more important and self-relevant it tends to be, with the highest order constituting the ideal self (Carver & Scheier, 1999).

Goals can also be characterized as being more or less integrated into the self with greater integration denoting that a goal is motivated by intrinsic, self-determined reasons, rather than by external pressure or coercion (Deci & Ryan, 2000). As such, Self-Determination Theory posits that the quality of the motivation, or driving force, behind a goal matters; that is, the same goal pursued for two different reasons will be associated with different probabilities of success and implications for well-being. For example, the concrete goal of preparing a salad might be associated with a higher-order goal of eating healthfully for one person *because it feels good* and *because they feel pressured to conform to society's beauty ideals* for another. This example illustrates the distinction between autonomous or "want to" motivation and controlled or "have to" motivation (Milyavskaya et al., 2015; Werner & Milyavskaya, 2019). Self-Determination Theory would predict that the person in the former example would be more likely to accomplish their higher-order goal because their motivation is autonomous rather than controlled.

Autonomous motivation refers to the extent to which goals have been internalized and are pursued for authentic reasons, such as providing meaning and purpose aligned with an individual's core values and identity (Deci & Ryan, 2000; Sheldon & Elliot, 1999). This type of motivation encompasses the motivational orientations outlined in Self-Determination Theory (Deci & Ryan, 2000) as intrinsic, integrated, and identified. Whereas intrinsic motivation refers to goals that are completely internalized and pursued for the sake of interest and enjoyment alone, integrated and identified motivation are less internalized, but are still pursued volitionally. On the other hand, controlled motivation refers to the extent to which goals are pursued due to external factors, such as societal pressure, rewards, or punishments–also referred to as external motivation–or to avoid

internal feelings, such as guilt or shame–which is referred to as introjected motivation. At their core, autonomous goals feel volitional and self-determined–you *want to* do them, whereas controlled goals feels obligatory–you *have to* do them.

Across a large number of studies, research has demonstrated that the reason why a person pursues a goal is critically important for both the probability of success, and for health and well-being more broadly (for reviews and meta-analyses, see Ng et al., 2012; Ryan et al., 2006; Slemp et al., 2018). In contrast to controlled motivation, autonomous motivation has been linked to more successful goal pursuit in a variety of domains (Milyavskaya et al., 2015; Werner & Milyavskaya, 2019; Judge et al., 2005; Sheldon & Elliot, 1998, 1999; Vansteenkiste et al., 2004; Koestner et al., 2002; Werner et al., 2018; Koestner et al., 2008). However, the mechanism underlying the relationship between motivation and successful goal pursuit remains unclear. One hypothesis is that autonomous motivation facilitates goal attainment because goal pursuit is experienced as less effortful and more automatic (Werner et al., 2016; Werner & Milyavskaya, 2019), making it easier to engage in self-regulation, which is defined as goal-congruent behavior (Carver & Scheier, 1982). Throughout this dissertation, self-regulation and pursuit of goals for relatively self-determined, intrinsic reasons will be referred to as autonomous self-regulation and autonomous goal pursuit, whereas those that are pursued for relatively extrinsic reasons will be referred to as controlled self-regulation and controlled goal pursuit.

There are a variety of strategies individuals use to regulate their behavior in service of their goals. Regulation becomes particularly important in the face of tempting, goal-incongruent alternatives, such as browsing Twitter instead of writing your

dissertation. During such dilemmas, individuals can engage in self-control to promote goal-congruent behavior. Although classic definitions of self-control have typically emphasized the effortful inhibition of impulses, more contemporary definitions recognize that self-control need not be effortful (Fujita, 2011; de Ridder et al., 2012; Gillebaart et al., 2018; de Ridder et al., 2018). Here, we use the operational definition of self-control as favoring distal, abstract goals over proximal, concrete goals when they are in conflict (Fujita, 2011). Self-control encompasses a variety of distinct strategies that can be used to navigate goal conflicts (Duckworth et al., 2018). Drawing a parallel to the process model of emotion regulation (Gross & Thompson, 2007), recent research has enumerated various personal strategies, including situation selection and modification, distraction, reappraisal, and suppression, that can be used to exert self-control as a goal conflict unfolds (Duckworth et al., 2016). This reflects a burgeoning integration between the fields of emotion regulation, self-control, and goal pursuit (Gross, 2015).

The studies in this dissertation focus on cognitive reappraisal, which is the reconstrual of a stimulus to change its affective meaning (Gross, 1998). Although much of the original research on cognitive reappraisal was conducted using aversive stimuli, there is growing acknowledgement that it can be used to regulate a variety of affective responses, including appetitive motivations (Giuliani & Berkman, 2015). Indeed, this strategy can be flexibly used to modulate affective responses in order to enhance the value of goal-congruent behavior (e.g., by focusing on how good making progress on your dissertation will feel) or to decrease the value of goal-incongruent behavior (e.g., by reframing Twitter browsing as a waste of time) by emphasizing relevant features of a stimulus (Giuliani et al., 2014; Hutcherson et al., 2012; Kober et al., 2010; Yokum &

Stice, 2013). Furthermore, brief training in cognitive reappraisal has been shown to improve healthy decision making (Boswell et al., 2018), underscoring the translational potential of this strategy. However, it is unclear how motivation might affect the ability or tendency to use self-regulatory strategies. If such strategies are the building blocks that enable successful goal pursuit, then investigating how motivation affects strategy implementation might help elucidate the mechanisms underlying the relationship between motivation and goal pursuit (Cosme & Berkman, 2020).

The paradox of choice

A common means of supporting autonomy and promoting autonomous motivation is to provide individuals with choice (Ryan & Deci, 2006). While many studies have demonstrated a positive relationship between choice and autonomous motivation (for a meta-analysis, see Patall et al., 2008), task performance (Murayama et al., 2015), engagement (Leotti & Delgado, 2011), persistence (Bonita et al., 2019), and self-regulation (Legault & Inzlicht, 2013), others have shown detrimental effects of choice on motivation (Botti & Iyengar, 2004; Iyengar & Lepper, 2000) and self-regulation (Vohs et al., 2008; Bigman et al., 2017). One possibility for these conflicting results is that the quality of the choice options matter. Self-Determination Theory suggests that to enhance autonomous motivation, choice must feel meaningful and self-determined (Reeve et al., 2003; Ryan & Deci, 2006). From this perspective, if choice does not actually confer personal control or if an individual feels pressured to choose a particular option, potential benefits of choice may be undermined (Moller et al., 2006; Sullivan-Toole et al., 2017; Legault & Inzlicht, 2013). On the other hand, some research has suggested that even superficial or illusory control can promote autonomous motivation and improve task

performance (Leotti & Delgado, 2011; Murayama et al., 2015; Langer, 1975). Indeed, a large meta-analysis on the effect of choice on autonomous motivation found that irrelevant choice had the strongest effect on motivation (Patall et al., 2008). It is difficult to reconcile these disparate results and also account for other moderating factors, such as goal difficulty (Sullivan-Toole et al., 2017), choice valence (Leotti & Delgado, 2011), the number of choice options and choices (Patall et al., 2008), and individual differences in preference for choice (Iyengar & Lepper, 1999) and need for autonomy (Schüler et al., 2014). Further research is necessary to determine when and for whom choice promotes autonomous motivation and successful goal pursuit. Throughout this dissertation, I use the term "choice" simply to denote when one or more option is present and "self-determined choice" when the choice architecture is autonomy-supportive and/or choice is perceived as autonomous.

Overview of studies and aims

The overarching goal of this dissertation was to explore whether and how choice affects motivation and goal pursuit during an appetitive self-regulation task. Across three studies, I investigated the following questions: Does choice help or hinder goal pursuit in this context? Does it promote autonomous motivation? Is controlled versus autonomous goal pursuit dissociable behaviorally or neurally? And are the effects of choice moderated by subjective task difficulty and/or individual differences in autonomous motivation? I addressed these questions in three samples of college students–largely during the transition to college–as this period is particularly important for the development of autonomous goal pursuit (Lamborn & Groh, 2009; Oudekerk et al., 2014; Gestsdottir &

Lerner, 2008) and individuals likely vary in the degree to which they have internalized self-regulatory goals and engage in them without external support (Koestner et al., 2010).

Study 1

The purpose of this study was to develop a cognitive reappraisal task that uses appetitive stimuli and incorporates choice. In order to robustly elicit appetitive motivation, we utilized personally-craved food as stimuli and adapted a commonly used craving regulation task (Giuliani et al., 2014; Giuliani & Pfeifer, 2015; Kober et al., 2010) by adding a choice condition. We employed this new task, the Regulation of Craving–Choice (ROC-C) task, in a sample of 33 incoming college freshmen while they underwent functional neuroimaging in an MRI scanner to investigate the neural and behavioral effects of choice on craving regulation.

Study 2

The goal of this study was twofold. First, we aimed to design an improved version of the ROC-C task, in order to control for potential confounds identified during Study 1. Second, we tested whether the effect of choice on task performance during the ROC-C task could be enhanced through experimental manipulation. We devised two between-subject manipulations with the goal of making choice more salient and personally-relevant during the ROC-C task in order to promote autonomous motivation. This pilot study was conducted in a sample of college students (N = 105).

Study 3

The goal of this study was to further investigate the effects of choice on autonomous motivation and goal pursuit during the ROC-C task in a large sample of incoming college freshmen (N = 117) while they underwent functional neuroimaging. We

tested whether choice enhanced goal pursuit, and whether these effects were moderated by the perceived difficulty of goal pursuit and individual differences in autonomous motivation. We also tested whether there was evidence that controlled goal pursuit was dissociable from autonomous goal pursuit neurally.

This dissertation contains published co-authored material. Study 1 (described in Chapter II) is published in *Social Cognitive and Affective Neuroscience* and was co-authored by A. Mobasser, D. Zeithamova, E. T. Berkman, and J. H. Pfeifer.

CHAPTER II

STUDY 1: CHOOSING TO REGULATE: DOES CHOICE ENHANCE CRAVING REGULATION?

This chapter is published in *Social Cognitive and Affective Neuroscience* and is therefore formatted according to the journal's publication standard–the American Psychological Association style manual. It was co-authored by A. Mobasser, D. Zeithamova, E. T. Berkman, and J. H. Pfeifer. With help from my colleagues, I designed and collected the data for this study; I preprocessed and analyzed the data, wrote the first draft of the manuscript, and revised it based on my colleagues' feedback.

Introduction

The ability to control appetitive urges, such as cravings for food or drugs, or impulses to engage in risky sexual behavior, is an essential skill for health and well-being. Craving is an affective state characterized by strong appetitive motivation and can be regulated using various strategies (Giuliani & Berkman, 2015; Kober & Mell, 2015), including cognitive reappraisal or the reconstrual of a stimulus to change its affective meaning (Gross, 1998). Recent research has shown that cognitive reappraisal can be used to effectively reduce cravings for a variety of appetitive stimuli, including food (Siep et al., 2012; Giuliani et al., 2013; Yokum & Stice, 2013; Giuliani et al., 2014), drugs (Kober et al., 2010; Kober et al., 2010) and alcohol (Naqvi et al., 2015) and elicits activity in a network of regions, including dorsolateral (dlPFC), ventrolateral prefrontal cortex and dorsomedial prefrontal cortex (dmPFC) (for a meta-analysis, see Buhle et al., 2014).

While the implementation of cognitive reappraisal has been studied extensively, much less is known about earlier stages in the emotion regulation process, including the decision to engage in regulation (Gross, 2015). As emotion regulation in the real-world typically begins with the decision to regulate, laboratory studies focusing exclusively on regulation implementation may actually misjudge individuals' emotion regulation abilities outside the lab where they might otherwise choose not to engage in emotion regulation in the first place, independent of ability. Indeed, previous research has indicated that regulation ability and frequency are only modestly related (McRae et al., 2012) if at all (Giuliani & Pfeifer, 2015).

Emotion regulation choice

Although this is a relatively new area, researchers have begun to investigate the process of choosing to engage in emotion regulation and factors affecting choice. Within the extended process model of emotion regulation (Gross, 2015), this antecedent stage is referred to as identification, and concerns the processes of forming an emotion regulation goal that ultimately leads to the decision to engage (or not engage) in regulation. Initial studies indicate that when given the choice whether to naturally view aversive images or engage in emotion regulation, individuals choose to regulate their emotions using cognitive reappraisal, though there are individual differences in frequency, and mean frequencies across individuals are lower than might be expected (Suri et al., 2015; Doré et al., 2017). For example, Suri et al. (2015) showed that when individuals were forced to make a choice between viewing aversive images and cognitively reappraising them, individuals chose to reappraise on approximately 40% of trials. However, when the forced choice was removed and the default option was to view (which may be more akin

to the default in the real world), participants chose to reappraise relatively infrequently (approximately 10% of trials), demonstrating that although individuals do choose to use cognitive reappraisal to reduce negative affect, their choices are strongly influenced by the choice architecture.

However, whether and how choosing to regulate affects regulation implementation remains unknown. While the extended process model does not make explicit predictions regarding this relationship, it does posit that the strength of the emotion regulation goal formed during identification will affect the efficacy of implementation, with stronger regulation goals leading to more effective implementation. One factor that likely affects the strength of the regulation goal and the subsequent implementation process is the degree to which the decision to regulate is self-determined.

Choice supports autonomous self-regulation

Self-Determination Theory (Deci & Ryan, 2000) suggests that the degree to which a goal is autonomous will affect the level of intrinsic motivation to regulate. Indeed, environments and choice architectures that promote autonomy facilitate self-regulation and improve health and well-being (Deci & Ryan, 2000; Ng et al., 2012). Although it is difficult to manipulate autonomy in the laboratory, autonomy can be supported by providing individuals with choice. For example, one study showed that choice improved self-regulation on the Stroop task, by increasing intrinsic motivation and heightening attentional engagement (Legault & Inzlicht, 2013). In the context of emotion regulation, one functional neuroimaging (fMRI) study compared the neural and affective consequences of freely chosen reappraisal of aversive images (choice condition) and instructed reappraisal of aversive images (no choice condition; Kühn et al., 2014). In line

with the findings from Legault & Inzlicht (2013), choice was associated with increased activity in regions associated with attention and control (e.g. dlPFC, dmPFC and posterior parietal cortex) and enhanced regulation success. However, it is unknown whether choice will similarly enhance emotion regulation in response to appetitive stimuli.

The present study

The present study integrates the extended process model of emotion regulation and Self-Determination Theory to investigate the relationship between regulation identification and implementation, and characterize whether choice enhances craving regulation at the behavioral and neural levels during reappraisal of appetitive stimuli. Participants were presented with images of personally craved foods and performed two actions: they either actively viewed the foods ('look') or reappraised their cravings for them ('regulate'). Choice was manipulated by instructing participants on each trial whether to view or reappraise ('no-choice') or asking them to choose whether to view or reappraise ('yes-choice'). We hypothesized that choice would increase intrinsic motivation to regulate, resulting in greater regulation success. As such, we expected an interaction between action (look vs regulate) and choice (yes vs no) on craving ratings, such that choice would increase regulation success. Neurally, we expected increased blood-oxygen-level-dependent (BOLD) signal in the frontoparietal control network (e.g. dlPFC, dmPFC and posterior parietal cortex) for the main effect of choice. Due to the lack of previously reported effects, we did not have strong hypotheses regarding regions involved in potential interactions between choice and action.

Materials and methods

Participants

Participants were 33 incoming college students (16 females, $M = 18.12$, $SD = 0.34$) recruited in the summer during freshman orientation at the University of Oregon, as part of a longitudinal study on health and well-being during the transition to college. Three participants were excluded from all analyses for failure to comply with instructions and one for indicating they disliked the food images. Two additional subjects were excluded from the univariate neural analyses because they exhibited excessive motion or did not complete the final run of the task. As follow-up multivariate analyses could still be performed on the participant missing the final task run, this participant was included in these analyses. This yielded a total of 29 participants for behavioral analyses, 27 for univariate neural analyses and 28 for multivariate neural analyses. This study was approved by the University of Oregon Institutional Review Board; all participants gave written informed consent and were compensated for their participation.

Procedure

Participants were presented with images of personally craved foods and completed a craving regulation task while in the MRI scanner. Prior to this, participants completed a structured training session to learn how to perform the craving regulation task and selected their top three 'most craved' foods from a list of 14 food categories (described below). Food craving was operationalized as having a strong desire to eat the food even when not hungry. To control for individual differences in hunger, participants reported their current hunger on a five-point scale (1 = not hungry at all, 5 = extremely hungry) and the time since their last meal. Body mass index (weight in kg/height in m^2)

was measured to control for individual differences in body mass. Participants were then situated in the MRI scanner and completed the craving regulation task (described below). To ensure task compliance, the experimenter interviewed participants after the first run of the task to help them improve their reappraisal strategy if they reported having difficulty and again after scanning to assess fidelity to the reappraisal instructions. Outside of the scanner, participants completed a short rating task in which they rated their craving for (i.e. the desire to eat) each of the food images they viewed while in the scanner. Participants also completed a number of survey measures as a part of the longitudinal study that will not be discussed further.

Stimuli

Stimuli were 84 appetizing images of food items based on participants' food preferences. Participants chose their top three 'most craved' food categories from the following menu: barbeque, burgers, candy, cheese, chips, chocolate, cookies, doughnuts, French fries, fruit, fruit desserts, pasta, pizza and roasted vegetables. Each category contained 28 images independently rated for desirability (stimuli available via http://dsn.uoregon.edu/foodie).

Craving regulation task

Participants completed a craving regulation task (Giuliani et al., 2014; Giuliani & Pfeifer, 2015) that was modified to include a choice manipulation. Participants either actively viewed ('look' condition) or reappraised their craving for ('regulate' condition) the food images. On half of the trials, participants freely chose whether to look or regulate ('yes-choice' condition), and on the other half, participants were instructed whether to look or regulate ('no-choice' condition). Therefore, the task design was a 2 × 2

within-subjects repeated measures factorial with action (look, regulate) and choice (yes, no) as factors. To ensure a sufficient number of observations per condition, participants were instructed to choose to look approximately 50% of the time and to regulate the other 50%. They were reassured, however, that it was fine if their ratio was not exactly 50/50. They were also informed that their choices should be spontaneous (e.g. not alternating between the two actions). Descriptive analyses confirmed that participants were generally able to follow these instructions. The average percentage of regulation trials in the choice condition was 49.4% (SD = 5.4%; range = 38.1%–61.0%). More information regarding the relationship between percentage of regulation trials and outcome measures can be found in the Supplementary material.

On all look trials, participants were instructed to imagine that the food items were real and to consider how they would interact with them. On all regulate trials, participants were instructed to reappraise their craving for the foods by considering short- or long-term negative health consequences associated with consumption (e.g. stomach aches, weight gain, cavities), and participants were instructed to try to imagine how the health effects would feel physically. With the help of the experimenter, participants generated several negative health consequences so as to have multiple strategies to use while completing the task.

Each trial (see Figure 2.1) was 15 seconds long and consisted of the following events: cue (2 seconds), image presentation (7 seconds), craving rating (4 seconds) and action report (2 seconds). Inter-trial intervals were selected from a gamma distribution jitter (M = 1.01, SD = 0.26), and participants viewed a fixation cross during this period. On each trial, participants were cued about the instruction to look or regulate (no-choice

condition) or to make a choice to look or regulate (yes-choice condition). The task consisted of three runs and each run consisted of 28 trials: 7 trials instructing participants to look, 7 trials instructing participants to regulate and 14 trials instructing participants to choose whether to look or regulate. To reduce potential image-related confounds (i.e. choosing to regulate on relatively less craved images and choosing to look on relatively more craved images) on choice trials, participants made their decision during the cue phase and were told that it was important to stick with their choice once made. After the cue, participants proceeded to look or regulate while viewing the food image, reported their craving for the food by rating how much they desired to eat the food item (1 = no desire, 5 = strong desire) and finally reported their instructed or chosen action. To minimize demand characteristics (e.g. reduced craving ratings on regulate trials), the experimenter stated that participants were not expected to be able to regulate well on every trial and stressed the importance of making honest craving ratings. Within each run, the trial order was optimized to maximize contrast estimation using a genetic algorithm (Wager & Nichols, 2003). Stimuli and trial order varied by subject, and run order was also counterbalanced across participants. Stimuli were presented using Psychtoolbox 3 (Brainard, 1997), and participants responded using a five-button box.

Figure 2.1. Task design. Each trial consisted of a 2 second cue period, followed by a 7 second image presentation during which participants looked or regulated while viewing the food image. Participants then had 4 seconds to rate their desire to eat the food and 2 seconds to report whether they looked or regulated on the trial. All trials ended with a jittered fixation cross for an average of 1 second.

Post-task craving ratings

Participants completed a rating task after the scan session to account for idiosyncratic reactions to stimuli (e.g. not liking some ice cream images due to the presence of a disliked topping). Participants were instructed to view the images afresh and rate their current craving, irrespective of their rating during the regulation task. Post-task ratings were centered within-subject to account for potential habituation effects.

Neuroimaging data acquisition

Data were acquired using a 3T Siemens Skyra scanner at the University of Oregon's Lewis Center for Neuroimaging. High resolution anatomical volumes were acquired using a T1-weighted MP-RAGE pulse sequence and functional volumes were acquired using a T2*-weighted echo-planar sequence (voxel size = 2 mm^3). Scan parameters are listed in Supplementary material.

Behavioral analysis

Multilevel modeling was used to test the effects of action and choice on self-reported craving ratings. Post-task craving ratings were included as a covariate to control for idiosyncratic reactions to stimuli. The model included the fixed effects of action,

choice, action × choice and post-task craving ratings, and the inclusion or exclusion of random effects was determined by sequentially removing effects that did not account for significant variance (see Supplementary material). Regulation success was defined as the mean difference in craving ratings between look and regulate conditions (look − regulate) and was calculated for each level of choice separately. Statistical analyses were performed in R 3.3.0 (R Core Team, 2016; https://www.r-project.org/) using the lme4 package (Bates et al., 2015). Behavioral data and related analysis scripts are available via the Open Science Framework (http://osf.io/e9cqv).

Univariate neural analysis

Images were preprocessed and analyzed using SPM12 (Wellcome Department of Cognitive Neurology; http://www.fil.ion.ucl.ac.uk/spm) with the following steps: realignment of functional images, coregistration of the anatomical image, manual reorientation of all images, and segmentation of the anatomical image. Segmented images for each subject were combined to form a group template using Dartel and flow fields were generated for each subject. Functional images were then spatially normalized to a Montreal Neurological Institute (MNI) standard using the Dartel template and individual flow fields, and smoothed using a 6 mm^3 full-width at half maximum (FWHM) Gaussian smoothing kernel.

In first-level statistical analyses, event-related condition effects were estimated using a fixed-effects general linear model and convolving the canonical hemodynamic response function with stimulus events. Separate regressors were entered for conditions of interest (no-choice look, yes-choice look, no-choice regulate and yes-choice regulate) and modeled during the image presentation period. Additional regressors were added for

the cue period, rating period and reporting period. Realignment parameters were transformed into five motion regressors, including absolute displacement from the origin in Euclidean distance and the displacement derivative for both translation and rotation, and a single trash regressor for images with >1 mm translation or rotation or visible motion artifacts (e.g. striping). These regressors were included as covariates of no interest. One participant was excluded from the group-level analysis for having >15% unusable volumes, which was more than 3 *SD* from the mean ($M = 2.26\%$, $SD = 4.08\%$). Additional regressors (covariates of no interest) were included as needed for trials in which participants failed to report whether they looked or regulated during yes-choice trials (N = 21, 0.87% of trials), or reported doing the opposite of the instruction during no-choice trials (N = 20, 0.83% of trials). All data were high-pass filtered at 128 seconds and modeled with a first-order autoregressive error structure. Linear contrasts for each condition of interest vs rest were estimated for each participant and used as inputs in second-level analyses.

A flexible factorial model was used to estimate second-level random effects. To determine the main effects of action, choice and their interaction, condition contrast images from each participant were used as inputs. This model was masked using a gray matter mask created by calculating the average of all subjects' segmented grey matter maps, smoothing the average with a 6 mm^3 FWHM Gaussian smoothing kernel and binarizing using the optimal thresholding protocol.

To correct for multiple comparisons, cluster-extent thresholding was implemented using AFNI version AFNI_16.1.06 (Cox, 1996). Smoothness was first estimated for each subject using AFNI's 3dFWHMx tool with the spatial autocorrelation function and then

averaged across subjects. To determine probability estimates of false-positive clusters given a random field of noise, Monte-Carlo simulations were conducted with AFNI's 3dClustSim. To achieve a whole-brain familywise error rate of $\alpha = 0.05$, a voxel-wise threshold of $p < 0.001$ and cluster extent of $k > 108$ was estimated (voxel dimensions = 2 mm^3).

Multivariate neural analysis

To further explore differences in neural activity between yes-choice and no-choice trials, we conducted a follow-up analysis using multi-voxel pattern analysis (MVPA). For each participant, functional images were realigned, coregistered to the high-resolution anatomical image and smoothed using a 2mm^3 FWHM Gaussian smoothing kernel in SPM12. The same first-level modeling procedure detailed above was followed, with the exception that models were run in native-space and each trial was entered in the model as a separate regressor (rather than grouped by condition). The resulting statistical maps for each trial were concatenated to create a beta-series (Rissman et al., 2004) and z-scored within run.

Classifier-based MVPA analyses were implemented in MATLAB 2014a (MathWorks; http://www.mathworks.com) using the Princeton MVPA Toolbox (Detre et al., 2006). To restrict the number of voxels, subject-specific masks were created using a standard parcellation atlas based on intrinsic connectivity from resting-state fMRI (Yeo et al., 2011). The frontoparietal network from this atlas was registered for each subject using FreeSurfer (Fischl, 2012; http://surfer.nmr.mgh.harvard.edu/) and binarized in SPM12. We then tested how well the trial-by-trial activation patterns in the frontoparietal network differentiated between look and regulate trials using a leave-one-out cross-

validation procedure. During each cross-validation fold, a linear logistic regression classifier was trained to distinguish between look and regulate trials from two of three functional runs and then applied to the remaining run. This procedure was repeated so that each run served as a testing run, yielding three cross-validation accuracies for each subject. To test whether classification accuracy differed as a function of level of choice, this procedure was conducted separately for yes-choice and no-choice trials and accuracy was regressed on choice using multilevel modeling with subject intercepts as random effects.

Results

Behavioral results

We used multilevel modeling to evaluate the effect of choice and action on self-reported craving ratings. All parameter estimates and relevant statistics can be found in Table 2.1. Consistent with previous findings, we found a significant main effect of action (see Figure 2.2), with lower ratings for food items on regulate trials ($M = 2.36$, $SD = 0.98$) than on look trials ($M = 3.72$, $SD = 1.14$). As expected, craving ratings on no-choice trials *(*$M = 3.04$, $SD = 1.29$) did not differ from yes-choice trials ($M = 3.05$, $SD = 1.24$) and the main effect of choice on craving ratings was not significant. The interaction between action × choice was significant (Figure 2.3), but contrary to our predictions, the difference between look and regulate trials was lower for yes-choice trials ($M_{diff} = 1.29$, $SD = 0.59$) than for no-choice trials ($M_{diff} = 1.42$, $SD = 0.60$). Further, visual inspection revealed that choice affected both the look and regulate conditions, with cravings on yes-choice look trials rated lower than on no-choice look trials and higher on yes-choice regulate trials than on no-choice regulate trials (Figure 3B). Including hunger, last meal time, and body

mass index did not improve model fit or change any of the results, $\chi 2(3) = 1.79$, $p = 0.616$.

Table 2.1

Parameter estimates for fixed effects behavioral analysis

Parameter	*b*	95% CI		*SE*	*df*	*t*	*p*
Intercept	3.70	3.51	3.90	0.10	32.00	37.48	< .001
Choice (yes)	-0.07	-0.16	0.03	0.05	2261.57	1.37	.171
Action (regulate)	-1.34	-1.57	-1.10	0.12	33.75	11.43	< .001
Average post-task rating	0.39	0.33	0.46	0.03	28.34	11.83	< .001
Choice × Action	0.15	0.01	0.29	0.07	2256.06	2.14	.032

Note. The reference group for Choice is no and the reference group for action is look. Degrees of freedom *(df)* were calculated using the Satterthwaite approximation. CI, confidence interval.

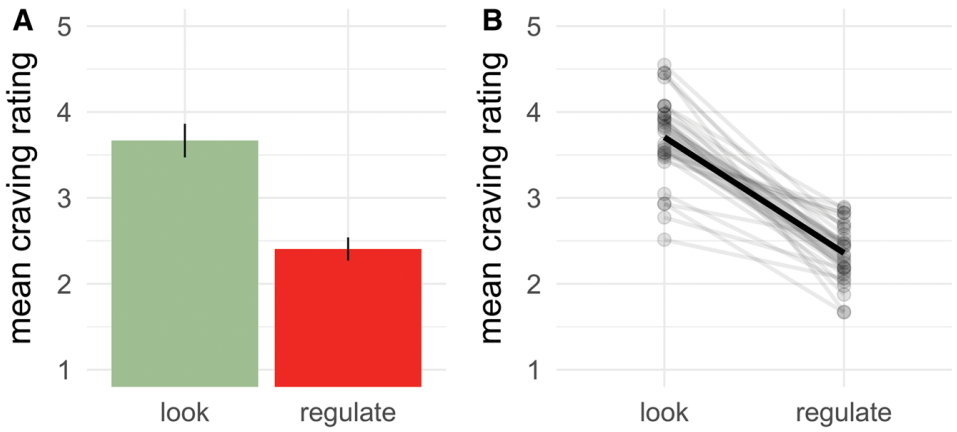

Figure 2.2. (A) Parameter estimates for the fixed-effect of action from the multilevel model predicting self-reported craving ratings and (B) the raw subject means. Error bars and bands are 95% confidence intervals.

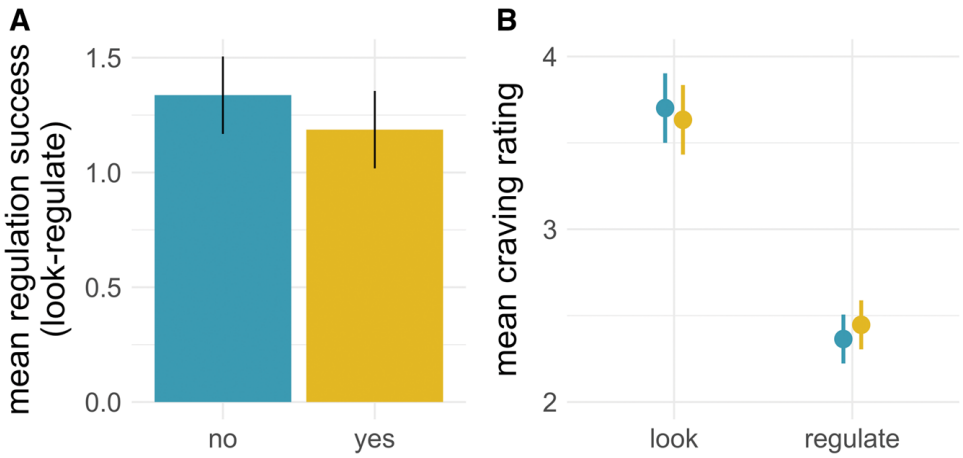

Figure 2.3. Parameter estimates from the multilevel model predicting self-reported craving ratings, plotted as (A) mean regulation success (look − regulate) for no- and yes-choice separately and (B) the interaction between Action and Choice (blue = no, yellow = yes). Error bars are 95% confidence intervals.

Univariate neural results

Main effect of choice. To investigate areas that showed relatively greater BOLD signal during implementation following choice, a contrast of yes > no was computed during the image presentation period (Figure 2.4). We observed increased BOLD signal in the frontoparietal control network, with significant clusters in bilateral posterior parietal cortex and lateral and medial prefrontal cortex. Additional clusters were found in left inferior temporal gyrus and left cerebellum. The reverse contrast, no > yes choice (Figure 2.4), revealed significant clusters of activation in bilateral ventromedial prefrontal cortex with a peak in left middle orbital gyrus. Table 2.2 shows the full results. Unthresholded statistical maps for this effect and all other effects reported in this article are available through NeuroVault (Gorgolewski et al., 2015; http://neurovault.org/collections/2427).

Table 2.2

Regions, MNI coordinates, cluster extent, and peak t values for the main effects of yes > no choice and no > yes choice

Contrast and region	MNI Coordinates (x, y, z)			Extent (k)	Peak *t*
Yes > No					
R Angular Gyrus	44	-50	38	1037	6.03
R Inferior Parietal Lobule	44	-44	60	1037	4.02
R Middle Frontal Gyrus	32	46	38	1952	5.88
R Middle Frontal Gyrus	42	50	20	1952	5.41
R Middle Orbital Gyrus	22	60	-8	1952	4.58
L Inferior Parietal Lobule	-44	-48	42	1013	5.23
L Superior Parietal Lobule	-32	-64	50	1013	3.67
L Cerebellum (VII)	-40	-72	-52	771	5.06
L Cerebellum (VIII)	-40	-48	-46	771	4.59
L Cerebellum (Crus 1)	-42	-80	-26	771	4.07
Bilateral PCC	0	-26	28	140	4.83
R Precuneus	12	-60	40	272	4.73
L Precuneus	-8	-66	40	272	4.53
L Superior Medial Gyrus	2	22	50	363	4.51
L Inferior Temporal Gyrus	-60	-34	-18	221	4.47
L Middle Frontal Gyrus	-32	54	18	265	4.41
R IFG (p. Orbitalis)	36	26	-6	142	4.39
R Superior Frontal Gyrus	18	18	54	326	4.08
R Middle Frontal Gyrus	38	10	52	326	3.88
L Inferior Parietal Lobule	-38	-52	44	1013	3.37
No > Yes					
L Mid Orbital Gyrus	-2	50	-8	334	4.91

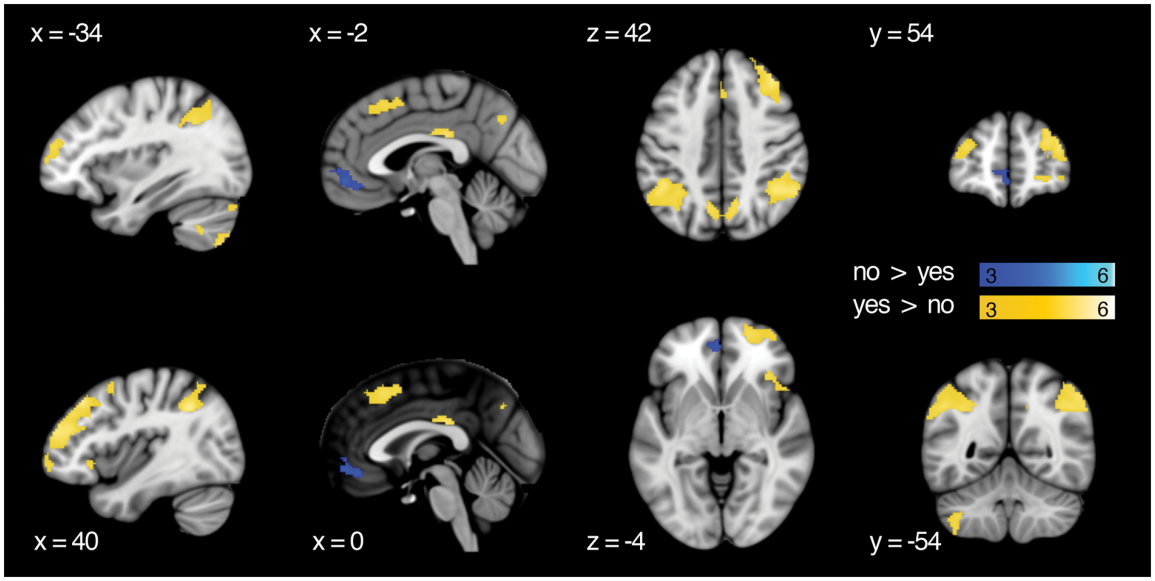

Figure 2.4. Univariate main effects for Choice. Results are thresholded at $p < .001$ and $k = 108$. Cluster extent (k) is measured in 2 mm^3 voxels.

Main effect of action. To assess which areas of the brain had relatively stronger BOLD response when participants were reappraising their cravings and actively viewing food items, we computed contrasts for regulate > look and look > regulate. These results maps are visualized in Figure 2.5, and clusters that survived thresholding are reported in Table 2.3.

Table 2.3

Regions, MNI coordinates, cluster extent and peak t values for the main effects of regulate > look and look > regulate

Contrast and region	MNI Coordinates (x, y, z)			Extent (k)	Peak *t*
Regulate > Look					
L Post. Med. Frontal Gyrus	-8	14	66	1796	7.49
L Superior Frontal Gyrus	-12	52	42	1796	6.63
L Superior Medial Gyrus	-8	34	52	1796	5.78
L Middle Frontal Gyrus	-44	10	54	782	6.88
L IFG (p. Orbitalis)	-48	34	-12	2495	6.83
L Temporal Pole	-40	14	-40	2495	6.06
L IFG (p. Triangularis)	-54	18	16	2495	5.91
R Cerebellum (VII)	32	-76	-44	1216	6.75
R Cerebellum (Crus 2)	10	-82	-26	1216	5.37
L Middle Temporal Gyrus	-66	-36	-2	167	4.38
Look > Regulate					
R IFG (p. Triangularis)	48	34	20	3284	6.02
R Middle Orbital Gyrus	38	48	-6	3284	5.87
R Superior Frontal Gyrus	20	58	10	3284	5.22
L Postcentral Gyrus	-50	-22	22	3657	5.89
L IFG (p. Opercularis)	-60	6	32	3657	5.61
L Postcentral Gyrus	-42	-32	60	3657	5.48
R Intraparietal Sulcus	30	-44	42	3125	5.53
R Rolandic Operculum	58	-18	22	3125	5.37
R Angular Gyrus	34	-66	52	3125	4.85
R Intraparietal Sulcus	30	-44	42	3125	5.53
R Insula Lobe	42	-2	12	181	5.42
R Insula Lobe	42	-2	12	181	5.42
L Post. Med. Frontal Gyrus	-2	-4	54	189	4.88
R MCC	10	-38	42	769	4.79
R Precuneus	6	-66	50	769	3.85
L Precuneus	-2	-46	62	769	3.59
R Inferior Temporal Gyrus	58	-40	-12	554	4.74
R Cerebellum (Crus 1)	48	-56	-24	554	3.72
R Inferior Temporal Gyrus	60	-20	-22	554	3.54
R IFG (p. Opercularis)	46	8	32	516	4.74
R IFG (p. Opercularis)	56	8	14	516	3.94
L Cerebellum (VIII)	-28	-70	-52	298	4.69
R Cerebellum (VIII)	22	-56	-52	260	4.29
R Calcarine Gyrus	10	-68	22	285	4.19
L Inferior Temporal Gyrus	-52	-58	-8	163	3.89

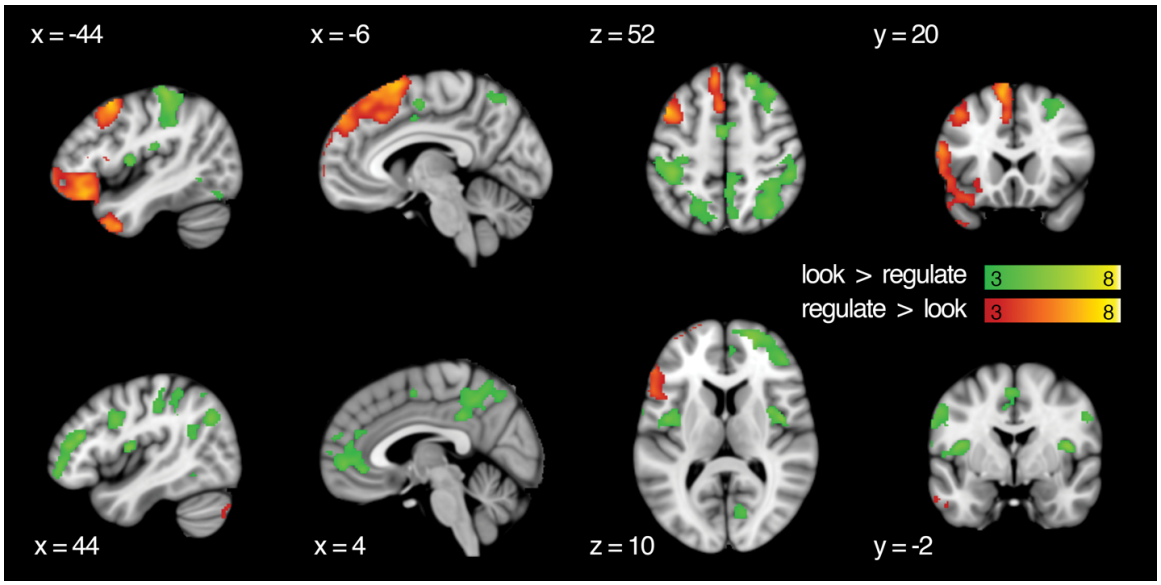

Figure 2.5. Univariate main effects for Action. Results are thresholded at $p < .001$ and k = 108. Cluster extent (k) is measured in 2 mm^3 voxels.

Interaction between action and choice. No significant clusters of activation for either the positive or negative effect of the interaction survived thresholding. However, to explore sub-threshold interactions, we parcellated the brain into 353 clusters (Craddock et al., 2012) and calculated the average effect size for the interaction within each parcel. This map, as well as similar maps for the simple effects, has been uploaded to the collection for this article on NeuroVault.

Post hoc multivariate neural results

We expected that choice would increase engagement with the task, resulting in increased activity in attention- and control-related regions and greater regulation success. Though we observed increased activity in the frontoparietal network following choice, behavioral results indicated *reduced* rather than enhanced regulation success. Although seemingly at odds, one hypothesis consistent with these findings is that choice may disrupt concurrent allocation of cognitive resources that are bandwidth limited (Vohs et

al., 2008). We reasoned that if choice disrupted cognitive resource allocation during implementation, then neural representations for look and regulate would be less distinguishable in the yes-choice vs no-choice condition, mirroring the reduced self-reported regulation success in the choice condition. To test this hypothesis, we conducted post hoc analyses using MVPA. We measured classification accuracy of look vs regulate trials in the frontoparietal network and predicted lower classification accuracy on yes-choice relative to no-choice trials. Consistent with this prediction, we observed significantly lower classification accuracy for yes-choice ($M = 0.65$, $SD = 0.16$) than for no-choice ($M = 0.70$, $SD = 0.17$) trials, $t(137.17) = 2.48$, $p = .014$. Parameter estimates and statistics are in Table 2.4 and visualized in Figure 2.6.

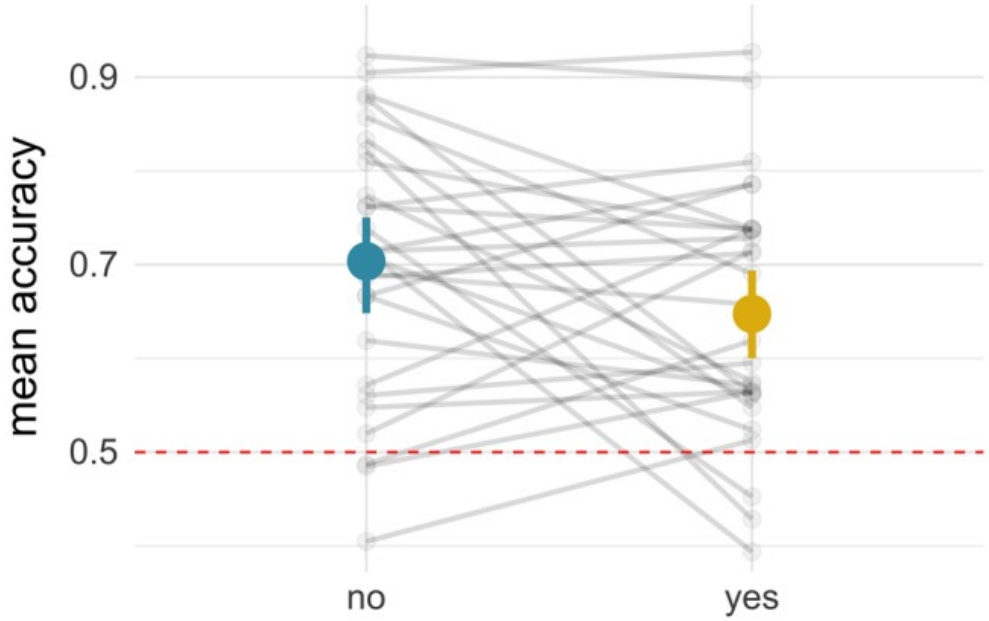

Figure 2.6. Mean group and subject classification accuracy from MVPA analyses classifying look and regulate trials, plotted separately for no- and yes-choice. Error bars are 95% confidence intervals and the dotted line at 50% represents chance accuracy.

Table 2.4

Parameter estimates for fixed effects of MVPA analysis

Parameter	*b*	95% CI		*SE*	*df*	*t*	*p*
Intercept	0.70	0.66	0.75	0.02	41.82	29.91	< .001
Choice (yes)	-0.05	-0.09	-0.01	0.02	137.17	2.48	.014

Note. The reference group for choice is no. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. CI, confidence interval.

Discussion

Our goal was to investigate whether and how choice affects appetitive regulation during a craving reappraisal task. As expected, reappraisal effectively reduced self-reported craving for personally craved foods. In line with previous studies, we also observed increased activity in regions associated with reappraisal (e.g. dlPFC, ventrolateral prefrontal cortex and dmPFC) and decreased activity in vmPFC, a region implicated in valuation and reward-processing (Hare et al., 2009; Kober et al., 2010; Giuliani et al., 2014). However, contrary to our prediction, choice slightly *reduced* rather than enhanced regulation success. This behavioral effect was not readily explainable by the univariate activation results. While choice was associated with relatively greater BOLD signal in the frontoparietal control network, there were no interactions at the whole-brain level that might explain the behavioral results. To reconcile the neural and behavioral findings, we hypothesized that choice may have disrupted allocation of cognitive resources during implementation. Consistent with this hypothesis, classifier-based MVPA demonstrated less differentiation between look and regulate trials in the yes-choice relative to no-choice condition.

Neural and behavioral effects of choice

Based on the theoretical premise that choice would enhance motivation for and engagement with the task, we expected to see increased BOLD signal in regions associated with attention and control following choice. In accordance, we replicated previous research showing increased activity in the frontoparietal control network during choice trials (Kühn et al., 2014). However, in contrast to Kühn et al. (2014), this activity was not accompanied by enhanced regulation success. Instead, choice slightly reduced regulation success on average.

One key difference between Kühn et al. (2014) and our study is that we used appetitive rather than aversive stimuli. Because appetitive stimuli like craved foods typically elicit approach tendencies rather than avoidance tendencies (Lang & Bradley, 2010), motivation to regulate affective responses likely differs between appetitive and aversive stimuli. This asymmetry may have made regulation more effortful in our study and could have undermined potential regulatory enhancement effects of choice. Although this has not been tested directly with emotional pictures, recent research has shown that affective context can modulate the effect of choice. For example, when both gains and losses are presented, individuals prefer choice in the gain, but not the loss condition (Leotti & Delgado, 2014).

Another potential explanation that reconciles these findings is that choice led to inefficient allocation of limited cognitive resources, such as attention and working memory. On choice trials, participants may have over-allocated attention to the decision during the choice phase (e.g. by tracking the number of times they chose to look and regulate) or equivocated about the decision during the implementation phase, resulting in

the combination of increased activity in the frontoparietal network and reduced implementation efficacy. Consistent with this explanation, the follow-up MVPA analyses suggested that the neural representations for look and regulate trials were less differentiable. The pattern of the behavioral results also supports this conclusion, as choice reduced implementation efficacy for both look and regulate trials. That is, craving ratings were *lower* on yes-choice look trials than on no-choice look trials and *higher* on yes-choice regulate trials than on no-choice regulate trials. Together, these results support the hypothesis that, rather than enhancing task engagement and regulation success, in some contexts, choice may disrupt regulation. These findings are significant because the majority of research on cognitive reappraisal has focused narrowly on regulation per se without considering the effects of the antecedent choice to regulate, and therefore may misjudge cognitive regulation ability outside the lab when individuals must first choose to regulate their emotions.

Helpful and harmful effects of choice

Although the present manipulation of choice did not enhance regulation success, other laboratory studies have demonstrated positive effects of choice on self-regulation (Legault & Inzlicht, 2013; Kühn et al., 2014) and task performance (Murayama et al., 2015) and engagement (Leotti & Delgado, 2011; Legault & Inzlicht, 2013) more generally. Although several of these studies manipulated choice in a similar fashion, it is possible that choice in the context of this study may have felt burdensome rather than motivating (Schwartz, 2000; Vohs et al., 2008).

Indeed, although choice often promotes autonomy and intrinsic motivation, in certain contexts, choice can be detrimental. For example, individuals report decreased

preference for choice in decisions involving unattractive or difficult options (Iyengar & Lepper, 2000; Botti & Iyengar, 2004). For choice to enhance motivation, choices should feel volitional and self-determined (Reeve et al., 2003; Ryan & Deci, 2006). If individuals feel pressured or compelled to choose a particular option, or if the choice does not confer actual agency (i.e. the locus of perceived causality is external), the positive effects of choice can be undermined (Moller et al., 2006; Legault & Inzlicht, 2013; Sullivan-Toole et al., 2017). In our study, we asked participants to try to look and regulate approximately equally. While necessary to ensure there were sufficient trials per condition, this may have reduced participants experience of self-determination on choice trials. Further, because we sought to study the effect of choice on craving regulation in a normative sample and therefore did not explicitly recruit participants based on health- or diet-related goals, it is possible that choice in this context may not have been meaningful to all participants. Future research assessing the relationship between choice and craving regulation may benefit from a stronger choice manipulation to support autonomy, such as by providing more personally relevant choices or studying this relationship in individuals with explicit health or dietary concerns.

This study has several limitations. First, on choice trials, participants chose before viewing the food images. We did this to avoid confounding the decision to regulate with stimulus features (e.g. looking when food images were relatively more craved and regulating when food images were relatively less craved), even though it restricted ecological validity. Second, our task was not designed to assess how choice affected neural activity separately during the choice and implementation phases. Because regulation choices likely involve a host of cognitive processes, such as working memory

to track previous decisions and effort calculations (Shenhav et al., 2013), we cannot rule out that these processes extended into the implementation phase. Indeed, this explanation would be consistent with the pattern of results indicating that choice disrupted implementation. Future studies may benefit from separating the choice and implementation phases to control for increases in cognitive load associated with choice (e.g. decision making and set shifting; Lo et al., 2012). It is possible that doing so would reduce the cognitive disruption and lead to enhanced regulatory success in the choice condition. However, it is important to note that implementation under the present conditions may more closely resemble the implementation process in the real-world. Third, to have sufficient trials per condition, participants were instructed to look and regulate approximately equally. This was necessary to ensure adequate power, but regulation frequency is likely an individual difference that should be investigated subsequently (see Supplementary material; McRae et al., 2012). Fourth, we did not measure affective experience, perceived effort or self-determination. Including these measures would help characterize the effects of choice on craving regulation. Fifth, we focused on cognitive reappraisal, but there are other effective regulatory strategies, such as mindfulness-based approaches, that require less effortful control (Westbrook et al., 2013; Kober & Mell, 2015). Because choice appears to have taxed limited cognitive resources, it may differentially affect such regulatory strategies and should be investigated in future studies. Finally, future studies should extend this work to include other outcomes measures, such as food choice (Hare et al., 2011; Hutcherson et al., 2012).

Conclusions

The present study is the first to investigate how choice affects appetitive regulation in the context of a craving reappraisal task. This study adds to the growing body of research on the cognitive regulation of appetitive motives, as well as emerging research on regulation choice. Contrary to the theoretical prediction that choice would increase task engagement and improve regulation, choice actually disrupted the implementation process, resulting in increased activity in the frontoparietal network and reduced regulation success. These unexpected results highlight the importance of considering upstream processes, such as regulation choice, when studying emotion regulation.

Supplementary material

Supplementary material for this study is included in Appendix A.

CHAPTER III

STUDY 2: A PILOT STUDY COMPARING THE EFFICACY OF TWO EXPERIMENTAL AUTONOMY MANIPULATIONS TO ENHANCE TASK PERFORMANCE

Introduction

Building on the results from Study 1, which suggested that choice may have taxed cognitive resources and felt burdensome rather than motivating, the purpose of this study was to redesign the Regulation of Craving–Choice (ROC-C) task and test whether the effect of choice on goal pursuit (i.e., task performance) could be enhanced through experimental manipulation. We reasoned that choice may only improve goal pursuit if it is perceived as self-determined–that is, it feels volitional and self-relevant–and therefore devised two between-subject manipulations with the goal of strengthening the connection between choice and autonomy.

The first experimental manipulation ("Food" manipulation) sought to bolster autonomy by giving participants meaningful choice about how they approached the task, by either emphasizing the consequences of eating the foods they saw in the ROC-C task or emphasizing the immediate experience of eating the foods. After choosing how they wanted to approach the task, they wrote a short paragraph elaborating on why they made this choice. The second experimental condition ("Agency" manipulation) sought to bolster autonomy by emphasizing the value of choice and highlighting choice as a form of self-expression and means of agency. Participants in this condition read a short paragraph about how choice is a fundamental part of being human and how choices–big

and small alike–shape identity, and then wrote a short paragraph about a specific choice they recently made that illustrated taking ownership of their life.

We also made several substantial modifications to the ROC-C task used in Study 1, which showed reduced regulation success and greater activity in the salience and frontoparietal control networks on choice trials. First, we altered the task design by grouping trials in sets of three to reduce potential set shifting costs and cognitive burden associated with choice. Thus, rather than choosing (or being instructed) on every trial individually, participants chose (or were instructed) to pursue the same goal for three trials in a row. Second, we added a short preview of the three upcoming foods prior to the choice/instruction cue and added a short break after the cue to more clearly separate the act of choosing from goal pursuit. Third, we unconstrained choice so that participants were encouraged to choose to look and regulate as frequently as they wanted, rather than doing so approximately evenly. Fourth, we added summaries of participant choices at the end of each task run to reduce potential cognitive load associated with keeping track of their choices throughout the task. Last, we added difficulty ratings after each trial to investigate the degree to which choice affects perceived difficulty of goal pursuit on a trial-by-trial basis.

The goal of this study was to pilot this new version of the ROC-C task and determine whether we could potentiate task effects by adding an experimental manipulation designed to make choice feel more self-determined. Across all experimental groups, we expected that choice would be associated with enhanced task performance. With respect to trial-level difficulty ratings, we expected that the Regulate condition would be rated as more difficult than the Look condition and that choice would be

associated with lower perceived difficulty (Werner et al., 2016; Milyavskaya et al., 2015). We also investigated the possibility that autonomous motivation enhanced by choice may only be helpful when goal pursuit is perceived as relatively difficult (Klein et al., 1999). If this were the case, then we would expect to observe an interaction between task Goal, Choice, and Difficulty. We used model comparison to determine whether the difficulty of goal pursuit accounted for additional variance and interpret effects of the between-subject autonomy manipulations in the best fitting model.

We expected that successful manipulations would be associated with stronger effects of choice on task performance, operationalized as the interaction between Goal and Choice (and potentially Difficulty). For participants in the Food autonomy manipulation group, we expected that improvements in task performance would be related to which approach they identified with and chose to focus on during the task. Specifically, we expected that those who chose to focus on the immediate experience of eating food during the task would show higher craving ratings when they chose to look, whereas those who focused on the consequences of consumption would show lower craving ratings when they chose to regulate. For those in the Agency autonomy manipulation group, we expected choice effects to operate on both task goals; that is, choosing to look would be associated with higher craving ratings and choosing to regulate would be associated with lower craving ratings. We also expected successful manipulations to be associated with increased perceived autonomous motivation rated after the ROC-C task was completed.

Method

Participants

Participants were 105 college students (65 females, 37 males, 3 not reported; M_{age} = 20.66, SD_{age} = 3.10) recruited through the University of Oregon Human Subjects Pool. No participants were excluded from this study. This study was approved by the University of Oregon Institutional Review Board; all participants gave written informed consent and were compensated with course credit for their participation.

Procedure

First, participants selected their three "most craved" foods from a list of 14 categories (described below) and completed a rating task to assess craving ratings prior to the ROC-C task. Food craving was operationalized as having a strong desire to eat the food, even when not hungry. Next, participants were randomly assigned to one of two experimental autonomy manipulation conditions, "Food" (N = 38) or "Agency" (N = 32), or a control condition, "Control" (N = 35). Participants in the Food and Agency manipulation conditions completed a writing task, whereas participants in the Control condition did not. After this, all participants completed a structured training session to learn how to perform the Regulation of Craving–Choice (ROC-C) task and completed a short practice task to familiarize themselves with the task timing. To ensure task compliance, the experimenter interviewed participants after the first run of the task to help them improve their reappraisal strategies if they reported having difficulty and again after the task to assess fidelity to the reappraisal instructions. After the task, participants completed the Intrinsic Motivation Inventory (Ryan, 1982; McAuley et al., 1989), as well as individual difference measures and experimental manipulation questions.

Measures

Agency manipulation. In an effort to increase the connection between choice and autonomy while completing the ROC-C task, participants in the Agency autonomy manipulation group completed an experimental manipulation inspired by Whitson & Galinsky (2008). In this manipulation, participants read the following passage, which emphasized choice as a form of self-expression and a means of agency:

> The following information will be important to keep in mind as you complete the rest of the study.
>
> "Our ability to make choices is fundamental to our sense of ourselves as human beings . . . . Whom we love; where we work; how we spend our time; what we buy; such choices define us in the eyes of ourselves and others . . . ."
> –Cass Sunstein, Legal Scholar
>
> "We are the captains of our own ships. Nearly each and every choice is yet another opportunity to steer the course of our lives."
> –Unknown
>
> As these quotes illustrate, making choices is an important part of being human. We make choices all the time. Some are big–which class to take, what career to pursue, who to marry; other choices are smaller–what to eat, which clothes to wear, or which route to take to school or work. No matter the size, making choices is a critical way in which we express and define ourselves, as well as take ownership of our lives. The ability to make choices is also important for health and well-being. Research shows that making choices and feeling in control are essential ingredients for leading a healthy, happy life.

They then wrote 4-6 sentences about a specific choice they made in the past few weeks that demonstrated having agency and taking ownership of their lives. The purpose of this manipulation was to emphasize that even small choices, including choosing which goal to pursue in the ROC-C task, can be expressions of one's identity and manifestations of autonomy.

Food manipulation. Because participants were not recruited based on whether they valued healthy eating or had explicit goals to control their desire for unhealthy foods, and therefore may not perceive choice during the ROC-C task as goal-relevant in a broader sense, this experimental manipulation sought to provide participants with a meaningful choice for how they approached the ROC-C task. Participants saw the following text and chose whether they wanted to emphasize the immediate experience of eating foods (more akin to the "look" condition in the ROC-C task; N = 22) or focus on the potential consequences of eating the foods (more akin to the "regulate" condition in the ROC-C task; N = 16). They then wrote 4-6 sentences explaining and elaborating on their preference for the approach to food that they chose to emphasize during the task.

> The following information will be important to keep in mind as you complete the rest of the study. Not everyone thinks about food the same way or to the same degree when choosing what to eat.
>
> Description 1:
> Sometimes, people focus on the potential effects of eating certain foods. They might think carefully about how eating those foods would affect their health *in the long run* and make food choices based on these factors. For example, beyond considering taste, they might also think about the food's ingredients, nutritional content, or origin, and anticipate how they'll feel after they've eaten the food.
>
> Description 2:
> Other times, people focus on the sensory experience of eating certain foods or simply don't think much about the foods at all. Their food choices tend to be rooted in how the foods will make them feel *in the moment* rather than in the long run. For example, they might think about the food's smell, texture, taste, or just anticipate the pleasure of eating the food.
>
> When making food choices, a person's thoughts might alternate between two descriptions above. For purposes of this study, we'd like for you to decide *which of them best depicts your thoughts about food right now*. In a few minutes, you'll do a task where you view your favorite foods and think about them in different ways. How would you prefer to approach today's food task? Would you like to emphasize the potential effects of eating the foods or simply focus on the immediate experience?

Stimuli and craving rating task. Stimuli were 90 appetizing images of food items based on participants' food preferences. Participants chose their top three "most craved" food categories from the following menu: barbeque, burgers, candy, cheese, chips, chocolate, cookies, doughnuts, French fries, fruit, fruit desserts, pasta, pizza, and roasted vegetables. Each category contained 45 images, the majority of which were procured from the FoodIE stimuli set, which was independently rated for desirability by a sample of individuals who reported craving that food category (available via http://dsn.uoregon.edu/foodie). Participants then completed a computerized task in which they rated their desire to eat the foods (1 = no desire to eat, 4 = strong desire to eat). Participants were also given the option to flag foods they have a strong aversion to or cannot eat. These ratings were ranked with respect to desirability and randomized within rating category. Flagged foods were removed and the top 90 images were selected to use in the craving regulation task. Of these 90 images, the top 60 were classified as relatively "more craved" and the next 30 were classified as relatively "less craved."

Regulation of Craving–Choice task. All participants completed a modified version of the Regulation of Craving–Choice (ROC-C) task used in Study 1. On each trial, participants either actively viewed ("Look" condition) or reappraised their craving for ("Regulate" condition) the foods. On 60% of the trials, participants freely chose whether to look or regulate ("Yes-Choice" condition), and on the other 40%, participants were instructed whether to look or regulate ("No-Choice" condition). Therefore, the task design was a 2 × 2 within-subjects repeated measures factorial with Goal (Look, Regulate) and Choice (Yes, No) as factors. On all Look trials, participants were instructed to imagine that the food items were real and to visualize how they would

interact with them. Their goal on these trials was to make the food feel as vivid and real as possible. On all Regulate trials, participants were instructed to reappraise their craving for the food by considering short- or long-term negative consequences associated with consumption (e.g., stomach aches, weight gain, cavities, guilt, embarrassment), and participants were instructed to try to imagine how these negative effects would feel physically. With the help of the experimenter, participants generated several, personally-relevant negative consequences so as to have multiple strategies to use while completing the task. The goal on Regulate trials was to make the negative consequences feel as real as possible. To ensure that all participants chose to look and regulate during the task, participants were told that it was up to them to decide whether they wanted to look or regulate on any given set, and how frequently they wanted to look and regulate throughout the task, but that they should do some of each. To help participants keep track of their choices, a summary of the number of times they chose to look and regulate were presented at the end of each run.

To reduce potential set shifting costs and the cognitive burden observed in Study 1, we modified the task so that trial-type switched after three trials, rather than every trial (Figure 3.1). To ensure the images across trial sets were relatively equivalent with respect to desirability, each set included two "more craved" images and one "less craved" image based on the rating task. At the beginning of each set, participants saw a preview of the three images in the set for 2 seconds, after which they saw a cue informing of the set type for 2 seconds. On No-Choice sets, participants simply pressed a button to acknowledge the set type (Look or Regulate), whereas on choice sets, they chose whether to Look or Regulate. Participants then viewed a fixation cross for 2 seconds before the food image

appeared, after which they completed three trials, pursuing the same goal (Look or Regulate) in each. On each trial, participants viewed a food image for 6 seconds while looking or regulating, and then rated their current to eat the food in (1 = no desire, 4 = strong desire). To minimize demand characteristics (e.g., reduced craving ratings on Regulate trials), the experimenter stated that participants were not expected to be able to regulate well on every trial and stressed the importance of making honest craving ratings. They then rated how difficult it was to fulfill their goal (1 = not hard, 4 = very hard). On Look trials, the goal was defined as the ability to make the food feel vivid and real, whereas on Regulate trials, the goal was to make the negative consequences feel vivid and real. Each rating was on the screen for 2.5 seconds and trials were separated by 2 seconds of fixation. The task consisted of three separate runs and each run consisted of 30 trials: 18 Choose trials (6 sets), 6 Look trials (2 sets), and 6 Regulate trials (2 sets). Stimuli were presented using Psychtoolbox 3 (Brainard, 1997) and participants responded using a keyboard.

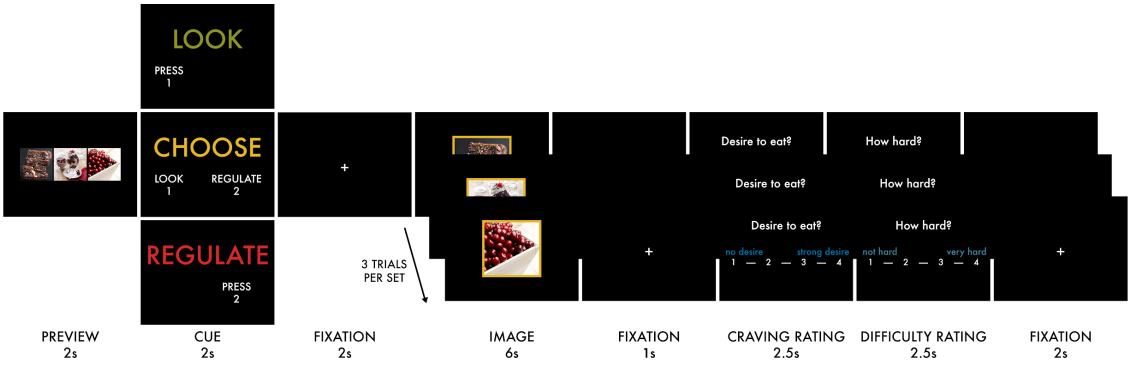

Figure 3.1. Modified ROC-C task design. Each set consisted of the following events: preview (2s), cue (2s), fixation (2s), and three trials. Each trial consisted of the following events: image presentation (6s), fixation (1s), craving rating (2.5s), and effort rating (2.5s). Trials were separated by 2s of fixation.

Phenomenology of choice. To characterize the affective experience of choice, and compare potential differences in autonomous motivation for Yes-Choice versus No-Choice trials during the task, participants rated Yes-Choice and No-Choice sets in a post-task survey on the following dimensions: enjoyment, engagement, motivation, and difficulty. Conditions were rated separately and for each statement (e.g., "I felt engaged with the task during these sets"), participants rated how much they agreed or disagreed (1 = strongly disagree, 5 = strongly agree). To assess autonomous motivation, we averaged the enjoyment, engagement, and motivation items for each condition separately. This measure and the difficulty item served as the primary manipulation checks to assess whether the Yes-Choice condition was associated with greater self-reported autonomous motivation and less perceived difficulty, and how they differed as a function of the experimental autonomy manipulations.

Intrinsic Motivation Inventory. To measure autonomous motivation during the ROC-C task as a whole, we administered the Intrinsic Motivation Inventory (Ryan, 1982; McAuley et al., 1989). This scale consists of 37 items measuring interest and enjoyment, perceived competence, perceived choice, and pressure and tension, during the task as a whole, as well as the value and usefulness of the task, the importance of the task and how much effort was put into it. Each item is scored on a 7-point scale (1 = not at all true, 7 = very true). The relatedness facet was omitted from this study as it was not directly related to our hypotheses.

Analysis plan

Due to the largely exploratory nature of this pilot study, we focus on estimating effect sizes rather than on statistical significance and therefore present effects with 95%

confidence intervals rather than *p*-values (Cumming, 2014). During model comparison, a model with an Akaike Information Criterion (AIC) value of at least two points lower than the comparator model was considered to better fit the data. For all analyses, participants in the Food autonomy manipulation group were separated based on whether they chose to focus on the immediate experience of eating (Food: Look group) or on the consequences of eating (Food: Regulate group) during the ROC-C task. Consequently, there were four autonomy manipulation groups in the analyses: Agency, Food: Look, Food: Regulate, and Control.

Autonomous motivation. We investigated the degree to which the experimental autonomy manipulations bolstered autonomous motivation during the task in two ways. First, we compared mean differences between each manipulation group and the control group on the Intrinsic Motivation Inventory to determine whether the autonomy manipulations increased autonomous motivation during the task as a whole (i.e., not as a function of the task choice condition) compared to the control group. Autonomous motivation was calculated by averaging the scores on each facet, with the pressure / tension scale reverse coded so that higher values indicated lower pressure / tension. We report mean differences for each facet of the scale separately, as well as for the combined measure of autonomous motivation. Next, we calculated mean differences between the Yes- and No-Choice conditions for items on the post-task manipulation check survey, for each group separately. This allowed us to assess whether the effects of the autonomy manipulations differed as a function of the task choice condition (i.e., versus during the task as a whole). Due to a technical error, these survey measures were not administered to two participants and therefore the sample size for these analyses is N = 103.

ROC-C task analysis. We used multilevel modeling and model comparison to investigate the effect of the autonomy manipulations on goal pursuit in the ROC-C task. Goal pursuit was operationalized as task performance, with higher craving ratings on Look trials and lower craving ratings on Regulate trials indicating more successful goal pursuit. In the base model (Model 1 – Base), we regressed trial-level craving ratings on the fixed effects of Goal, Choice, and the interaction between Goal and Choice, and included the fixed effects of Trial and trial-level Baseline Craving collected prior to the task to control for habituation and idiosyncratic responses to the stimuli, respectively. In the next model (Model 2 – Difficulty), we added fixed effects for trial-level Difficulty and its interactions with Goal and Choice. We then compared how well these two models fit the data using AIC as the model fit index and specified a third model to test for moderation by autonomy manipulation group (Model 3 – Group) in the best fitting model. In all models, intercepts, Goal, and Baseline Craving were treated as random effects nested within person (Cosme et al., 2018b). Baseline Craving and Difficulty were Z-scored across participants and Trial was centered at 45 and scaled in units of 10. We report parameter estimates and 95% confidence intervals for the fixed effects from the best fitting model. Confidence intervals for predicted effects plots were generated using the bootMer function from the lme4 package with 1000 parametric simulations (Bates et al., 2015).

Results

Regulation choices

Across the four autonomy manipulation groups, there was moderate variability in the percentage of trials in which participants chose to regulate their cravings (Figure 3.2;

SD range = 7.0 - 9.1). On average, participants in both the Agency and Control groups chose to regulate approximately 50% of the time ($M_{Control}$ = 49.8%, M_{Agency} = 50.3%), whereas those in the Food group chose to regulate slightly less frequently ($M_{Food:\ Look}$ = 48.4%, $M_{Food:\ Regulate}$ = 45.9%).

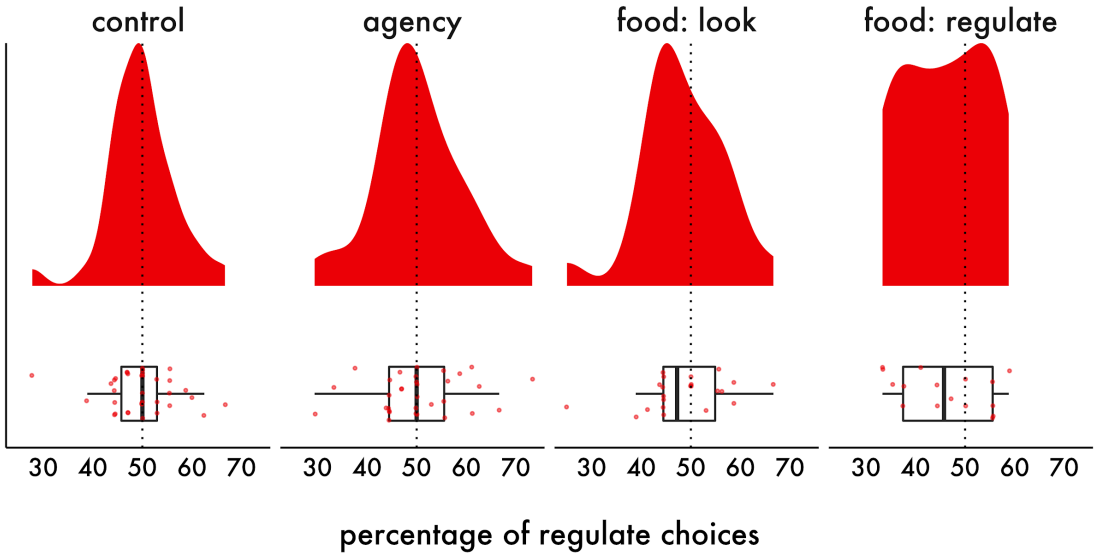

Figure 3.2. Distribution of the percentage of trials in which participants chose to regulate their cravings as a function of autonomy manipulation group. The dotted line indicates 50%; dots represent individuals.

Autonomous motivation

When considering autonomous motivation during the task as a whole, the Agency autonomy manipulation group reported the highest autonomous motivation compared to the Control group (Figure 3.3B), followed by the Food: Regulate group, and finally the Food: Look group, which reported less autonomous motivation than the Control group (Table 3.1). On the subfacets of the scale, the Agency and Food: Regulate groups also reported higher levels of perceived choice during the task than the Control group, whereas the Food: Look group reported similar perceived choice. The Agency group reported similar levels of effort/importance and value/usefulness as the Control group,

whereas both Food groups reported lower levels of effort/importance. The Food: Regulate group endorsed greater value/usefulness than the Control group, and the Food: Look group endorsed less. The Food: Regulate group reported the most interest/enjoyment, followed by the Agency group, and finally the Food: Look group, which reported slightly lower interest/enjoyment than the Control group. All experimental groups reported lower perceived pressure and tension than the control group. All mean differences and confidence intervals are reported in Table 3.1.

Table 3.1
Mean differences and 95% confidence intervals between each autonomy manipulation group and the control group on the facets of the Intrinsic Motivation Inventory

Facet	Choice	Food: Look	Food: Regulate
Autonomous motivation	0.14 [0.49, -0.21]	-0.04 [0.37, -0.45]	0.11 [0.50, -0.27]
Competence	-0.05 [0.44, -0.54]	0.01 [0.61, -0.60]	-0.20 [0.38, -0.79]
Effort / importance	-0.03 [0.42, -0.48]	-0.26 [0.24, -0.76]	-0.45 [0.15, -1.04]
Interest / enjoyment	0.08 [0.58, -0.41]	-0.03 [0.52, -0.59]	0.41 [1.07, -0.24]
Perceived choice	0.53 [1.04, 0.02]	0.02 [0.55, -0.50]	0.58 [1.10, 0.06]
Pressure / tension	-0.27 [0.33, -0.87]	-0.22 [0.49, -0.94]	-0.16 [0.52, -0.84]
Value / usefulness	0.02 [0.67, -0.63]	-0.22 [0.52, -0.96]	0.19 [1.07, -0.70]

Note. Autonomous motivation is a composite measure of all facets in the Intrinsic Motivation Inventory with pressure / tension items reverse coded so that higher values indicated lower pressure / tension. Positive values indicate that the autonomy manipulation group mean is greater than the control group mean.

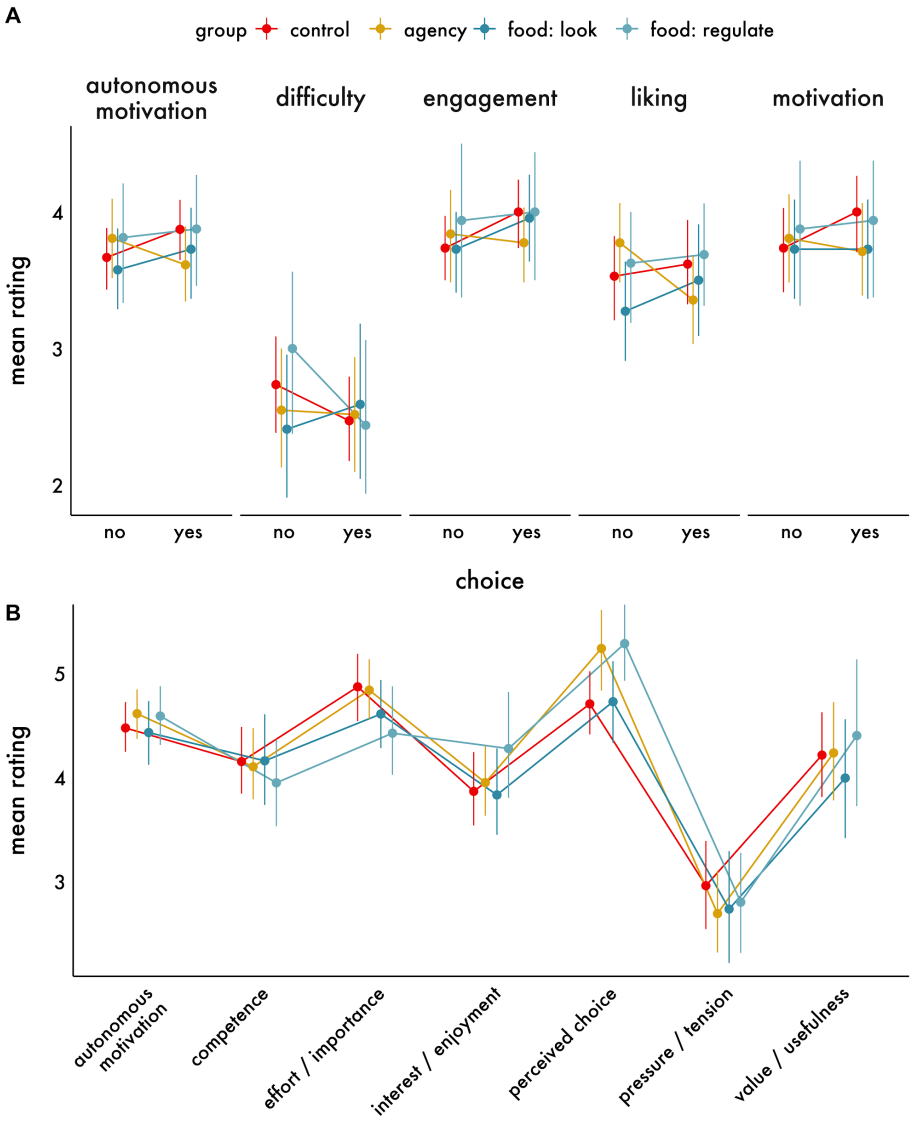

Figure 3.3. Mean ratings on the A) post-task survey and B) Intrinsic Motivation Inventory (IMI) as a function of autonomy manipulation group. Items on the post-task survey were asked separately for each choice condition, whereas items in the IMI were asked about the task as a whole. Autonomous motivation is a composite measure of the engagement, liking, and motivation items in the post-task survey, and all facets in the IMI with pressure / tension items reverse coded so that higher values indicated lower pressure / tension. Error bars are 95% confidence intervals across ratings.

We next considered whether the autonomy manipulation had specific effects on autonomous motivation and perceived difficulty as a function of the choice conditions during the ROC-C task (Figure 3.3A). The Control group reported the largest difference

in autonomous motivation between the choice conditions, experiencing greater autonomous motivation during Yes-Choice trials (Table 3.2). Both the Food groups also reported greater autonomous motivation during Yes-Choice trials, whereas the Agency group reported lower autonomous motivation during Yes-Choice trials. The Food: Regulate group had the largest difference in difficulty, reporting less difficulty on Yes-Choice than No-Choice trials. The Control group also reported less difficulty on the Yes-Choice trials, whereas the Agency group reported equivalent difficulty, and the Food: Look group reported more difficulty on Yes-Choice trials. Mean differences between the ratings for the Yes- and No-Choice conditions and confidence intervals around them are reported for all items in Table 3.2.

Table 3.2
Mean differences and 95% confidence intervals between the Yes-Choice and No-Choice conditions on the post-task survey for each autonomy manipulation group

Facet	Control	Choice	Food: Look	Food: Regulate
Autonomous motivation	0.21 [0.55, -0.14]	-0.19 [0.22, -0.60]	0.15 [0.64, -0.34]	0.06 [0.70, -0.58]
Difficulty	-0.26 [0.24, -0.77]	-0.03 [0.60, -0.67]	0.18 [0.98, -0.62]	-0.56 [0.37, -1.49]
Engagement	0.26 [0.64, -0.11]	-0.06 [0.40, -0.53]	0.23 [0.70, -0.25]	0.06 [0.89, -0.76]
Liking	0.09 [0.56, -0.38]	-0.42 [0.03, -0.87]	0.23 [0.81, -0.35]	0.06 [0.64, -0.51]
Motivation	0.26 [0.69, -0.16]	-0.10 [0.39, -0.58]	-0.00 [0.54, -0.54]	0.06 [0.86, -0.74]

Note. Autonomous motivation is a composite measure of the engagement, liking, and motivation items in the post-task survey. Positive values indicate that the Yes-Choice mean is greater than the No-Choice mean.

ROC-C task analysis

Model comparison revealed that trial-level difficulty explained additional variance and this model (Model 2 – Difficulty) fit the data better than the base model (Table 3.3). Furthermore, adding autonomy manipulation Group and its interactions with Goal, Choice, and Difficulty further improved model fit. In this model, participants reported lower cravings when they were regulating (Table 3.4), as expected. This effect

was moderated by Difficulty; higher perceived difficulty of goal pursuit was associated with worse task performance (i.e., lower craving ratings on Look trials and higher craving ratings on Regulate trials). We expected there would be an interaction between Goal and Choice across all groups, but this was only the case for the Agency group. In this group, choice was associated with better task performance on trials of average difficulty, with higher craving ratings on Look trials and lower craving ratings on Regulate trials, as expected (Figure 3.4). However, on relatively difficult trials, there was an interaction between Goal and Choice. On Look trials, choice on relatively difficult trials was associated with better performance in the Agency group, but worse performance in the Food: Regulate group, and no difference in the Control and Food: look groups. On Regulate trials, choice on more difficult trials was associated with slightly better performance in the Control and Agency groups, but worse performance in both Food groups.

Table 3.3
Comparison of multilevel models with trial-level craving ratings as the criterion

Model	Model *df*	AIC
Model 1 – Base	13	22503.02
Model 2 – Difficulty	17	22050.17
Model 3 – Group	**41**	**22038.05**

Note. The best fitting model is bolded.

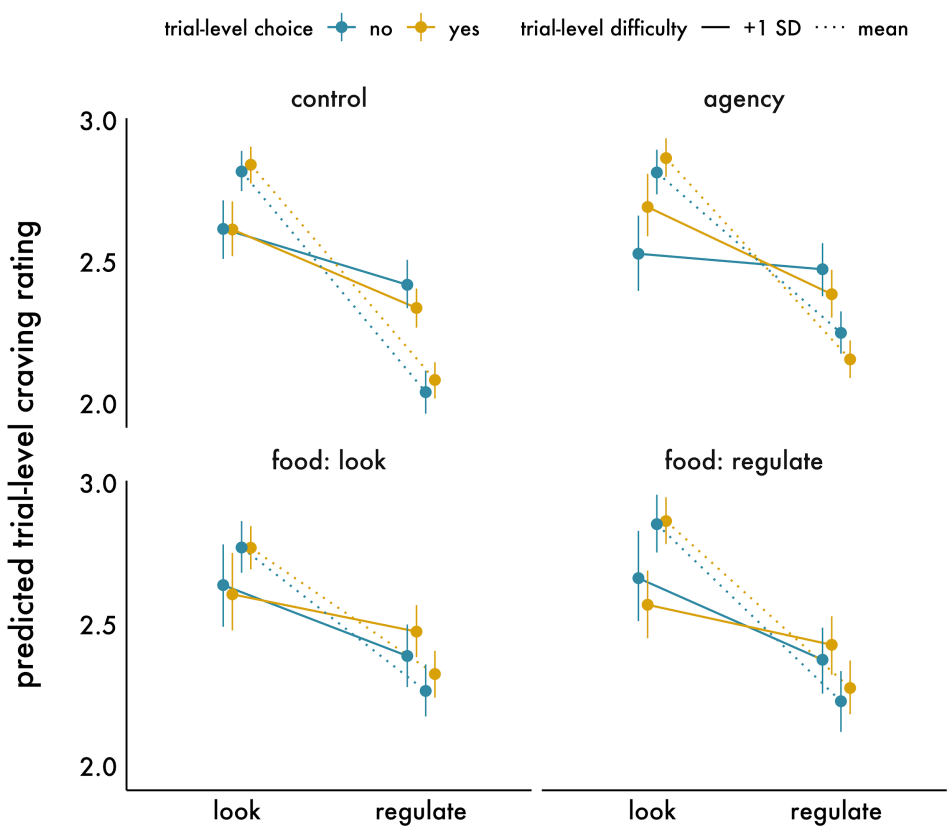

Figure 3.4. Predicted trial-level craving ratings from the best fitting multilevel model (Model 3) as a function of trial-level Goal, Choice, and Difficulty, and autonomy manipulation Group. Better task performance is indicated by higher ratings on Look trials and lower ratings on Regulate trials. Error bars are bootstrapped 95% confidence intervals.

Table 3.4

Parameter estimates from the best fitting multilevel model (Model 3 – Group)

Fixed effect	*b* [95% CI]	*df*
Intercept (Look, No-Choice)	2.93 [2.81, 3.05]	166.82
Goal	-0.78 [-0.95, -0.61]	158.90
Choice	0.02 [-0.06, 0.11]	8630.51
Difficulty	-0.19 [-0.27, -0.12]	8626.28
Group Agency	-0.01 [-0.18, 0.16]	167.26
Group Food: Look	-0.04 [-0.23, 0.14]	165.62
Group Food: Regulate	0.04 [-0.16, 0.24]	159.03
Trial	-0.02 [-0.03, -0.02]	8651.24
Baseline Craving	0.31 [0.27, 0.36]	94.53
Goal × Choice	0.02 [-0.11, 0.14]	8633.42
Goal × Difficulty	0.57 [0.47, 0.67]	8791.40
Choice × Difficulty	-0.03 [-0.12, 0.07]	8674.84
Goal × Group Agency	0.21 [-0.04, 0.45]	157.13
Goal × Group Food: Look	0.27 [-0.00, 0.55]	156.48
Goal × Group Food: Regulate	0.15 [-0.16, 0.45]	158.49
Choice × Group Agency	0.02 [-0.10, 0.15]	8643.95
Choice × Group Food: Look	-0.02 [-0.16, 0.12]	8633.57
Choice × Group Food: Regulate	-0.02 [-0.17, 0.13]	8627.61
Difficulty × Group Agency	-0.09 [-0.21, 0.02]	8668.54
Difficulty × Group Food: Look	0.06 [-0.07, 0.18]	8698.87
Difficulty × Group Food: Regulate	0.01 [-0.12, 0.15]	8755.99
Goal × Choice × Difficulty	-0.10 [-0.22, 0.03]	8659.92
Goal × Choice × Group Agency	-0.15 [-0.33, 0.03]	8642.29
Goal × Choice × Group Food: Look	0.05 [-0.15, 0.24]	8626.27
Goal × Choice × Group Food: Regulate	0.03 [-0.19, 0.25]	8629.71
Goal × Difficulty × Group Agency	-0.06 [-0.21, 0.09]	8790.65
Goal × Difficulty × Group Food: Look	-0.31 [-0.47, -0.15]	8800.41
Goal × Difficulty × Group Food: Regulate	-0.25 [-0.43, -0.07]	8813.22
Choice × Difficulty × Group Agency	0.14 [-0.00, 0.28]	8683.75
Choice × Difficulty × Group Food: Look	0.00 [-0.15, 0.16]	8678.12
Choice × Difficulty × Group Food: Regulate	-0.09 [-0.26, 0.08]	8666.84
Goal × Choice × Difficulty × Group Agency	-0.01 [-0.19, 0.18]	8670.60
Goal × Choice × Difficulty × Group Food: Look	0.14 [-0.05, 0.34]	8664.86
Goal × Choice × Difficulty × Group Food: Regulate	0.22 [-0.00, 0.44]	8672.91

Random effects	variance	*SD*
Participant		
Intercept	0.08	0.29

Table 3.4 (continued)

Random effects	variance	*SD*
Participant		
Goal	0.19	0.44
Baseline Craving	0.03	0.19
Residual	0.65	0.81

Note. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. Statistically significant parameters at $p < .05$ are bolded. The reference condition for Group is Control, for Goal is Look, for Choice is No-Choice; Difficulty and Baseline Craving are Z-scored; and Trial is centered at 45 and is units of 10 trials.

Post hoc task analysis

We ran a follow-up multilevel model to test whether the act of choosing itself negatively affected task performance in this modified version of the ROC-C task. We reasoned that if this were the case, we would expect that 1) task performance would be worse on the first trial of the three-trial sets, 2) this decrement should be exclusive to the Yes-Choice condition, and 3) it should not differ as a function of autonomy manipulation group. To test this, we added fixed effects for the interactions between set trial number (i.e., 1, 2, or 3) and Goal, Choice, and Difficulty to the best fitting model, Model 3 – Group. This model did not better fit the data ($AIC_{Model\ 3} = 22038.05$ v. $AIC_{Model\ 4} = 22039.40$) and task performance was equivalent or better on the first trial compared to the last trial. Furthermore, improvements were greater in the Yes-Choice condition (Figure 3.5), which provides evidence that there were not negative effects directly associated with the act of choosing itself.

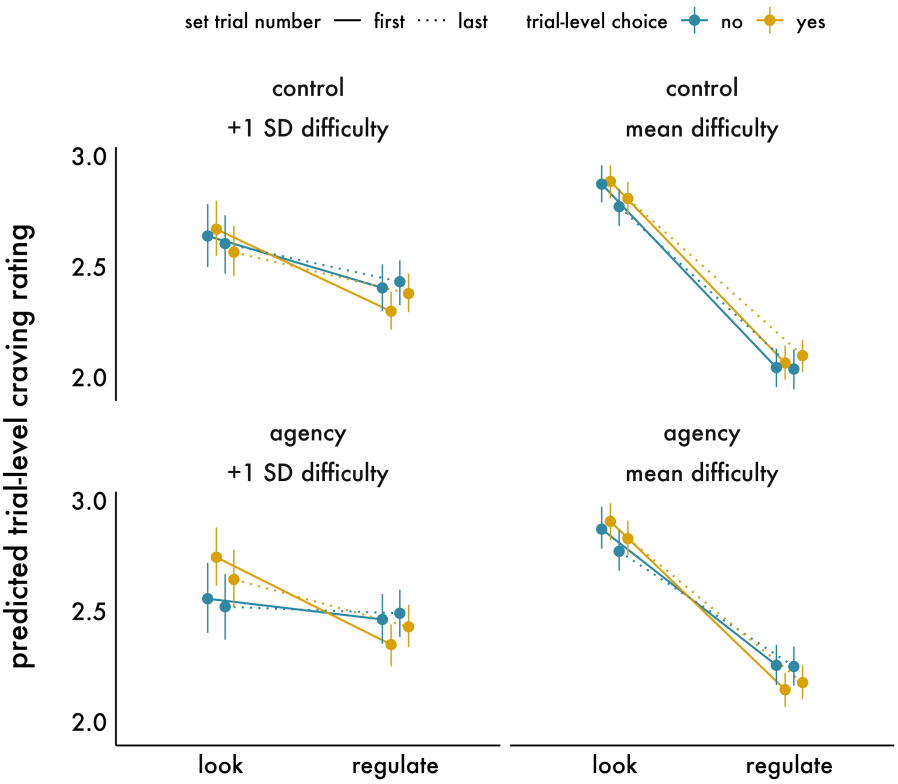

Figure 3.5. Predicted trial-level craving ratings from the post hoc multilevel model including set trial number as a function of trial-level set trial number, Goal, Choice, and Difficulty, and autonomy manipulation Group. For simplicity, these effects are visualized for the Control and Agency groups only. Better task performance is indicated by higher ratings on Look trials and lower ratings on Regulate trials. Error bars are bootstrapped 95% confidence intervals.

Discussion

The goal of this study was to pilot a new version of the Regulation of Craving–Choice (ROC-C) task and test whether two different experimental manipulations to enhance autonomous motivation improved goal pursuit. On the whole, the new task performed as expected and participants successfully controlled their food cravings using cognitive reappraisal. Although we expected that task performance would vary as a function of whether or not participants chose, differences between the choice condition emerged primarily when goal pursuit was perceived as more difficult. Of the autonomy

manipulations, the writing exercise in which participants reflected on how choice affords autonomy in their lives (i.e., the Agency group) was most promising. Participants in this group reported greater perceived choice and slightly higher autonomous motivation than the control group. Furthermore, whereas choice was associated with worse task performance in both the Food autonomy manipulation groups, the Agency group performed better across both task goals when choosing.

Effect of difficulty on goal pursuit

We included trial-level difficulty ratings in this version of the ROC-C task in order to investigate how perceived difficulty of goal pursuit was related to task performance and whether it might moderate the effects of self-determined choice. In this study, reappraisal was associated with higher difficulty ratings and greater difficulty was related to worse performance for both goals. Although we are unaware of research directly assessing the relationship between difficulty and regulation success, these results are in line with research showing negative associations between effort and task performance (Sullivan-Toole et al., 2017; Kool et al., 2010). Furthermore, previous research on emotion regulation choice has shown that higher perceived difficulty of reappraisal (i.e., lower reappraisal affordance) is associated with a lower probability of choosing to reappraise aversive stimuli, suggesting that participants strategically choose emotion regulation strategies (Suri et al., 2017). Although the present study was not designed to test this hypothesis, it would be informative for future research to assess out of sample prediction of choice from average ratings of reappraisal difficulty to determine whether there is evidence of strategic emotion regulation choice with appetitive stimuli.

Does choice help or harm goal pursuit?

Based on the notion that self-determined choice supports autonomous motivation during goal pursuit (Legault & Inzlicht, 2013), we expected that choice would be associated with better task performance. However, we only observed this effect for the Agency autonomy manipulation group. For all other groups, choice was associated with equivalent performance on Look trials and slightly worse performance on Regulate trials at mean-level difficulty. Although we redesigned the ROC-C task to reduce potential sources of cognitive burden associated with choice, these results suggest that there may be residual effects of choice not necessarily related to cognitive load or misallocation of attentional resources. Indeed, post hoc analyses assessing whether trial number within each set–which served as a proxy for cognitive burden directly associated with choice–was related to decrements in task performance on choice trials, revealed the opposite. Task performance was *better* on the first trial in both choice conditions and this effect was stronger for Yes-Choice trials. Together, these results indicate that choice-related decreases in task performance cannot be fully explained by cognitive load associated with the choice. This finding is consistent with recent research on emotion regulation of aversive stimuli showing negative effects of choice on reappraisal success that could not be attributed to cognitive load (Bigman et al., 2017), and other work documenting adverse effects of choice more generally (Iyengar & Lepper, 2000; Botti & Iyengar, 2004; Vohs et al., 2008).

In contrast, when goal pursuit was perceived as more difficult, choice improved task performance but only for the Agency autonomy manipulation group. Since this group also reported higher levels of autonomous motivation and perceived choice during

the task as a whole, this finding is consistent with other research showing that positive effects of choice on inhibitory control task performance were partially mediated by autonomous motivation (Legault & Inzlicht, 2013). However, it adds nuance to the notion that choice invariably improves task performance and supports the position that the context in which choices are made matters (Patall et al., 2008). Although other studies have demonstrated positive effects of choice on performance without considering difficulty (Murayama et al., 2015; Patall et al., 2008), the present findings are consistent with a recent study that varied difficulty and choice independently and found that choice was only beneficial when difficulty was relatively high (Sullivan-Toole et al., 2017). Furthermore, it is important to note that this interaction was observed only in the Agency autonomy manipulation group, suggesting that potential positive effects of choice in this context are subtle and contingent.

Despite showing improved task performance and greater autonomous motivation during the task as a whole, it is notable that when considering Yes- and No-Choice sets separately, the Agency autonomy manipulation group reported lower autonomous motivation during Yes-Choice relative to No-Choice trials. In particular, this effect was driven primarily by lower liking ratings. This may indicate that the manipulation was successful in promoting autonomous motivation and improving task performance generally, but there may have been elements specifically associated with choice that participants reduced their preference for it. One possibility is that the summaries at the end of each task run reminding participants of the number of times they chose to look and regulate may have inadvertently undermined autonomy in this group. Although participants were not instructed to choose to look and regulate evenly, this group chose to

regulate on average 50% of the time, and the run summaries may have implicitly reinforced the perception that participants should choose evenly, diminishing autonomous motivation (Moller et al., 2006). Although this was consistent for all groups, the effect on the Agency group may have been compounded by the manipulation itself, which detailed how even the smallest of choices are opportunities to express oneself and take ownership of one's behavior. While Self-Determination Theory posits that important and personally-relevant choices should have the strongest effects on autonomous motivation (Reeve et al., 2003; Ryan & Deci, 2006), other research has suggested that these features of choice can actually undercut potential benefits (for a meta-analysis, see Patall et al., 2008).

It is also noteworthy that Food autonomy manipulation was not effective. The purpose of this manipulation was to give participants a meaningful choice about how they approached the task that reflected their natural inclination towards food. Although the Food: Regulate group did report greater autonomous motivation, finding the task more useful and enjoyable than the other groups, the Food: Look enjoyed and valued it least. In combination with the higher perceived choice for the Food: Regulate group, this suggests that while participants in this group who chose to focus on the consequences of consumption felt choice was meaningful, it did not translate into better task performance. We hypothesized that self-determined choice would be associated with better performance when participants in this group cognitively reappraised their food craving and when participants in the Food: Look group actively viewed, but both groups showed equivalent or slightly worse performance on Yes-Choice trials. Overall, this autonomy manipulation does not appear to have been successful and this approach is unlikely to be a useful way to promote autonomy.

Limitations

The results of this pilot study should be considered in light of several limitations. First, the sample size was relatively small. Although this is not necessarily problematic for estimating task effects which included many trials per participant, it makes precise estimation of between-group effects challenging given the relatively large confidence intervals. Furthermore, the design of the Food autonomy manipulation caused participants to be split into two separate groups, which further reduced power. Second, we did not assess autonomous motivation for each goal separately in the post-task survey. This precluded us from assessing whether differences in self-reported autonomous motivation and difficulty mirrored the asymmetrical effects of choice on task performance during the ROC-C task. Last, though the target population for this pilot study was college students, the results may not generalize beyond this population.

CHAPTER IV

STUDY 3: DISSOCIABILITY OF AUTONOMOUS AND CONTROLLED GOAL PURSUIT: ASSESSING THE EFFECTS OF SELF-DETERMINED CHOICE ON APPETITIVE SELF-REGULATION

This chapter is being prepared for submission and is therefore formatted according to the journal's standard–the American Psychological Association style manual.

Introduction

Autonomy is recognized as a fundamental human need and is autonomous motivation is associated with more successful self-regulation, and better health and well-being (Deci & Ryan, 2000; Ng et al., 2012; Ryan et al., 2006; Sheldon & Elliot, 1999; Slemp et al., 2018). This research highlights the importance of the motivation underlying behavior. Recent research has suggested that autonomous motivation makes goal pursuit and self-regulation feel effortless (Werner et al., 2016; Werner & Milyavskaya, 2019), but the underlying mechanism remains unclear. Initial research investigating the relationship between autonomy and self-regulation while participants exerted inhibitory control (Legault & Inzlicht, 2013) suggested enhanced attention and sensitivity to feedback as a potential mechanism. However, it is broadly acknowledged that self-regulation is supported by a whole suite of cognitive skills beyond the effortful control of impulses (Fujita, 2011; de Ridder et al., 2012; Gillebaart & de Ridder, 2015) and it is therefore important to examine whether the same mechanism underlies this relationship in other types of self-regulatory strategies. In this paper, we therefore focus on cognitive

reappraisal, which is an antecedent-focused self-regulation strategy that can be used to flexibly modulate affective responses to goal-relevant stimuli (Gross, 1998). Our primary goal was to use behavioral and functional neuroimaging (fMRI) data to assess the dissociability of motivational orientation during goal pursuit and test several theoretical predictions about the relationship between autonomy and self-regulation posited by Self-Determination Theory (Deci & Ryan, 2000). We extend previous research by examining how choice supports autonomy and goal pursuit in the context of an appetitive self-regulation task with relatively high ecological validity in which participants use cognitive reappraisal to control desires.

Why the "why" matters

Motivation is the driving force behind goal pursuit and refers to the reasons why a goal is pursued. Two individuals can pursue the same goal (e.g., completing a PhD) but for very different reasons; Student A may be motivated by their deep curiosity and enjoyment of the research process, while Student B may be motivated by the status and high salary they'll obtain once they've finished. The former is an example of autonomous or "want to" motivation, whereas the latter represents controlled or "have to" motivation (Werner & Milyavskaya, 2019). Autonomous motivation refers to the extent to which goals are pursued because of genuine interest and enjoyment, and because they provide meaning and purpose that is aligned with an individuals' identity and values. This type of motivation encompasses the motivational orientations classically referred to as intrinsic, integrated, and identified in Self-Determination Theory (Deci & Ryan, 2000). On the other hand, controlled motivation refers to the extent to which goals are pursued due to external factors, such as societal pressure, rewards, or punishments, also referred to as

external motivation, or to avoid internal feelings, such as guilt or shame, which is referred to as introjected motivation. At its core, autonomous behavior feels volitional and self-determined–you *want* to do it, whereas controlled behavior feels obligatory–you *have* to do it. Across a broad body of literature, autonomous motivation has been linked to more successful goal pursuit and task performance in a wide variety of domains (Milyavskaya et al., 2015; Werner & Milyavskaya, 2019; Judge et al., 2005; Sheldon & Elliot, 1998, 1999; Vansteenkiste et al., 2004; Koestner et al., 2002; Werner et al., 2018; Koestner et al., 2008). Autonomous motivation is associated with greater persistence (Pelletier et al., 2001), less stress and burnout (Slemp et al., 2018; Lonsdale et al., 2009), and better overall well-being (Ryan et al., 2006). Based on this evidence, we would expect that Student A would be more likely to successfully complete their PhD with their health and well-being relatively intact, while Student B would be more likely to drop out or struggle under the pressure.

But what is it about the quality of motivation that makes it so potent? Recent research suggests that autonomous motivation facilitates goal achievement because goal pursuit is experienced as less effortful and more automatic (Werner et al., 2016; Werner & Milyavskaya, 2019), and reduces susceptibility to and magnitude of goal-incongruent temptations (Milyavskaya et al., 2015; Lopez et al., 2016). These qualities are thought to enhance self-regulation, which is defined as any behavior that is goal-congruent (Carver & Scheier, 1982). However, this broad definition makes it practically challenging to uncover specific mechanisms underlying the relationship between motivation and self-regulation. Because self-regulation encompasses such a vast number of processes, there

may be numerous ways in which motivation might affect self-regulation depending on particular context.

Effects of autonomous motivation during self-regulation

An alternative approach for elucidating mechanisms is to focus on how motivation affects goal pursuit while individuals are utilizing specific self-regulatory strategies, such as inhibitory control and emotion regulation. Although motivation can be challenging to manipulate experimentally, autonomy can be supported by giving individuals choice. Indeed, choice is a hallmark of autonomy-supportive environments (Ryan & Deci, 2006). Laboratory experiments on inhibitory control and cognitive reappraisal of aversive stimuli suggest that autonomy-supportive, also known as self-determined, choice may improve self-regulation via heightened attentional engagement and enhanced error-monitoring (Kühn et al., 2014; Legault & Inzlicht, 2013). Both of these studies reported that choice, either at the task-level (Legault & Inzlicht, 2013) or the trial-level (Kühn et al., 2014), was associated with stronger engagement of neural indices associated with attention and executive control.

However, previous research from our lab investigating the effect of choice on self-regulation during cognitive reappraisal of appetitive stimuli showed that while choice was associated with increased activation in these same brain networks, it actually reduced task performance rather than enhancing it (Cosme et al., 2018b). Follow-up analyses indicated that choice may have disrupted cognitive resource allocation during the task, but it is possible that this pattern of results may have been due to the task design. In this study, participants made choices on half of the trials, which may have felt like choice overload (Patall et al., 2008; Iyengar & Lepper, 2000). Cognitive reappraisal was also

implemented directly after the choice, making it difficult to separate the neural activation associated with the choice from that associated with reappraisal, because they were closely correlated in time. It is also possible that choice simply did not feel self-determined in this context, which has been shown to undermine potential positive effects on task performance (Moller et al., 2006; Legault & Inzlicht, 2013; Sullivan-Toole et al., 2017). Indeed, in Legault & Inzlicht (2013) the relationship between choice and better inhibitory control was partially mediated by perceived autonomous motivation. This suggests that choice may only improve self-regulation when individuals *feel* autonomously motivated by it.

The present study

In this preregistered study, we build on these findings to investigate the effects of choice on autonomous motivation and goal pursuit in the context of an appetitive self-regulation task in which participants control their cravings for personally-desired foods using cognitive reappraisal. We chose to focus on appetitive rather than aversive stimuli because goal-incongruent temptations that require regulation are often appetitive in nature, and we utilized food cues because food is a primary reward, robustly elicits appetitive motivation, and is easily customizable to individual tastes (Hill, 2007; Kober & Mell, 2015). Cognitive reappraisal, or the reframing of a stimulus to change its affective meaning (Gross, 1998), is a flexible strategy that can be used to enhance the value of goal-congruent behavior (e.g., healthy eating) or decrease the value of goal-incongruent behavior (e.g., unhealthy eating) by emphasizing relevant features of the stimulus (e.g., by focusing on positive or negative consequences of consumption). In this study, participants completed a cognitive reappraisal task while in the MRI scanner. They saw

images of personally-craved foods and either actively viewed them (Look condition) or reappraised their desire for the foods by visualizing the negative consequences of consumption (Regulate condition). We supported autonomy by providing choice, and choice was manipulated by instructing participants whether to look or reappraise (No-Choice condition) or asking them to choose whether to look or reappraise (Yes-Choice condition). To reduce potential cognitive burden associated with choice, trials were blocked in sets of three. After each trial, participants rated their craving for the food and how difficult it was for them to achieve their goal, which was defined as making the food feel real on Look trials and making the negative consequences feel real on Regulate trials.

Behaviorally, we expected that choice would be associated with higher levels of perceived autonomous motivation as well as better performance across both task goals (i.e., Look or Regulate). Using model comparison, we also tested whether this effect was moderated by trial-by-trial perceived difficulty and by individual differences in autonomous motivation during the task. We reasoned that motivation may matter most when goal pursuit is difficult (Klein et al., 1999), and that choice may only enhance performance if it is perceived as motivating. Because autonomous motivation has been characterized as facilitating "effortless" goal pursuit (Werner et al., 2016; Werner & Milyavskaya, 2019), we conducted parallel analyses to assess whether choice and perceived autonomous motivation are associated with lower difficulty ratings on a trial-by-trial basis.

Finally, we utilized univariate and multivariate neuroimaging methods to assess whether neural activity during goal pursuit differs as a function of choice; that is, are autonomous and controlled goal pursuit dissociable? Due to the relative novelty of this

research, we did not have strong spatial hypotheses, but reasoned that increased activity in the salience and/or frontoparietal control network for Yes-Choice > No-Choice would be consistent with the hypothesis that autonomous motivation increases attention and engagement (Lee & Reeve, 2012; Legault & Inzlicht, 2013), whereas increased activity in the reward and/or default mode network would be consistent with a reward-based account of self-determined choice (Murayama et al., 2015; Reeve & Lee, 2017). Because we compared the effects of choice during actual goal pursuit and not while participants made choices, the critical test is whether there are differences between choice conditions during goal pursuit at all. Whereas the univariate main effect of Choice will inform us about potential differences irrespective of goal, the interaction between Goal and Choice will inform us about potential differences that vary with respect to goal. We complemented these univariate contrasts by using multivoxel pattern analysis (MVPA). We expected that if autonomous and controlled goal pursuit are dissociable, we would observe greater than chance accuracy classifying Yes-Choice versus No-Choice within brain regions supporting goal pursuit in this task.

Methods

Open science statement

This study was preregistered and the preregistration, as well as all analysis scripts and behavioral data will be made available on the Open Science Framework (https://osf.io/pnc7m). Deviations from the preregistered analysis plan are noted in the manuscript. Group-level univariate contrast maps and multivariate classification weight maps are available on NeuroVault (Gorgolewski et al., 2015; https://neurovault.org/collections/NDHWTOBQ).

Participants

Participants included 117 (73 females, as defined by biological sex) incoming college students at the University of Oregon recruited during the summer prior to freshman year. These participants were part of a larger longitudinal study on health and well-being during the transition to college. Participants were eligible if they were incoming freshmen between 17-19 years old (M = 18.01, SD = 0.28), right-handed, had not previously attended college at a different institution, and were planning to live on campus during their first year of college. Potential participants were not enrolled if they endorsed one or more of the following items: diagnosis of a psychiatric, learning, or neurologic disorder; presence of disordered eating or diagnosis of a condition that significantly impacted their diet; use of psychotropic medications; significant visual impairment or color blindness; concussion or other brain trauma; MRI contraindications (e.g. metal implants, biomedical devices, pregnancy). We excluded participants from the fMRI analyses for failure to comply with task instructions (n = 1) or missing data due to a technical failure (n = 1). Task runs were individually excluded from fMRI analyses if participants exhibited excessive head motion (n = 9; as defined below), technical errors (n = 8), or missing trials from at least one condition (n = 4). Several participants (n = 4) did not complete the post-task survey measures and are therefore not included in analyses using these measures. This yielded 115 participants for the neural analyses and 111 participants for behavioral analyses. All available data were used unless the analysis method required complete data. This study was approved by the University of Oregon Institutional Review Board; all participants gave written informed consent and were compensated for their participation.

Procedure

All participants completed an MRI session during the summer prior to, or during the first week of, freshman year. After consent, participants completed a rating task in which they selected their three most craved foods from a list of 13 food categories and rated the palatability of 45 images within each category. They then completed a brief writing exercise designed to strengthen the association between choice and autonomy. After this, participants were trained how to do the Regulation of Craving–Choice (ROC-C) task and worked with the researcher to develop personalized craving reappraisals. Participants then completed the ROC-C task while undergoing functional neuroimaging in the MRI scanner. After the scan, participants completed post-task experimental manipulation checks, as well as individual difference survey described below. They also completed other tasks and surveys related to the larger study on health and well-being not discussed in this manuscript.

Materials

Writing exercise. Although choice is a primary means of supporting autonomy, choice and autonomy are not identical (Ryan & Deci, 2006; Moller et al., 2006; Sullivan-Toole et al., 2017). In order to increase the salience of the connection between choice and autonomy during the ROC-C task, all participants completed the Agency writing exercise from Study 2, which highlighted how choice is a form of self-expression and a means of exerting autonomy. Participants read a passage and then wrote 4-6 sentences about a specific choice they made in the last few weeks and how it demonstrated taking ownership of their lives.

Stimuli and baseline craving rating task. Stimuli were 90 appetizing images of food items based on participants' food preferences. Participants chose their top three "most craved" food categories from the following menu: barbeque, burgers, cheese, chips, chocolate, cookies, doughnuts, French fries, fruit, fruit desserts, pasta, pizza, and roasted vegetables. Each category contained 45 images, most of which came from the FoodIE stimuli set, which was independently rated for desirability by individuals who reported craving that food category (available via http://dsn.uoregon.edu/foodie). Participants then completed a computerized task in which they rated their craving for the foods (1 = no desire to eat, 4 = strong desire to eat). Participants were also able to flag foods they have a strong aversion to or cannot eat. These ratings were then ranked by desirability and randomized within rating category (1-4). Flagged foods were removed and the 90 highest rated images were selected to use in the craving regulation task. Of these 90 images, the top 60 were coded as relatively "more craved" and the next 30 were coded as relatively "less craved."

Regulation of Craving–Choice (ROC-C) task. All participants completed a modified version of the ROC-C task used in Cosme et al. (2018) while in the MRI scanner. On each trial, participants either actively viewed ("Look" condition) or reappraised their craving for ("Regulate" condition) the foods. On 60% of the trials, participants freely chose whether to look or regulate ("Yes-Choice" condition), and on the other 40%, participants were instructed whether to look or regulate ("No-Choice" condition). Therefore, the task was a 2 × 2 within-subjects repeated measures factorial design with Goal (Look, Regulate) and Choice (Yes, No) as factors. On Look trials, participants were instructed to imagine that the foods were real and to visualize how they

would interact with them, with the goal of making the food feel as vivid and real as possible. On all Regulate trials, participants were instructed to reappraise their craving for the food by visualizing short- or long-term negative consequences associated with consumption (e.g., stomach aches, weight gain, guilt), and participants were instructed to try to imagine how these negative effects would feel viscerally. With the help of the experimenter, participants generated multiple personally-relevant negative consequences in order to have multiple strategies to use while completing the task. The goal on Regulate trials was to make the negative consequences feel as real as possible. With respect to Choice, participants were told that it was up to them to decide whether they wanted to look or regulate on any given choice set, and how frequently they wanted to pursue each goal throughout the task, but that they should both look and regulate some of the time.

To reduce potential set shifting costs and cognitive load (Cosme et al., 2018b), we modified the task so that trial-type switched every third trial, instead of every trial (Figure 4.1). To ensure the images across trial sets were relatively equivalent with respect to desirability, each set included two relatively "more craved" images and one "less craved" image identified during the rating task. At the beginning of each set, participants saw a preview of the three images and then saw a cue signaling the set type. On No-Choice sets, participants simply pressed the correct button to acknowledge the set type (Look or Regulate), whereas on Yes-Choice sets, they chose whether to Look or Regulate. To reduce the blood-oxygen-level-dependent (BOLD) signal correlation between the cue and image in future MRI studies utilizing this task, participants viewed a jittered fixation cross before the food image appeared. Participants then completed three trials, pursuing

the same task goal (Look or Regulate) in each. On each trial, participants viewed a food image while looking or regulating, and then rated their present desire to eat the food (1 = no desire, 4 = strong desire). To minimize demand characteristics (e.g., reporting lower craving ratings on Regulate trials), the experimenter emphasized that participants weren't expected to be able to regulate well on every trial and stressed the importance of making honest ratings. Participants then rated how difficult it was to fulfill their goal (1 = not hard, 4 = very hard). On Look trials, the goal was defined making the foods feel vivid and real, whereas on Regulate trials, it was making the negative consequences feel vivid and real. The task consisted of three runs and each run consisted of 30 trials: 18 Choose trials (6 sets), 6 Look trials (2 sets), and 6 Regulate trials (2 sets). Within each run, the trial order was optimized to maximize contrast estimation for MRI studies using a genetic algorithm (Wager & Nichols, 2003). Stimuli were presented using Psychtoolbox 3 (Brainard, 1997) and participants responded using a button box.

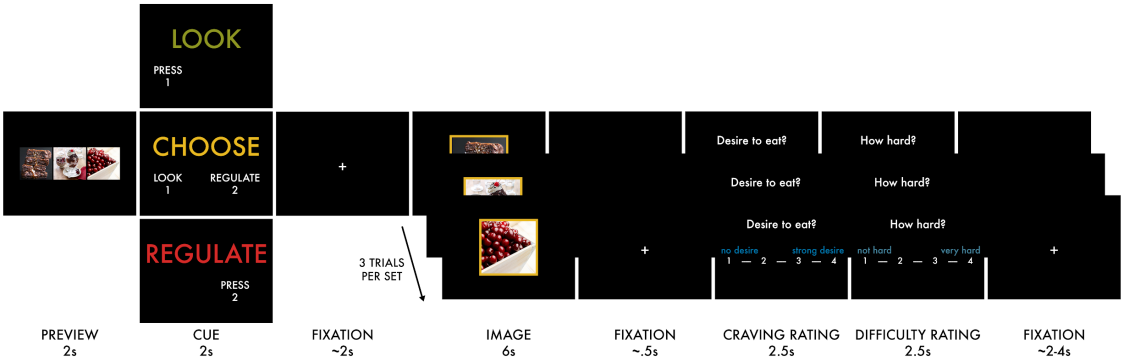

Figure 4.1. ROC-C task design. Each set consisted of the following events: preview (2s), cue (2s), jittered fixation (2 seconds), and three trials. Each trial consisted of the following events: image presentation (6s), fixation (.5s), craving rating (2.5s), and effort rating (2.5s). Trials within a set were separated by 4s of jittered fixation, whereas trials at the end of a set were separated by 2s jittered fixation.

Post-task manipulation check questions. To characterize the affective experience of choice, and compare potential differences in autonomous motivation for

Yes-Choice versus No-Choice trials during the task, participants rated each set type in a post-task survey on the following dimensions: enjoyment, engagement, motivation, and difficulty. Choice conditions (Yes-Choice or No-Choice) were rated separately. For each statement (e.g., "I liked the task during these sets"), participants rated the degree to which they agreed or disagreed (1 = strongly disagree, 5 = strongly agree). These items were used to determine whether the Yes-Choice condition was associated with greater self-reported autonomous motivation and lower perceived difficulty.

Intrinsic Motivation Inventory. To measure autonomous motivation during the ROC-C task as a whole, we administered the 22 item version of the Intrinsic Motivation Inventory (Ryan, 1982; McAuley et al., 1989), which is used to assess dimensions of motivation during targeted activities. This scale measures interest and enjoyment, perceived competence, perceived choice, and pressure and tension, during the task as a whole. Each item is scored on a 7-point Likert-type scale (1 = not at all true, 7 = very true).

Behavioral analyses

Post-task autonomous motivation and task difficulty analysis. We used multilevel modeling to assess the degree to which post-task ratings of autonomous motivation and difficulty differed as a function of Choice condition. Task autonomous motivation was operationalized as the mean of the enjoyment, engagement, and motivation items from the post-task manipulation check questions, calculated separately for each choice condition. Task difficulty was measured using a single item. Multilevel models were implemented using the lme4 package (Bates et al., 2015) in R 3.5.1 (R Core

Team, 2018; https://www.r-project.org). Each model included a fixed effect of Choice; participant intercepts will be specified as random effects.

ROC-C trial-level craving analyses. We compared a series of multilevel models to test the degree to which choice helps or harms goal pursuit during the task, and assess potential moderation effects of trial-level difficulty and subject-level autonomous motivation. Goal pursuit was operationalized as task performance, with higher craving ratings on Look trials and lower craving ratings on Regulate trials indicating more successful goal pursuit. In all models, we regressed trial-level craving ratings on the fixed effects of Goal, Choice, and the interaction between Goal and Choice. We also included fixed effects for baseline craving ratings to control for idiosyncratic responses to foods and trial number to control for habituation effects. Trial number was centered at 45 and scaled in units of 10. Consistent with Cosme et al. (2018), we treated participant intercepts, baseline cravings, and Goal as random effects within participant. Baseline cravings were Z-scored across participants. This model specification (Model 1 – Choice) tested the effect of Choice on craving ratings as a function of Goal. In the second model (Model 2 – Difficulty), we added the fixed effect of trial-level Difficulty (Z-scored across participants), the 2-way interactions between Goal and Difficulty, and Choice and Difficulty, and the 3-way interaction between Goal, Choice, and Difficulty. This model tested the degree to which perceived difficulty moderated the interaction between Goal and Choice. Because these models are nested, we used a chi-squared difference test to compare model fit; models were treated as better fitting if $p < .05$. We then compared the best fitting trial-level model to a third model (Model 3 – Autonomous Motivation), which included a second-level fixed effect of task Autonomous Motivation. This term was Z-

scored across participants and we included all cross-level interactions between Autonomous Motivation and Goal, Choice, and Difficulty. Again, we compared model fit and interpret the parameters from the best fitting model. Confidence intervals for predicted effects plots were generated using the bootMer function from the lme4 package with 1000 parametric simulations (Bates et al., 2015).

ROC-C trial-level difficulty analyses. We tested the degree to which choice affects perceived difficulty of goal pursuit at the trial-level. In this model, (Model 1 – Choice) we regressed trial-level difficulty ratings on the fixed effects of Goal, Choice, and their interaction, as well as trial number and baseline craving rating. The same random effects structure and Z-scoring procedures as in the craving models was used. To parallel the craving rating analysis, we specified additional post hoc (i.e., not preregistered) models and compared them to determine whether individual differences in perceived autonomous motivation during the task moderated the relationships between Goal, Choice, and trial-level difficulty. We compared the first model (Model 1 – Choice) to models that included the fixed effect of Autonomous Motivation and two-way cross-level interactions with Goal and Choice (Model 2 – Autonomous Motivation × Choice) and the three-way cross-level interaction between Goal, Choice, and Autonomous Motivation (Model 3 – Autonomous Motivation × Choice × Goal). Confidence intervals for predicted effects plots were generated using the bootMer function from the lme4 package with 1000 parametric simulations (Bates et al., 2015).

Post hoc individual difference analyses. We conducted follow-up multilevel models to determine whether autonomous motivation, assessed about the task as a whole (via the Intrinsic Motivation Inventory) and separately as a function of choice condition,

was related to regulation success and whether these relationships were moderated by choice. Regulation success was defined as the difference between an individual's average craving rating in the Look and Regulate conditions and were calculated for each level of choice separately. In each model, we regressed the regulation success on Choice, Autonomous Motivation (either from the IMI or the post-task survey), and the interactions between these variables. Autonomous Motivation was Z-scored across individuals. Intercepts were treated as random effects. The same bootstrapping procedure was used to estimate 95% confidence intervals for visualization.

Neuroimaging data acquisition and preprocessing

Neuroimaging data were acquired on a 3T Siemens Skyra scanner at the University of Oregon Lewis Center for Neuroimaging. We acquired a high-resolution anatomical T1-weighted MP-RAGE scan (TR/TE = 2500.00/3.43ms, 256 × 256 matrix, 1mm thick, 176 sagittal slices, FOV = 208 × 208mm), functional images with a T2*-weighted echo-planar sequence (72 axial slices, TR/TE = 2000.00/25.00ms, 90-degree flip angle, 104 × 104 matrix, 2mm thick, FOV = 208 × 208mm), and opposite phase encoded echo-planar images to correct for magnetic field inhomogeneities (72 axial slices, TR/TE = 6390.00/47.80ms, 90-degree flip angle, 104 ×104 matrix, 2mm thick, FOV = 208 × 208mm), resulting in a 2 × 2 × 2 mm voxel size.

Neuroimaging data were preprocessed using fMRIPrep 1.1.4 (Esteban et al., 2019). Preprocessing details appear in Supplementary Material in Appendix B, but briefly, anatomical images were segmented and normalized to MNI space using FreeSurfer (Fischl, 2012); functional images were susceptibility distortion corrected,

realigned, and coregistered to the normalized anatomical images. Normalized functional data were then smoothed (6mm FWHM) in SPM12.

Univariate neural analysis

In first-level statistical analyses, event-related condition effects were estimated using a fixed-effects general linear model and convolving the canonical hemodynamic response function with stimulus events using SPM12 (Wellcome Department of Cognitive Neurology; http://www.fil.ion.ucl.ac.uk/spm). Separate regressors were entered for conditions of interest (No-Choice Look, No-Choice Regulate, Yes-Choice Look, Yes-Choice Regulate) and the duration was modeled as the 6s image presentation. Additional regressors of no interest were included for the following events: food preview, condition cue, craving ratings, and difficulty ratings. An additional regressor of no interest was included for trials in which participants failed to respond to both the craving and difficulty ratings (modeled as the duration of the image presentation period). Ratings were modeled as the response time; if there was no response, it was modeled as the duration of the event (2.5s). Five motion regressors were modeled as covariates of no interest. Realignment parameters were transformed into Euclidean distance for translation and rotation separately; we also included the displacement derivative of each transformed regressor. Another "trash" regressor marked images with motion artifacts (e.g., striping) identified via automated motion assessment (Cosme et al., 2018a) and visual inspection. Nine participant task runs were excluded from the group-level analysis for having >10% unusable volumes, which was more than 2.5 SD from the mean (M = 1.50%, SD = 3.23%). All data were high-pass filtered at 128 seconds and temporal autocorrelation was modeled using the FAST method (Corbin et al., 2018). Linear contrasts for each

condition of interest versus rest were estimated across runs for each participant and used as inputs in second-level analyses.

Second-level, random effects were estimated by specifying a 2 × 2 within subject repeated measures ANOVA using a flexible factorial model in SPM12. This model was masked using a binarized average of participants' grey matter tissue probability maps generated by fMRIPrep. From this model, we generated the following contrasts of interest: Regulate > Look, Yes-Choice > No-Choice, and Yes-Choice (Regulate > Look) > No-Choice (Regulate > Look). Multiple comparisons were corrected using cluster-extent thresholding implemented in AFNI version 18.2.04 (Cox, 1996). In accordance with recent guidelines (Cox et al., 2017), the spatial autocorrelation function was first estimated for each subject and task run separately using AFNI's 3dFWHMx, and then averaged across subjects. To determine probability estimates of false-positive clusters given a random field of noise, Monte-Carlo simulations were conducted with AFNI's 3dClustSim using the average autocorrelation across subjects. A voxel-wise threshold of $p < 0.001$ and cluster extent of $k = 60$ was estimated (voxel dimensions = 2 × 2 × 2 mm) to achieve a whole-brain familywise error rate of $\alpha = 0.05$. Contrast tables were generated using BSPMVIEW (Spunt, 2016).

Post hoc trial-level analysis. We conducted a follow-up multilevel model adding trial-level pattern expression of the unthresholded whole-brain group-level Yes-Choice > No-Choice statistical map to the best fitting behavioral model in order to test whether choice-related neural activation was related to the task effects. Pattern expression reflects the degree to which a functional brain image corresponds to a target brain map and was calculated by taking the dot product of the group-level Yes-Choice > No-Choice contrast

and each trial statistical map. Trial-level maps were generated using the same first-level modeling procedure described previously with the exception that each trial was modeled as a separate regressor rather than grouped by condition (Rissman et al., 2004). Dot products were calculated using the 3ddot function in AFNI. Dot products were converted to Z-scores and trials that were more than 3 SDs from the mean were winsorized to 3 SDs. We then added this variable and its interaction with Goal, Choice, Difficulty, and Autonomous Motivation as fixed effects to Model 3 – Autonomous Motivation.

Multivariate neural analysis

We complemented the univariate analyses with multivoxel pattern analysis (MVPA) implemented using NLTools 0.3.11 (Chang et al., 2018). Because there were relatively few trials per condition and run, and the number of trials different based on participant choices, we conducted these analyses between-subjects in MNI space using average condition effects for each participant as the input data. We conducted the MVPA analyses within a binarized mask of the univariate main effect of Goal, which was computed as an F-contrast on data from the group-level univariate model. Classification of Look versus Regulate within this mask confirmed that the patterns of activation in it contained information that distinguished Goal (cross-validation accuracy = 0.78, 95% CI [0.74, 0.82], $p < .001$).

We then trained a logistic classifier to decode Yes-Choice versus No-Choice in this mask using 5-fold cross-validation. Although we originally preregistered using leave-one-subject-out cross-validation, we selected this procedure instead because it yielded equivalent results when classifying Goal and the k-fold approach requires substantially less computational resources. Within each fold, data from 92 participants served as the

training set and the data from the remaining 23 participants served as the test set. In addition to classifying Choice collapsed across Goal, we conducted four additional analyses, classifying Choice within Regulate and Look separately, as well as classifying Goal within Yes-Choice and No-Choice separately.

Results

Behavioral analyses

Post-task autonomous motivation and task difficulty analysis. After completing the ROC-C task, participants rated how autonomously motivated they felt and how difficult they perceived the Yes-Choice and No-Choice task conditions (Figure 4.2). Participants reported higher autonomous motivation during Yes-Choice trials (M = 4.09, SD = 0.68) than No-Choice trials (M = 4.01, SD = 0.65), but this difference was not statistically significant (b = 0.08, SE = 0.07, $t(111)$ = 1.16, p = .249). This appears to be due to the fact that the individual items differed in their relationship to choice. That is, motivation was rated as being higher during Yes-Choice than No-Choice trials (M_{diff} = 0.25, SD = 0.96), whereas they were rated equivalently for engagement (M_{diff} = 0.03, SD = 0.87) and liking (M_{diff} = -0.04, SD = 0.93). With respect to difficulty, participants rated Yes-Choice trials (M = 2.05, SD = 1.06) as less difficult than No-Choice trials (M = 2.33, SD = 1.15), and this difference was statistically significant (b = -0.28, SE = 0.10, $t(111)$ = 2.66, p = .009).

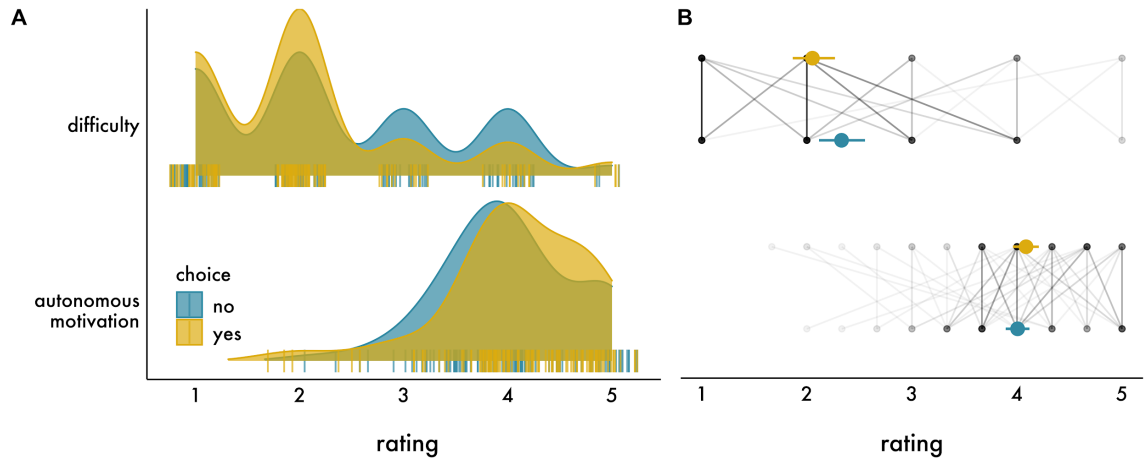

Figure 4.2. Post-task ratings of autonomous motivation and task difficulty as a function of choice. A) shows the distribution of ratings and B) shows means and 95% confidence intervals overlaid on individual data. The lines in panel B indicate the difference between the Yes- and No-Choice conditions for each participant; the darker the line, the more observations.

Because these post-task manipulation check items were not part of a previously validated measure, we conducted post hoc analyses (Figure 4.3) to assess their validity. Pearson correlations among the liking, engagement, and motivation items showed moderate to high correlations within choice condition (r range = .39 to .65) and these items were correlated negatively with difficulty (r range = -.32 to -.46). Furthermore, as expected, the aggregate measures of autonomous motivation derived from these items were moderately to highly correlated (r range = .35 to .54) with indicators of autonomous motivation on the previously validated Intrinsic Motivation Inventory (IMI; Ryan, 1982; McAuley et al., 1989), including interest and enjoyment, and perceived competence during the task, and uncorrelated with pressure and tension during the task (r range = -.03 to .00). However, the correlations between the perceived choice facet on the IMI was less strongly correlated with the aggregate measure derived from items on the post-task manipulation check survey (r range = .13 to .21).

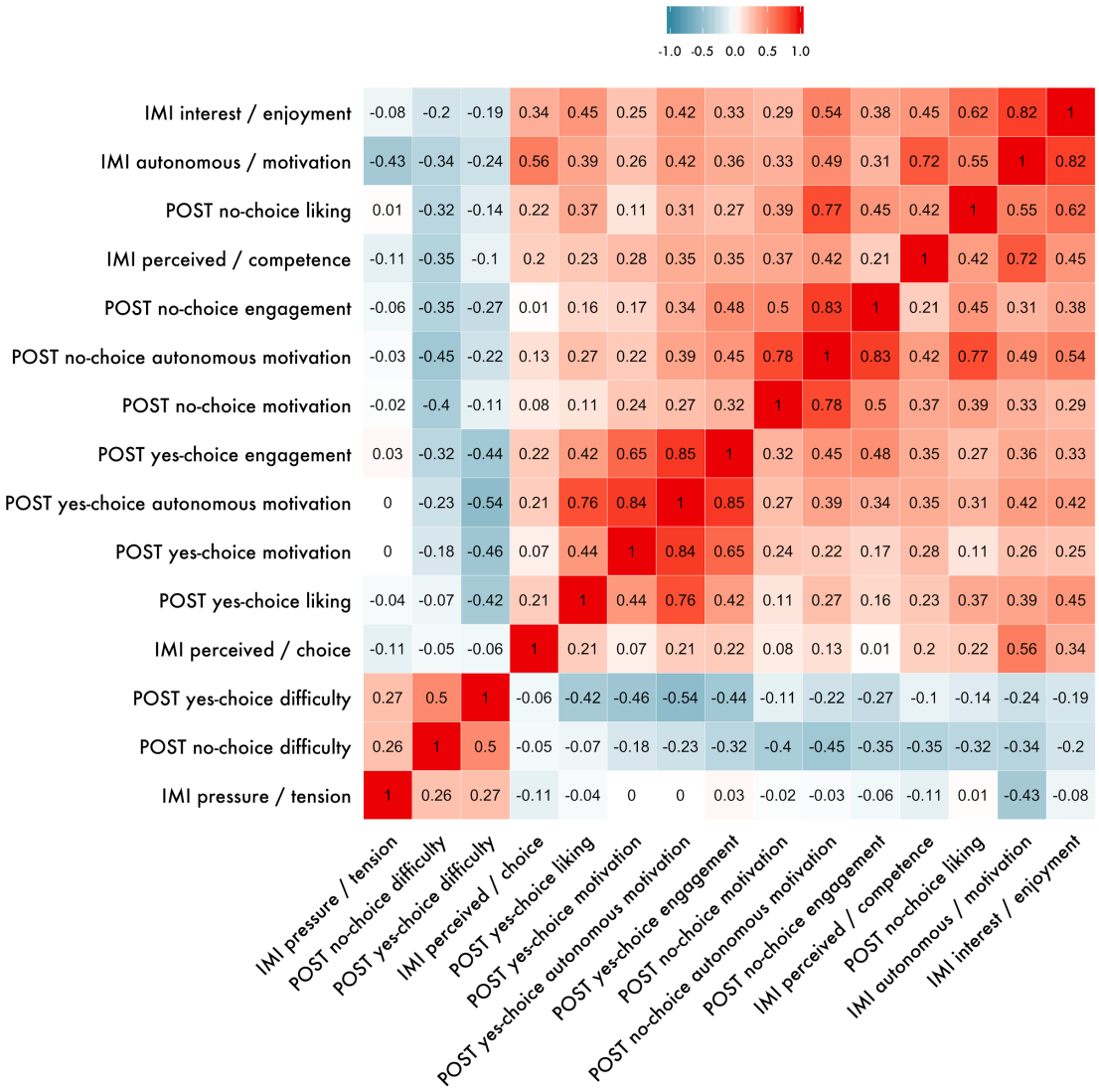

Figure 4.3. Bivariate correlations among measures from the post-task manipulation check survey (POST) and the Intrinsic Motivation Inventory (IMI). Autonomous motivation is a composite measure of the engagement, liking, and motivation items in the post-task survey, and all facets in the IMI with pressure / tension items reverse coded so that higher values indicated lower pressure / tension.

Table 4.1

Means and standard deviations for facets of the Intrinsic Motivation Inventory

Facet	*M*	*SD*
Autonomous motivation	5.13	0.58
Interest / enjoyment	4.56	1.21
Perceived choice	6.33	0.64
Perceived competence	4.79	0.92
Pressure / tension	3.14	0.72

Note. Autonomous motivation is a composite measure of all facets in the IMI with pressure / tension items reverse coded so that higher values indicated lower pressure / tension.

Task choice distribution. There was substantial variability in the percentage of trials in which participants chose to regulate (Figure 4.4). On average, participants chose to regulate 46.6% of the time (SD = 9.2%).

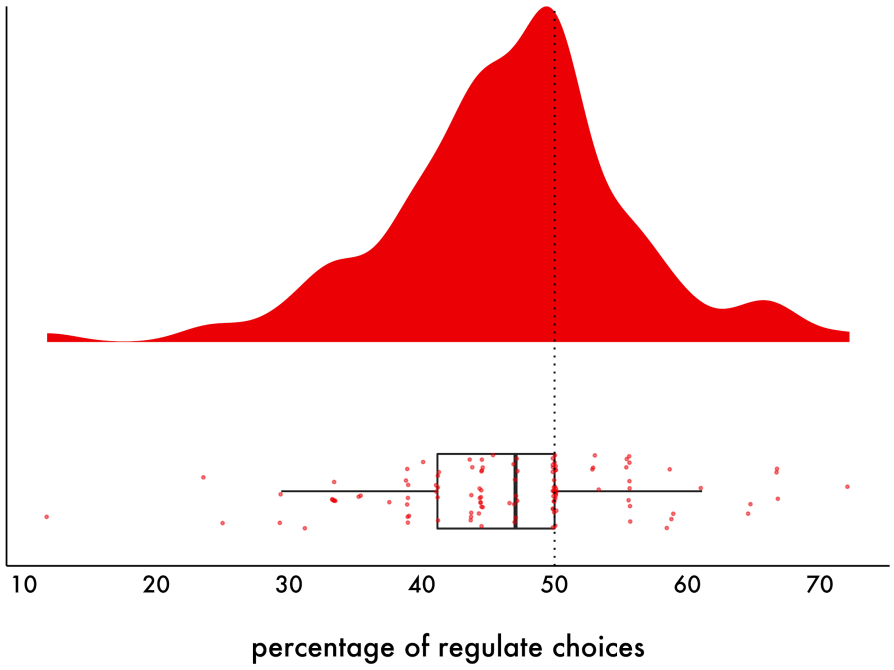

Figure 4.4. Density distribution and box plot of the percentage of trials in which participants chose to regulate.

ROC-C trial-level craving analyses. We compared three multilevel models and found that Model 3 – Autonomous Motivation best fit the data (Table 4.2). In this model,

participants reported lower cravings on Regulate trials than Look trials. Trials perceived as more difficult were associated with lower craving ratings on Look trials and higher ratings on Regulate trials, indicating worse performance when goal pursuit was difficult. This interaction was magnified by autonomous motivation on No-Choice trials, such that stronger autonomous motivation was associated with further decrements to task performance. Specifically, higher autonomous motivation on No-choice trials was associated with even lower craving ratings for more difficult Look trials (b = -0.07, p < .001) and even higher craving ratings for more difficult regulate trials (b = 0.07, p = .011). However, this relationship was reversed for Yes-Choice trials. Participants with relatively greater autonomous motivation on Yes-Choice trials reported higher craving ratings for difficult Look trials (b = 0.09, p = .001) and lower craving ratings for difficult Regulate trials (b = -0.10, p = .002), indicating better task performance compared to No-Choice trials. Parameter estimates and statistics for all models terms are listed in Table 4.3 and the predicted effects are visualized in Figure 4.5. We also conducted a post hoc analysis modeling the fixed effects of autonomous motivation during Yes-Choice and No-Choice sets separately rather than as a single individual differences variable. This allowed us to determine whether increased perceived autonomous motivation for Yes- and No-Choice were uniquely related to the corresponding choice condition during the task. This model fit the data better than Model 3, $X^2(8) = 27.71$, $p < .001$ (Table B1), and confirmed that the effect of autonomous motivation on task performance was unique to the specific choice condition (Table B2). That is, higher autonomous motivation during Yes-Choice trials was not related to task performance on No-Choice trials and vice versa

(Figure B1). The full model and model comparison is reported and visualized in Supplementary material in Appendix B.

Table 4.2

Comparison of multilevel models with trial-level craving ratings as the criterion

Model	Model *df*	AIC	X^2	X^2 *df*	*p*
Model 1 – Choice	13	22844.13	–	–	–
Model 2 – Difficulty	17	22159.90	692.24	4	< .001
Model 3 – Autonomous Motivation	**25**	**22150.26**	**25.63**	**8**	**.001**

Note. The best fitting model is bolded.

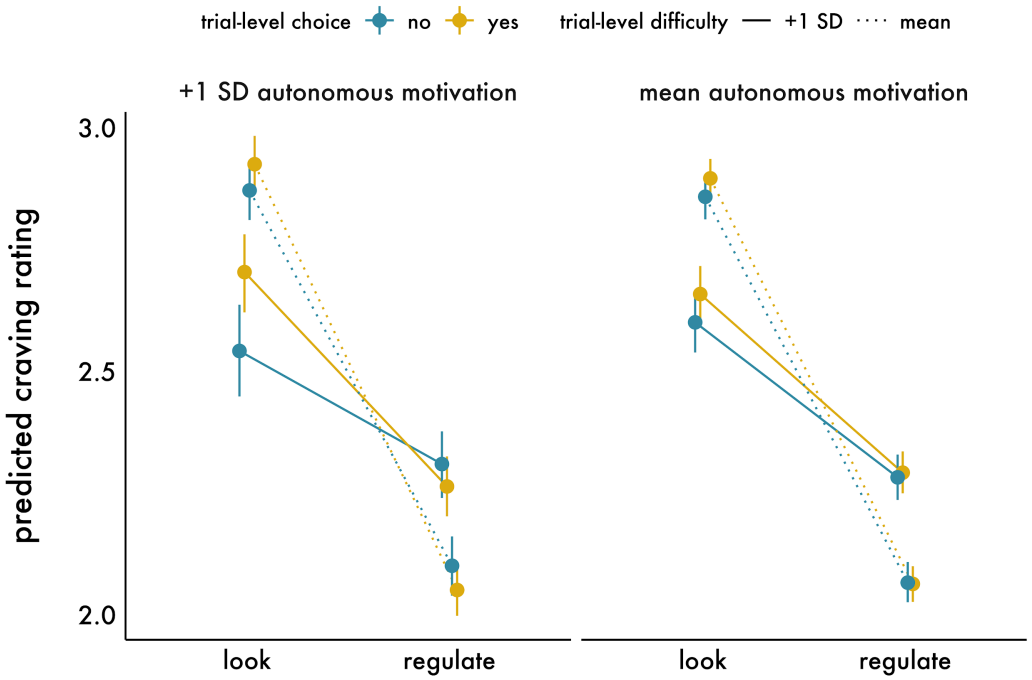

Figure 4.5. Predicted trial-level craving ratings from the best fitting multilevel model (Model 3 – Autonomous Motivation) as a function of trial-level Goal, Choice, and Difficulty, and person-level Autonomous Motivation rated post-task. Error bars are bootstrapped 95% confidence intervals.

Table 4.3

Results from the best fitting trial-level craving rating multilevel model

Fixed effects	*b* [95% CI]	*SE*	*t*	*df*	*p*
Intercept (Look, No-Choice)	**2.91 [2.85, 2.98]**	**0.03**	**84.07**	**148.21**	**< .001**
Goal	**-0.79 [-0.90, -0.69]**	**0.05**	**-15.26**	**146.09**	**< .001**
Choice	0.04 [-0.01, 0.08]	0.02	1.73	9327.99	.084
Difficulty	**-0.26 [-0.30, -0.22]**	**0.02**	**-12.88**	**9445.41**	**< .001**
AM	0.02 [-0.02, 0.06]	0.02	0.86	4382.26	.389
Trial	**-0.01 [-0.02, -0.01]**	**0.00**	**-4.15**	**9343.70**	**< .001**
Baseline Craving	**0.26 [0.23, 0.29]**	**0.02**	**16.06**	**89.66**	**< .001**
Goal × Choice	-0.04 [-0.10, 0.02]	0.03	-1.30	9327.05	.193
Goal × Difficulty	**0.48 [0.42, 0.53]**	**0.03**	**18.33**	**9497.92**	**< .001**
Choice × Difficulty	0.02 [-0.03, 0.07]	0.03	0.83	9373.60	.407
Goal × AM	0.03 [-0.03, 0.09]	0.03	1.00	4476.93	.317
Choice × AM	0.02 [-0.03, 0.07]	0.03	0.84	8170.75	.399
Difficulty × AM	**-0.07 [-0.11, -0.03]**	**0.02**	**-3.53**	**9431.30**	**< .001**
Goal × Choice × Difficulty	-0.01 [-0.07, 0.06]	0.03	-0.24	9381.03	.808
Goal × Choice × AM	-0.06 [-0.14, 0.01]	0.04	-1.70	8243.77	.088
Goal × Difficulty × AM	**0.07 [0.02, 0.12]**	**0.03**	**2.54**	**9494.30**	**.011**
Choice × Difficulty × AM	**0.09 [0.04, 0.13]**	**0.02**	**3.47**	**9455.02**	**.001**
Goal × Choice × Difficulty × AM	**-0.10 [-0.16, -0.03]**	**0.03**	**-3.03**	**9500.58**	**.002**

Random effects	variance	*SD*
Participant		
Intercept	0.10	0.31
Goal	0.23	0.48
Baseline Craving	0.02	0.14
Residual	0.55	0.74

Note. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. Statistically significant parameters at $p < .05$ are bolded. The reference condition for Goal is Look; the reference condition for Choice is No-Choice; Difficulty, Autonomous Motivation, and Baseline Craving are Z-scored; and Trial is centered at 45 and is units of 10 trials. AM = Autonomous Motivation.

ROC-C trial-level difficulty analyses. Model comparison revealed the Model 2 – Autonomous Motivation × Choice best fit the data (Table 4.4). In this model, participants reported more difficulty on Regulate than Look trials ($b = 0.44$, $p < .001$). Choice was associated with lower difficulty ratings ($b = -0.05$, $p = .030$) and this effect

did not differ as a function of Goal (b = 0.01, p = .757). However, the effect of Choice was moderated by individual differences in autonomous motivation, such that Yes-Choice trials were rated as less difficult for individuals who reported also higher autonomous motivation during these trials (Figure 4.6). Parameter estimates and statistics for all models terms are listed in Table 4.5.

Table 4.4

Comparison of multilevel models with trial-level difficulty ratings as the criterion

Model	Model *df*	AIC	X^2	X^2 *df*	*p*
Model 1 – Choice	13	24124.17	–	–	–
Model 2 – Autonomous Motivation × Choice	**15**	**24114.27**	**13.90**	**2**	**.001**
Model 3 – Autonomous Motivation × Choice × Goal	17	24114.55	3.72	2	.156

Note. The best fitting model is bolded.

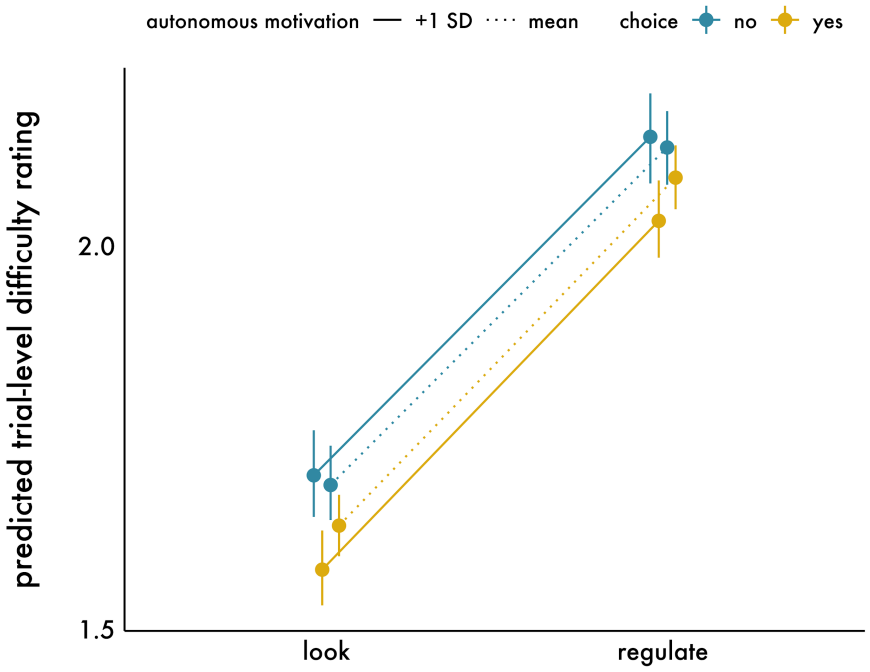

Figure 4.6. Predicted trial-level difficulty ratings from the best fitting multilevel model (Model 2 – Autonomous Motivation × Choice) as a function of trial-level Goal and Choice, and person-level Autonomous Motivation rated post-task. Error bars are bootstrapped 95% confidence intervals.

Table 4.5

Results from the best fitting trial-level difficulty rating multilevel model

Fixed effects	*b* [95% CI]	*SE*	*t*	*df*	*p*
Intercept (Look, No-Choice)	**1.69 [1.62, 1.76]**	**0.04**	**46.26**	**152.24**	**< .001**
Goal	**0.44 [0.35, 0.53]**	**0.05**	**9.64**	**168.49**	**< .001**
Choice	**-0.05 [-0.10, -0.01]**	**0.02**	**-2.17**	**9352.20**	**.030**
Autonomous Motivation	0.02 [-0.01, 0.06]	0.02	1.27	6685.77	.204
Trial	-0.00 [-0.01, 0.01]	0.00	-0.20	9371.21	.841
Baseline Craving	-0.01 [-0.04, 0.01]	0.01	-0.97	90.32	.335
Goal × Choice	0.01 [-0.06, 0.08]	0.03	0.31	9342.56	.757
Choice × Autonomous Motivation	**-0.07 [-0.11, -0.03]**	**0.02**	**-3.59**	**9109.02**	**< .001**

Random effects	variance	*SD*
Participant		
Intercept	0.11	0.33
Goal	0.16	0.40
Baseline Craving	0.01	0.08
Residual	0.68	0.82

Note. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. Statistically significant parameters at $p < .05$ are bolded. The reference condition for Goal is Look; the reference condition for Choice is No-Choice; Autonomous Motivation and Baseline Craving are Z-scored; and Trial is centered at 45 and in units of 10 Trials.

Post hoc individual difference analyses. We ran two multilevel models regressing regulation success on Choice, Autonomous Motivation, and their interaction (Table 4.6). When autonomous motivation was assessed toward the task as a whole in the Intrinsic Motivation Inventory, autonomous motivation was positively associated with regulation success across both choice conditions, but this relationship was stronger in the Yes-Choice condition (Figure 4.7). For autonomous motivation assessed separately for each choice condition during the post-task survey, autonomous motivation was only positively associated with regulation success in the Yes-Choice condition.

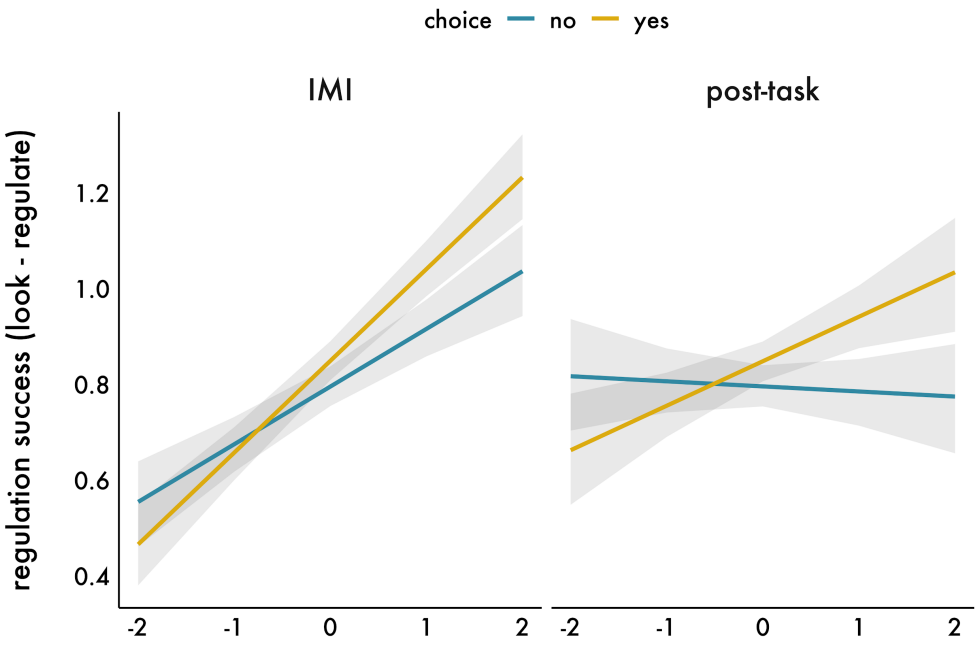

Figure 4.7. Predicted regulation success during the Regulation of Craving–Choice task as a function of Autonomous Motivation and Choice. Autonomous motivation was assessed about the task as a whole using the Intrinsic Motivation Inventory) and as a function of choice on the post-task manipulation check survey (post-task). Error bands are bootstrapped 95% confidence intervals.

Table 4.6

Results from the individual difference multilevel models

IMI	*b* [95% CI]	*SE*	*t*	*df*	*p*
Intercept (No-Choice)	**0.80 [0.70, 0.89]**	**0.05**	**16.02**	**131.18**	**< .001**
Choice	0.05 [-0.00, 0.11]	0.03	1.81	110	.073
Autonomous Motivation	**0.12 [0.02, 0.22]**	**0.05**	**2.44**	**131.18**	**.016**
Choice × Autonomous Motivation	**0.07 [0.01, 0.13]**	**0.03**	**2.44**	**110**	**.016**
Post-task					
Intercept (No-Choice)	**0.80 [0.69, 0.90]**	**0.05**	**15.48**	**128.95**	**< .001**
Choice	0.05 [-0.00, 0.11]	0.03	1.83	107.85	.070
Autonomous Motivation	-0.03 [-0.09, 0.03]	0.03	-1.06	138	.290
Choice × Autonomous Motivation	**0.11 [0.04, 0.17]**	**0.03**	**3.05**	**116.43**	**.003**

Note. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. Statistically significant parameters at $p < .05$ are bolded. The reference condition for Choice is No-Choice; Autonomous Motivation is Z-scored across participants. IMI = Intrinsic Motivation Inventory; Post-task = post-task manipulation check survey.

Univariate neural analyses

To identify brain regions that showed relatively greater BOLD signal during autonomous goal pursuit, we contrasted Yes-Choice > No-Choice trials (Figure 4.8). We observed increased BOLD signal in the frontoparietal control network, with significant clusters in left dorsolateral prefrontal cortex (dlPFC), inferior frontal gyrus (IFG), and inferior parietal lobule. Additional clusters were found in bilateral pre-supplementary motor cortex (pre-SMA) and visual cortex. The reverse contrast, No-Choice > Yes-Choice, revealed small significant clusters of activation in bilateral superior temporal cortex, cuneus, and posterior cingulate cortex, as well as in other regions listed in Table 4.7. We also observed several small clusters of activations in bilateral postcentral gyrus, right posterior insula and amygdala, and left precuneus, when contrasting Yes-Choice (Regulate > Look) > No-Choice (Regulate > Look). All cluster locations and statistics are listed in Table 4.7. Unthresholded statistical maps for this effect and all other effects reported in this article are available through NeuroVault (Gorgolewski et al., 2015; https://neurovault.org/collections/NDHWTOBQ/).

Table 4.7

Regions, MNI Coordinates, cluster extent, and peak t-values for choice contrasts

Contrast	Region	MNI Coordinates (x, y, z)			Extent (*k*)	Peak *t*
Yes > No	L Lingual Gyrus	-12	-96	-10	8945	8.82
	R Cerebellum (VI)	12	-88	-10	8945	8.06
	L Cerebellum (Crus 1)	-32	-82	-14	8945	7.08
	L Middle Occipital Gyrus	-26	-68	42	1360	5.28
	L Inferior Parietal Lobule	-48	-40	52	1360	4.16
	L Inferior Parietal Lobule	-36	-60	60	1360	3.91
	L Superior Frontal Gyrus	-4	12	50	567	5.80
	L IFG (p. Triangularis)	-56	14	36	522	4.85
	R Superior Occipital Gyrus	30	-66	34	179	3.90
	L IFG (p. Triangularis)	-58	22	2	103	4.02
	L Middle Frontal Gyrus	-50	46	8	70	3.90
No > Yes	L PCC	-20	-46	14	312	7.30
	L Caudate Nucleus	-20	-24	28	312	4.50
	L Caudate Nucleus	-20	0	28	312	4.45
	R Cuneus	14	-82	36	224	4.83
	R PCC	24	-44	18	172	6.29
	R Fusiform Gyrus	34	-54	2	172	4.07
	L Cuneus	-8	-84	36	169	4.28
	L Calcarine Gyrus	-20	-74	18	169	3.95
	R Superior Temporal Gyrus	54	-24	12	140	3.94
	R Postcentral Gyrus	26	-32	64	138	4.53
	L Superior Temporal Gyrus	-58	-32	12	74	3.91
Yes (Reg. > Look) >	R Medial Temporal Pole	54	14	-30	96	4.47
No (Reg. > Look)	R Rolandic Operculum	48	-26	24	132	4.34
	R Amygdala	28	-4	-14	66	4.25
	L Precuneus	-10	-40	56	60	3.98
	R Postcentral Gyrus	24	-38	76	60	3.81
	L Postcentral Gyrus	-22	-38	72	65	3.70

Note. Cluster family-wise error correction for $\alpha = 0.05$ and $p < 0.001$ is $k = 60$. Cluster extent (k) is measured in 2 mm^3 voxels.

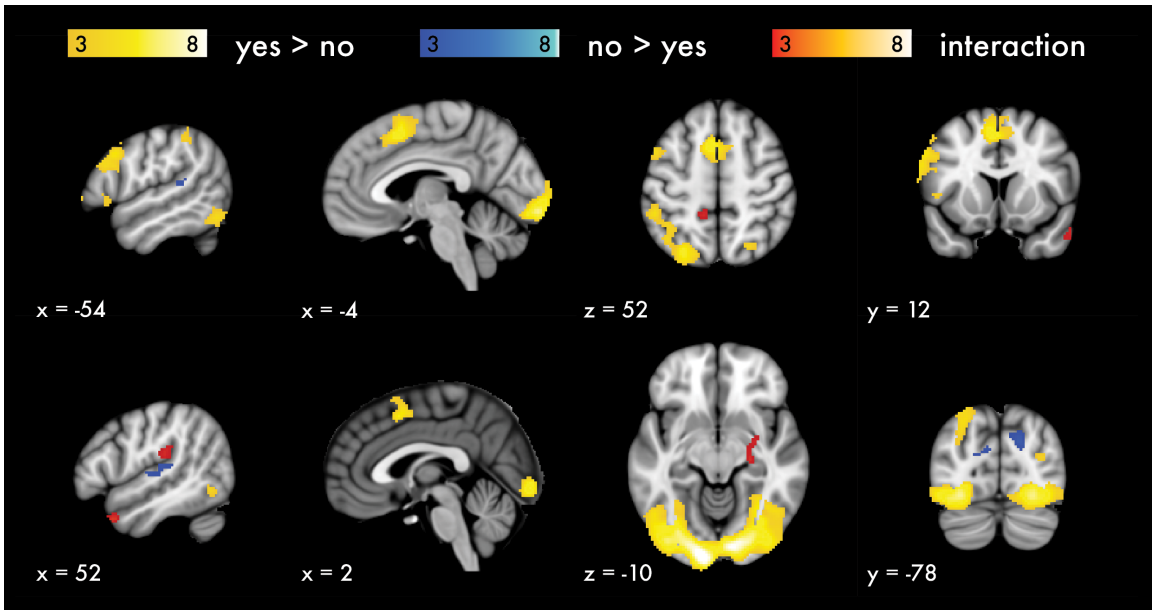

Figure 4.8. Univariate main effects for Choice and the interaction between Choice and Goal: Yes-Choice (Regulate > Look) > No-Choice (Regulate > Look). Results are thresholded at $p < .001$ and $k = 60$. Cluster extent (k) is measured in 2 × 2 × 2mm voxels.

In line with previous research on cognitive reappraisal (for meta-analyses, see Buhle et al., 2014; Han et al., 2018), we observed robust activation in regions within the frontoparietal control network when contrasting Regulate > Look (Figure 4.9). There were large clusters of bilateral activation in IFG, anterior temporal cortex, middle temporal cortex, posterior parietal cortex, posterior cingulate cortex, pre-SMA and dorsomedial prefrontal cortex, and dorsal and ventral striatum, as well as in left dlPFC. The reverse contrast Look > Regulate was associated with relatively greater BOLD signal in bilateral postcentral gyrus, mid and posterior insula, precuneus, anterior and mid cingulate cortex, subgenual anterior cingulate cortex, as well as right anterior ventromedial prefrontal cortex. Spatial and statistical information about all clusters are specified in Table 4.8.

Table 4.8

Regions, MNI Coordinates, cluster extent, and peak t-values for goal contrasts

Contrast	Region	MNI Coordinates (x, y, z)			Extent (*k*)	Peak *t*
Regulate > Look	L Superior Frontal Gyrus	-8	14	68	19251	13.77
	R IFG (p. Orbitalis)	-52	36	-12	19251	13.59
	L Superior Medial Gyrus	-6	42	54	19251	12.90
	R Cerebellum (Crus 2)	32	-84	-38	3546	11.51
	R Cerebellum (Crus 2)	12	-84	-26	3546	8.88
	R Cerebellum (Crus 1)	34	-60	-32	3546	6.73
	L Angular Gyrus	-54	-64	36	1858	10.01
	L Inferior Parietal Lobule	-46	-62	56	1858	6.94
	R IFG (p. Orbitalis)	50	30	-10	995	7.53
	R IFG (p. Orbitalis)	32	20	-10	995	6.15
	R IFG (p. Triangularis)	60	24	12	995	5.24
	R Medial Temporal Pole	46	8	-44	815	7.85
	R Medial Temporal Pole	52	16	-26	815	6.23
	L MCC	-2	-18	36	804	8.90
	L PCC	-4	-46	26	804	6.51
	L Lingual Gyrus	-12	-80	6	594	5.49
	L Cerebellum (Crus 2)	-36	-86	-34	443	5.87
	L Cerebellum (Crus 2)	-8	-86	-24	443	4.16
	L Precuneus	-6	-74	38	438	7.35
	R Superior Temporal Gyrus	46	-32	-4	216	5.03
	R Cerebellum (IX)	6	-58	-42	213	5.59
	R Precentral Gyrus	40	-18	40	156	4.47
	R Postcentral Gyrus	20	-28	68	67	4.75
	R Angular Gyrus	52	-56	42	63	3.95
Look > Regulate						
	L Postcentral Gyrus	-42	-28	58	8220	9.88
	L Insula Lobe	-40	-2	16	8220	8.67
	L Postcentral Gyrus	-62	-24	42	8220	8.40
	R Rolandic Operculum	58	-18	22	3459	7.84
	R Postcentral Gyrus	48	-30	54	3459	6.40
	R Middle Occipital Gyrus	42	-72	32	3459	5.68
	L MCC	-6	-6	52	882	7.54
	L ACC	-2	14	30	882	4.74
	L MCC	-10	-26	50	882	3.58
	R Insula Lobe	40	0	14	750	6.39
	R Amygdala	26	-2	-8	750	4.96
	R Putamen	36	-18	0	750	4.36
	R Inferior Temporal Gyrus	60	-46	-8	710	6.32

Table 4.8 (continued)

Contrast	Region	MNI Coordinates (x, y, z)			Extent (*k*)	Peak *t*
	R IFG (p. Opercularis)	60	10	22	568	5.79
	R Precentral Gyrus	24	-10	58	465	4.81
	L IFG (p. Opercularis)	-60	6	32	311	8.10
	R Superior Orbital Gyrus	30	60	2	307	4.44
	R Mid Orbital Gyrus	4	62	0	307	3.88
	R Middle Frontal Gyrus	24	40	32	289	4.34
	R Cerebellum (VIII)	28	-44	-52	260	5.04
	R Lingual Gyrus	12	-68	-2	226	5.43
	R Mid Orbital Gyrus	0	18	-6	215	5.38
	L Inferior Temporal Gyrus	-58	-58	-6	214	3.98
	L Middle Occipital Gyrus	-34	-84	36	201	4.27
	R Middle Frontal Gyrus	46	40	12	194	4.23
	R Calcarine Gyrus	6	-64	24	172	4.73
	L Fusiform Gyrus	-32	-40	-16	115	4.47

Note. Cluster family-wise error correction for $\alpha = 0.05$ and $p < .001$ is $k = 60$. Cluster extent (k) is measured in 2 × 2 × 2 mm voxels.

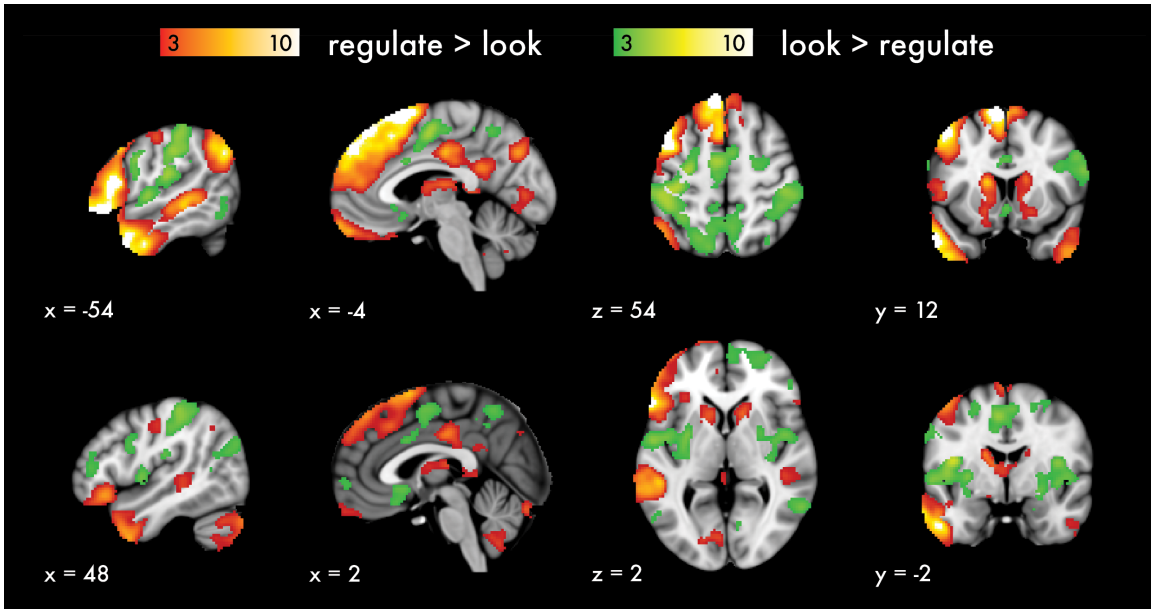

Figure 4.9. Univariate main effects for Goal. Results are thresholded at $p < .001$ and $k = 60$. Cluster extent (k) is measured in 2 × 2 × 2mm voxels.

Post hoc trial-level analysis. The model including trial-level pattern expression of the Yes-Choice > No-Choice group-level contrast explained additional variance

compared to the best fitting behavioral model, $X^2(16) = 36.15$, $p = .003$. Adding trial-level pattern expression did not alter the effects reported in Model 3 –Autonomous Motivation, but revealed additional statistically significant interactions between Pattern Expression and Goal, Difficulty, and Autonomous Motivation (Table 4.9). Specifically, stronger expression of the whole-brain autonomous goal pursuit pattern (i.e., Yes-Choice > No-Choice) on relatively difficult No-Choice trials was associated with worse task performance for both the Look and Regulate conditions (Figure 4.10). We also observed a four-way interaction between these variables, such that individuals with greater autonomous motivation and pattern expression on relatively difficult No-Choice Regulate trials had further decrements in task performance. In contrast, stronger expression of the autonomous goal pursuit pattern during Yes-Choice trials was associated with better performance with increasing difficulty and autonomous motivation across both Look and Regulate conditions. However, although the effect sizes were similar for Yes- and No-Choice trials, the effects for Yes-Choice were not statistically significant at $p < .05$.

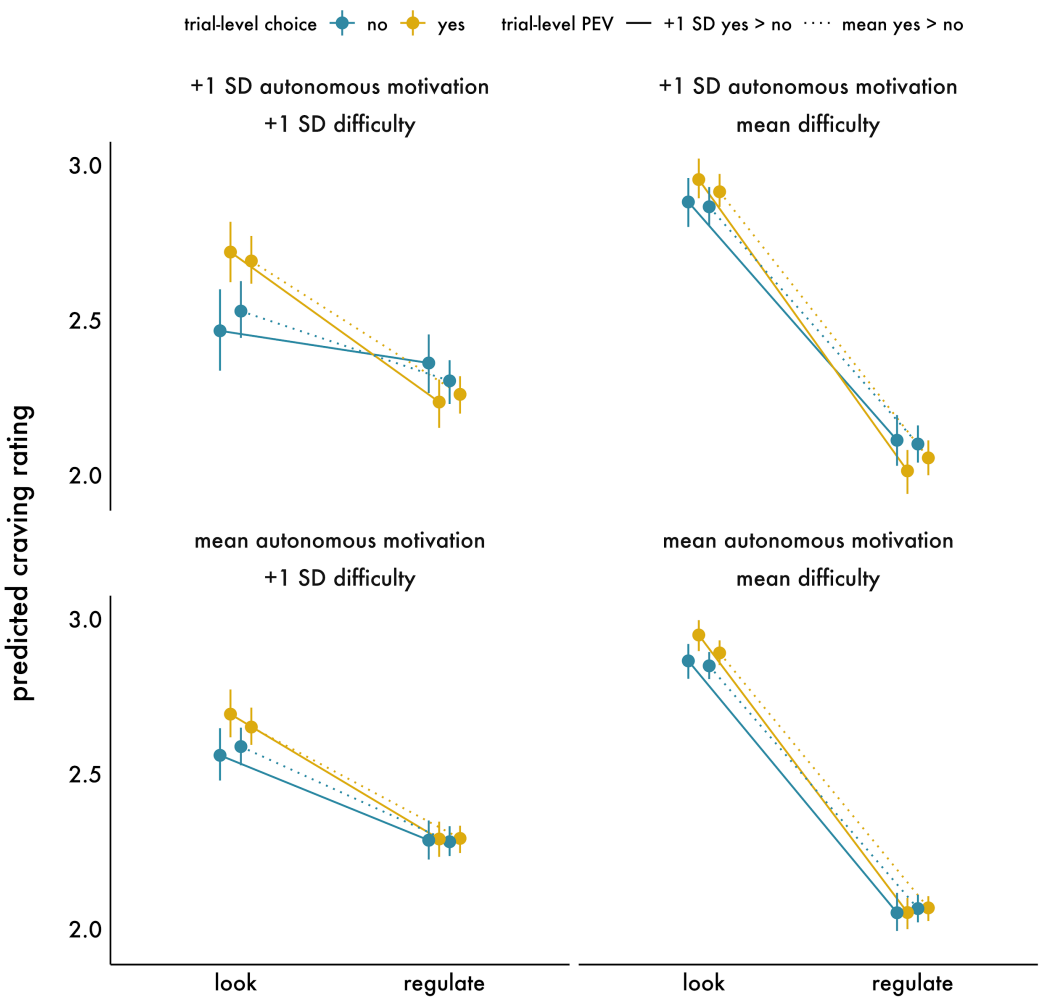

Figure 4.10. Predicted craving ratings from the post hoc multilevel model including neural pattern expression of the Yes-Choice > No-Choice group-level contrast as a function of trial-level Goal, Choice, Difficulty, and pattern expression, and person-level Autonomous Motivation rated post-task. The top panel describes these interactions one standard deviation above mean Autonomous Motivation, whereas the bottom panel shows the interactions at mean Autonomous Motivation. The left panel visualized them at one standard deviation above mean Difficulty, and the right panel shows them at mean Difficulty. Error bars are bootstrapped 95% confidence intervals. AM = Autonomous Motivation; PEV = pattern expression value.

Table 4.9

Results from the post hoc trial-level craving rating multilevel model

Fixed effects	*b* [95% CI]	*SE*	*t*	*df*	*p*
Intercept (Look, No-Choice)	**2.91 [2.84, 2.98]**	**0.03**	**83.69**	**149.23**	**< .001**
Goal	**-0.78 [-0.89, -0.68]**	**0.05**	**-15.21**	**147.11**	**< .001**
Choice	0.04 [-0.00, 0.09]	0.02	1.84	9057.17	.065
Difficulty	**-0.26 [-0.30, -0.22]**	**0.02**	**-12.82**	**9169.30**	**< .001**
PEV	0.01 [-0.02, 0.05]	0.02	0.59	9148.8	.557
AM	0.02 [-0.02, 0.07]	0.02	0.96	4176.83	.336
Trial	**-0.01 [-0.02, -0.01]**	**0.00**	**-4.36**	**9095.37**	**< .001**
Baseline Craving	**0.26 [0.23, 0.29]**	**0.02**	**15.79**	**88.61**	**< .001**
Goal × Choice	-0.04 [-0.10, 0.02]	0.03	-1.20	9056.85	.229
Goal × Difficulty	**0.48 [0.43, 0.53]**	**0.03**	**18.22**	**9221.09**	**< .001**
Choice × Difficulty	0.02 [-0.03, 0.07]	0.03	0.94	9100.72	.347
Goal × PEV	-0.02 [-0.07, 0.03]	0.03	-0.79	9117.26	.430
Choice × PEV	0.04 [-0.00, 0.09]	0.02	1.94	9110.50	.053
Difficulty × PEV	**-0.04 [-0.08, -0.01]**	**0.02**	**-2.3**	**9148.79**	**.021**
Goal × AM	0.03 [-0.03, 0.09]	0.03	0.96	4108.48	.336
Choice × AM	0.01 [-0.04, 0.06]	0.03	0.50	7917.91	.617
Difficulty × AM	**-0.07 [-0.11, -0.04]**	**0.02**	**-3.71**	**9152.46**	**< .001**
PEV × AM	0.00 [-0.04, 0.04]	0.02	0.03	9172.47	.976
Goal × Choice × Difficulty	-0.02 [-0.08, 0.05]	0.03	-0.55	9107.46	.584
Goal × Choice × PEV	-0.05 [-0.11, 0.02]	0.03	-1.46	9108.60	.144
Goal × Difficulty × PEV	**0.06 [0.01, 0.11]**	**0.03**	**2.33**	**9168.36**	**.020**
Choice × Difficulty × PEV	0.03 [-0.02, 0.08]	0.02	1.10	9123.93	.271
Goal × Choice × AM	-0.05 [-0.13, 0.02]	0.04	-1.45	7945.69	.146
Goal × Difficulty × AM	**0.06 [0.01, 0.11]**	**0.03**	**2.42**	**9218.02**	**.016**
Choice × Difficulty × AM	**0.09 [0.04, 0.14]**	**0.02**	**3.63**	**9179.32**	**< .001**
Goal × PEV × AM	0.02 [-0.03, 0.08]	0.03	0.85	9166.10	.396
Choice × PEV × AM	-0.02 [-0.06, 0.03]	0.02	-0.64	9177.18	.520
Difficulty × PEV × AM	-0.03 [-0.07, 0.01]	0.02	-1.69	9136.43	.090
Goal × Choice × Difficulty × PEV	-0.03 [-0.10, 0.03]	0.03	-0.92	9114.11	.356
Goal × Choice × Difficulty × AM	**-0.10 [-0.16, -0.03]**	**0.03**	**-3.00**	**9226.42**	**.003**
Goal × Choice × PEV × AM	-0.04 [-0.11, 0.03]	0.04	-1.06	9180.15	.291
Goal × Difficulty × PEV × AM	**0.06 [0.01, 0.11]**	**0.03**	**2.46**	**9145.39**	**.014**
Choice × Difficulty × PEV × AM	0.04 [-0.01, 0.08]	0.02	1.53	9122.07	.126
Goal × Choice × Difficulty × PEV × AM	-0.06 [-0.13, 0.00]	0.03	-1.86	9129.49	.063

Table 4.9 (continued)

Random effects	variance	*SD*
Participant		
Intercept	0.10	0.31
Goal	0.22	0.47
Baseline Craving	0.02	0.14
Residual	0.55	0.74

Note. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. Statistically significant parameters at $p < .05$ are bolded. The reference condition for Goal is Look; the reference condition for Choice is No-Choice; Difficulty, Yes-Choice > No-Choice Pattern Expression, Autonomous Motivation, and Baseline Craving are Z-scored across participants; and Trial is centered at 45 and is units of 10 trials. AM = Autonomous Motivation; PEV = Pattern Expression Value.

Multivariate neural analysis

The MVPA analyses revealed that autonomous goal pursuit was distinguishable from controlled goal pursuit above chance accuracy (Figure 4.11). This was the case when collapsed across Goal, as well as for Regulate and Look separately. Overall, classification accuracy was the highest when decoding Choice within the Look condition only (accuracy = 0.59, 95% CI [0.52, 0.65]), followed by the Regulate condition only (accuracy = 0.57, 95% CI [0.50, 0.63]), and lowest when collapsed across Goal (accuracy = 0.55, 95% CI [0.50, 0.60]). All statistics are reported in Table 4.10.

We also investigated whether choice reduced classification accuracy when decoding Goal. We observed somewhat higher classification accuracy during autonomous goal pursuit (accuracy = 0.77, 95% CI [0.71, 0.82]) than during controlled goal pursuit (accuracy = 0.75, 95% CI [0.69, 0.81]), but the difference was not statistically significant.

Table 4.10

Cross-validated MVPA analysis results

Choice	Accuracy [95% CI]	*p*	Sensitivity	Specificity
Look & Regulate	0.55 [0.50, 0.60]	.018	0.52	0.58
Regulate only	0.57 [0.50, 0.63]	.028	0.53	0.60
Look only	0.59 [0.52, 0.65]	.005	0.55	0.63
Goal				
Yes- & No-Choice	0.78 [0.74, 0.82]	< .001	0.78	0.78
Yes-Choice only	0.75 [0.69, 0.81]	< .001	0.78	0.72
No-Choice only	0.77 [0.71, 0.82]	< .001	0.75	0.78

Note. Chance accuracy is 0.5.

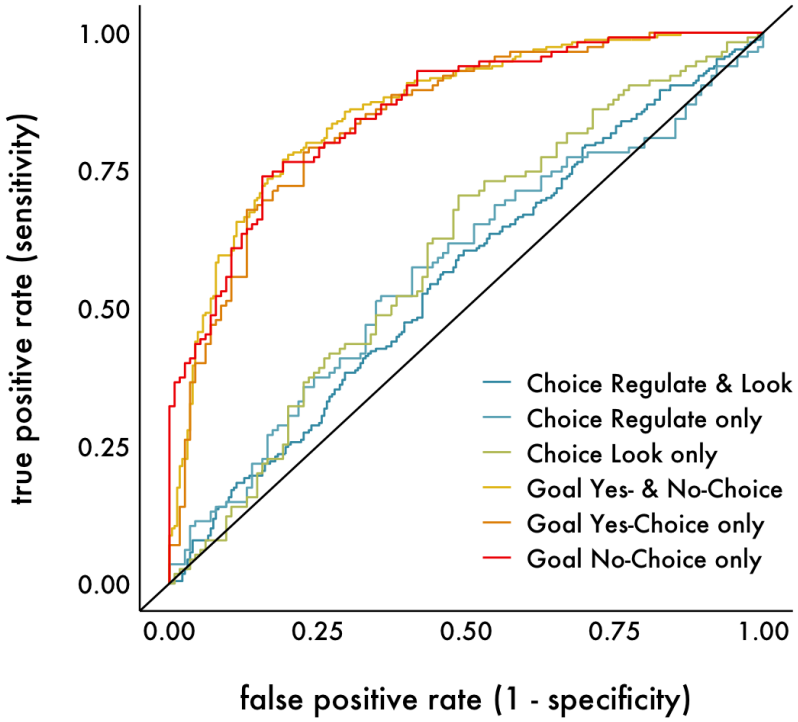

Figure 4.11. Receiver operating characteristic curves as a function of classification model. Choice was decoded across the Look and Regulate conditions (Choice Regulate & Look), and for Look and Regulate separately (Choice Look only and Choice Regulate only, respectively). Goal was decoded across the Yes- and No-Choice conditions (Goal Yes- & No-Choice), and for the Yes- and No-Choice conditions separately (Goal Yes-Choice only and Goal No-Choice only,
respectively).

Discussion

The goal of this study was to investigate potential mechanisms underlying the relationships between choice, autonomous motivation, and goal pursuit during a cognitive reappraisal task. The results showed that on average, choice was associated with lower perceived difficulty, but not greater autonomous motivation. However, individual differences in perceived autonomous motivation reported after the task were related to task performance. Individuals reporting higher autonomous motivation were more successful at the task when they choose on relatively difficult trials. We observed similar results when modeling trial-level difficulty; greater autonomous motivation was associated with lower difficulty ratings when participants had choice. Neurally, choice was associated with stronger engagement of brain regions associated with attention and cognitive control across both task goals (i.e., Look and Regulate) in univariate models. Furthermore, we observed greater than chance accuracy when classifying choice condition during goal pursuit, further indicating that autonomous and controlled goal pursuit are dissociable.

Behavioral effects of choice

It is notable that choice was not associated with increased self-reported autonomous motivation during the post-task manipulation check. This is in contrast to other studies reporting a positive association between choice and autonomous motivation (Legault & Inzlicht, 2013; Patall et al., 2008), but may be due to the fact that the three items (liking, engagement, and motivation) used to create the preregistered measure of autonomous motivation varied in their relationship to choice. Specifically, participants reported stronger motivation during choice, but equivalent liking and engagement during

choice and no-choice trials. However, post hoc analyses indicated that the items were moderately to highly correlated, suggesting that averaging across items was appropriate. In addition, this measure of autonomous motivation was moderately to highly correlated with a separate validated measure of autonomous motivation administered in relation to the task as a whole (i.e., not separated by choice condition), suggesting convergent validity. Despite not observing an effect of choice on autonomous motivation on average, there was substantial variability across people and individual differences in this measure were related to task effects, which is consistent with prior research detailing individual differences in preference for choice (Iyengar & Lepper, 1999).

In the cognitive reappraisal task, we investigated how choice affects goal pursuit (operationalized as task performance), and how this relationship might be moderated by trial-level perceived difficulty of goal pursuit and individual differences in autonomous motivation. Given that 1) choice supports autonomy, 2) autonomous motivation is associated with successful goal pursuit and self-regulation, and 3) motivation may matter most when goal pursuit is difficult, we expected that choice would be related to better task performance on more difficult trials for individuals who reported higher autonomous motivation. We observed this effect across both task goals, indicating that choice was associated with task goal pursuit broadly rather than while engaging in cognitive reappraisal specifically. While this result is in contrast to previous research showing that choice was associated with decreased task performance during cognitive reappraisal of food cravings (Cosme et al., 2018b) and aversive pictures (Bigman et al., 2017), it is consistent with other research showing that choosing to view aversive images was associated with greater negative emotional intensity, whereas reappraisal was associated

with lower intensity (Kühn et al., 2014). The difference in the direction of the effect between this study and Cosme et al. (2018) is likely due to differences in task design that were made in order to reduce potential cognitive burden associated with choice, which may have led to reduced task performance in the previous study.

Another interesting finding is that post hoc analyses indicated that the task interaction was also specific to choice condition and that more successful goal pursuit was only related to autonomous motivation experienced during the Yes-Choice condition. That is, higher autonomous motivation in the Yes-Choice condition was only associated with better performance on Yes-Choice trials and not No-Choice trials. Further, autonomous motivation on Yes-Choice trials was associated with better performance, whereas No-Choice autonomous motivation was associated with worse performance. This suggests that choice only promotes more successful goal pursuit when it is accompanied by feelings of subjective autonomous motivation. This is consistent with research showing that the association between choice and better inhibitory control was partially mediated by subjective autonomous motivation (Legault & Inzlicht, 2013). We were precluded from testing mediation with the current design, but this is an important avenue for future research.

The relationship between choice and subjective difficulty

Previous research has suggested that autonomous motivation makes goal pursuit feel easier (Werner & Milyavskaya, 2019; Werner et al., 2016; Milyavskaya et al., 2015), but the mechanism underlying this association is unclear. Here, we tested the relationship between autonomous motivation and goal pursuit while individuals deployed a regulatory strategy–cognitive reappraisal–and found that choice was indeed associated with lower

subjective difficulty, both when reflecting on the task as a whole and on a trial-by-trial basis. However, the effect of choice was consistent across both task goals, indicating that it affected goal pursuit broadly, rather than this self-regulation strategy specifically. Mirroring the effects on craving, this finding was also moderated by the degree to which individuals felt autonomously motivated; higher self-reported autonomous motivation during choice was associated with further reductions in perceived difficulty of goal pursuit during choice. It is notable that the effect of autonomous motivation on difficulty was only present in the context of choice, suggesting that motivation may only become relevant when it is environment supports autonomy (i.e., via choice).

Neural effects of choice

In this study, we utilized functional neuroimaging to test whether and how autonomous goal pursuit differed from controlled goal pursuit. Across both task goals, autonomous goal pursuit was associated with stronger activation in brain regions associated with attention and cognitive control, largely replicating Cosme et al. (2018). This is notable given that the current task design was modified substantially in order to reduce potential cognitive disruption associated with choice. In addition, in the present study, this neural activation occurred in the context of enhanced rather than reduced task performance, which is in line with the prediction that choice enhances attention to and engagement with stimuli relevant for goal pursuit (Legault & Inzlicht, 2013; Kühn et al., 2014). Indeed, post hoc analyses showed a moderating effect of increased pattern expression of the Yes-Choice > No-Choice group-level contrast indicating that the more that individuals expressed the group-level pattern during Yes-Choice trials, the better they performed, whereas higher expression on No-Choice trials was associated with

worse performance. Although inferences related to this analysis should be approached with caution given that it was not preregistered and relies on reverse inference, these results provide further conditional evidence that attentional enhancement may be a candidate mechanism through which choice facilitates goal pursuit.

However, it was somewhat surprising that greater self-reported autonomous motivation and pattern expression of the group-level autonomous goal pursuit pattern were related to worse task performance during controlled goal pursuit. Given their positive associations with task performance during autonomous goal pursuit, it is unclear why they'd be negatively associated with performance on No-Choice trials. While further research is needed to better understand this finding, it highlights the complexity of the relationships between choice, motivation, and goal pursuit.

We complimented the univariate analyses, which provide spatial information about mean activation differences between conditions, using MVPA, which tested whether patterns of activation contain information that can distinguish conditions. This is the first study that we are aware of that has attempted to decode motivational orientation during goal pursuit. This approach revealed that choice could be decoded with greater than chance accuracy from patterns of activation in the regions associated with goal pursuit during the task. This is remarkable given the fact that we modeled the data during goal pursuit (not during the actual choice) and the only difference between conditions was that participants chose. It is also notable that accuracy was highest when choice was classified in the Look condition only, which mirrors the behavioral results showing somewhat larger effects when participant's goal was to visualize the food as real and in front of them. Although overall accuracy might have been higher if the analysis had been

conducted within-person (Clithero et al., 2010), which affords greater idiosyncrasy of brain patterns, a strength of this between-person design is that other researchers can utilize this classifier and apply it to new or existing data. This analytic approach enables researchers to test the generalizability of this predictive model of autonomous versus controlled motivation in new tasks, contexts, and populations to assess the degree to which it represents information related to a common underlying mechanism.

Theoretical implications

Combined, these results have several important theoretical implications that add nuance to the relationships between choice, motivation, difficulty, and goal pursuit. First, they suggest that subjective difficulty of goal pursuit and choice are important moderators of the relationship between autonomous motivation and goal pursuit. With a few notable exceptions (Sullivan-Toole et al., 2017), most research has focused on subjective difficulty as a consequence, rather than a moderator, of motivation (Werner et al., 2016), positing that autonomous motivation facilitates goal progress by making goal pursuit feel easier. Although the present study found evidence in support of this hypothesis, we also observed that motivation only mattered when goal pursuit was perceived as relatively difficult. This suggests that when the goal is easy to attain, motivation may not be particularly relevant (Klein et al., 1999). This is an under-researched yet important area for future inquiry.

Second, we sought to investigate potential mechanisms underlying the relationship between motivation and goal pursuit by assessing it while individuals actually utilized an effective self-regulatory strategy–cognitive reappraisal. Though a similar approach has been taken to study the effect of autonomy-supportive choice on

inhibitory control (Legault & Inzlicht, 2013), this study lacked a non self-regulatory condition and therefore could not address whether choice facilitates goal pursuit generally or self-regulation specifically. The results presented here suggest that, at least in the context of cognitively reappraising food cravings, the effect of choice operates on goal pursuit broadly. This implies that the underlying mechanism may be a more basic processes that is not tied to self-regulation per se.

Third, the neural results suggest that attentional enhancement during self-determined goal pursuit is a potential mechanism through which choice might facilitate goal pursuit. This is consistent with research showing increased sensitivity to error-related feedback (Legault & Inzlicht, 2013) and stronger activation in the salience (Lee & Reeve, 2012) and frontoparietal control networks (Kühn et al., 2014) during autonomous goal pursuit. While we were unable to test this mechanistic hypothesis directly, future research could adopt a similar approach as in this study to assess whether a classifier trained to distinguish high versus low attentional engagement could predict choice condition in a separate task, and whether the relationship between choice and task performance was mediated by changes in pattern expression in this network.

Limitations and future directions

The results of this study should be considered in light of several limitations. First, the design precluded us from testing causal relationships and therefore the direction of effects is unclear. Future research could adopt structural equation modeling approach to test directionality. Second, we did not use a validated measure of autonomous motivation in the post-task manipulation questions. Although the post hoc analyses indicated that our operationalization was reasonable and this measure correlated as expected with global

indicators of autonomous motivation during the task, it is important to replicate these results using validated measures in the future. Third, this study only included college freshmen and it therefore it may not be warranted to generalize beyond this population. Fourth, we did not recruit participants who had healthy eating goals. We sought to study the ability to utilize cognitive reappraisal, which is a flexible self-regulatory strategy that can be applied in various contexts to increase the value of goal-congruent and decrease the value of goal-incongruent stimuli, in a normative sample, but studying this strategy in a dieting sample could provide additional insight into these relationships when the task is highly relevant to individual goals.

Conclusions

In this preregistered study, we tested theoretical predictions about how and whether autonomous motivation facilitates goal pursuit in the context of a novel appetitive self-regulation paradigm that included choice. We used choice to support autonomy and found that autonomous and controlled goal pursuit were dissociable neurally using both univariate and multivariate neuroimaging methods, and that autonomous goal pursuit more strongly engaged brain regions associated with attention and cognitive control. Autonomous goal pursuit was also perceived as less difficult, particularly for individuals who reported higher autonomous motivation. More autonomously motivated individuals were more successful at pursuing task goals during autonomous goal pursuit on relatively difficult trials. These effects were consistent across both task goals and were not uniquely present when participants engaged in cognitive reappraisal, suggesting a more basic underlying mechanism, such as enhanced attentional

processing. Overall, these findings add nuance to theories of how motivation and self-regulation interact, and help refine potential mechanistic explanations.

CHAPTER V

GENERAL DISCUSSION

Chapter overview

Given the comprehensive discussion of results provided within each study separately, this general discussion will focus primarily on integrating the findings across studies. I will highlight consistencies and discrepancies among the studies and discuss the collective practical and theoretical implications of this research. I will also discuss limitations and future directions before presenting general conclusions.

Integrative summary of results and implications

The goal of this dissertation was to assess whether and how choice impacts goal pursuit during a novel appetitive self-regulation task. Since choice is a primary method for supporting autonomy, and autonomy is associated with greater intrinsic motivation and more successful goal pursuit, we expected that manipulating motivation via choice would result in enhanced goal pursuit during this Regulation of Craving–Choice (ROC-C) task. However, in the initial task design (Study 1), we observed that choice reduced rather than enhanced task performance. Because this performance decrement occurred in the context of greater activation in brain regions associated with attention and cognitive control, we hypothesized that the design of the task may have inadvertently undermined potential benefits of autonomy. In particular, making many choices throughout the task and not separating the choice and goal pursuit phases may have increased the cognitive burden and led to inefficient allocation of cognitive resources during goal pursuit, ultimately resulting in worse task performance. However, because we did not explicitly assess the affective experience of choice to determine whether choice felt autonomous, it

was unclear whether decrements during the task were due to methodological issues, because choice did not feel self-determined, or both.

To better account for these potential alternatives, in Study 2, we redesigned the task to alleviate potential cognitive load directly associated with choice. We also included trial-level difficulty to investigate its interaction with choice and goal pursuit, and devised two between-subject experimental manipulations in an effort to make choice feel more self-determined. Overall, only participants in the experimental manipulation characterizing choice as a means of exerting autonomy and as a form of self-expression (the Agency manipulation group), displayed the expected pattern of results. This group reported higher levels of autonomous motivation and perceived choice during the task as a whole, and performed better on the task during autonomous goal pursuit, particularly when goal pursuit was perceived as difficult. However, this group unexpectedly reported lower autonomous motivation–in particular lower liking–for choice sets. One possible explanation for this result is that participants may have felt subtly pressured to choose to look and regulate evenly by the run summaries at the end of each run, which were included to alleviate potential cognitive burden keeping track of choices. While this was the same across experimental groups, any undermining effect may have been magnified in this group because the pre-task manipulation emphasized the importance of each choice made. In Study 3, we removed these run summaries and utilized the ROC-C task in a large sample incoming college freshmen. Participants in this sample showed greater variability in their choices, and higher overall autonomous motivation and perceived choice, and lower difficulty than participants in Study 2, suggesting that removing the run summaries may have alleviated potential undermining effects.

Though not directly comparable, there was general consistency between the ROC-C task results in Study 3 and the Agency autonomy manipulation group in Study 2. Across both samples, choice was associated with better task performance on relatively more difficult trials. In both studies, this effect was also stronger when individuals chose to visualize the foods as being real (Look condition), rather than visualizing the negative consequences associated with consumption (Regulate condition). It is not clear what is driving this effect, though it is unlikely to be accounted for by differences in subjective difficulty between the task goals because difficulty was equivalent across the conditions in these models. One possibility is that participants felt more motivated when they chose to look, but since we did not measure autonomous motivation for the goals separately, we cannot be sure. However, this explanation would be consistent with other research showing differential preference for choice as a function of valence (Leotti & Delgado, 2014) and preferences for less effortful tasks more generally (Sullivan-Toole et al., 2017; Kool et al., 2010).

Across both Studies 2 and 3, the effect of choice on goal pursuit was consistent but relatively small. Therefore, the practical significance of these findings is unclear. Theoretically speaking, albeit small, these results bolster the notion that choice in and of itself does not enhance goal pursuit. Rather, choice only supports goal pursuit insofar as it elicits feelings of autonomous motivation. This also suggests that not all choice is inherently self-determined and that individual differences in the perceptions of choice are critically important. Given that most studies addressing the effect of choice either operationalize motivation as the outcome or use choice as a proxy for motivation and assess goal pursuit without measuring motivation explicitly (Patall et al., 2008), these

findings add important evidence that choice does not inherently enhance motivation (Legault & Inzlicht, 2013) and that empirical studies should measure both motivation and goal pursuit when investigating the effects of choice. These findings also indicate that future studies should include measures of the subjective difficulty of goal pursuit as it moderated the effect of choice on goal pursuit.

Because even small effects can have important behavioral consequences over time, one indicator of practical significance might be the extent to which these relationships are reflected at the individual, rather than trial, level. Post hoc correlational analyses in Study 3 provided at least some evidence that this was the case. Specifically, they showed that individual differences in autonomous motivation during the task as a whole were positively related to regulatory success and that this relationship was stronger when participants chose. This suggests that although choice might enhance the relationship between autonomous motivation and successful goal pursuit, this effect may be small in comparison to preexisting individual differences. That is, individuals who feel more autonomously motivated during goal pursuit may be more successful regardless of whether they have a choice, but they may be slightly more successful during autonomous goal pursuit.

These results also highlight a challenge of experimentally manipulating motivation to identify underlying mechanisms. Although research assessing goal progress for participant generated goals as a function of motivation has identified "effortless" goal pursuit as a possible mechanism (Milyavskaya et al., 2015; Werner et al., 2016), this type of study design makes it difficult to disentangle the motivation from the goal since goals are self-selected. More successful goal pursuers may simply select goals they are more

autonomously motivated to pursue (Weinstein et al., 2012). Indeed, this would be consistent with research suggesting individuals with higher self-control engage in more automatic and "effortless" regulatory strategies (Gillebaart & de Ridder, 2015) and that self-control is linked to greater autonomous motivation during goal pursuit (Converse et al., 2019). In this dissertation, we attempted to control for this possibility by limiting the goals available for pursuit and manipulating motivation by providing or withholding choice. Consistent with the hypothesis that autonomous motivation enhances goal pursuit by reducing subjective difficulty, we observed that self-determined choice was associated with lower perceived difficulty, independent of goal. However, the relationship with task performance was more complicated. Here, self-determined choice was related to more successful goal pursuit (i.e., better task performance), but only when goal pursuit was perceived as relatively difficult. Because we only collected subjective difficulty ratings, it is impossible to determine whether improvements in task performance at higher objective difficulty is due to the perception that it is less difficult. Future research could disentangle these effects by comparing the subjective difficulty at different levels of objective (e.g., normed ratings across a large pool individuals) difficulty.

Finally, across Studies 1 and 3, autonomous and controlled goal pursuit were dissociable and autonomous goal pursuit engaged a highly similar network of brain regions. Specifically, choice was associated with greater activation in brain regions associated with attention and cognitive control. However, this activation occurred in the presence of reduced task performance in Study 1, and enhanced task performance in Study 3, making its specific role unclear. In Study 1, we reasoned that the study design may have led to overallocation of cognitive resources to the choice, resulting in

diminished task performance. Although this may have been the case in Study 1, it is unclear why we would observe the same network of regions in the redesigned task in Study 3 in the context of better task performance. One possibility is that this activation is incidental and unrelated to task performance. However, we tested this possibility in a post hoc analysis in Study 3, and found that stronger pattern expression of the whole-brain autonomous goal pursuit pattern was associated with task performance over and above the effects of autonomous motivation and difficulty, making this account unlikely. Additional research is needed to systematically investigate the role brain regions supporting attention and cognitive control play in autonomous and controlled goal pursuit.

Limitations and future directions

One primary limitation of this work is that it was conducted exclusively in college students, and primarily college freshmen. We focused on this population because this period may be an inflection point in the development of autonomous self-regulation and the degree to which young adults have internalized self-regulatory goals may have implications for how successfully they navigate the transition to college. Studies 1 and 3 were conducted as part of a larger project on health and well-being during this transition and we plan to integrate the findings from this dissertation to investigate the relationship between individual differences in autonomous and controlled self-regulation, as index by neural and behavioral effects in the ROC-C task, and changes in health and well-being during freshman year. However, it is important that future studies assess the generalizability of the task effects detailed here in more diverse samples across a broad age range. Additionally, although autonomy is theorized to be a basic psychological need

(Deci & Ryan, 2000), it may be more or less relevant in particular developmental stages. For example, the need for autonomy may be particularly salient during mid-late adolescence when self-exploration is heightened (Crone & Dahl, 2012). Future research should also investigate other factors that may affect the degree to which choice promotes autonomous motivation during goal pursuit. Here, we focused exclusively on autonomous motivation and difficulty related to the task, but individual differences in the preference for choice (Iyengar & Lepper, 1999; Kehl et al., 2015) and need for autonomy (Schüler et al., 2014) are likely important moderators. Adopting an individual difference approach may help resolve conflicting evidence in the literature on motivation and goal pursuit.

Another limitation is that this dissertation employed a single goal-relevant task. In order to investigate potential mechanisms through which autonomous motivation might enhance goal pursuit, we focused on a specific self-regulatory strategy–cognitive reappraisal–that can be used to favor goal-congruent behavior in the face of tempting goal incongruent options. Therefore, it is unclear whether choice has similar effects on other self-regulatory strategies. Assessing the effect of choice on a broad array of self-regulatory strategies in the same sample would help identify common underlying mechanisms that are not tied to a specific task.

Another fruitful avenue for future research is to investigate the antecedents of choice. In this dissertation, we only characterized choice as a predictor variable to understand how it is associated with motivation and goal pursuit, but predicting regulatory choice would help further our understanding how and under what circumstances regulatory goals are formed. For example, research on cognitive reappraisal of negative emotion identified reappraisal affordance (i.e., how easy it is to

generate effective reappraisals) as an important predictor of choosing to regulate affect via reappraisal independent of stimulus intensity, but it is unclear whether the same is true for appetitive stimuli.

Finally, most analyses in this dissertation are correlational in nature. Although we experimentally manipulated choice across all studies, the present design did not allow us to disentangle the direction of effects between choice and difficulty. Future research could employ structural equation modeling to better test the unique of choice and difficulty on goal pursuit.

General conclusions

Across three experiments, we investigated whether and how choice affects autonomous motivation and goal pursuit in the context of an appetitive self-regulation task. We showed that autonomous and controlled goal pursuit were dissociable neurally, and that autonomous goal pursuit was perceived as less difficult across task goals. Furthermore, we demonstrated that the degree to which choice helps or hinders goal pursuit is dependent on how self-determined and autonomously motivated choice feels. Together, these results help refine neurobiological and social psychological theories of motivation, self-regulation, and goal pursuit.

APPENDIX A

STUDY 1 SUPPLEMENTARY MATERIAL

Exclusion criteria

Potential participants were excluded prior to enrollment if they were not incoming college freshman aged 18-19 years, planning to live on campus, or possessed other exclusion criteria (i.e., left handedness; pregnancy; presence of neurological, mood, or eating disorders; presence of MRI contraindications).

Neuroimaging scan sequence parameters

High resolution anatomical volumes were acquired using a T1-weighted 3D MP-RAGE pulse sequence (TR = 2500 ms, TE = 3.41 ms, matrix size = 256 x 256, voxel size = 1 mm^3, sagittal slices = 176, FOV = 256). Functional volumes were acquired using a T2*-weighted echo-planar sequence (TR = 2000 ms, TE = 25.0 ms, flip angle = 90˚, matrix size = 100 x 100, voxel size = 2 mm^3, axial slices = 72, FOV = 200).

Percentage of regulation trials in the Choice condition

To ensure there were enough trials in each condition, within the Choice condition, participants were instructed to try to regulate and look approximately equally. Although most individuals were within one standard deviation from the mean, individuals varied in the degree to which they choose to regulate. The average percentage of regulation trials in the Choice condition was 49.4% (*SD* = 5.4%; range = 38.1% to 61.0%). The percentage of regulation trials was negatively correlated with regulation success (the mean difference between craving ratings in the look and regulate conditions), such that the more trials individuals choose to regulate, the worse regulation success they had. This

was true for both no-choice, r = -.41, 95%CI [-.67, -.05], $t(29)$ = 2.32, p = .028, and yes-choice trials, r = -.40, 95%CI [-.67, -.04], $t(29)$ = 2.24, p = .032 (see Figure A.1).

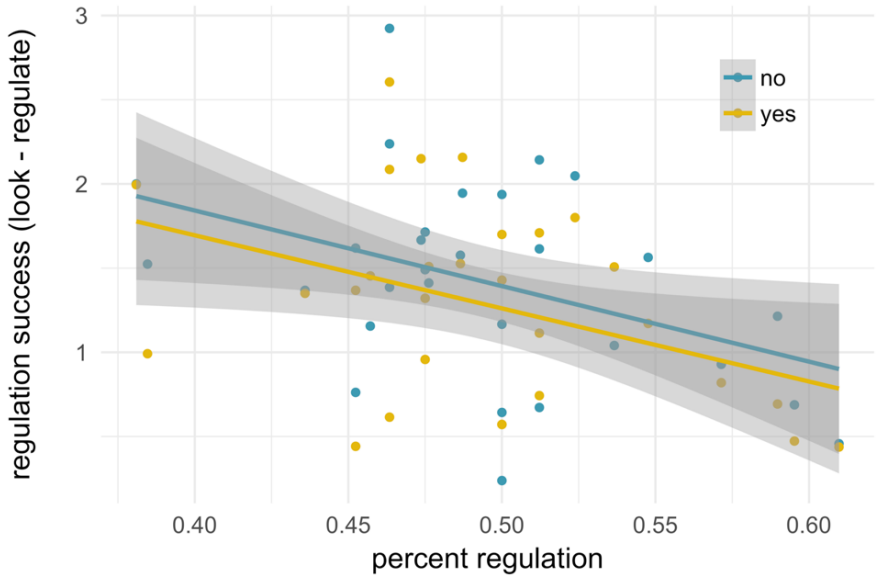

Figure A.1. Correlation between the percentage of trials on which participants chose to regulate and regulation success, defined as the mean difference in craving ratings on look and regulate trials. The correlations are plotted separately for each level of Choice (blue = no, yellow = yes). Data points represent subjects.

Dividing individuals based on whether they chose to regulate more (> 50% regulate trials), look more (> 50% look trials), or look and regulate equally revealed that those that chose to look more rated their cravings higher on look trials and lower on regulate trials (see Figure A.2). This relationship was slightly blunted in the no-choice relative to the yes-choice condition.

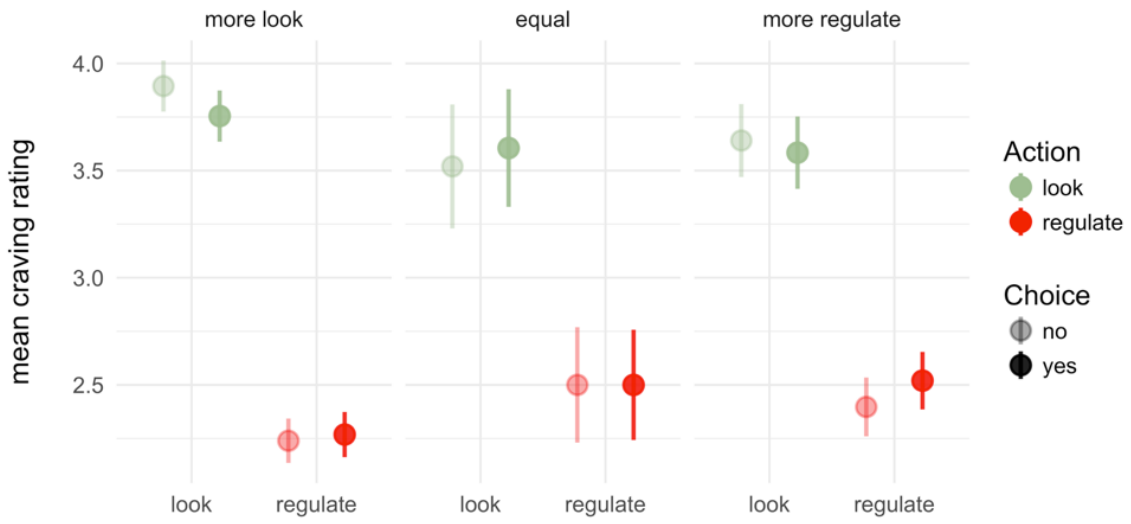

Figure A.2. The relationship between the percentage of trials on which participants chose to regulate and mean craving ratings as a function of Action and Choice. The "equal" group consists of participants that chose to look and regulate equally, the "more look" group consists of participants that chose to look > 50% of trials, and the "more regulate" group consists of participants that chose to regulate > 50% of trials.

With respect to neural activity, we extracted mean parameter estimates from clusters in the regulate > look contrast (FWE-corrected at $p < .05$ to separate clusters, k = 108) and correlated them with percentage of regulation trials. No correlations were statistically significant, rs = -.16 to -.04, ps > .44 (Figure A.3).

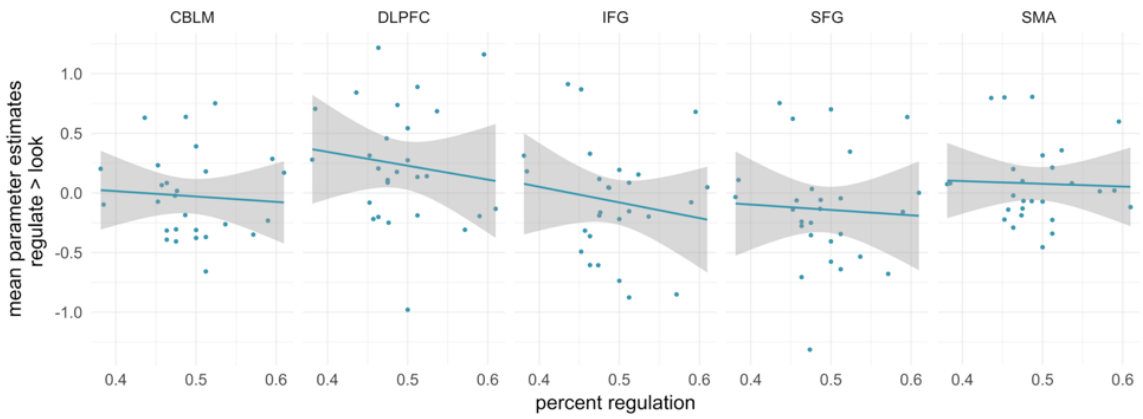

Figure A.3. Correlations between the percentage of trials on which participants chose to regulate and mean parameter estimates extracted from the regulate > look contrast, thresholded at FWE-corrected $p < .05$, $k = 108$. CBLM = right cerebellum, DLPFC = left dorsolateral prefrontal cortex, IFG = left inferior frontal gyrus, SFG = left superior frontal gyrus, SMA = left supplementary motor area. Data points represent subjects.

Model selection

Multilevel modeling was used to test the effects of Action and Choice on self-reported craving ratings and the best fitting model was selected via model comparison. In the null model, fixed and random effects were estimated for the intercept as well as for Action, Choice, and post-task craving ratings. In each subsequent model, random effects were removed sequentially in the following order: Choice, post-task craving ratings, Action. In the final model, the fixed effect of post-task craving ratings was removed, and therefore only the fixed effects of Action and Choice and the random effects of the intercept were estimated. Comparing these models revealed that including fixed effects for Action, Choice, the interaction between Action and Choice, and post-task craving ratings, and random effects for Action, post-task craving ratings, and the intercept, produced the best fit (see Table A1 for full results). Consequently, results from this model are reported in the paper. The equation for this model is:

First level equation:

Y_{ij} (Task craving rating of image *i* by person *j*) = $\beta_{0j} + \beta_{1j}(\text{Choice}_i) + \beta_{2j}(\text{Action}_i) +$

$\beta_{3j}(\text{Choice}_i * \text{Action}_i) + \beta_{4j}(\text{post-task craving ratings}_i) + \varepsilon_{ij}$

Second level equations:

$\beta_{0j} = \gamma_{00} + \mu_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20} + \mu_{2j}$

$\beta_{3j} = \gamma_{30}$

$\beta_{4j} = \gamma_{40} + \mu_{4j}$

Table A1

Model comparison for behavioral analysis

Model	Model *df*	AIC	BIC	Deviance	χ^2 *df*	χ^2	*p*
Model 4	6	6778.71	6813.22	6766.71	–	–	–
Model 3	7	6214.95	6255.22	6200.95	1	565.75	< .001
Model 2	9	6058.93	6110.70	6040.93	2	160.03	< .001
Model 1	**12**	**5979.64**	**6048.67**	**5955.64**	**3**	**85.29**	**< .001**
Null model	16	5986.66	6078.70	5954.66	4	0.98	.913

Note. Null Model = includes fixed and random effects for the intercept as well as for Action, Choice and post-task craving ratings; Model 1 = removed random effect of Choice; Model 2 = removed random effect of post-task craving ratings; Model 3 = removed random effect of Action; Model 4 = removed fixed effect of post-task craving ratings. Model 1 (bolded) was selected as the best fitting model.

APPENDIX B

STUDY 3 SUPPLEMENTARY MATERIAL

Neuroimaging preprocessing

Neuroimaging data were preprocessed using fMRIPrep 1.1.4 (Esteban et al., 2018, RRID:SCR_016216), which is based on Nipype 1.1.1 (Gorgolewski et al., 2011; Gorgolewski et al., 2018, RRID:SCR_002502). The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) using N4BiasFieldCorrection (Tustison et al., 2010, ANTs 2.2.0), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped using antsBrainExtraction.sh (ANTs 2.2.0), using OASIS as target template. Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1, RRID:SCR_001847, Dale, Fischl, & Sereno, 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (Klein et al., 2009, RRID:SCR_002438). Spatial normalization to the ICBM 152 Nonlinear Asymmetrical template version 2009c (Fonov, Evans, McKinstry, Almli, & Collins, 2009), RRID:SCR_008796) was performed through nonlinear registration with antsRegistration (ANTs 2.2.0, RRID:SCR_004757, Avants, Epstein, Grossman, & Gee, 2008), using brain-extracted versions of both T1w volume and template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID:SCR_002823, Zhang, Brady, & Smith, 2001).

For each of the functional runs per subject (across all tasks), the following preprocessing was performed. First, a reference volume and its skull-stripped version

were generated using a custom methodology of fMRIPrep. A deformation field to correct for susceptibility distortions was estimated based on two echo-planar imaging (EPI) references with opposing phase-encoding directions, using 3dQwarp (AFNI). Based on the estimated susceptibility distortion, an unwarped BOLD reference was calculated for a more accurate co-registration with the anatomical reference. Head-motion parameters with respect to the BOLD reference (transformation matrices and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson, Bannister, Brady, & Smith, 2002). The BOLD time-series were resampled onto their original, native space by applying a single, composite transform to correct for head-motion and susceptibility distortions. These resampled BOLD time-series will be referred to as preprocessed BOLD in original space, or just preprocessed BOLD. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve & Fischl, 2009). Co-registration was configured with nine degrees of freedom to account for distortions remaining in the BOLD reference. The BOLD time-series were resampled to surfaces in fsnative space. The BOLD time-series were resampled to MNI152NLin2009cAsym standard space, generating a preprocessed BOLD run in MNI152NLin2009cAsym space.

Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD), DVARS and three region-wise global signals. FD and DVARS are calculated for each functional run, both using their implementations in Nipype (following the definitions by Power et al., 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of

physiological regressors were extracted to allow for component-based noise correction (CompCor, Behzadi, Restom, Liau, & Liu, 2007). Principal components are estimated after high-pass filtering the preprocessed BOLD time-series (using a discrete cosine filter with 128s cut-off) for the two CompCor variants: temporal (tCompCor) and anatomical (aCompCor). Six tCompCor components are then calculated from the top 5% variable voxels within a mask covering the subcortical regions. This subcortical mask is obtained by heavily eroding the brain mask, which ensures it does not include cortical GM regions. For aCompCor, six components are calculated within the intersection of the aforementioned mask and the union of CSF and WM masks calculated in T1w space, after their projection to the native space of each functional run (using the inverse BOLD-to-T1w transformation). The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. All resamplings can be performed with a single interpolation step by composing all the pertinent transformations (i.e., head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and template spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos, 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer). Many internal operations of fMRIPrep use Nilearn 0.4.2 (Abraham et al., 2014, RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see the section corresponding to workflows in fMRIPrep's documentation.

Figure and tables from post-hoc behavioral analyses

We conducted a post-hoc analysis modeling the fixed effects of autonomous motivation during Yes-Choice and No-Choice sets separately rather than as a single individual differences variable, yoked to choice. This allowed us to determine if increased perceived autonomous motivation for Yes- and No-Choice were uniquely related to the corresponding choice condition during the task. This model fit the data better than Model 3, $X^2(8) = 27.71$, $p < .001$ (Table B1), and confirmed that the effect of autonomous motivation on task performance was unique to the specific choice condition in which it was measured (Table B2). That is, higher autonomous motivation during Yes-Choice trials was not related to task performance on No-Choice trials and vice versa (Figure B.1).

Table B1

Comparison of multilevel models with trial-level craving ratings as the criterion

Model	Model *df*	AIC	X^2	X^2 *df*	*p*
Model 1 – Choice	13	22844.13	–	–	–
Model 2 – Difficulty	17	22159.90	692.24	4	< .001
Model 3 – Autonomous Motivation	25	22150.26	25.63	8	.001
Model 4 – Separated	**33**	**22138.55**	**27.71**	**8**	**.001**

Note. The best fitting model is bolded.

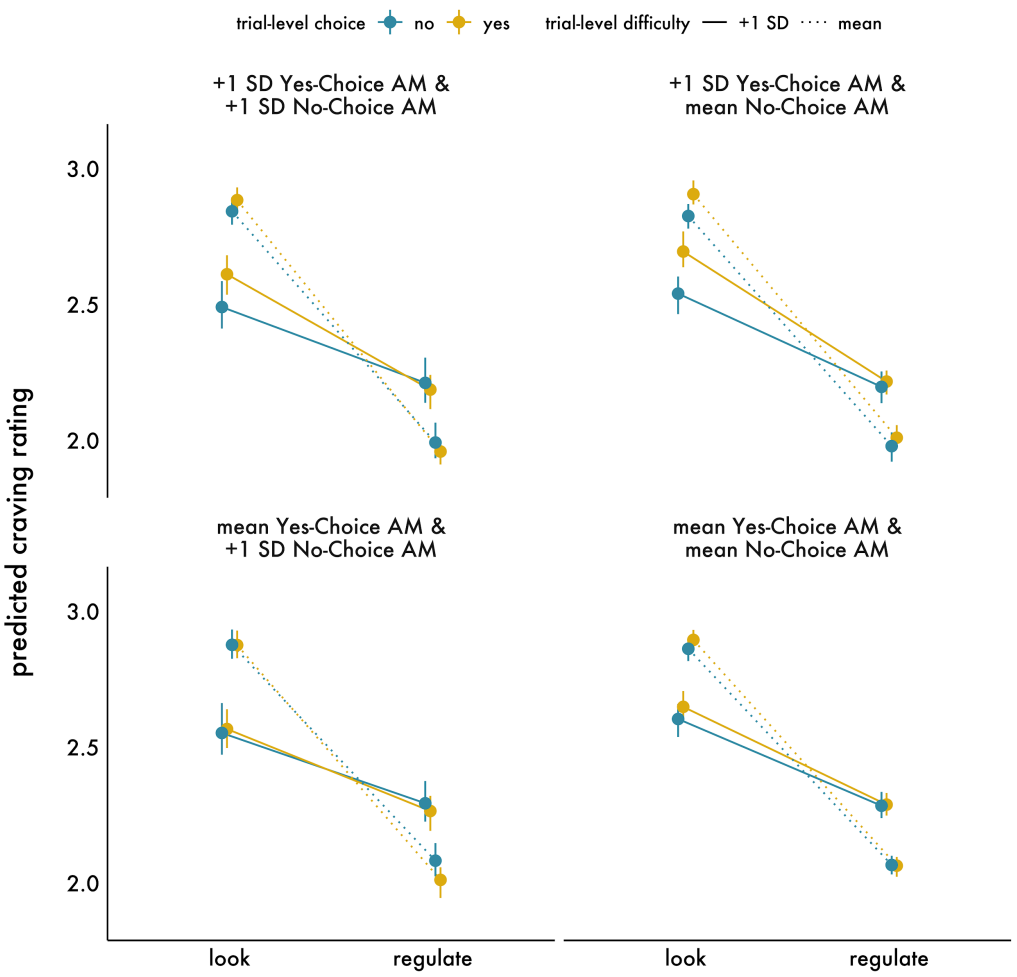

Figure B.1. Predicted craving ratings from the best fitting post-hoc multilevel model (Model 4) as a function of trial-level Goal, Choice, and Difficulty, and person-level Yes- and No-Choice Autonomous Motivation rated post-task. The top panel describes these interactions one standard deviation above mean Yes-Choice Autonomous Motivation, whereas the bottom panel shows the interactions at mean Yes-Choice Autonomous Motivation. The left panel visualized them at one standard deviation above mean No-Choice Autonomous Motivation, and the right panel shows them at mean No-Choice Autonomous Motivation. Error bars are 95% confidence intervals. AM = Autonomous Motivation

Table B2

Results from the best fitting post hoc trial-level craving rating multilevel model

Fixed effects	*b* [95% CI]	*SE*	*t*	*df*	*p*
Intercept (Look, No-Choice)	**2.91 [2.84, 2.98]**	**0.03**	**84.03**	**148.58**	**< .001**
Goal	**-0.79 [-0.89, -0.69]**	**0.05**	**15.39**	**147.71**	**< .001**
Choice	0.03 [-0.01, 0.08]	0.02	1.49	9328.75	.135
Difficulty	**-0.26 [-0.30, -0.22]**	**0.02**	**12.97**	**9447.96**	**< .001**
Yes AM	-0.03 [-0.11, 0.04]	0.04	0.97	155.44	.333
No AM	0.01 [-0.06, 0.08]	0.04	0.36	160.86	.722
Trial	**-0.01 [-0.02, -0.01]**	**0.00**	**4.11**	**9346.15**	**< .001**
Baseline Craving	**0.26 [0.23, 0.30]**	**0.02**	**16.13**	**90.10**	**< .001**
Goal × Choice	-0.04 [-0.10, 0.03]	0.03	1.13	9329.30	.260
Goal × Difficulty	**0.48 [0.43, 0.53]**	**0.03**	**18.39**	**9502.44**	**< .001**
Choice × Difficulty	0.02 [-0.03, 0.07]	0.03	0.68	9365.56	.497
Goal × Yes AM	-0.06 [-0.16, 0.05]	0.05	1.08	147.02	.283
Choice × Yes AM	**0.06 [0.01, 0.10]**	**0.02**	**2.35**	**9336.10**	**.019**
Difficulty × Yes AM	-0.03 [-0.07, 0.01]	0.02	1.56	9459.64	.118
Goal × No AM	0.01 [-0.09, 0.11]	0.05	0.16	144.76	.877
Choice × No AM	-0.04 [-0.09, 0.00]	0.02	1.79	9322.81	.073
Difficulty × No AM	**-0.06 [-0.10, -0.02]**	**0.02**	**2.79**	**9426.72**	**.005**
Goal × Choice × Difficulty	-0.00 [-0.07, 0.06]	0.03	0.12	9375.88	.907
Goal × Choice × Yes AM	-0.02 [-0.09, 0.05]	0.03	0.52	9339.31	.605
Goal × Difficulty × Yes AM	0.03 [-0.02, 0.09]	0.03	1.31	9520.85	.191
Choice × Difficulty × Yes AM	**0.06 [0.02, 0.11]**	**0.02**	**2.67**	**9344.48**	**.008**
Goal × Choice × No AM	-0.03 [-0.10, 0.04]	0.03	0.85	9322.63	.397
Goal × Difficulty × No AM	**0.06 [0.00, 0.11]**	**0.03**	**2.10**	**9518.01**	**.036**
Choice × Difficulty × No AM	-0.01 [-0.06, 0.05]	0.03	0.19	9373.06	.847
Goal × Choice × Difficulty × Yes AM	**-0.09 [-0.16, -0.03]**	**0.03**	**2.85**	**9389.78**	**.004**
Goal × Choice × Difficulty × No AM	0.03 [-0.04, 0.10]	0.03	0.78	9377.51	.434

Random effects	variance	*SD*
Participant		
Intercept	0.10	0.31
Goal	0.23	0.48
Baseline Craving	0.02	0.14
Residual	0.55	0.74

Note. Degrees of freedom (*df*) were calculated using the Satterthwaite approximation. Statistically significant parameters at $p < .05$ are bolded. The reference condition for Goal is Look; the reference condition for Choice is No-Choice; Difficulty, Yes Autonomous Motivation, No Autonomous Motivation and Baseline Craving are Z-scored across participants; and Trial is centered at 45 and is units of 10 trials. AM = Autonomous Motivation.

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