EXTERNAL AND INTERNAL FACTORS AFFECTING EMOTION REGULATION

By

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Abstract

Emotion regulation is defined as changing or maintaining one’s emotions. The Selection, Optimization, and Compensation model of Emotion Regulation (SOC-ER) posits that emotion regulation is influenced by external factors, such as properties of a stimulus, and internal factors, such as cognitive processes. The purpose of this series of studies was to distinguish how external and internal factors contribute to emotion regulation. In Study 1, I identified how ambivalence, an external factor, influences emotion regulation choice. I predicted that participants would be more likely to choose to reappraise ambivalent images compared to non-ambivalent images. Studies 2 and 3 examined how internal factors influence emotion regulation ability. In Study 2, I combined brain imaging and behavioural tasks to determine brain activity produced during emotion regulation could be used to predict individual differences in working memory performance. I predicted that differences in brain activity between reappraise and view conditions would predict working memory scores. In Study 3, I used intrinsic network functional connectivity to evaluate whether differences in network connectivity could be used to predict whether one is reappraising or viewing a negative stimulus. I expected network connectivity to predict emotion regulation ability greater than chance, and that networks associated with emotion (salience network), networks associated with cognitive control (attention control network, frontoparietal networks), and the default mode network would make a reliable contribution to significant classification. Our hypotheses for Studies 1 and 2 were supported, and Study 3 was partially supported. This study has contributed new knowledge to the literature on the neurocognitive mechanisms of emotion regulation by testing predictions derived from the SOC-ER model, which can help identify ways to improve one’s emotion regulation.

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with larger z-values during the reappraisal condition while negative linear coefficients are associated with larger z-values during the view condition. In the upper triangle, the most reliable features are labelled with a white star.

Chapter 1: Introduction

When someone is in an emotional situation, such as having to give a speech when one is afraid of public speaking, what needs to be done to feel better? The person could simply choose not to give the speech, changing the situation they are in. They could try to distract themselves from the stress of public speaking, modifying how they deploy attention. They could try to rethink the situation they are in and remind themselves that the speech will be over before they know it, allowing them to change their appraisal of the situation. Another thing this person could do is keep a poker face throughout the speech, refusing to show their fear, modifying their response to the emotional situation. All these options are examples of emotion regulation, which is the ability to change or maintain one's emotional state (Gross, 1998). While the definition of emotion varies heavily across theory (Adolphs, 2017; Feldman, 2017; LeDoux & Hoffman, 2018), emotion can be described as in internal affective state associated with behavioural and physiological responses (Gross, 2002). In emotion regulation research, these emotional responses are often measured using subjective self-report, such as Likert scales and physiological measures, such as skin conductance. While some researchers use bipolar measures of positive and negative, I have opted to use an evaluative space grid approach with unipolar measures positive and negative emotion, as they provide information similar to that of unipolar valence and intensity measures (Cacioppo et al., 1997, 1999; Cacioppo & Berntson, 1994; Kron et al., 2013; Larsen et al. 2009). Furthermore, emotion serves as an internal subjective state, I focused on differences within subjects when determining differences involving these measures.

Each of the methods in our example falls in line with the modal model of emotion regulation. The modal model first divides emotion generation into four stages: situation, attention, appraisal, and response (Gross, 2002, 2014); and second, describes how emotional reactivity can be modified by targeting each of the four stages of emotion generation with five different regulation approaches. Situation selection and situation modification involve emotion regulation either by changing one's choice of situation or by modifying the situation in some manner (Gross, 2002). Attentional deployment involves redirecting one's focus and includes methods such as distraction (Gross, 2002). Cognitive change involves thinking about the meanings of an emotional stimulus and includes methods such as cognitive reappraisal, or thinking about one's emotions (Gross, 1998, 2002). Finally, response modification refers to changing one's response to an emotion once it is experienced (Gross, 2002). A great amount of emotion regulation research is focused on reappraisal and distraction (Ochsner et al., 2012). For this reason, along with the fact that I wish to examine emotion regulation after someone has entered a situation, this research will be focused on reappraisal and distraction.

In order to successfully regulate an emotional stimulus, one must have the resources to regulate, optimize one's regulation, and then compensate for any failures of regulation, typically by ulitizing other emotion regulation methods. The Selection, Optimization, and Compensation with Emotion Regulation (SOC-ER) model is one example of a framework for potentially understanding the cognitive resources required of emotion regulation. The SOC-ER model states that people select the type of emotion regulation to do based on available external and internal factors, optimize the emotion regulation method, and then compensate for any failed emotion regulation methods (Opitz et al., 2012; Urry & Gross, 2010). Therefore, if one has less resources (external or internal) required for a particular emotion regulation method, they are not only less likely to choose that emotion regulation method but also may perform that method of emotion regulation less effectively (Opitz et al., 2012). External resources include the features of a stimulus and emotional affordances that allow for regulation (Suri et al., 2018) such as intensity of an image (Sheppes, 2014; Sheppes et al., 2011). Meanwhile, internal resources may include the cognitive control processes underpinning emotion regulation as well as patterns of brain activity and connectivity. Following the SOC-ER model, emotion regulation failure, or emotion dysregulation can occur when there is a lack of external or internal resources needed to select or optimize an effective emotion regulation strategy. Emotion dysregulation is a cornerstone of several mental illnesses, particularly anxiety and mood disorders (S. G. Hofmann et al., 2012). According to this model, a lack of regulatory resources in those with anxiety and mood disorders leads to greater emotional dysregulation (Opitz et al., 2012), which in turn causes anxiety and mood disorders to form (S. G. Hofmann et al., 2012). Therefore, identifying which external and internal factors play a role in emotion regulation success can be used to improve an individual's coping mechanisms and subsequently, their wellbeing.

External factors include environmental cues of a stimulus. For example, intensity of a stimulus has been shown to play a role in emotion regulation choice, with people more likely to choose reappraisal for low intensity stimuli and distraction for high intensity stimuli (Sheppes, 2014; Sheppes et al., 2011). In addition, environmental affordances, or environmental cues that can influence the meaning of a stimulus, can also affect emotion regulation choice (Milyavsky et al., 2018; Sheppes et al., 2014; Suri et al., 2018). Environmental affordances that make reappraisal easier are referred to as reappraisal affordances and can make people more likely to select reappraisal (Milyavsky et al., 2018; Sheppes et al., 2014; Suri et al., 2018). One potential external factor that may serve as a reappraisal affordance is ambivalence, or the presence of a positive and negative affective cues in a stimulus (Larsen & McGraw, 2014). Ambivalent emotions are associated with greater coping ability (Braniecka et al., 2014; Hay & Diehl, 2011), which may be due to their combination of positive and negative cues.

There are several internal factors that could affect emotion regulation that have been considered in the literature. For example, one aspect of cognitive control, working memory, has been revealed to be associated with emotion regulation ability (Schmeichel & Tang, 2015). Various cognitive processes that could be considered aspects of cognitive control are used at every step in Gross' modal model of emotion regulation (Ochsner et al., 2012), and impairments in cognitive control are associated with anxiety and depression (Snyder et al., 2015). Therefore, it may be the case that people's emotion regulation ability, and subsequently their wellbeing, is tied more generally to mechanisms of cognitive control. Executive function, a closely related concept to cognitive control, consists of shifting, inhibition, and working memory. While these three functions are independent, research has found that they are also correlated with one another (Friedman et al., 2008; Friedman & Miyake, 2017; Snyder et al., 2015). The fact that many aspects of cognitive control are interrelated suggests that individual differences in cognitive processes play a role in emotion regulation. In the case of working memory, it may be the case that individual differences in emotion regulation efficacy are associated with individual differences working memory performance.

In addition, the state of one's brain may also play a role in emotion regulation efficacy. When doing a reappraisal task, brain networks associated with reappraisal impact emotionality less (Jacob et al., 2019), which suggests that differences in brain activity may also serve as an internal factor in emotion regulation efficacy. Emotion regulation, particularly reappraisal, is typically associated with activation in the dorsolateral prefrontal cortex (dlPFC) and ventrolateral prefrontal cortex (vlPFC) (Buhle et al., 2014; Goldin et al., 2008; McRae et al., 2010; Ochsner et al., 2012; Silvers, Weber, et al., 2015). In addition, aspects of the parietal lobe are activated in some emotion regulation studies (Buhle et al., 2014; Kanske et al., 2011; McRae et al., 2010).

These areas are associated with cognitive control networks such as the frontoparietal networks and the attention control network (ACN). The dlPFC in particular is associated with both reappraisal and working memory (Kanske et al., 2011; McRae et al., 2010), suggesting a shared mechanism. During down-regulation of emotion using reappraisal, the activation of the lateral prefrontal cortices is paired with deactivation in the insula (Goldin et al., 2008; Min et al., 2022) and the amygdala (Buhle et al., 2014; Goldin et al., 2008; Ochsner et al., 2012; Silvers, Weber, et al., 2015). The insula is associated with the salience network (SN), which plays a role in attention to emotion (Menon & Uddin, 2010). Meanwhile, the amygdala is associated with the limbic network, which is associated with emotional responses (Laird et al., 2011).

While it is evident that networks associated with cognition and networks associated with emotion regulation, it is unclear as to whether the connection between these networks is direct or implicates other networks. Many brain areas outside of these networks are involved in emotion regulation as well. For example, the vmPFC acts on the amygdala during both up-regulation (Greening et al., 2014) and down-regulation (Hermann et al., 2021; Johnstone et al., 2007). Furthermore, the PMC is also active during reappraisal (Mcrae et al., 2010). Both the vmPFC and PMC are parts of the default mode network (DMN), which is associated with processing emotion (Saarimäki et al., 2022). Indeed, looking at connectivity between networks may provide insight into internal factors of emotion regulation past brain activity.

The purpose of the proposed research is to determine how environmental affordances and internal resources affect emotion regulation. Below, I review the literature as it pertains to this general purpose. I will begin by discussing how environmental factors affect emotion regulation. Then I will discuss the relationship between emotion regulation and cognitive processes. Then I will discuss how emotions affect cognitive processes and vice versa. I will then discuss the cognitive control mechanisms, particularly working memory, and the relationship they have with emotion regulation. During this, I will also discuss the contributions of brain activity to emotion regulation. I will discuss the benefits of taking a functional connectivity approach when studying emotion regulation. Finally, I will discuss the three experiments implemented that aimed to further our understanding of the relationship of which external and internal resources affect emotion regulation.

Emotion Regulation and Environmental Affordances

As SOC-ER notes, environmental factors can affect one's emotion regulation behavior (Opitz et al., 2012; Urry & Gross, 2010). One major example of this comes from the intensity of an image. Research has shown that people are more likely to reappraise from low intensity images than high intensity images and more likely to distract from high intensity images than low intensity images (Sheppes, 2014; Sheppes et al., 2011, 2014). This may be because reappraisal is associated with engaging with a stimulus**,** while distraction is associated with disengaging with a stimulus. People are more likely to choose emotion regulation methods that involve greater disengagement for high intensity stimuli (Sheppes et al., 2014). The difficulty of an emotion regulation method can also affect emotion regulation choice, with people more likely to choose an easier prompted reappraisal instruction over a more difficult unprompted reappraisal instruction (Sheppes et al., 2014). Reappraisal is also chosen more often when people consider their long-term goals (Sheppes et al., 2014). In fact, when reappraisal affordances, or opportunities for reappraisal, are offered in a stimulus, a person is more likely to reappraise the image (Suri et al., 2018; Young & Suri, 2020). Thus, using a mindset about what constitutes a reappraisal affordance can therefore serve to help determine which external factors impact emotion regulation selection.

One potential reappraisal affordance would be simultaneous positive and negative affect in a stimulus, otherwise known as ambivalence (Larsen & McGraw, 2014). While ambivalence is rare, there is evidence of people feeling simultaneously positive and negative (Larsen & McGraw, 2011; Schimmack, 2005). As our definition of ambivalence looks at the simultaneous presence of positive and negative cues, an evaluative space model approach with unipolar scales for positive and negative emotion is ideal for looking at emotional response in this research (Cacioppo et al., 1997, 1999; Cacioppo & Berntson, 1994; Kron et al., 2013; Larsen et al., 2009; Thompson & Zanna, 1995). Not only can people successfully regulate ambivalent emotions (Norris & Wu, 2021), but ambivalent emotions are also associated with improved emotion regulation ability (Braniecka et al., 2014; Hay & Diehl, 2011). Thus, it is possible that the positive affect of ambivalent emotions may function as a reappraisal affordance and make emotion regulation easier. If this is the case, then people should be more likely to reappraise ambivalent images than non-ambivalent images.

Emotion Regulation and Cognitive Processes

Emotions are intertwined with cognition, and this is especially true for emotion regulation. In fact, cognitive processes, particularly cognitive control, are necessary to maintain, monitor, switch, and stop emotion regulation methods (Pruessner et al., 2020). In the modal model of emotion regulation, attention and cognition are two aspects of emotion regulation that one can change (Gross, 2002, 2014). Distraction, meditation (Wadlinger & Isaacowitz, 2011), and working memory shifting (Thiruchselvam et al., 2012) are examples of changing one’s attentional deployment to regulate emotion, while reappraisal is an example of changing one’s cognition (Gross, 2002). Furthermore, there is evidence that cognitive control and emotion regulation show activity in overlapping brain areas. Specifically, cognitive control is driven by activity in the prefrontal cortex and parietal areas (Friedman & Miyake, 2017; Laird et al., 2011). Distraction is associated with increased activity in prefrontal areas such as the dorsomedial prefrontal cortex (dmPFC) and the anterior cingulate cortex (ACC) (Kanske et al., 2011; McRae et al., 2010). Reappraisal is found to increase activity in the dlPFC and vlPFC(Denny et al., 2015; Goldin et al., 2008; Morawetz, Bode, et al., 2016; Ochsner et al., 2004), as well as aspects of the parietal lobe (Buhle et al., 2014; Kanske et al., 2011; McRae et al., 2010). From these patterns in neural activity, it is possible that neurocognitive processes involved in cognitive control play a large role in emotion regulation. While our research is primarily focused on reappraisal, and only focused on behavioral aspects of distraction, it is important to consider how cognition- and attention-based forms of emotion regulation affect similar brain regions.

Distraction and reappraisal are both associated with greater activity in the dlPFC and dmPFC (Kanske et al., 2011), along with greater activity in the dACC (McRae et al., 2010). Activity in these areas is of interest because dlPFC and dmPFC activity is also associated with cognitive processes, particularly working memory (Friedman & Miyake, 2017; Kanske et al., 2011; McRae et al., 2012). The ACC is an area of interest as well, as it is associated with emotional attention and pulling resources from prefrontal areas (Pessoa, 2009). Distraction and reappraisal are also associated with decreased amygdala activity (Buhle et al., 2014; Goldin et al., 2008; Kanske et al., 2011; McRae et al., 2010; Ochsner et al., 2012) and decreased insula activity (Goldin et al., 2008; Min et al., 2022). Combined, these findings suggest that distraction and reappraisal, particularly when decreasing emotional response, show activity increases in networks associated with cognition and decreases in networks associated with emotion. However, distraction also leads to more activation in dmPFC and less activation in the amygdala and ventromedial prefrontal cortex (vmPFC) compared to reappraisal (Kanske et al., 2011;

McRae et al., 2010). This may be due to attention, as distraction is associated with less attention to emotional stimuli than reappraisal (Bartolomeo et al., 2020; Strauss et al., 2016), while changes in attention are occasionally reported, but not necessary for cognitive reappraisal (Bebko et al., 2014; Urry, 2010). Differences in neural activity between distraction and reappraisal tend to decrease with age. While younger adults have less activity in the PMC during reappraisal compared to distraction, older adults have comparable levels (Martins et al., 2014). These findings suggest that while distraction and reappraisal are separate strategies, they have considerable overlap.

Both distraction and reappraisal are associated with activity in the prefrontal cortex, with both overlapping and differing areas of the prefrontal cortex being associated with each method (Kanske et al., 2011; McRae et al., 2010). This is similar to the unity and diversity model, which suggests that the various aspects of cognitive control (shifting, inhibition, and working memory) share similarities and differences in both behavioral performance and neural activity (Friedman et al., 2008; Friedman & Miyake, 2017). Reappraisal and distraction involve differing behaviors and brain activity, suggesting a degree of diversity, while also having a considerable amount of overlap, suggesting similarly between the two, suggesting that findings regarding reappraisal may partially generalize to other forms of emotion regulation.

One way to identify if the neurocognitive processes driving emotion regulation is through multivariate pattern analysis (MVPA), in which patterns in fMRI activity are used to predict something such as behavior or performance (Gabrieli et al., 2015). MVPA has been used to identify what emotion regulation strategies are used (Martins et al., 2014), as well as whether emotions were being up-regulated or down-regulated (Morawetz, Bode, et al., 2016). Given that

MVPA has shown evidence of predicting patterns of emotion regulation, it is possible that brain activity during emotion regulation may be a predictor for cognitive control ability.

Emotion and Cognitive Processes

While there is a heavy debate as to whether emotions are affective states that result in behaviors (Adolphs, 2017) or predictive appraisals resulting from prior experiences (Barrett, 2017), most can agree that emotions can be defined as an internal affective state. In humans, these affective states can be measured using self-report measures, such as Likert ratings or yes-no responses, or physiological measures, such as skin conductance response or brain activity. In research focusing on emotion regulation, I am particularly interested in the extent to which emotions are felt, as that can serve as a measure of emotion regulation efficacy. Previous research looking at quantifying emotion has primarily used bipolar valence and arousal ratings, also known as the circumplex model (Russell, 1980). However, one alternative is the evaluative space model, which quantifies emotion using unipolar positivity and negativity ratings (Cacioppo et al., 1997, 1999; Cacioppo & Berntson, 1994; Kron et al., 2013; Larsen et al. 2009). Ratings from the evaluative space model often reflect ratings of bipolar valence and arousal (Kron et al., 2013) and are supported by neuroscience literature more than circumplex models (Salzman & Fusi, 2010). Thus, I opt to define emotion as an internal subjective affective state which can be quantified using unipolar ratings of positivity and negativity, as well as physiological activity. As emotions have a degree of subjectivity to them, it is also important to use within-subject measures to determine differences in emotion regulation selection and efficacy.

Emotional responses and reactivity relate to emotion regulation (Kappas, 2011). For this reason, it is important to discuss the effect of emotion on cognition and vice versa. One cognitive process that very clearly relates to emotions is attentional capture. Emotional information is given priority when attending to a stimulus (Compton, 2003; Pessoa, 2009). The dual competition model states that emotional information can bias attention, enhancing cognitive processes if the emotional stimulus is task-relevant, or impairing cognitive processes if the emotional stimulus is task-irrelevant (Pessoa, 2009). One example of this model is the attentional blink, in which people fail to attend to stimuli shortly after a target is presented due to attention being pulled away (Anderson, 2005; Mishra et al., 2017) When the target is emotional, the attentional blink increases (Anderson, 2005), but when the distractor is emotional, the attentional blink decreases (de Martino et al., 2009). This is also consistent with the idea that emotional stimuli are more perceptually salient and are more likely to grab one's attention. Another example is emotion-induced blindness, in which emotional stimuli impair perception of prior stimuli even when the emotional stimuli are not the target (Bocanegra & Zeelenberg, 2009). According to Pessoa's (2009) dual competition model, the high intensity of an emotional distraction pulls executive resources from non-emotional target stimuli, leading to targets not being attended. Indeed, attentional blink is associated with the rostral anterior cingulate cortex (rACC) (de Martino et al., 2009), which is associated with emotional attention (Pessoa, 2009), suggesting that the ACC is pulling attentional resources to attend to emotional stimuli. Attentional blink also shows a heightened late positive potential (LPP) towards an emotional word, which could predict if the target was attended to after a short blink (MacLeod et al., 2017), showing that attention is greater for emotional stimuli and less for surrounding stimuli.

The findings from attentional blink can be applied to emotional attention as a whole. Inhibition of attention for example is associated with prefrontal areas, such as the middle frontal gyrus (Marini et al., 2016). The vlPFC shows greater activity in correctly identified changes in identity of faces (Achaibou et al., 2015). Meanwhile, amygdala activity increases when people view emotional faces (Achaibou et al., 2015; Bishop et al., 2004). When participants looked at emotional faces, the amygdala was found to have more positive connectivity to lower-level visual areas (Gschwind et al., 2012). Taking Pessoa's (2009) dual competition model into account, activity in the amygdala can result in the increased activity through lateral aspects of the prefrontal cortex via the ACC. Indeed, the amygdala is also active when attention towards emotional faces is reduced (Anderson et al., 2013) or when the emotion faces are subliminal (Williams et al., 2004), suggesting that amygdala activity alone is not responsible for attention, but instead relies on connectivity to areas such as the ACC and prefrontal cortex to attend to emotional stimuli (Pessoa, 2009). As emotion regulation can be automatic, emotional reactivity is greatly tied into emotion regulation (Kappas, 2011). For example, one study found that when people were told to attend to images and let emotion regulation occur naturally, there was greater activity in the dlPFC and dmPFC when people reported lower ratings and greater activity in the amygdala when people reported higher ratings (Silvers, Wager, et al., 2015). The dlPFC and dmPFC are not only associated in many cognitive control processes, but also are recruited by the ACC when one attends to an emotional stimulus (Pessoa, 2009). This suggests emotional reactivity, and automatic forms of emotion regulation pull from areas associated with cognitive control.

However, while emotion influences cognition, cognition can also inhibit emotional stimuli. For example, performance on a stop signal task, a measure of inhibition, improved with low intensity emotional stimuli and worsened with high intensity emotion stimuli (Pessoa et al., 2012). Emotional information is also less distracting under a high perceptual load compared to a low perceptual load (Tavares et al., 2016). This is supported by the dual competition model, as emotional stimuli can increase processing of a target under certain conditions (Pessoa, 2009).

Meanwhile, emotional information is more distracting under a high working memory load compared to a low working memory load (Tavares et al., 2016).While on the one hand, emotional stimuli can draw upon cognitive control resources and impair working memory performance at higher loads, high perceptual demand can inhibit emotional stimuli.

Attention, Cognitive Control, and Emotion Regulation

In Gross's (2002) modal model, attention serves as one of the steps in emotion regulation, so it is not farfetched to suggest attention plays a role in emotion regulation. Overall, people who down-regulate emotion view emotionally relevant aspects of a stimulus less often than those who attend or up-regulate emotion (van Reekum et al., 2007). In addition, during distraction, attention is being deployed to disengage from a stimulus, while reappraisal is associated with engaging with a stimulus (Gross, 2002; Sheppes et al., 2014). While it is evident that distraction involves attention, it is the case that reappraisal involves attention as well, albeit to a lesser extent. While reappraisal is seen as effective when gaze is held constant (Bebko et al., 2014; Urry, 2010), reappraisal is associated with an attentional gaze pattern of attending to the arousing aspects of an image at first and then fixating on other stimuli (Strauss et al., 2016). People who spend more dwell time on arousing aspects of negative images report feeling more negatively during cognitive reappraisal (Strauss et al., 2016). This suggests that visual attention plays a role in reappraisal as well as distraction, particularly in the efficacy of emotion regulation. In the context of the SOC-ER model, a degree of attention may serve as a factor which affects successful emotion regulation (Opitz et al., 2014; Urry & Gross, 2010).

Current research in attention suggests that attentional networks are a more accurate measure of attention than brain areas (Rosenberg et al., 2017). The dorsal attention network shows great activity in attention tasks where performance fluctuates, while the DMN shows greater activity in attention tasks when a person is performing optimally (Rosenberg, Finn, Constable, et al., 2015). Furthermore, research has found that increased connectivity between the dorsal attention network and DMN is associated with reappraisal (Sripada et al., 2014), supporting the idea that attentional networks are involved in emotion regulation.

In addition to attention being involved in emotion regulation, two forms of cognitive control, shifting and inhibition, show overlap with emotion regulation. Shifting involves switching one's attention between tasks or goals, while inhibition is the process of stopping or preventing prepotent responses (Miyake et al., 2000). While research of the relationship between shifting and emotion regulation is mixed (Schmeichel & Tang, 2015), there is evidence that shifting is related to emotion regulation. For example, higher levels of optimism decrease the negative effect of pain on an attention shifting task (Boselie et al., 2017). As optimism is associated with coping and emotion regulation, this suggests a relationship between attentional shifting and emotion regulation exists. Inversely, inhibition shows positive associations with emotion regulation efficacy, especially for cognitive reappraisal (Schmeichel & Tang, 2015; Tabibnia et al., 2011).

One form of attentional shifting is attentional biases, or what stimulus people are more likely to attend to, which is often measured using a dot probe task. Recent attentional bias studies use dot probe to determine the rate at which people either engage to, or begin attending to, or disengage from, or stop attending to a stimulus. Attentional biases towards angry faces were negatively associated with emotion regulation success (Harrison et al., 2010) while slower engagement toward angry faces was associated with greater reappraisal (Kim et al., 2016). These findings are relevant, as according to the SOC-ER model (Opitz et al., 2014; Urry & Gross, 2010), internal resources are important to regulate emotion, and if one has trouble shifting between emotional and non-emotional stimuli, it is possible they may have trouble regulating emotion. Indeed, training attentional biases away from negative stimuli can improve emotion regulation efficacy (Johnson, 2009; Van Bockstaele et al., 2019; Wadlinger & Isaacowitz, 2011). Attentional biases are associated with amygdala activity, which remains constant with repetition (Weber et al., 2016). In addition, structural connectivity between the amygdala and the ACC plays a role in attention bias (Carlson et al., 2014). Attentional bias modification leads to decreased activity in the amygdala and ACC when looking at negative images (Hilland et al., 2020). This supports the idea that the limbic network and the salience network, networks that play a role in emotion regulation (Morawetz, Kellermann, et al., 2016), may play a role in attentional switching. Default mode network connectivity was also associated with engagement and disengagement speeds (Evans et al., 2020). Returning to the SOC-ER model, this may be due to attentional bias tasks are associated with similar brain areas, and thus attention bias modification gives people the internal resources to regulate emotion more successfully (Opitz et al., 2012).

As shifting shows neural overlap with emotion regulation, as does inhibition. Greater grey matter volume in the inferior frontal gyrus is also associated with both cognitive reappraisal ability and performance on an inhibition task (Tabibnia et al., 2011). The inferior frontal gyrus has been shown to be active during emotion regulation as well (McRae et al., 2010). The relationship between inhibition and reappraisal has been further supported in a study in which depressed individuals who exhibited less inhibition also used less cognitive reappraisal (Joormann & Gotlib, 2010). Following the SOC-ER model, this would suggest that one internal resource that people may need to reappraise an emotional stimulus is the ability to inhibit the stimulus, and as people with depression have problems with inhibition, they would also have problems performing certain types of emotion regulation and would be less likely to select them and successfully regulate. However, the individual differences between emotion regulation and inhibition have not been looked at in detail in a healthy population.

Working Memory and Emotion Regulation

Previously, I discussed the idea of emotional stimuli pulling from cognitive processes. This combined with previous discussion of other aspects of cognitive control influencing emotion regulation suggests that working memory is related to emotion regulation. Performance on working memory tasks has been shown to be positively associated with reappraisal efficacy (Hendricks & Buchanan, 2016; W. Hofmann et al., 2012; Opitz et al., 2014) and reappraisal frequency (Jasielska et al., 2015). In addition, people who did working memory training also showed greater emotion regulation success (Schmeichel & Tang, 2015; Schweizer et al., 2013). This suggests a causal relationship between working memory and emotion regulation, with improved working memory leading to improved emotion regulation, and may also suggest that emotion regulation and working memory are underpinned by similar mechanisms.

In addition, emotional stimuli can disrupt working memory. For example, emotional distractors have can lead to worse performance on task with high working memory load, while having no effect on a task with low working memory load (Tavares et al., 2016). There are also individual differences in how much emotional stimuli impacts working memory performance. In particular, those who show greater working memory impairments from emotional stimuli show greater activity in the amygdala and less activity in the dlPFC (Dolcos et al., 2013). Another example is people with post-traumatic stress disorder (PTSD), who show worse performance on working memory tasks regardless of whether a stimulus is emotionally salient or not (Morey et al., 2009). These results imply that worse working memory performance is associated with greater emotionality, perhaps as a result of difficulty in regulation. Within the context of the SOC-ER model, this would imply poorer coping mechanisms are associated with deficits in working memory (Opitz et al., 2012; Urry & Gross, 2010).

In addition, there is neural evidence for shared mechanisms between emotion regulation and working memory. On a network level, frontoparietal networks are associated with both working memory ability (Laird et al., 2011) and emotion regulation efficacy (Moreira et al., 2021; Schweizer et al., 2013; Wessing et al., 2015), suggesting similar brain areas are involved in both. Further evidence of overlap is seen with the ACC, which is active in both emotion regulation and emotional working memory (Schweizer et al., 2013; Smith et al., 2018). However, while this is only focused on emotional working memory, it is uncertain whether this overlap also exists between emotion regulation and emotionally neutral working memory. Finally, the dlPFC, has been implicated in a breadth of emotion regulation research (Kanske et al., 2011; McRae et al., 2010; Ochsner et al., 2012; Scult et al., 2017). Activity in the dlPFC during a working memory task also predicted how often people reappraised their emotions (Scult et al., 2017). Combined, these findings suggest that working memory and emotion regulation may be underpinned by the same neural mechanism. However, some argue that this is merely a coincidental overlap (Lee & Xue, 2018). Thus, more research is needed in order to determine whether working memory share neural mechanisms. If this were to be the case, it would mean that working memory ability serves as an internal factor in emotion regulation.

Functional Connectivity and Emotion Regulation

Rather than looking at the activation of given brain regions or networks, one final internal factor to consider is the pattern of functional connectivity between regions or networks in the brain. This is an inter-network functional connectivity based view of the brain and how the pattern of network connectivity contributes to emotion regulation.

I have previously discussed the role that aspects of the lateral PFC and parietal areas play in emotion regulation, which are implicated in the frontoparietal and attention control networks. The left frontoparietal network is believed to be involved in language and working memory performance, while the right frontoparietal network is associated with memory, including working memory, divided attention, and inhibition (Laird et al., 2011). In general, emotion regulation involves greater activity in the frontoparietal networks (Moreira et al., 2021; Schweizer et al., 2013; Wessing et al., 2015). A similar network, the attentional control network (ACN), plays a role in motor movements associated with attention, as well as cognitive control (Roye et al., 2020). Like the frontoparietal networks, greater activity in the ACN is also associated with emotion regulation (Fusina et al., 2022; Sripada et al., 2014; Viviani, 2013). However, as I will discuss further, these networks are not the only ones associated with emotion regulation, which highlights the importance of focusing on inter-network functional connectivity in emotion regulation.

As activity in the aspects of the frontal and parietal lobes increase, amygdala (Buhle et al., 2014; Goldin et al., 2008; Kanske et al., 2011; McRae et al., 2010; Ochsner et al., 2012) and insula (Goldin et al., 2008; Min et al., 2022) activity will also decrease in down-regulation of emotion. The salience network (SN) includes the insula as well as the ACC and is associated with attention, shifting, and working memory, particularly in emotional contexts (Denny et al., 2018; Menon & Uddin, 2010). Meanwhile, the limbic network includes the amygdala as well as medial temporal areas and is associated with attention to emotional images (Laird et al., 2011), which is important in the context of our emotion regulation paradigm. Interconnectivity in limbic areas is also associated with susceptibility to emotional distractors, particularly in people with anxiety and depression (Bijsterbosch et al., 2018).

Another network we are interested in, the DMN, includes the vmPFC and PMC (Buckner et al., 2008). The DMN is typically associated with mind wandering and self-referential processing (Finn, 2021; Gusnard et al., 2001), and more noteworthy, processing of emotion (Saarimäki et al., 2022). The DMN plays a nuanced role in emotion regulation, as decreased connectivity between aspects of the vmPFC and PMC are associated with greater self-reported reappraisal (Fresco et al., 2017; Lieberman et al., 2023), while greater connectivity between the PMC and other aspects of the DMN is associated with greater reappraisal (Y. Chen et al., 2024).

If emotion regulation is driven by similar neurocognitive processes as cognitive control, then intrinsic canonical networks such as the ACN and frontoparietal networks should play a role in emotion regulation. Reappraisal is typically associated with negative connectivity between the aspects of ACN and frontoparietal networks, such as the dlPFC, dmPFC, and vlPFC, and aspects of the limbic network, such as the amygdala (Kanske et al., 2011; Morawetz, Kellermann, et al., 2016), and aspects of the SN, such as the insula (Li et al., 2021), so I would expect negative connectivity between those networks during emotion regulation. Furthermore, increased positive connectivity between the SN and DMN is typically also associated with more emotionality in emotion regulation (Fresco et al., 2017; Lieberman et al., 2023). In addition, greater reappraisal performance is associated with more positive connectivity between the dorsal attention network and the DMN (Sripada et al., 2014). Thus, it is likely that positive connectivity between these networks will also be seen during emotion regulation.

While research focuses on how these networks interact with one another as a function of emotion regulation, there are two inherent issues with this. First of all, studies typically only focus on pairs of networks, such as the frontoparietal networks and the salience network (Kanske et al., 2011; Li et al., 2021). There is, however, research that looks at the contributions of multiple network connections in emotion regulation, of note being the relationship between the dorsal attentional network and the DMN being greater in emotion regulation conditions compared to view conditions (Sripada et al., 2014). One issue this study has is using seeds to compare connectivity between whole networks, leading to a multiple comparisons problem. An alternative approach to functional network connectivity is to evaluate canonical resting state networks using an independent components analysis (ICA) (Laird et al., 2011; T. H. Lee et al., 2017a; Reineberg et al., 2015; Roye et al., 2020). Using ICA can drastically decrease the number of connections tested in connectivity analysis, going from tens of thousands, to over a hundred.

Objectives

The purpose of the research presented in these three studies is to further our knowledge as to the external and internal factors that underpin emotion regulation. I intend to address this purpose across three studies. Firstly, I will identify how ambivalence, an environmental factor, affects emotion regulation choice. Second, I will focus on internal factors and will determine how brain activity during emotion regulation predicts individual differences in cognitive control, notably working memory performance. Finally, I will determine whether patterns of functional connectivity between the various intrinsic canonical networks can be used to dissociate attending to negative stimuli versus reappraising negative stimuli, and whether the networks associated with said classification are also associated with cognitive control. Overall, I predict that environmental external qualities as well as neural internal processes associated with cognitive control underpin emotion regulation selection and performance, which I evaluate across the studies below.

Study 1 – External Factors Affecting Emotion Regulation Choice

The purpose of this research is to determine if the ambivalence of a stimulus affects emotion regulation choice. Previous research has found that people are more likely to choose reappraisal for low intensity images than high intensity images. However, this research does not account for ambivalence, defined as the presence of both positive and negative affect information in a single emotional stimulus. I hypothesize that the ambivalence of an image would affect one's emotion regulation choice, with people more likely to choose reappraisal for an ambivalent image than a non-ambivalent image.

While this study is, to our knowledge, the first to investigate the role of ambivalence in emotion regulation choice, it is possible that the positive affect of ambivalent stimuli serves as an affordance for reappraisal. For this reason, I predict that the ambivalence of an image also plays a role in emotion regulation choice.

Study 2 – Neural Bases of Emotion Regulation

The purpose of Study 2 is to identify whether the pattern of brain activity associated with emotion regulation can be used to predict individual differences in working memory. While there is overlap in the brain areas associated with working memory and cognitive ability, it is unclear as to whether that is coincidental (T. W. Lee & Xue, 2018). I expect brain activity to predict working memory performance at a rate greater than chance. I use data already collected in which participants completed an emotion regulation task in the MRI scanner. Participants also completed the Wechsler Adult Intelligence Scale IV (WAIS-IV), which assesses one's working memory, verbal comprehension, perceptual reasoning, and processing speed. I was particularly interested in the working memory index of the WAIS-IV. First, I look at covariate effects of working memory on differential brain activity. Second, I use whole-brain multivariate pattern analysis (MVPA) with 10-fold cross validated support vector regression analysis in regions of interest (ROIs) associated with working memory to determine if I could predict individual differences in working memory from the brain results associated with the down-regulation contrast images. This study will help uncover cognitive mechanisms of emotion regulation in more detail as well as identify areas involved in both emotion regulation and cognitive control.

Study 3 – Functional Connectivity in Emotion Regulation

The litany of resting-state fMRI research over the past two decades has identified several canonical brain networks. Each of these networks is often comprised of several different brain regions, which can be spatially adjacent or spatially disparate to varying degrees. One way of determining these networks is to see what areas correlate with one another using independent components analysis (ICA) (Laird et al., 2011). Network names are based on the regions most associated with them and the processes most associated with those regions. The attention control network, for example includes prefrontal areas and is associated with attention and cognitive control (Roye et al., 2020). The saliency network includes areas such as the amygdala, the insula, and ACC, and is associated with emotional activity (Y.-Y. Chen et al., 2021; Denny et al., 2018). The DMN consists of frontal and parietal areas and is associated with resting state activation (Finn, 2021) and optimal attention (Rosenberg, Finn, Constable, et al., 2015). However, relatively less research has been concerned with understanding how the dynamics of these brain networks change as a function of varying tasks demands (Finn, 2021). The purpose of this study was to test the prediction that the patterns of functional connectivity associated between the intrinsic canonical networks, specifically those networks associated with process relating to cognitive control such as the attention control network and saliency network, 1) were associated with negative emotion regulation (i.e., reappraise negative versus attend negative) and 2) had patterns of connectivity which could be used to predict whether participants are reappraising versus attending to negative information.

I was particularly interested in the pattern of functional connectivity associated with the ACN, SN, visual network, left and right frontoparietal networks, and the DMN and their relationships with each other. Our primary hypothesis is that connectivity between emotion-driven network (i.e. the SN and the limbic network) and cognitive control networks (i.e. the ACN and frontoparietal network) would be more negative in reappraisal condition compared to view conditions, connectivity between the DMN and ACN would be more positive during the reappraisal condition compared to the view condition, and connectivity between the DMN and SN would be more positive in the view condition compared to the reappraise condition. These hypotheses reflected the inhibitory role of the cognitive control networks on the SN in emotion regulation, the role of the DMN and ACN in inhibition and emotion regulation, and the decreases in emotionality in the SN. Second, I used multivariate pattern classification and leave-one-subject-out cross-validation to test the hypothesis that the pattern of functional connectivity between all pairwise combinations of the canonical networks could be used to predict whether participants are reappraising or viewing negative images. I believe this study was the first to look at inter-network functional connectivity using whole networks and MVPA analyses.

Chapter 1 References

Achaibou, A., Loth, E., & Bishop, S. J. (2015). Distinct frontal and amygdala correlates of change detection for facial identity and expression. *Social Cognitive and Affective Neuroscience*, *11*(2), 225–233. https://doi.org/10.1093/scan/nsv104

Adolphs, R. (2017). How should neuroscience study emotions? by distinguishing emotion states, concepts, and experiences. *Social Cognitive and Affective Neuroscience*, *12*(1), 24–31. https://doi.org/10.1093/scan/nsw153

Anderson, A. K. (2005). Affective influences on the attentional dynamics supporting awareness. *Journal of Experimental Psychology: General*, *134*(2), 258–281. https://doi.org/10.1037/0096-3445.134.2.258

Anderson, A. K., Christoff, K., Panitz, D., De Rosa, E., & Gabrieli, J. D. E. (2013). Neural correlates of the automatic processing of threat facial signals. *Social Neuroscience: Key Readings*, *23*(13), 185–198. https://doi.org/10.4324/9780203496190

Barrett, L. F. (2017). The theory of constructed emotion: an active inference account of interoception and categorization. *Social Cognitive and Affective Neuroscience*, *12*(1), 1–23. https://doi.org/10.1093/scan/nsw154

Bartolomeo, L. A., Culbreth, A. J., Ossenfort, K. L., & Strauss, G. P. (2020). Neurophysiological evidence for emotion regulation impairment in schizophrenia: The role of visual attention and cognitive effort. *Journal of Abnormal Psychology*, *129*(6), 670–676. https://doi.org/10.1037/abn0000580

Bebko, G. M., Franconeri, S. L., Ochsner, K. N., & Chiao, J. Y. (2014). Attentional deployment is not necessary for successful emotion regulation via cognitive reappraisal or expressive suppression. *Emotion*, *14*(3), 504–512. https://doi.org/10.1037/a0035459

Bijsterbosch, J. D., Ansari, T. L., Smith, S., Gauld, O., Zika, O., Boessenkool, S., Browning, M., Reinecke, A., & Bishop, S. J. (2018). Stratification of MDD and GAD patients by resting state brain connectivity predicts cognitive bias. *NeuroImage: Clinical*, *19*(March), 425–433. https://doi.org/10.1016/j.nicl.2018.04.033

Bijsterbosch, J. D., Smith, S., & Bishop, S. J. (2015). Functional Connectivity under Anticipation of Shock: Correlates of Trait Anxious Affect versus Induced Anxiety. *Journal of Cognitive Neuroscience*, *27*(9), 1–26. https://doi.org/10.1162/jocn

Bishop, S. J. (2009). Trait anxiety and impoverished prefrontal control of attention. *Nature Neuroscience*, *12*(1), 92–98. https://doi.org/10.1038/nn.2242

Bishop, S. J., Duncan, J., & Lawrence, A. D. (2004). State anxiety modulation of the amygdala response to unattended threat-related stimuli. *Journal of Neuroscience*, *24*(46), 10364–10368. https://doi.org/10.1523/JNEUROSCI.2550-04.2004

Bishop, S. J., Jenkins, R., & Lawrence, A. D. (2007). Neural processing of fearful faces: Effects of anxiety are gated by perceptual capacity limitations. *Cerebral Cortex*, *17*(7), 1595–1603. https://doi.org/10.1093/cercor/bhl070

Bocanegra, B. R., & Zeelenberg, R. (2009). Dissociating Emotion-Induced Blindness and Hypervision. *Emotion*, *9*(6), 865–873. https://doi.org/10.1037/a0017749

Boselie, J. J. L. M., Vancleef, L. M. G., & Peters, M. L. (2017). Increasing Optimism Protects Against Pain-Induced Impairment in Task-Shifting Performance. *Journal of Pain*, *18*(4), 446–455. https://doi.org/10.1016/j.jpain.2016.12.007

Braniecka, A., Trzebińska, E., Dowgiert, A., & Wytykowska, A. (2014). Mixed emotions and coping: The benefits of secondary emotions. *PLoS ONE*, *9*(8). https://doi.org/10.1371/journal.pone.0103940

Buckner, R. L., Andrews-Hanna, J. R., & Schacter, D. L. (2008). The brain's default network: Anatomy, function, and relevance to disease. *Annals of the New York Academy of Sciences*, *1124*(1), 1–38. https://doi.org/10.1196/annals.1440.011

Buhle, J. T., Silvers, J. A., Wager, T. D., Lopez, R., Onyemekwu, C., Kober, H., Weber, J., & Ochsner, K. N. (2014). Cognitive Reappraisal of Emotion: A Meta-Analysis of Human Neuroimaging Studies. *Cerebral Cortex*, *24*(11), 2981–2990. https://doi.org/10.1093/cercor/bht154

Cacioppo, J. T., & Berntson, G. G. (1994). Relationship between attitudes and evaluative space: A critical review, with emphasis on the separability of positive and negative substrates. *Psychological Bulletin*, *115*(3), 401–423. https://doi.org/https://doi.org/10.1037/0033-2909.115.3.401

Cacioppo, J. T., Gardner, W., & Berntson, G. G. (1997). Beyond bipolar conceptualizations and measures: The case of attitudes and evaluative space. *Personality and Social Psychology Review*, *1*(1), 3–25.

Cacioppo, J. T., Gardner, W. L., & Berntson, G. G. (1999). The affect system has parallel and integrative processing components: Form follows function. *Journal of Personality and Social Psychology*, *76*(5), 839–855. https://doi.org/10.1037/0022-3514.76.5.839

Carlson, J. M., Cha, J., Harmon-Jones, E., Mujica-Parodi, L. R., & Hajcak, G. (2014). Influence of the BDNF genotype on amygdalo-prefrontal white matter microstructure is linked to nonconscious attention bias to threat. *Cerebral Cortex*, *24*(9), 2249–2257. https://doi.org/10.1093/cercor/bht089

Chen, Y., Zhang, L., & Yin, H. (2024). Different emotion regulation strategies mediate the relations of corresponding connections within the default-mode network to sleep quality. *Brain Imaging and Behavior*, *18*(2), 302–314. https://doi.org/10.1007/s11682-023-00828-9

Chen, Y.-Y., Uljarevic, M., Neal, J., Greening, S., Yim, H., & Lee, T.-H. (2021). Excessive functional coupling with less variability between salience and default-mode networks in Autism Spectrum Disorder. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*. https://doi.org/10.1016/j.bpsc.2021.11.016

Cisler, J. M., James, G. A., Tripathi, S., Mletzko, T., Heim, C., Hu, X. P., Mayberg, H. S., Nemeroff, C. B., & Kilts, C. D. (2013). Differential functional connectivity within an emotion regulation neural network among individuals resilient and susceptible to the depressogenic effects of early life stress. *Psychological Medicine*, *43*(3), 507–518. https://doi.org/10.1017/S0033291712001390

Compton, R. (2003). The interface between emotion and attention: A review of evidence from psychology and neuroscience. *Behavioral and Cognitive Neuroscience Reviews*, *2*(2), 115–129. https://doi.org/10.1177/1534582303002002003

de Martino, B., Kalisch, R., Rees, G., & Dolan, R. J. (2009). Enhanced processing of threat stimuli under limited attentional resources. *Cerebral Cortex*, *19*(1), 127–133. https://doi.org/10.1093/cercor/bhn062

Denny, B. T., Fan, J., Fels, S., Galitzer, H., Schiller, D., & Koenigsberg, H. W. (2018). Sensitization of the neural salience network to repeated emotional stimuli following initial habituation in patients with borderline personality disorder. *American Journal of Psychiatry*, *175*(7), 657–664. https://doi.org/10.1176/appi.ajp.2018.17030367

Denny, B. T., Inhoff, M. C., Zerubavel, N., Davachi, L., & Ochsner, K. N. (2015). Getting over it: Long-lasting effects of emotion regulation on amygdala response. *Psychological Science*, *26*(9), 1377–1388. https://doi.org/10.1177/0956797615578863

Dolcos, F., Iordan, A. D., Kragel, J., Stokes, J., Campbell, R., McCarthy, G., & Cabeza, R. (2013). Neural correlates of opposing effects of emotional distraction on working memory and episodic memory: An event-related fMRI investigation. *Frontiers in Psychology*, *4*(JUN), 1–16. https://doi.org/10.3389/fpsyg.2013.00293

Evans, T. C., Bar-Haim, Y., Fox, N. A., Pine, D. S., & Britton, J. C. (2020). Neural mechanisms underlying heterogeneous expression of threat-related attention in social anxiety. *Behaviour Research and Therapy*, *132*(June), 103657. https://doi.org/10.1016/j.brat.2020.103657

Finn, E. S. (2021). Is it time to put rest to rest? *Trends in Cognitive Sciences*, *25*(12), 1021–1032. https://doi.org/10.1016/j.tics.2021.09.005

Fresco, D. M., Roy, A. K., Adelsberg, S., Seeley, S., García-Lesy, E., Liston, C., & Mennin, D. S. (2017). Distinct functional connectivities predict clinical response with emotion regulation therapy. *Frontiers in Human Neuroscience*, *11*. https://doi.org/10.3389/fnhum.2017.00086

Friedman, N. P., & Miyake, A. (2017). Unity and diversity of executive functions: Individual differences as a window on cognitive structure. *Cortex*, *86*, 186–204. https://doi.org/10.1016/j.cortex.2016.04.023

Friedman, N. P., Miyake, A., Young, S. E., DeFries, J. C., Corley, R. P., & Hewitt, J. K. (2008). Individual differences in executive functions are almost entirely genetic in origin. *Journal of Experimental Psychology: General*, *137*(2), 201–225. https://doi.org/10.1037/0096-3445.137.2.201

Fusina, F., Marino, M., Spironelli, C., & Angrilli, A. (2022). Ventral Attention Network Correlates With High Traits of Emotion Dysregulation in Community Women — A Resting-State EEG Study. *Frontiers in Human Neuroscience, 16*. https://doi.org/10.3389/fnhum.2022.895034

Gabrieli, J. D. E., Ghosh, S. S., & Whitfield-Gabrieli, S. (2015). Prediction as a humanitarian and pragmatic contribution from human cognitive neuroscience. *Neuron*, *85*(1), 11–26. https://doi.org/10.1016/j.neuron.2014.10.047

Goldin, P. R., McRae, K., Ramel, W., & Gross, J. J. (2008). The neural bases of emotion regulation: Reappraisal and suppression of negative emotion. *Biological Psychiatry*, *63*(6), 577–586. https://doi.org/10.1016/j.biopsych.2007.05.031

Greening, S. G., Osuch, E. A., Williamson, P. C., & Mitchell, D. G. V. (2014). The neural correlates of regulating positive and negative emotions in medication-free major depression. Social Cognitive and Affective Neuroscience, 9(5), 628–637. https://doi.org/10.1093/scan/nst027

Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. *Review of General Psychology*, *2*(3), 271–299. https://doi.org/https://doi.org/10.1037/1089-2680.2.3.271

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology*, *39*, 281–291. https://doi.org/10.1002/9780470177334.ch3

Gross, J. J. (2014). *Emotion regulation: Conceptual and empirical foundations*.

Gschwind, M., Pourtois, G., Schwartz, S., Van De Ville, D., & Vuilleumier, P. (2012). White-matter connectivity between face-responsive regions in the human brain. *Cerebral Cortex*, *22*(7), 1564–1576. https://doi.org/10.1093/cercor/bhr226

Gusnard, D. A., Akbudak, E., Shulman, G. L., & Raichle, M. E. (2001). Medial prefrontal cortex and self-referential mental activity: Relation to a default mode of brain function. *Proceedings of the National Academy of Sciences*, *98*(7), 4259–4264. https://doi.org/10.1073/pnas.071043098

Harrison, A., Sullivan, S., Tchanturia, K., & Treasure, J. (2010). Emotional functioning in eating disorders: Attentional bias, emotion recognition and emotion regulation. *Psychological Medicine*, *40*(11), 1887–1897. https://doi.org/10.1017/S0033291710000036

Hay, E. L., & Diehl, M. (2011). Emotion complexity and emotion regulation across adulthood. *European Journal of Ageing*, *8*(3), 157–168. https://doi.org/10.1007/s10433-011-0191-7

Hendricks, M. A., & Buchanan, T. W. (2016). Individual differences in cognitive control processes and their relationship to emotion regulation. *Cognition and Emotion*, *30*(5), 912–924. https://doi.org/10.1080/02699931.2015.1032893

Hermann, A., Neudert, M. K., Schäfer, A., Zehtner, R. I., Fricke, S., Seinsche, R. J., & Stark, R. (2021). Lasting effects of cognitive emotion regulation: neural correlates of reinterpretation and distancing. Social Cognitive and Affective Neuroscience, 16(3), 268–279. https://doi.org/10.1093/scan/nsaa159

Hilland, E., Landrø, N. I., Harmer, C. J., Browning, M., Maglanoc, L. A., & Jonassen, R. (2020). Attentional bias modification is associated with fMRI response toward negative stimuli in individuals with residual depression: A randomized controlled trial. *Journal of Psychiatry and Neuroscience*, *45*(1), 23–33. https://doi.org/10.1503/jpn.180118

Hofmann, S. G., Sawyer, A. T., Fang, A., & Asnaani, A. (2012). Emotion dysregulation model of mood and anxiety disorders. *Depression and Anxiety*, *29*(5), 409–416. https://doi.org/10.1002/da.21888

Hofmann, W., Schmeichel, B. J., & Baddeley, A. D. (2012). Executive functions and self-regulation. *Trends in Cognitive Sciences*, *16*(3), 174–180. https://doi.org/10.1016/j.tics.2012.01.006

Jacob, Y., Shany, O., Goldin, P. R., Gross, J. J., & Hendler, T. (2019). Reappraisal of interpersonal criticism in social anxiety disorder: A brain network hierarchy perspective. *Cerebral Cortex*, *29*(7), 3154–3167. https://doi.org/10.1093/cercor/bhy181

Jasielska, A., Kaczmarek, L., Brońska, A., Dominiak, M., Niemier, K., Patalas, D., Sokołowski, A., & Tomczak, M. (2015). The relationship between working memory and emotion regulation strategies. *Annals of Psychology*, *18*(4), 567–578.

Johnson, D. R. (2009). Emotional Attention Set-Shifting and Its Relationship to Anxiety and Emotion Regulation. *Emotion*, *9*(5), 681–690. https://doi.org/10.1037/a0017095

Johnstone, T., van Reekum, C. M., Urry, H. L., Kalin, N. H., & Davidson, R. J. (2007). Failure to Regulate: Counterproductive Recruitment of Top-Down Prefrontal-Subcortical Circuitry in Major Depression. The Journal of Neuroscience, 27(33), 8877–8884. https://doi.org/10.1523/JNEUROSCI.2063-07.2007

Joormann, J., & Gotlib, I. H. (2010). Emotion regulation in depression: Relation to cognitive inhibition. *Cognition and Emotion*, *24*(2), 281–298. https://doi.org/10.1080/02699930903407948

Kanske, P., Heissler, J., Schönfelder, S., Bongers, A., & Wessa, M. (2011). How to regulate emotion? Neural networks for reappraisal and distraction. *Cerebral Cortex*, *21*(6), 1379–1388. https://doi.org/10.1093/cercor/bhq216

Kappas, A. (2011). Emotion and regulation are one! *Emotion Review*, *3*(1), 17–25. https://doi.org/10.1177/1754073910380971

Kim, S. A., Kim, H., & Kim, S. H. (2016). Reappraisal modulates attentional bias to angry faces. *Frontiers in Psychology*, *7*, 1–9. https://doi.org/10.3389/fpsyg.2016.01841

Kron, A., Goldstein, A., Lee, D. H. J., Gardhouse, K., & Anderson, A. K. (2013). How Are You Feeling? Revisiting the Quantification of Emotional Qualia. *Psychological Science*, *24*(8), 1503–1511. https://doi.org/10.1177/0956797613475456

Laird, A. R., Fox, P. M., Eickhoff, S. B., Turner, J. A., Ray, K. L., Mckay, D. R., Glahn, D. C., Beckmann, C. F., Smith, S. M., & Fox, P. T. (2011). Behavioral interpretations of intrinsic connectivity networks. *Journal of Cognitive Neuroscience*, *23*(12), 4022–4037. https://doi.org/10.1162/jocn_a_00077

Larsen, J. T., & McGraw, A. P. (2011). Further evidence for mixed emotions. *Journal of Personality and Social Psychology*, *100*(6), 1095–1110. https://doi.org/10.1037/a0021846

Larsen, J. T., & McGraw, A. P. (2014). The case for mixed emotions. *Social and Personality Psychology Compass*, *8*(6), 263–274. https://doi.org/10.1111/spc3.12108

Larsen, J. T., Norris, C. J., McGraw, A. P., Hawkley, L. C., & Cacioppo, J. T. (2009). The evaluative space grid: A single-item measure of positivity and negativity. *Cognition and Emotion*, *23*(3), 453–480. https://doi.org/10.1080/02699930801994054

LeDoux, J. E. & Hoffman, S. G. (2018). The subjective experience of emotion: A fearful view. *Current Opinion in Behavioral Sciences, 19*. 67-72. https://doi.org/10.1016/j.cobeha.2017.09.011

Lee, T. H., Miernicki, M. E., & Telzer, E. H. (2017). Behavioral and neural concordance in parent-child dyadic sleep patterns. *Developmental Cognitive Neuroscience, 26*(June), 77–83. https://doi.org/10.1016/j.dcn.2017.06.003

Lee, T. W., & Xue, S. W. (2018). Does emotion regulation engage the same neural circuit as working memory? A meta-analytical comparison between cognitive reappraisal of negative emotion and 2-back working memory task. *PLoS ONE*, *13*(9). https://doi.org/10.1371/journal.pone.0203753

Li, W., Yang, P., Ngetich, R. K., Zhang, J., Jin, Z., & Li, L. (2021). Differential involvement of frontoparietal network and insula cortex in emotion regulation. *Neuropsychologia*, *161*. https://doi.org/10.1016/j.neuropsychologia.2021.107991

Lieberman, J. M., Rabellino, D., Densmore, M., Frewen, P. A., Steyrl, D., Scharnowski, F., Théberge, J., Neufeld, R. W. J., Schmahl, C., Jetly, R., Narikuzhy, S., Lanius, R. A., & Nicholson, A. A. (2023). Posterior cingulate cortex targeted real-time fMRI neurofeedback recalibrates functional connectivity with the amygdala, posterior insula, and default-mode network in PTSD. *Brain and Behavior*, *13*(3). https://doi.org/10.1002/brb3.2883

MacLeod, J., Stewart, B. M., Newman, A. J., & Arnell, K. M. (2017). Do emotion-induced blindness and the attentional blink share underlying mechanisms? An event-related potential study of emotionally-arousing words. *Cognitive, Affective and Behavioral Neuroscience*, *17*(3), 592–611. https://doi.org/10.3758/s13415-017-0499-7

Marini, F., Demeter, E., Roberts, K. C., Chelazzi, L., & Woldorff, M. G. (2016). Orchestrating proactive and reactive mechanisms for filtering distracting information: Brain-behavior relationships revealed by a mixed-design fMRI study. *Journal of Neuroscience*, *36*(3), 988–1000. https://doi.org/10.1523/JNEUROSCI.2966-15.2016

Martins, B., Ponzio, A., Velasco, R., Kaplan, J., & Mather, M. (2014). Dedifferentiation of emotion regulation strategies in the aging brain. *Social Cognitive and Affective Neuroscience*, *10*(6), 840–847. https://doi.org/10.1093/scan/nsu129

McRae, K., Hughes, B., Chopra, S., Gabrieli, J. D. E., Gross, J. J., & Ochsner, K. N. (2010). The neural bases of distraction and reappraisal. *Journal of Cognitive Neuroscience*, *22*(2), 248–262. https://doi.org/10.1162/jocn.2009.21243

McRae, K., Misra, S., Prasad, A. K., Pereira, S. C., & Gross, J. J. (2012). Bottom-up and top-down emotion generation: Implications for emotion regulation. *Social Cognitive and Affective Neuroscience*, *7*(3), 253–262. https://doi.org/10.1093/scan/nsq103

Menon, V., & Uddin, L. Q. (2010). Saliency, switching, attention and control: a network model of insula function. *Brain Structure & Function*, *214*(5–6), 655–667. https://doi.org/10.1007/s00429-010-0262-0

Milyavsky, M., Webber, D., Fernandez, J. R., Kruglanski, A. W., Goldenberg, A., Suri, G., & Gross, J. J. (2018). To reappraise or not to reappraise? Emotion regulation choice and cognitive energetics. *Emotion*, *19*(6), 964–981. https://doi.org/10.1037/emo0000498

Min, J., Nashiro, K., Yoo, H. J., Cho, C., Nasseri, P., Bachman, S. L., Porat, S., Thayer, J. F., Chang, C., Lee, T. H., & Mather, M. (2022). Emotion Downregulation Targets Interoceptive Brain Regions While Emotion Upregulation Targets Other Affective Brain Regions. *Journal of Neuroscience*, *42*(14), 2973–2985. https://doi.org/10.1523/JNEUROSCI.1865-21.2022

Mishra, M. V., Ray, S. B., & Srinivasan, N. (2017). Effect of emotions on temporal attention. In *Progress in Brain Research* (1st ed., Vol. 236). Elsevier B.V. https://doi.org/10.1016/bs.pbr.2017.08.014

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology*, *41*(1), 49–100. https://doi.org/10.1006/cogp.1999.0734

Morawetz, C., Bode, S., Baudewig, J., Jacobs, A. M., & Heekeren, H. R. (2016). Neural representation of emotion regulation goals. *Human Brain Mapping*, *37*(2), 600–620. https://doi.org/10.1002/hbm.23053

Morawetz, C., Kellermann, T., Kogler, L., Radke, S., Blechert, J., & Derntl, B. (2016). Intrinsic functional connectivity underlying successful emotion regulation of angry faces. *Social Cognitive and Affective Neuroscience*, *11*(12), 1980–1991. https://doi.org/10.1093/scan/nsw107

Moreira, J. F. G., Mclaughlin, K. A., & Silvers, J. A. (2021). Characterizing the Network Architecture of Emotion Regulation Neurodevelopment. *Cerebral Cortex*, *31*(9), 4140–4150. https://doi.org/10.1093/cercor/bhab074

Morey, R. A., Dolcos, F., Petty, C. M., Cooper, D. A., Hayes, J. P., LaBar, K. S., & McCarthy, G. (2009). The role of trauma-related distractors on neural systems for working memory and emotion processing in posttraumatic stress disorder. *Journal of Psyciatric Resilience*, *43*(8), 809–817. https://doi.org/10.1016/j.jpsychires.2008.10.014.The

Norris, C. J., & Wu, E. (2021). Accentuate the positive, eliminate the negative: Reducing ambivalence through instructed emotion regulation. *Emotion*, *21*(3), 499–512. https://doi.org/10.1037/emo0000716

Ochsner, K. N., Ray, R. D., Cooper, J. C., Robertson, E. R., Chopra, S., Gabrieli, J. D. E., & Gross, J. J. (2004). For better or for worse: Neural systems supporting the cognitive down- and up-regulation of negative emotion. *NeuroImage*, *23*(2), 483–499. https://doi.org/10.1016/j.neuroimage.2004.06.030

Ochsner, K. N., Silvers, J. A., & Buhle, J. T. (2012). Functional imaging studies of emotion regulation: A synthetic review and evolving model of the cognitive control of emotion. *Annals of the New York Academy of Sciences*, *1251*, 1–24. https://doi.org/10.1111/j.1749-6632.2012.06751.x.Functional

Opitz, P. C., Gross, J. J., & Urry, H. L. (2012). Selection, optimization, and compensation in the domain of emotion regulation: Applications to adolescence, older age, and major depressive disorder. *Social and Personality Psychology Compass*, *6*(2), 142–155. https://doi.org/10.1111/j.1751-9004.2011.00413.x

Opitz, P. C., Lee, I. A., Gross, J. J., & Urry, H. L. (2014). Fluid cognitive ability is a resource for successful emotion regulation in older and younger adults. *Frontiers in Psychology*, *5*(JUN), 1–13. https://doi.org/10.3389/fpsyg.2014.00609

Pessoa, L. (2009). How do emotion and motivation direct executive control? *Trends in Cognitive Sciences*, *13*(4), 160–166. https://doi.org/10.1016/j.tics.2009.01.006

Pessoa, L., Padmala, S., Kenzer, A., & Bauer, A. (2012). Interactions between cognition and emotion during response inhibition. *Emotion*, *12*(1), 192–197. https://doi.org/10.1037/a0024109

Pruessner, L., Barnow, S., & Holt, D. V. (2020). A cognitive control framework for understanding emotion regulation flexibility. *Emotion*, *20*(1), 21–29. https://doi.org/10.1037/emo0000658.supp

Reineberg, A. E., Andrews-Hanna, J. R., Depue, B. E., Friedman, N. P., & Banich, M. T. (2015). Resting-state networks predict individual differences in common and specific aspects of executive function. *NeuroImage*, *104*, 69–78. https://doi.org/10.1016/j.neuroimage.2014.09.045

Rosenbaum, D., Kroczek, A. M., Hudak, J., Rubel, J., Maier, M. J., Sorg, T., Weisbender, L., Goldau, L., Mennin, D., Fresco, D. M., Fallgatter, A. J., & Ehlis, A. C. (2020). Neural correlates of mindful emotion regulation in high and low ruminators. *Scientific Reports*, *10*(1), 1–15. https://doi.org/10.1038/s41598-020-71952-5

Rosenberg, M. D., Finn, E. S., Constable, R. T., & Chun, M. M. (2015). Predicting moment-to-moment attentional state. *NeuroImage*, *114*, 249–256. https://doi.org/10.1016/j.neuroimage.2015.03.032

Rosenberg, M. D., Finn, E. S., Scheinost, D., Constable, R. T., & Chun, M. M. (2017). Characterizing attention with predictive network models. *Trends in Cognitive Sciences*, *21*(4), 290–302. https://doi.org/10.1016/j.tics.2017.01.011

Rosenberg, M. D., Finn, E. S., Scheinost, D., Papademetris, X., Shen, X., Constable, R. T., & Chun, M. M. (2015). A neuromarker of sustained attention from whole-brain functional connectivity. *Nature Neuroscience*, *19*(1), 165–171. https://doi.org/10.1038/nn.4179

Roye, S., Castagna, P. J., Calamia, M., De Vito, A. N., Lee, T. H., & Greening, S. G. (2020). Relationships between multiple dimensions of executive functioning and resting-state networks in adults. *Neuropsychologia*, *141*, 1–9. https://doi.org/10.1016/j.neuropsychologia.2020.107418

Russell, J. A. (1980). A circumplex model of emotion. *Journal of Personality and Social Psychology*, *39*(6), 1161–1178.

Saarimäki, H., Glerean, E., Smirnov, D., Mynttinen, H., Jääskeläinen, I. P., Sams, M., & Nummenmaa, L. (2022). Classification of emotion categories based on functional connectivity patterns of the human brain. *NeuroImage*, *247*. https://doi.org/10.1016/j.neuroimage.2021.118800

Salzman, C. D., & Fusi, S. (2010). Emotion, cognition, and mental state representation in amygdala and prefrontal cortex. *Annual Review of Neuroscience*, *33*, 173–202. https://doi.org/10.1146/annurev.neuro.051508.135256

Schimmack, U. (2005). Response latencies of pleasure and displeasure ratings: Further evidence for mixed feelings. *Cognition and Emotion*, *19*(5), 671–691. https://doi.org/10.1080/02699930541000020

Schmeichel, B. J., & Tang, D. (2015). Individual differences in executive functioning and their relationship to emotional processes and responses. *Current Directions in Psychological Science*, *24*(2), 93–98. https://doi.org/10.1177/0963721414555178

Schweizer, S., Grahn, J., Hampshire, A., Mobbs, D., & Dalgleish, T. (2013). Training the emotional brain: Improving affective control through emotional working memory training. *Journal of Neuroscience*, *33*(12), 5301–5311. https://doi.org/10.1523/JNEUROSCI.2593-12.2013

Scult, M. A., Knodt, A. R., Swartz, J. R., Brigidi, B. D., & Hariri, A. R. (2017). Thinking and Feeling: Individual Differences in Habitual Emotion Regulation and Stress-Related Mood Are Associated With Prefrontal Executive Control. *Clinical Psychological Science*, *5*(1), 150–157. https://doi.org/10.1177/2167702616654688

Sheppes, G. (2014). Emotion regulation choice: Theory and findings. In J. J. Gross (Ed.), *Handbook of Emotion Regulation* (pp. 126–139). The Guilford Press.

Sheppes, G., Scheibe, S., Suri, G., & Gross, J. J. (2011). Emotion-regulation choice. *Psychological Science*, *22*(11), 1391–1396. https://doi.org/10.1177/0956797611418350

Sheppes, G., Scheibe, S., Suri, G., Radu, P., Blechert, J., & Gross, J. J. (2014). Emotion regulation choice: A conceptual framework and supporting evidence. *Journal of Experimental Psychology: General*, *143*(1), 163–181. https://doi.org/10.1037/a0030831

Silvers, J. A., Wager, T. D., Weber, J., & Ochsner, K. N. (2015). The neural bases of uninstructed negative emotion modulation. *Social Cognitive and Affective Neuroscience*, *10*(1), 10–18. https://doi.org/10.1093/scan/nsu016

Silvers, J. A., Weber, J., Wager, T. D., & Ochsner, K. N. (2015). Bad and worse: Neural systems underlying reappraisal of high-and low-intensity negative emotions. *Social Cognitive and Affective Neuroscience*, *10*(2), 172–179. https://doi.org/10.1093/scan/nsu043

Smith, R., Lane, R. D., Alkozei, A., Bao, J., Smith, C., Sanova, A., Nettles, M., & Killgore, W. D. S. (2018). The role of medial prefrontal cortex in the working memory maintenance of one's own emotional responses. *Scientific Reports*, *8*(1). https://doi.org/10.1038/s41598-018-21896-8

Snyder, H. R., Miyake, A., & Hankin, B. L. (2015). Advancing understanding of executive function impairments and psychopathology: Bridging the gap between clinical and cognitive approaches. *Frontiers in Psychology*, *6*(MAR). https://doi.org/10.3389/fpsyg.2015.00328

Sripada, C., Angstadt, M., Kessler, D., Phan, K. L., Liberzon, I., Evans, G. W., Welsh, R. C., Kim, P., & Swain, J. E. (2014). Volitional regulation of emotions produces distributed alterations in connectivity between visual, attention control, and default networks. *NeuroImage*, *89*, 110–121. https://doi.org/10.1016/j.neuroimage.2013.11.006

Strauss, G. P., Ossenfort, K. L., & Whearty, K. M. (2016). Reappraisal and distraction emotion regulation strategies are associated with distinct patterns of visual attention and differing levels of cognitive demand. *PLoS ONE*, *11*(11), 1–18. https://doi.org/10.1371/journal.pone.0162290

Suri, G., Sheppes, G., Young, G., Abraham, D., McRae, K., & Gross, J. J. (2018). Emotion regulation choice: the role of environmental affordances. *Cognition and Emotion*, *32*(5), 963–971. https://doi.org/10.1080/02699931.2017.1371003

Tabibnia, G., Monterosso, J. R., Baicy, K., Aron, A. R., Poldrack, R. A., Chakrapani, S., Lee, B., & London, E. D. (2011). Different forms of self-control share a neurocognitive substrate. *Journal of Neuroscience*, *31*(13), 4805–4810. https://doi.org/10.1523/JNEUROSCI.2859-10.2011

Tavares, T. P., Logie, K., & Mitchell, D. G. V. (2016). Opposing effects of perceptual versus working memory load on emotional distraction. *Experimental Brain Research*, *234*(10), 2945–2956. https://doi.org/10.1007/s00221-016-4697-2

Thiruchselvam, R., Hajcak, G., & Gross, J. J. (2012). Looking inward: Shifting attention within working memory representations alters emotional responses. *Psychological Science*, *23*(12), 1461–1466. https://doi.org/10.1177/0956797612449838

Urry, H. L. (2010). Seeing, thinking, and feeling: Emotion-regulating effects of gaze-directed cognitive reappraisal. *Emotion*, *10*(1), 125–135. https://doi.org/10.1037/a0017434

Urry, H. L., & Gross, J. J. (2010). Emotion regulation in older age. *Current Directions in Psychological Science*, *19*(6), 352–357. https://doi.org/10.1177/0963721410388395

Van Bockstaele, B., Notebaert, L., MacLeod, C., Salemink, E., Clarke, P. J. F., Verschuere, B., Bögels, S. M., & Wiers, R. W. (2019). The effects of attentional bias modification on emotion regulation. *Journal of Behavior Therapy and Experimental Psychiatry*, *62*, 38–48. https://doi.org/10.1016/j.jbtep.2018.08.010

van Reekum, C. M., Johnstone, T., Urry, H. L., Thurow, M. E., Schaefer, H. S., Alexander, A. L., & Davidson, R. J. (2007). Gaze fixations predict brain activation during the voluntary regulation of picture-induced negative affect. *NeuroImage*, *36*(3), 1041–1055. https://doi.org/10.1016/j.neuroimage.2007.03.052

Viviani, R. (2013). Emotion regulation, attention to emotion, and the ventral attentional network. *Frontiers in Human Neuroscience*, *7*(NOV), 1–24. https://doi.org/10.3389/fnhum.2013.00746

Wadlinger, H. A., & Isaacowitz, D. M. (2011). Fixing our focus: Training attention to regulate emotion. *Personality and Social Psychology Review*, *15*(1), 75–102. https://doi.org/10.1177/1088868310365565

Weber, M. A., Morrow, K. A., Rizer, W. S., Kangas, K. J., & Carlson, J. M. (2016). Sustained, not habituated, activity in the human amygdala: A pilot fMRI dot-probe study of attentional bias to fearful faces. *Cogent Psychology*, *3*(1). https://doi.org/10.1080/23311908.2016.1259881

Wessing, I., Rehbein, M. A., Romer, G., Achtergarde, S., Dobel, C., Zwitserlood, P., Fürniss, T., & Junghöfer, M. (2015). Cognitive emotion regulation in children: Reappraisal of emotional faces modulates neural source activity in a frontoparietal network. *Developmental Cognitive Neuroscience*, *13*, 1–10. https://doi.org/10.1016/j.dcn.2015.01.012

Willems, C., & Martens, S. (2016). Time to see the bigger picture: Individual differences in the attentional blink. *Psychonomic Bulletin and Review*, *23*(5), 1289–1299. https://doi.org/10.3758/s13423-015-0977-2

Williams, M. A., Morris, A. P., McGlone, F., Abbott, D. F., & Mattingley, J. B. (2004). Amygdala responses to fearful and happy facial expressions under conditions of binocular suppression. *Journal of Neuroscience*, *24*(12), 2898–2904. https://doi.org/10.1523/JNEUROSCI.4977-03.2004

Young, G., & Suri, G. (2020). Emotion regulation choice: a broad examination of external factors. *Cognition and Emotion*, *34*(2), 242–261. https://doi.org/10.1080/02699931.2019.1611544

Chapter 2: Looking on the bright side: The impact of ambivalent images on emotion regulation choice

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Abstract

Previous research has found that people choose to reappraise low intensity images more often than high intensity images. However, this research does not account for image ambivalence, which is [the] presence of both positive and negative cues in a stimulus. The purpose of this research was to determine differences in ambivalence in high intensity and low intensity images used in previous research ([Experiments] 1-2), and if ambivalence played a role in emotion regulation choice in addition to intensity ([Experiments] 3-4). Experiments 1 and 2 found that the low intensity images were more ambivalent than the high intensity images. Experiment 2 further found a positive relationship between ambivalence of an image and reappraisal affordances. Experiments 3 and 4 found that people chose to reappraise ambivalent images more often than non-ambivalent images, and they also chose to reappraise low intensity

images more often than high intensity images. These experiments support the idea that ambivalence is a factor in emotion regulation choice. Future research should consider the impact ambivalent stimuli have on emotion regulation, including the potential for leveraging ambivalent stimuli to improve one's emotion regulation ability.

Introduction

When one sees an injured animal on the street, they may feel upset and have a difficult time reappraising or thinking of a positive aspect to this situation. In this case, they may try to distract from the situation by thinking of what they must do later in the day. On the other hand, if they see someone tending to the injured animal, they may think to themselves that the animal is going to be okay, thereby easily reappraising the situation rather than needing to distract. Reappraisal and distraction are examples of changing one's emotions, known as emotion regulation (Gross, 1998). While both are effective at decreasing one's emotional response, the presence of environmental or contextual factors in the emotional situation can affect the choice of regulation strategy made by rendering one strategy easier or more effective than another.

Reappraisal and distraction are two of the most studied forms of emotion regulation (Ochsner et al., 2012). While reappraisal involves engaging with and attending to a [presented] stimulus to change the feeling towards a stimulus, distraction focuses on disengaging from a [presented] stimulus (Sheppes, 2014). There has been a growing interest in determining what factors affect the emotion regulation strategies chosen when faced with an emotional situation.

The Selection, Optimization, and Compensation with Emotion Regulation (SOC-ER) model provides a framework for understanding which factors affect emotion regulation choice. According to the SOC-ER model, the method of emotion regulation, how the selected method is optimized, and how one compensates for failures in emotion regulation are underpinned by a combination of internal factors and external factors (Opitz et al., 2012; Urry & Gross, 2010). While internal factors include individual differences in cognitive processes such as executive function (Schmeichel & Tang, 2015) or fluid intelligence (Opitz et al., 2014), external factors can include the qualities of a stimulus that may allow a certain emotion regulation method to work better (Suri et al., 2018). Thus, as in the opening example, the individual attending to the injured animal provides an external quality that the onlooker can use to inform reappraisal.

The external factor that has perhaps received the most attention with respect to emotion regulation choice is the intensity of the emotional situation. Reappraisal is chosen more often for low intensity images, and distraction is chosen more often for high intensity images (Sheppes et al., 2011), which has been replicated across multiple scenarios (A. C. Hay et al., 2015; Opitz et al., 2015; Scheibe et al., 2015; Sheppes, 2020; Sheppes et al., 2014; Young & Suri, 2020). High intensity images also drive greater attentional disengagement, or less attention to the stimulus, which causes disengaging emotion regulation tasks, such as distraction, to be chosen (Sheppes et al., 2014). In addition, intense feelings can also cause people to select distraction more often than reappraisal (Feldman & Freitas, 2023; Murphy & Young, 2018; Shafir et al., 2016). Another factor that affects emotion regulation choice is the difficulty associated with implementing a given emotion regulation method. For example, people choose reappraisal more often when given a generated reappraisal prompt than when they are simply instructed to use reappraisal (Sheppes et al., 2014) or when they are told to rethink a stimulus as fake rather than positive (Milyavsky et al., 2018). External incentives also affect emotion regulation such as monetary reward for implementing an emotion regulation strategy and long-term goals motivating reappraisal (Sheppes et al., 2014).

Environmental affordances, which are the distinct cues that influence the meaning or interpretation of an emotional stimulus are an additional external factor that may impact emotion regulation. Recently, Suri et al. (2018) found that emotional stimuli that are chosen for reappraisal rather than distraction have greater affordance ratings, or ratings of how easy it was to reappraise stimuli, on average. In particular, environmental affordances associated with reappraisal (which will be referred to reappraisal affordances moving forward) are predictive of the choice to reappraise rather than distract (Young & Suri, 2020). However, the notion of reappraisal affordances is a general concept focused on one's perception of how easy it is to reappraise an image. One specific factor that could allow for greater reappraisal affordances is the ambivalence of the emotional stimulus.

In the present study, ambivalence refers to the content of a stimulus containing both positive and negative elements or cues (Itkes et al., 2019). Ambivalent stimuli can elicit an ambivalent emotional response or mixed feelings or emotions, or the subjective experience of simultaneous positive and negative affect (Larsen & McGraw, 2014). Additionally, an ambivalent stimulus or response is not required to be *equally* positive and negative, but requires the presence of at least minimal positive and negative affective content (i.e. a highly negative stimulus with minimal positive cues can be seen as ambivalent) (Itkes et al., 2019; Larsen & McGraw, 2014).

While mixed emotions are seen as rare, research has found that people can feel simultaneously sad and happy in response to ambivalent stimuli (Larsen & McGraw, 2011; Schimmack, 2005). These mixed emotions also show different physiological signatures from non-mixed emotions (Kreibig et al., 2015). While prior emotion research has often focused on a circumplex model that includes a single dimension for valence (Russell, 1980), another body of research suggests that emotions are best measured using an evaluative space model in which one unipolar scale is provided for positive affect and one is provided for negative affect (Cacioppo et al., 1997, 1999; Cacioppo & Berntson, 1994; Diener & Emmons, 1984; Kron et al., 2013; Larsen et al., 2009; Schimmack, 2005). The evaluative space model supports the idea that positive and negative emotions can be experienced simultaneously and allows ambivalent stimuli to be measured using an independent rating of each variable (Thompson & Zanna, 1995). Regardless of the specific theoretical perspective, there appears to be agreement in the literature that an emotional stimulus can contain positive and negative content simultaneously (Larsen & McGraw, 2014).

Recent research has begun to evaluate whether emotion regulation can affect mixed emotions, and vice versa. Using a mixed gambling task in which winning and losing were simultaneously possible, Norris & Wu (2021) demonstrated that emotion regulation via focusing on either the positive or the negative aspects of an ambivalent situation decreased self-reported ambivalence. Conversely, other research found that more frequent feelings of mixed emotions are associated with successful emotion regulation ability (E. L. Hay & Diehl, 2011). Mixed emotions after appraisals are also associated with healthier coping ability and greater resilience (Braniecka et al., 2014). As ambivalent stimuli are more likely to be perceived semantically (Itkes et al., 2019), it is possible that ambivalence requires cognitive processes to down-regulate negative emotions. These studies suggest that ambivalent images can elicit mixed emotions, and thus have an influence on reappraisal. Therefore, it is possible that ambivalent images can affect the ease with which an image can be reappraised. One possibility which has not been evaluated experimentally is that because ambivalent stimuli have both positive and negative features, people can prioritize attending to the positive cues if the goal is to decrease negative emotion. If this is the case, it is possible that ambivalent images have higher reappraisal affordances than non-ambivalent images.

While it is possible that ambivalence may be a factor in reappraisal affordances, the previous findings regarding the impact of intensity on emotion regulation choice (Sheppes et al.,

2011) did not account for ambivalence. Specifically, it is possible that the lower intensity images contained both positive and negative affective cues. Consistent with the SOC-ER framework (Opitz et al., 2012; Urry & Gross, 2010), we predict that the external qualities of ambivalent images (i.e., the presence of positive affective cues in addition to negative cues) will lead to people selecting to reappraise ambivalent images more often than selecting to distract from them. Across four experiments, the overall purpose of the present study was to determine if the ambivalence of an emotional stimulus or situation affects emotion regulation choice. Experiment 1 first evaluated whether there were differences in ambivalence in the high versus low intensity images used in the experiment of Sheppes and colleagues (2011). If low intensity images are seen as more ambivalent than high intensity images, then ambivalence of an image may also affect emotion regulation choice. Experiment 2 sought to replicate and extend the findings of [Experiment] 1 by also evaluating the relationships between ambivalence ratings, intensity ratings, and reappraisal affordance ratings of a given negative image. If ambivalence is a factor influencing reappraisal affordances, then ambivalence may influence emotion regulation choice. Finally, [Experiments] 3-4 aimed to identify if participants chose to reappraise ambivalent images more often than non-ambivalent images irrespective of the intensity of those images in an online ([Experiment] 3) and an in-person ([Experiment] 4) setting. Specifically, using a pre-registered design, [Experiments] 3-4 employed a paradigm with a distinct set of ambivalent versus nonambivalent images. We predicted that people would choose reappraisal more often than distraction when viewing ambivalent images compared to non-ambivalent images of a similar intensity.

Experiment 1

The purpose of [Experiment] 1 was to establish whether there was a difference in ambivalence levels for high and low intensity images used by Sheppes and colleagues (2014). We hypothesized that high intensity negative images will be less ambivalent than low intensity negative images.

Methods

Participants

19 participants signed up for the in-person study through the Louisiana State University psychology department's research system. No age or gender data was collected. All participants provided informed consent and the study was approved by the Louisiana State University Institutional Review Board.

Stimuli

The stimuli used were 82 high and low intensity images used in [Experiments] 1 (40 low intensity images and 35 high intensity images) and 2 (seven high intensity images) of Sheppes et al (2014), originally derived from the International Affective Picture System (IAPS) dataset (Lang et al., 1997). 42 of the images were high intensity and 40 of the images were low intensity. High intensity images included angry animals and bloody injuries, while low intensity images included sad people and dirty environments. For the sake of time and the exploratory nature of [Experiment] 1, the stimuli were separated into two unique sets, Set A and Set B. Each set had 21 high intensity images and 20 low intensity images. The purpose for separating the images into sets was to ensure the experiment was a reasonable length of time as participants were asked to rate the images along 10 distinction dimensions or categories.

Procedure

Participants were randomly assigned to either Group A (n=10) or Group B (n=9). Those in Group A were presented only images from Set A, and those in Group B were presented only images from Set B. On a trial-by-trial basis, each participant looked at each of the 41 images in the set and rated each image along 10 distinct dimensions or categories. Images were presented in random order. Specifically, participants rated the extent to which they felt pleasantness and unpleasantness, as well as anger, contentment, disgust, fear, happiness, intensity, sadness, and surprise on a 1-9 Likert scale for each image, with 1 being “Not at all” and 9 being “Extremely.” On a given trial, the image was on the screen for the entire time while participants made each of the 10 ratings. The trial ended after the tenth rating, and the whole trial was self-paced.

Analysis

For the purposes of this study, the primary concern was ratings of unpleasantness and pleasantness. The ambivalence of images was measured using the ambivalence formula $\frac{P+N}{2} - |P-N|$ (Schneider et al., 2016; Thompson & Zanna, 1995), where N is the unpleasantness rating an individual gave a picture on the 1-9 scale and P is the pleasantness rating an individual gave a picture on the 1-9 scale. Use of this formula allowed us to represent ambivalence as a single summary statistic, where higher values mean greater ambivalence. Although other research has more simply taken the minimum positive or negative rating as the measure of ambivalence (such that a score of >= 2 denotes ambivalence) (Larsen et al., 2004; Schimmack, 2001), this formula has the benefit of also factoring the relative distance between the positive and negative ratings. To identify significant differences between ambivalence scores of high and low intensity images, ambivalence scores were analysed with a 2x2 [analysis of variance

(ANOVA)] with a between-subjects factor of Group (A and B) and a within-subjects factor of Intensity (High or Low). The study and these analyses were not preregistered.

Results

The 2x2 ANOVA revealed a main effect of intensity such that high intensity images were significantly less ambivalent (M = -1.88, SD = 1.64) than low intensity images (M = -0.36, SD = 1.62), F(1,17) = 87.949, *p* < .001, η_p^2 = 0.838 (fig. 1A). There was no main effect of Group on ambivalence score (F(1,17) = 0.315, *p* = .582, η_p^2 = 0.018), nor was there an interaction effect of Group and Intensity on ambivalence scores (F(1,17) = 1.816, *p* = .195, η_p^2 = 0.096).

To better understand how negative and positive affect are uniquely present in the stimuli, we performed two additional ANOVAs, one on the unpleasantness ratings and a second on the pleasantness ratings. The 2x2 ANOVA of unpleasantness ratings revealed a main effect of intensity such that high intensity images (M = 7.14, SD = 2.22) were rated as more unpleasant than low intensity images (M = 4.06, SD = 2.68), F(1,17) = 137.856, p < .001, η_p^2 = 0.464. There was no significant main effect of group on unpleasantness ratings, F(1,17) = 3.927, *p* = .064, η_p^2 = 0.188. There was also a significant interaction between Group and Intensity on unpleasantness ratings, F(1,17) = 6.244, *p* = .023, η_p^2 = 0.269. Post hoc comparisons using the Bonferroni method indicate that there was a significant effect of group on unpleasantness ratings for low intensity images, with Group A rating low intensity images as more unpleasant than Group B (*p* < .001). However, there was no main effect of Group on unpleasantness ratings for high intensity images (*p* = .291).

The 2x2 ANOVA of pleasantness ratings revealed a main effect of Intensity such that high intensity images (M = 1.20, SD = 0.90) were rated as less pleasant than low intensity images ($M = 1.68$, $SD = 1.44$), $F(1,17) = 14.721$, $p = 0.001$, $\eta_p^2 = 0.890$. There was no significant main effect of Group on pleasantness ratings ($F(1,17) = 0.569$, $p = 0.461$, $\eta_p^2 = 0.032$), nor was there an significant interaction effect ($F(1,17) = 0.158$, $p = 0.696$, $\eta_p^2 = 0.009$).

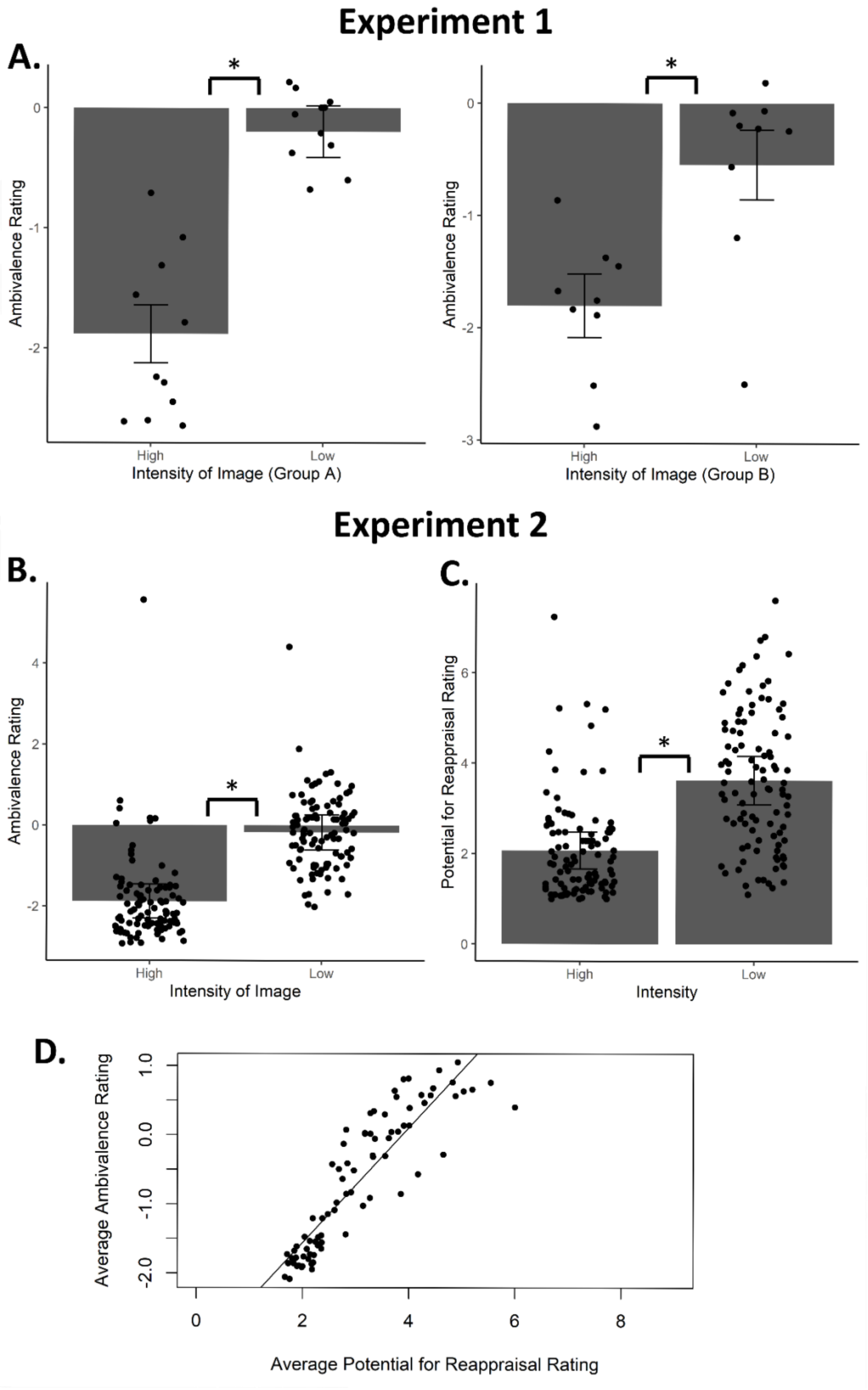
Experiment 1
A.
*
Ambivalence Rating
0
-1
-2
High
Low
Intensity of Image (Group A)
*
Ambivalence Rating
0
-1
-2
-3
High
Low
Intensity of Image (Group B)
Experiment 2
B.
*
Ambivalence Rating
4
2
0
-2
High
Low
Intensity of Image
C.
*
Potential for Reappraisal Rating
6
4
2
0
High
Low
Intensity
D.
Average Ambivalence Rating
1.0
0.0
-1.0
-2.0
0
2
4
6
8
Average Potential for Reappraisal Rating

Figure 1: Results for [Experiments] 1 and 2. A) The differences in ambivalence between high and low intensity images across the two experimental groups in [Experiment] 1. B) The differences in ambivalence between high and low intensity images in [Experiment] 2. C) The differences in reappraisal affordance ratings between high and low intensity images in [Experiment] 2. D) The correlation between average reappraisal affordance ratings and average ambivalence scores for each image. Each dot represents one of the 82 images.

Experiment 2

Experiment 2 was designed as a robust replication of [Experiment] 1 using a within-subject design and a larger sample size. We hypothesized that if ambivalence played a role in emotion regulation choice, then ambivalence levels would differ between the high and low intensity images, with high intensity images being less ambivalent than low intensity images. In addition, we hypothesized that reappraisal affordance ratings would be higher for low intensity images than high intensity images and would be associated with ambivalence ratings.

Methods

Participants

206 participants signed up for the online study through the University of Manitoba psychology department’s research system. Of those, 71 were removed as they did not finish the experiment. Of the remaining 135 participants, 28 were removed for answering more than 25% of responses either too slowly (more than 10,000 ms) or too quickly (less than 300 ms) and 7 were removed for repeated consecutive responses for over 25% of consecutive trials. However, if a participant had valid responses on 75% or more of the trials, all data was kept. Thus, we were left with 100 participants (18-25 years, Mean age = 18.91 years). 85 participants were female, 14 were male, and one declined to state gender. A sensitivity analysis with 100

participants α = 0.05 and β = 0.95 found a Cohen's d' of 0.364. All participants gave informed consent, and the experiment was approved by the University of Manitoba Research Ethics Board. This study was not pre-registered.

Stimuli

The stimuli were the same as in [Experiment] 1, with the exception that all participants looked at all 82 images. The experiment was created using lab.js and hosted on open-lab.online (Shevchenko, 2022).

Procedure

The procedure was similar to [Experiment] 1 with some exceptions. Participants were asked about the ten dimensions from [Experiment] 1. We also assessed participants' self-reported reappraisal affordance for each image by asking them "How easily can you find a bright side to this image?" While this was not the exact wording used by previous studies (Suri et al., 2018; Young & Suri, 2020), it allowed us to ask participants about reappraisal affordances laconically, and in a manner that included a positive connotation. We did not want to simply ask how easy participants could reappraise a given image, but rather how easy they could reframe a given image as positive. Data collection took place during winter of 2021 during the COVID-19 pandemic. Therefore, the study took place online instead of in-person. In addition, to gather additional descriptive information about the sample, at the beginning of the experiment, participants filled out a series of questionnaires including the attentional control scale (ACS), the state-trait anxiety inventory (STAI), the positive and negative affect schedule (PANAS), the emotion regulation questionnaire (ERQ), the cognitive emotion regulation questionnaire (CERQ), and a demographic questionnaire (see Supplemental). The questionnaire data was not analysed in this study.

Analysis

As in Experiment 1, the ambivalence of the images was computed using the formula $\frac{P+N}{2} - |P - N|$ (Schneider et al., 2016; Thompson & Zanna, 1995). A paired samples t-test was used to determine significant differences in ambivalence and reappraisal ability in high and low intensity images. We also ran a regression analysis predicting reappraisal ability with image intensity and ambivalence as predictors. The study and these analyses were not preregistered.

Results

The initial paired samples t-test looking at differences in ambivalence scores at high and low levels of intensity revealed a significant effect of intensity on ambivalence scores, with high intensity images, (M = -1.87, SD = 2.13) being less ambivalent than low intensity images (M = -0.17, SD = 2.18), t(99) = -21.79, *p* < .001; *d* = -2.18 (fig. 1B). To identify the unique contribution of unpleasantness and pleasantness, two additional paired samples t-tests were run. The first paired samples t-test revealed that low intensity images (M = 4.85, SD = 2.66) were rated as significantly less unpleasant than high intensity images (M = 7.60, SD = 2.19), t(99) = 25.10, *p* < .001; *d* = 2.51. The second t-test revealed that low intensity images (M = 2.16, SD = 1.93) were rated more positively than high intensity images (M = 1.38, SD = 1.36), t(99) = -13.35, *p* < .001; *d* = -1.34.

Regarding the reappraisal affordance ratings of the images, a paired samples t-test revealed that the low intensity images (M = 3.62, SD = 2.70) had significantly higher reappraisal affordance than high intensity images (M = 2.07, SD = 2.05), t(99) = 13.81, *p* <.001; *d* = -1.38 (fig. 1C).

Next, we evaluated whether image-level differences in ambivalence predicted image level differences in the reappraisal affordance. When using average ratings of ambivalence and reappraisal affordance for each image, a regression analysis revealed that the ambivalence scores positively predicted reappraisal affordance ratings (β = 1.505, t(79) = 8.291 *p* < .001) when controlling for intensity (β = 0.414, t(79) = 3.112 *p* = .003), F(2, 79) = 192.9, R^2 = 0.83, *p* < .001 (fig. 1D).

Additionally, we ran follow-up exploratory regressions. The first model did not include any interaction factors and revealed that pleasantness (β = 0.387, t(78) = 3.113 *p* = .003) and unpleasantness ratings (β = -0.695, t(78) = -5.477 *p* < .001) predicted reappraisal affordance ratings when controlling for intensity (β = 0.277, t(78) = 2.300 *p* = .024), F(3, 78) = 215.4, R^2 = 0.89, *p* < .001.The second model included an interaction factor and revealed that only unpleasantness ratings (β = -0.891, t(77) = -5.619 *p* < .001) predicted reappraisal affordance ratings when controlling for intensity (β = 0.371, t(77) = 2.842, *p* = .006), while pleasantness ratings did not (β = 0.049, t(77) = 0.226 *p* = .822), F(4, 77) = 178.9, R^2 = 0.90, *p* < .001. However, there was also a marginal interaction between pleasantness and unpleasantness ratings (β = 0.116, t(77) = 1.895 *p* = .062) and the prediction of reappraisal affordance ratings.

Discussion Experiments 1 and 2

Both [Experiments] 1 and 2 supported our hypothesis that the low intensity images are more ambivalent than the high intensity images. While this does not necessarily mean that ambivalence of an image is driving emotion regulation choice, it does mean that ambivalence may play a role in emotion regulation choice since ambivalence was not controlled for in previous research (Sheppes et al., 2011). In addition, pleasant cues were minimal. While low intensity images were rated as more pleasant than high intensity images, the ratings were still low, being only slightly higher than 2 on a 1-9 Likert scale, and suggesting images were predominantly negative. However, it is worth noting that pleasantness having a score higher than one implies that on average participants identified positive content in the images, if only a small amount.

In [Experiment] 2, participants also rated reappraisal affordance and found that low intensity images were believed to be easier to reappraise than high intensity images. A regression analysis found that ambivalence of an image predicted reappraisal affordance of an image. Ambivalence may be a type of reappraisal affordance as ambivalent images had more positive aspects to them, and therefore were seen as easier to reappraise.

On the other hand, the exploratory regression analysis containing the interaction between unpleasantness and pleasantness as a predictor suggested that the unpleasantness of the images was the strongest predictor of reappraisal affordance. However, there was also a marginal trend indicating that the interaction between pleasantness and unpleasantness ratings predicted reappraisal affordance. In addition, when the interaction factor was not included, pleasantness and unpleasantness ratings predicted reappraisal affordance. However, combined with the previous literature on emotion regulation choice (Sheppes et al., 2014; Suri et al., 2018), the present findings suggest that ambivalence in addition to intensity may play a role in emotion regulation choice.

Experiment 2 differed from [Experiment] 1 in that all participants rated all images, rather than assigning participants to a group with 41 separate images each. Experiment 2 also had a considerably larger sample size than [Experiment] 1. These differences were due to using an online study with a longer study run. However, one limitation of [Experiment]2 is that more participants were removed from the final sample due to either user errors, technical failures, or issues relating to participant inconsistencies such as going through trials too quickly and/or too slowly. Another limitation of [Experiments] 1 and 2 is that ambivalence of the images was determined from participant ratings of unpleasantness and pleasantness, which are at least partially informed by the participants' subjective feelings towards the stimuli, rather than some more objective semantic, or knowledge-focused, measurement of the number of negative and positive cues present in each image (Itkes et al., 2017). Nevertheless, as described in the introduction, ambivalent stimuli, in addition to containing both positive and negative cues, would be expected to elicit mixed feelings. Finally, while [Experiment] 2 identified ambivalence as a variable believed to play a role in emotion regulation ability, ambivalence was not experimentally manipulated. Thus, a third experiment was required to experimentally manipulate the ambivalence of the stimuli to evaluate if ambivalence plays a causal role in emotion regulation choice.

Experiment 3

Experiments 1 and 2 showed that there was a difference in ambivalence between low and high intensity images, and that ambivalence, intensity, and reappraisal affordance were related. Therefore, the next step was to identify how the ambivalence of an image affects emotion regulation choice using an experimental emotion regulation choice task, and to explore the potential relationship between ambivalence and intensity. Thus, in [Experiment] 3, we tested the hypothesis that participants would choose to reappraise rather than distract from ambivalent images more often than non-ambivalent images. The secondary purpose of [Experiment] 3 was to evaluate the potential relationship between the ambivalence of an image versus the intensity of an image. Here we tested two competing predictions: 1) intensity has no effect on emotion regulation choice when controlling for ambivalence, and 2) in addition to an effect of ambivalence, participants would reappraise low intensity images more often than high intensity images (Sheppes, 2014; Sheppes et al., 2011; Suri et al., 2018). If this latter prediction is true, it would suggest that the findings in [Experiments] 1 and 2 do not exclude the possibility that intensity is an external factor affecting emotion regulation choice that is at least partially independent of ambivalence. Experiment 3 was preregistered using AsPredicted #71798.

Methods

Participants

100 participants signed up for the online experiment through the University of Manitoba psychology department’s research system. Behavioural exclusion criteria were preregistered in AsPredicted and included the same exclusion criteria as those in [Experiment] 2, with one additional exclusion relating to participants changing their minds with respect to their regulation strategy. Specifically, we excluded any trials in which one regulation strategy was chosen at the start of the trial then used the opposite strategy at the end of the trial (i.e., trials where distraction was selected but reported reappraising at the end of the trial and vice versa). Of the 100 participants who signed up for the study, nine were removed for not completing the study. 52 additional participants were dropped from the analysis: 1) 33 participants were dropped because 25% or more of their main trials were excluded due to answering too slowly or too quickly, 2) 12 participants were dropped because they changed their mind while regulating an image on 25% or more of the main trials, and 3) 17 participants were dropped for a combination of 1 and 2 on 25% or more of the main trials. Thus, we were left with 29 participants (18-33 years, Mean age = 21.76 years). A sensitivity analysis with 29 participants and $\alpha = 0.05$ and $\beta = 0.95$ determined our η_p^2 was .194. 21 participants were female, seven were male, and one declined to state gender. All participants gave informed consent, and the experiment was approved by the University of Manitoba Research Ethics Board.

Stimuli

32 images were selected from the IAPS and the Nencki Affective Picture System (NAPS) datasets (Lang et al., 1997; Marchewka et al., 2014). Raters were instructed to view IAPS and NAPS images and list the ones they perceived as ambivalent, and that an ambivalent image was one that was both positive and negative. Ambivalent images were selected in one of two ways. Either two of three raters had to [identify an image] as ambivalent, or if only one rater identified an image as ambivalent it had to have a happiness and sadness rating of 2 or higher on a 1-9 Likert scale when looking at available normed data (Libkuman et al., 2007). Of the images, 16 were ambivalent, half of which were high intensity, and the other half were low intensity, and 16 were non-ambivalent, half of which were high intensity and the other half low intensity. Of the ambivalent images, 10 were rated as ambivalent by two or more raters and six were rated as ambivalent by one rater (see Supplemental). Eight images were high intensity ambivalent images ($M_{valence} = 4.30$, $SD_{valence} = 0.64$, $M_{intensity} = 5.54$, $SD_{intensity} = 0.73$), eight were low intensity ambivalent images ($M_{valence} = 4.30$, $SD_{valence} = 0.67$, $M_{intensity} = 3.75$, $SD_{intensity} = 0.64$), eight were high intensity non-ambivalent images ($M_{valence} = 3.22$, $SD_{valence} = 0.74$, $M_{intensity} = 5.56$, $SD_{intensity} = 0.79$), and eight were low intensity non-ambivalent images ($M_{valence} = 4.35$, $SD_{valence} = 0.38$, $M_{intensity} = 3.82$, $SD_{intensity} = 0.65$). The valence and arousal ratings for these images were gathered from previously published norms (Libkuman et al., 2007; Riegel et al., 2016). Paired [t-tests] found no significant difference in intensity between ambivalent and non-ambivalent images ($t(30) = 0.107$, $p = .915$; $d = 0.113$). Additionally, there was no significant difference in bipolar valence between ambivalent and non-ambivalent images, $t(30) = 2.008$, $p = .054$; $d = 1.924$, though there may be a trend towards significance. This was to be expected as it is very difficult to avoid valence ratings differences between the

ambivalent versus non-ambivalent images as ambivalent images have both a positive and negative aspect to them, which can result in an image being rated misleadingly as neutral (or closer to neutral) when using a bivalent scale (Schneider et al., 2016). The experiment was created using lab.js and hosted on open-lab.online (Shevchenko, 2022).

Procedure

Participants completed the experimental task, which was divided into three distinct blocks: a training block, in which they learned how to distract and reappraise when presented with the images; a practice block, in which they practiced the emotion regulation choice task; and the main task block. Instructions and definitions of distraction and reappraisal given were slightly modified from those used in Sheppes et al. (2014). Overall, the instructions remained the same, with slight changes in sentences for the sake of brevity (see Supplemental for specific instructions). The training block consisted of two trials. On both trials, participants saw an image for 500 ms, after which the visual instruction to "distract" or "reappraise" was presented for 1000 ms. Next, participants viewed the image again, this time while carrying out the instructed regulation strategy (i.e., distraction or reappraisal) for 5000 ms. Then, participants completed two self-paced scales rating how positive and negative the images made them feel. Participants were then asked whether they were reappraising or distracting from the image. After the training block, participants completed the practice block, which was comprised of four trials. On one trial, participants were instructed to distract, and on another trial, participants were instructed to reappraise. On the two remaining trials, participants were allowed to choose between distraction and reappraisal after viewing the image for 500ms, prior to carrying out their chosen strategy during the 5000ms re-presentation of the image.

The main task block consisted of 32 trials. Each trial included one image from the set of 32 images. Images were presented in random order. Participants looked at the image for 500 ms, then were asked to choose between distraction and reappraisal, next they looked at the image for 5000 ms while carrying out the emotion regulation strategy they chose. Participants then rated how positive and negative the image made them feel on the same 1-9 Likert scale used in experiments 1 and 2. However, as participants were allowed to choose an emotion regulation strategy, the positivity and negativity scores vary and cannot be used as a measure of ambivalence and were not analysed. Then, participants reported which emotion regulation strategy they carried out. As this was an online study, this final epoch in which participants note the emotion regulation strategy they used was included to verify that participants were following the instructions. The images used in the training block, practice block, and main task block were all different, and no images were ever presented more than once. For descriptive purposes, at the start of the experiment, participants completed the STAI, the PANAS, and a demographic questionnaire. After the main task, participants completed the ACS, the ERQ, the CERQ, and the Vividness of Object and Spatial Imagery questionnaire (VOSI). The questionnaire data were not analysed in this study. Finally, participants were debriefed.

Analysis

The primary dependent variable was the proportion of times a participant selected reappraisal for each condition (e.g., 75% for ambivalent versus 50% non-ambivalent stimuli). We conducted a 2x2 repeated measures ANOVA with factors Ambivalence (Ambivalent and Non-ambivalent) and Intensity (High and Low) to assess whether there was a significant main effect of ambivalence or image intensity in the proportion of reappraisal choices. This study and these analyses were preregistered at AsPredicted #71798.

Results

Preregistered Analyses

A 2x2 ANOVA revealed a significant main effect of Ambivalence (Figure 2), such that participants reappraised Ambivalent images (M = .7088, SD = .2716) significantly more often than Non-ambivalent images (M = .6214, SD = .2857), F(1, 28) = 8.19, $p = .0079$, $\eta_p^2 = 0.23$. There was also a significant main effect of Intensity, such that people reappraised High intensity images (M = .6047, SD = .2649) significantly less often than Low intensity images (M = .7256, SD = .2858), F(1, 28) = 11.14, $p = .0024$, $\eta_p^2 = 0.28$. There was no significant interaction effect between ambivalence and intensity on proportion of times reappraisal was chosen, F(1, 28) = 2.15, $p = .154$, $\eta_p^2 = 0.07$. Of note, inferentially similar results were found when the images rated as ambivalent by one rater were removed (see Supplemental for detailed results), though this specific analysis was not preregistered.

Exploratory Analyses

Due to a high attrition rate on our preregistered analysis, we performed exploratory analyses which focused only on decision data and did not drop trials when participants changed their mind about emotion regulation choice (n = 58). These exploratory analyses found inferentially similar results, such that participants reappraised Ambivalent images (M = .6455, SD = .2601) significantly more often than to Non-ambivalent images (M = .5593, SD = .2551), F(1, 57) = 19.68, $p < .001$, $\eta_p^2 = 0.26$. There was also a significant main effect of Intensity, such that people reappraised High intensity images (M = .5614, SD = .2530) significantly less often than Low intensity images (M = .6433, SD = .2629), F(1, 57) = 13.19, $p < .001$, $\eta_p^2 = 0.19$. There was no significant interaction effect between Ambivalence and Intensity on proportion of times reappraisal was chosen, F(1, 57) = 2.92, $p = .927$, $\eta_p^2 = 0.05$.

An exploratory logistic regression found that ambivalence predicted emotion regulation choice, such that ambivalent images were more likely to be reappraised, $\beta = 0.673$, $z = 2.893$, $p = .004$. Intensity marginally predicted emotion regulation choice, such that low intensity images were more likely to be reappraised, $\beta = -0.476$, $z = -1.930$, $p = .054$. There was no interaction between ambivalence and intensity, $\beta = -0.421$, $z = -1.222$, $p = .222$.

Before removing participants for mismatched trials (i.e., trials where people chose distraction but ended up reporting that they reappraised and vice versa), we found that participants reported using the chosen emotion regulation strategy on 83.30% of trials. A [chi-square] test indicated that participants reported having used the same strategy from the one they chose when what they chose was distraction (M=76.69%) less often compared to reappraisal (M=87.66%) $\chi^2(1) = 38.401$, $p < .001$. A chi-square test revealed no difference in strategy changes between the four conditions of high intensity ambivalent images (M=81.87%), high intensity non-ambivalent images (M=79.12%), low intensity ambivalent images (M=82.69%), and low intensity non-ambivalent images (M=84.07%) $\chi^2(3) = 6.413$, $p = .093$.

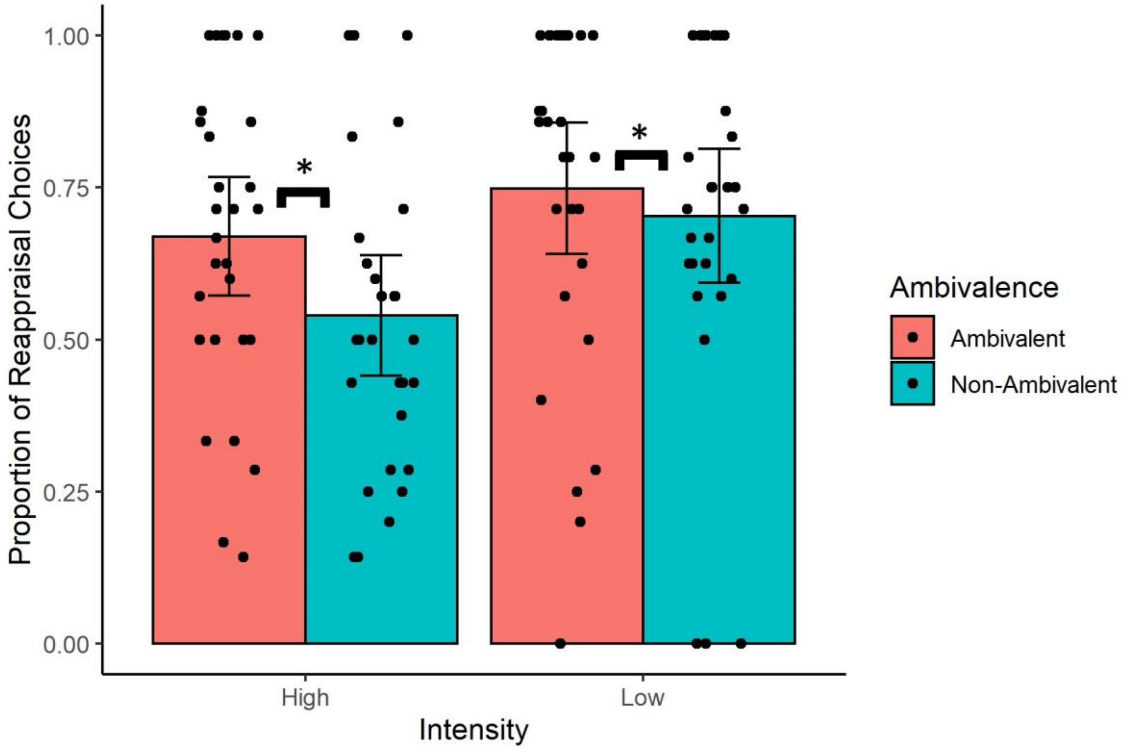

Figure 2: Proportion of reappraisal choices for high intensity ambivalent (M = 66.83%, SD = 25.13%), low intensity ambivalent (M = 74.53%, SD = 28.45%), and high intensity nonambivalent (M = 53.83%, SD = 25.63%), and low intensity non-ambivalent images (M = 69.70%, SD = 28.92%) for [Experiment] 3. The error bars represent a 95% confidence interval.

Discussion Experiment 3

Experiment 3 revealed that people chose reappraisal more often when an image was ambivalent compared to non-ambivalent irrespective of image intensity, which supported our hypothesis. This is in line with previous research, as ambivalence is associated with improved emotion regulation ability (Braniecka et al., 2014; Gordon et al., 2016; E. L. Hay & Diehl, 2011).

The secondary purpose of this experiment was to replicate the findings from Sheppes and colleagues (2011) with respect to the role of intensity in emotion regulation choice. In support of our secondary hypothesis and in line with previous research (Sheppes et al., 2011, 2014), we observed that participants chose reappraisal more often for low intensity images compared to high intensity images.

It is worth pointing out that we did not replicate the preference for distraction in high intensity images found in previous research (Sheppes, 2020; Sheppes et al., 2011, 2014) in which participants chose distraction greater than 50% of high intensity trials. Instead, we found that for both non-ambivalent and ambivalent high intensity images despite lower rates of reappraisal compared to low intensity images there remained a general preference for reappraisal compared to distraction. One potential reason for this is that our high intensity images were of a lower intensity than those used by Sheppes and colleagues (2014). Whereas our high intensity images had a mean intensity rating of 5.55 according to the rating norms, the stimuli used in Sheppes et al. (2011), for example, had a mean intensity rating of 6.12.

Experiment 4

Experiment 3 identified that ambivalence of an image played a role in emotion regulation choice; however, due to the study being online and the preregistered analysis plan, the number of excluded data points for [Experiment] 3 was very high (71%). Therefore, the purpose of [Experiment] 4 was to replicate [Experiment] 3 using in-person data collection to potentially reduce the number of participants we needed to exclude from the analysis. We employed the same preregistered data analysis plan as in [Experiment] 3. We hypothesized that, similar to [Experiment] 3, participants would be more likely to reappraise high intensity images than low intensity images.

Methods

Participants

A power analysis with α of 0.05 and η_p^2 of .23 (as identified by [Experiment] 3) determined we would need 11-20 participants for our study with power of 0.95 to 0.995. 39 participants signed up for [the experiment] through the University of Manitoba psychology department's research system. Behavioural exclusion criteria were preregistered in AsPredicted #125267 and included the same exclusion criteria as those in [Experiment] 3. Of the 39 participants who signed up for the study, six participants were dropped from analysis because 25% or more of their main trials were excluded due to answering too slowly or too quickly. Five participants were dropped from the study because they changed their mind while regulating an image on 25% or more of the main trials. Thus, we were left with 28 participants (18-27 years, Mean age = 19.36 years), which was an exclusion rate below ~29% and an improvement from [Experiment] 3's attrition rate of 71%. 17 participants were female and 11 were male. All participants gave informed consent, and the experiment was approved by the University of Manitoba Research Ethics Board.

Procedure

The procedure for [Experiment] 4 was identical to [Experiment] 3 with a few exceptions. Firstly, participants completed the study in person in a computer lab instead of online. In addition, participants were verbally instructed before the experiment began to try and stay as consistent as they could during each trial, to prevent attrition with participants changing their minds. Finally, all questionnaires were removed except the demographic questionnaire.

Analysis

Analysis of [Experiment] 4 was identical to [Experiment] 3.

Results

Preregistered Analyses

A 2x2 ANOVA revealed a significant main effect of Ambivalence (Figure 3), such that participants reappraised Ambivalent images (M = .6078, SD = .2756) significantly more often than Non-ambivalent images (M = .5265, SD = .2816), F(1, 27) = 8.12, p = .0083, η_p^2 = 0.23. There was also a significant main effect of Intensity, such that people reappraised High intensity images (M = .4982, SD = .2695) significantly less often than Low intensity images (M = .6361, SD = .2763), F(1,27) = 11.078, p = .0025, η_p^2 = 0.28. There was no significant interaction effect between ambivalence and intensity on proportion of times reappraisal was chosen, F(1, 27) = 0.51, p = .481, η_p^2 = 0.02.

While not preregistered, we further confirmed that inferentially similar results were found when the images rated as ambivalent by only one rater were removed (see Supplemental for detailed results).

Exploratory Analyses

An exploratory logistic regression found that ambivalence (β = 0.508, z = 2.343, p = .019) and intensity (β = -0.604, z = -2.721, p = .007) significantly predicted emotion regulation choice, such that ambivalent images and low intensity images were more likely to be reappraised. There was no interaction between ambivalence and intensity, β = -0.203, z = -0.653, p = .514.

Before removing participants for mismatched trials (i.e., trials where people chose distraction but ended up reporting that they reappraised and vice versa), we found that participants reported using the chosen emotion regulation strategy on 91.03% of trials. A [chi-square] test indicated that participants reported having used the same strategy from the one they chose when what they chose was distraction (M=88.95%) less often compared to reappraisal (M=92.62%) $\chi^2(1) = 5.068$, *p* = .024. A chi-square test revealed no difference in strategy changes between the four conditions of high intensity ambivalent images (M=91.35%), high intensity non-ambivalent images (M=89.42%), low intensity ambivalent images (M=92.31%), and low intensity non-ambivalent images (M=91.03%) $\chi^2(3) = 1.648$, *p* = .649.

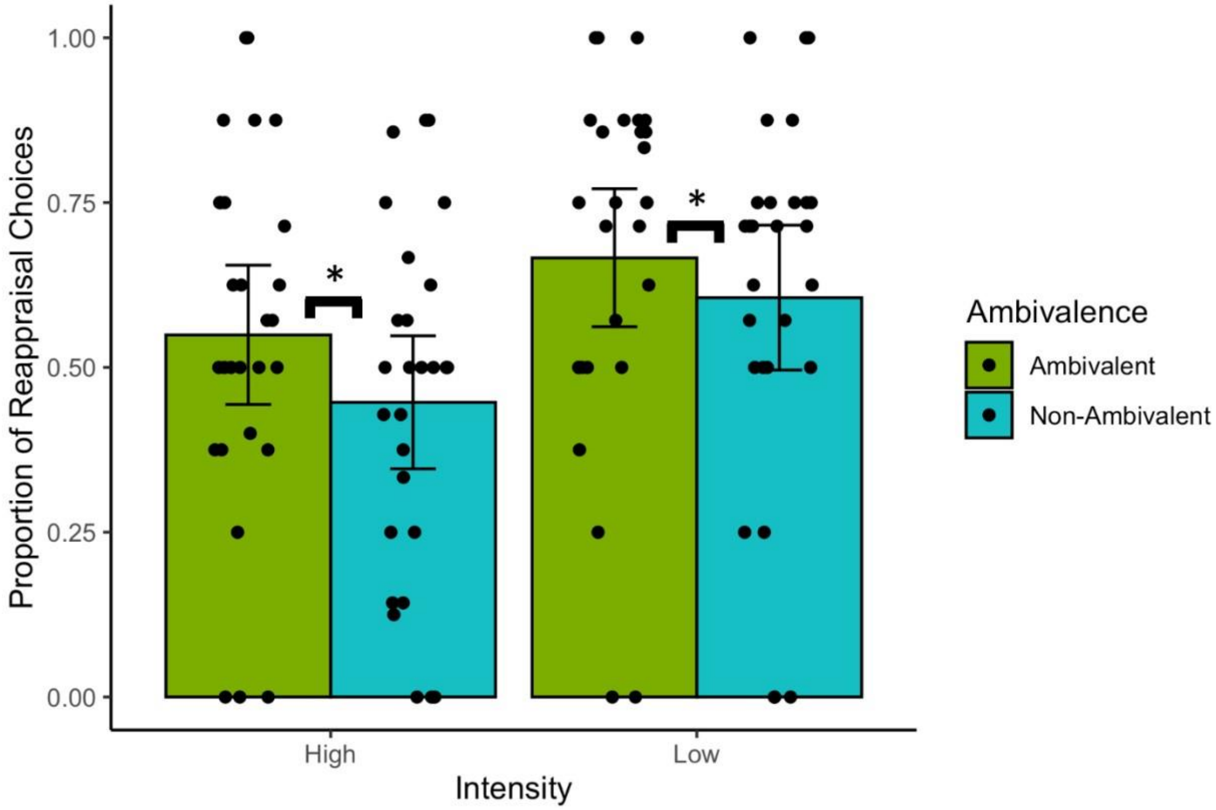

Figure 3: Proportion of reappraisal choices for high intensity ambivalent (M = 54.94%, SD = 27.31%), low intensity ambivalent (M = 66.62%, SD = 27.03%), and high intensity nonambivalent (M = 44.71%, SD = 26.06%), and low intensity non-ambivalent images (M = 60.59%, SD = 28.39%) for [Experiment] 4. The error bars represent a 95% confidence interval.

Experiment 4 Discussion

Experiment 4 was an in-person replication of [Experiment] 3, which found inferentially similar results to [Experiment] 3. Namely, participants chose to reappraise ambivalent images more often than non-ambivalent images, which was in line with previous research (Braniecka et al., 2014; Gordon et al., 2016; E. L. Hay & Diehl, 2011).

In addition, we were once again able to replicate the findings from Sheppes and colleagues (2011; 2014) with respect to the role of intensity in emotion regulation choice. We observed that participants chose reappraisal more often for low intensity images compared to high intensity images. Both findings were replicated using the sample collected in person, and we had a considerably lower attrition rate.

General Discussion

The SOC-ER model posits that external factors can influence the emotion regulation selection process. Across four experiments, the present study sought to identify how one external factor, ambivalence, affects emotion regulation choice. First ([Experiments] 1 and 2), we sought to evaluate if ambivalence could potentially explain the previous literature showing that participants reappraise low intensity images more often than high intensity images (Sheppes et al., 2011). After identifying that this was the case, we next sought to identify whether ambivalence affects participant beliefs about how readily a stimulus can be reappraised ([Experiment] 2). Finally, we sought to determine whether participants choose to reappraise ambivalent images more often than non-ambivalent images, and whether image intensity also affects emotion regulation choice when controlling for ambivalence ([Experiments] 3 and 4).

We first established that there was a difference in ambivalence between the high intensity versus low intensity images used by Sheppes and colleagues (2014) in their emotion regulation choice study in [Experiment] 1. This effect was replicated in [Experiment] 2 in which low intensity images were rated as more ambivalent than high intensity images despite some notable differences in experimental methods. Experiment 1 had a relatively small sample size and between group design in which participants only saw half the images, while [Experiment] 2 had a large sample size and a within-subjects design, where participants saw all the images. Importantly, despite the differences in the design of [Experiments] 1 and 2, the results suggest that the findings replicate across samples and designs. Experiment 1 was also completed in person at a university in the southern United States, while [Experiment] 2 was in an online format at a university in western Canada, potentially increasing the generalizability of our study as the effect remained regardless. Inferentially, the results of both [Experiments] 1 and 2 indicate at least two possibilities. First, the intensity of images may have been entirely confounded by ambivalence, in which case image intensity does not affect emotion regulation choice independent of ambivalence. This first possibility seems unlikely given the number of studies that appear to consistently find that intensity affects emotion regulation choice (Shafir et al., 2016; Sheppes, 2020; Sheppes et al., 2011, 2014). The second possibility is that the intensity of an image is not the only external factor affecting emotion regulation choice in the paper by Sheppes and colleagues (2011), and that ambivalence is another factor that has yet to be considered. Experiments 3 and 4 found that the latter was true, and that ambivalence and intensity are separate factors that influence emotion regulation.

Experiment 2 also identified that ambivalence affected participants beliefs about how easily reappraisal can be undertaken. Specifically, participants on average believed that more ambivalent images were easier to reappraise. Beliefs about reappraisal ability are of interest because while it is not a direct measure of emotion regulation choice, previous research has found that if a person believes they can reappraise a stimulus more easily, they will reappraise that stimulus more often than a stimulus perceived as more difficult to reappraise (Suri et al., 2018). While Suri and colleagues (2018) identified that beliefs about emotion regulation affect emotion regulation choice, they did not identify specific factors which may influence beliefs about emotion regulation. Our findings extend the findings of Suri et al. (2018) by implicating the emotional content of a stimulus and more specifically whether the emotional content is ambivalent or not. As the low intensity images in [Experiments] 1 and 2 of the present study are rated as more ambivalent than the high intensity images, we infer that it is the presence of positive emotional cues that are a key factor that explains the reappraisal affordance. Our findings are also consistent with research showing that ambivalence increases emotional complexity, which is associated with greater emotion regulation ability (E. L. Hay & Diehl, 2011). This might at least partially explain how ambivalence affects beliefs about emotion regulation capabilities. Nevertheless, while [Experiment] 2 demonstrates a relationship between ambivalence and reappraisal affordance, it does not allow us to make causal claims about ambivalence influencing emotion regulation choice.

Finally, the present study established the causal role ambivalence plays in emotion regulation choice. Specifically, [Experiments] 3 and 4 revealed that people chose reappraisal for ambivalent images more often than non-ambivalent images. This supported our hypothesis that ambivalence affects emotion regulation choice. This inference is consistent with [Experiment] 2, in which participants rated more ambivalent images as easier to reappraise, as well as previous research, which has shown beliefs about reappraisal affect emotion regulation choice (Suri et al., 2018). However, this is the first experiment we know of that manipulated ambivalence to measure how it impacts emotion regulation choice. All three experiments together suggest that ambivalent stimuli are related to beliefs about emotion regulation, which in turn can influence emotion regulation choice. In terms of the SOC-ER model, the results of [Experiments] 3 and 4 indicate that ambivalent stimuli have external qualities (i.e., positive cues) that make choosing reappraisal more common than choosing to distract (Opitz et al., 2012; Urry & Gross, 2010).

Experiments 3 and 4 also found further evidence that intensity affects emotion regulation choice. People chose reappraisal for low intensity images more often than for high intensity images, consistent with previous findings (Sheppes et al., 2011, 2014; Suri et al., 2018). This finding also appears to refute the prediction that intensity's effect on emotion regulation choice is entirely confounded by ambivalence, as ambivalence and intensity appear to be external factors that affect emotion regulation choice independently of one another. This may be because they are at least somewhat dissociable environmental features of an emotional stimulus (Opitz et al., 2012; Suri et al., 2018; Urry & Gross, 2010).

While these four experiments suggest that stimulus ambivalence is an environmental factor affect participant beliefs and choices regarding emotion regulation, the mechanisms, or how ambivalent emotional stimuli are more often selected for reappraisal than non-ambivalent stimuli, is unknown. Although the present study cannot speak to this directly, previous research into emotion regulation suggests at least a couple of possibilities.

The first possibility may involve the relationship between creativity or divergent thinking and emotional reappraisal (Fink et al., 2017). The presence of positive emotion cues in ambivalent images reduce the demand for creativity in generating a reappraisal thereby facilitating emotion regulation. It should, however, be noted that the present study focused on affective images that were primarily negative. Future research is needed to evaluate whether regulation choice is similarly affected by ambivalent images that are primarily positive.

Another option is that reappraisal is underpinned by the mechanisms of selective attention. To successfully down-regulate the negativity of a stimulus, participants must attend to a positive (or at least less negative) perceptual and/or semantic representation to outcompete the negative representation for prioritized processing (Greening et al., 2022; Greening, Lee, et al., 2014). In this framework, ambivalent stimuli may be more readily selected for reappraisal because they contain positive affective cues to which one can selectively attend, thereby facilitating the goal-directed prioritization of a more positive mental representation (McRae et al., 2012). Similarly, previous research suggest that it is more difficult to disengage attention from negative stimuli (Fox et al., 2002; Grafton & Macleod, 2016; Sheppes et al., 2013). However, as ambivalent stimuli also have positive affective cues present, which can facilitate attentional engagement (B. A. Anderson et al., 2011), it is possible that disengagement from the negative affective cues might be easier thereby aiding emotion regulation (Greening, Osuch, et al., 2014; van Reekum et al., 2007). This framework may also explain the mechanism by which intensity affects emotion regulation choice, as intensely negative stimuli capture and hold one's attention (A. K. Anderson, 2005; Compton, 2003).

As the potential explanations above allude, while ambivalence is a reappraisal affordance, it might interact with various internal processes that have been associated with emotion regulation previously. Future research could explore whether ambivalent images interact with creativity by disproportionately increasing reappraisal strategies in participants lower, compared to higher, in creativity. That is, ambivalent stimuli may reduce the overall demand for creativity in the generation of reappraisal strategies. Similarly, future research could evaluate whether those lower in attention or cognitive control display greater increases in decisions to reappraise compared to those higher in those internal abilities. Another limitation that could be focused on in future research is that we did not ask participants to perform a specific kind of reappraisal, only giving them general instructions on how to reappraise images.

Future research could give participants choices between various methods of reappraisal (e.g., distancing, reinterpretation) to determine the role ambivalence may play in more specific emotion regulation choice. It is also worth noting that based on [Experiments] 1 and 2, ambivalence appears to be a type of reappraisal affordance, or at least a factor that influences reappraisal affordance judgments. While research has been done on the role of affordances in emotion regulation choice (Suri et al., 2018; Young & Suri, 2020), this study adds to the literature by elucidating a novel type or factor of affordance.

One potential limitation of the present study is the image selection for [Experiments] 3 and 4. Only one of the raters needed to approve an image for it to be ambivalent provided normed data suggested the image was both happy and sad. Future research could replicate the study with a different set of ambivalent images normed primarily based the presence of both positive and negative cues (Itkes et al., 2019). Another option is to use more potent ambivalent stimuli such as videos used in previous research (Itkes et al., 2019; Larsen & McGraw, 2011).

While the present study does not attempt to adjudicate between the various theories of ambivalence or mixed emotions (Hoemann et al., 2017; Larsen & McGraw, 2014), it suggests that ambivalence is an environmental factor that ought to be considered in studies of emotion regulation. Specifically, the presents study demonstrates that ambivalence is an environmental factor that may be more common in low intensity images and that affects one’s choice of emotion regulation strategy. Knowledge regarding the relationship between ambivalence and choosing reappraisal may also be useful in applied research attempting to enhance or improve one’s emotion regulation behaviour, which is particularly important for people who struggle with emotion dysregulation. As emotion dysregulation is common in people with anxiety and depression (Hofmann et al., 2012), identifying external factors that influence emotion regulation may be useful in informing future assessment and treatment practices in those with emotion dysregulation.

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Disclosure statement

No potential conflict of interest was reported by the authors.

Data availability statement

The data from the three experiments that support the findings of this study are openly available in Open Science Framework https://osf.io/ckujd/.

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[Chapter 2] References

Anderson, A. K. (2005). Affective influences on the attentional dynamics supporting awareness. *Journal of Experimental Psychology: General*, *134*(2), 258–281. https://doi.org/10.1037/0096-3445.134.2.258

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011). Value-driven attentional capture. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(25), 10367–10371. https://doi.org/10.1073/pnas.1104047108

Braniecka, A., Trzebińska, E., Dowgiert, A., & Wytykowska, A. (2014). Mixed emotions and coping: The benefits of secondary emotions. *PLoS ONE*, *9*(8). https://doi.org/10.1371/journal.pone.0103940

Cacioppo, J. T., & Berntson, G. G. (1994). Relationship between attitudes and evaluative space: A critical review, with emphasis on the separability of positive and negative substrates. *Psychological Bulletin*, *115*(3), 401–423. https://doi.org/https://doi.org/10.1037/0033-2909.115.3.401

Cacioppo, J. T., Gardner, W., & Berntson, G. G. (1997). Beyond bipolar conceptualizations and measures: The case of attitudes and evaluative space. *Personality and Social Psychology Review*, *1*(1), 3–25.

Cacioppo, J. T., Gardner, W. L., & Berntson, G. G. (1999). The affect system has parallel and integrative processing components: Form follows function. *Journal of Personality and Social Psychology*, *76*(5), 839–855. https://doi.org/10.1037/0022-3514.76.5.839

Compton, R. (2003). The interface between emotion and attention: A review of evidence from psychology and neuroscience. *Behavioral and Cognitive Neuroscience Reviews*, *2*(2), 115–129. https://doi.org/10.1177/1534582303002002003

Diener, E., & Emmons, R. A. (1984). The independence of positive and negative affect. *Journal of Personality and Social Psychology*, *47*(5), 1105–1117. https://doi.org/10.1037/0022-3514.47.5.1105

Fink, A., Weiss, E. M., Schwarzl, U., Weber, H., de Assunção, V. L., Rominger, C., Schulter, G., Lackner, H. K., & Papousek, I. (2017). Creative ways to well-being: Reappraisal inventiveness in the context of anger-evoking situations. *Cognitive, Affective and Behavioral Neuroscience*, *17*(1), 94–105. https://doi.org/10.3758/s13415-016-0465-9

Fox, E., Russo, R., & Dutton, K. (2002). Attentional bias for threat: Evidence for delayed disengagement from emotional faces. *Cognition and Emotion*, *16*(3), 355–379. https://doi.org/10.1080/02699930143000527

Gordon, N. S., Chesney, S. A., & Reiter, K. (2016). Thinking positively: Optimism and emotion regulation predict interpretation of ambiguous information. *Cogent Psychology*, *3*(1), 1–13. https://doi.org/10.1080/23311908.2016.1195068

Grafton, B., & Macleod, C. (2016). Engaging with the wrong people: The basis of selective attention to negative faces in social anxiety. *Clinical Psychological Science*, *4*(5), 793–804. https://doi.org/10.1177/2167702615616344

Greening, S. G., Lee, T. H., Burleigh, L., Grégoire, L., Robinson, T., Jiang, X., Mather, M., & Kaplan, J. (2022). Mental imagery can generate and regulate acquired differential fear conditioned reactivity. *Scientific Reports*, *12*(1), 1–23. https://doi.org/10.1038/s41598-022-05019-y

Greening, S. G., Lee, T.-H., & Mather, M. (2014). A dual process for the cognitive control of emotional significance: Implications for emotion regulation and disorders of emotion. *Frontiers in Human Neuroscience*, *8*, 1–2. https://doi.org/10.3389/fnhum.2014.00253

Greening, S. G., Osuch, E. A., Williamson, P. C., & Mitchell, D. G. V. (2014). The neural correlates of regulating positive and negative emotions in medication-free major depression. *Social Cognitive and Affective Neuroscience*, *9*(5), 628–637. https://doi.org/10.1093/scan/nst027

Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. *Review of General Psychology*, *2*(3), 271–299. https://doi.org/https://doi.org/10.1037/1089-2680.2.3.271

Hay, E. L., & Diehl, M. (2011). Emotion complexity and emotion regulation across adulthood. *European Journal of Ageing*, *8*(3), 157–168. https://doi.org/10.1007/s10433-011-0191-7

Hoemann, K., Gendron, M., & Barrett, L. F. (2016). *Mixed emotions in the predictive brain*. *515,* 1–22.

Isen, A. M., Daubman, K. A., & Nowicki, G. P. (1987). Positive affect facilitates creative problem solving. *Journal of Personality and Social Psychology*, *52*(6), 1122–1131. https://doi.org/10.1037/0022-3514.52.6.1122

Itkes, O., Eviatar, Z., & Kron, A. (2019). Semantic and affective manifestations of ambi (valence). *Cognition and Emotion*, *33*(7), 1356–1369. https://doi.org/10.1080/02699931.2018.1564249

Kreibig, S. D., Samson, A. C., & Gross, J. J. (2015). The psychophysiology of mixed emotional states: Internal and external replicability analysis of a direct replication study. *Psychophysiology*, *52*(7), 873–886. https://doi.org/10.1111/psyp.12425

Kron, A., Goldstein, A., Lee, D. H. J., Gardhouse, K., & Anderson, A. K. (2013). How Are You Feeling? Revisiting the Quantification of Emotional Qualia. *Psychological Science*, *24*(8), 1503–1511. https://doi.org/10.1177/0956797613475456

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). International affective picture system (IAPS): Technical manual and affective ratings. *NIMH Center for the Study of Emotion and Attention*, 39–58.

Larsen, J. T., & McGraw, A. P. (2011). Further evidence for mixed emotions. *Journal of Personality and Social Psychology*, *100*(6), 1095–1110. https://doi.org/10.1037/a0021846

Larsen, J. T., & McGraw, A. P. (2014). The case for mixed emotions. *Social and Personality Psychology Compass*, *8*(6), 263–274. https://doi.org/10.1111/spc3.12108

Larsen, J. T., Norris, C. J., McGraw, A. P., Hawkley, L. C., & Cacioppo, J. T. (2009). The evaluative space grid: A single-item measure of positivity and negativity. *Cognition and Emotion*, *23*(3), 453–480. https://doi.org/10.1080/02699930801994054

Libkuman, T. M., Otani, H., Kern, R., Viger, S. G., & Novak, N. (2007). Multidimensional normative ratings for the International Affective Picture System. *Behavior Research Methods*, *39*(2), 326–334. https://doi.org/10.3758/BF03193164

Marchewka, A., Żurawski, Ł., Jednoróg, K., & Grabowska, A. (2014). The Nencki Affective Picture System (NAPS): Introduction to a novel, standardized, wide-range, high-quality, realistic picture database. *Behavior Research Methods, 46*(2), 596–610. https://doi.org/10.3758/s13428-013-0379-1

McRae, K., Misra, S., Prasad, A. K., Pereira, S. C., & Gross, J. J. (2012). Bottom-up and top-down emotion generation: Implications for emotion regulation. *Social Cognitive and Affective Neuroscience*, *7*(3), 253–262. https://doi.org/10.1093/scan/nsq103

Milyavsky, M., Webber, D., Fernandez, J. R., Kruglanski, A. W., Goldenberg, A., Suri, G., & Gross, J. J. (2018). To reappraise or not to reappraise? Emotion regulation choice and cognitive energetics. *Emotion*, *19*(6), 964–981. https://doi.org/10.1037/emo0000498

Norris, C. J., & Wu, E. (2021). Accentuate the positive, eliminate the negative: Reducing ambivalence through instructed emotion regulation. *Emotion*, *21*(3), 499–512. https://doi.org/10.1037/emo0000716

Ochsner, K. N., Silvers, J. A., & Buhle, J. T. (2012). Functional imaging studies of emotion regulation: A synthetic review and evolving model of the cognitive control of emotion. *Annals of the New York Academy of Sciences*, *1251*, 1–24. https://doi.org/10.1111/j.1749-6632.2012.06751.x.Functional

Opitz, P. C., Gross, J. J., & Urry, H. L. (2012). Selection, optimization, and compensation in the domain of emotion regulation: Applications to adolescence, older age, and major depressive disorder. *Social and Personality Psychology Compass*, *6*(2), 142–155. https://doi.org/10.1111/j.1751-9004.2011.00413.x

Opitz, P. C., Lee, I. A., Gross, J. J., & Urry, H. L. (2014). Fluid cognitive ability is a resource for successful emotion regulation in older and younger adults. *Frontiers in Psychology*, *5*(JUN), 1–13. https://doi.org/10.3389/fpsyg.2014.00609

Riegel, M., Żurawski, Ł., Wierzba, M., Moslehi, A., Klocek, Ł., Horvat, M., Grabowska, A., Michałowski, J., Jednoróg, K., & Marchewka, A. (2016). Characterization of the Nencki Affective Picture System by discrete emotional categories (NAPS BE). *Behavior Research Methods*, *48*(2), 600–612. https://doi.org/10.3758/s13428-015-0620-1

Russell, J. A. (1980). A circumplex model of emotion. *Journal of Personality and Social Psychology*, *39*(6), 1161–1178.

Schimmack, U. (2005). Response latencies of pleasure and displeasure ratings: Further evidence for mixed feelings. *Cognition and Emotion*, *19*(5), 671–691. https://doi.org/10.1080/02699930541000020

Schmeichel, B. J., & Tang, D. (2015). Individual differences in executive functioning and their relationship to emotional processes and responses. *Current Directions in Psychological Science*, *24*(2), 93–98. https://doi.org/10.1177/0963721414555178

Sheppes, G. (2014). Emotion regulation choice: Theory and findings. *Handbook of Emotion Regulation*, 126–139.

Sheppes, G., Luria, R., Fukuda, K., & Gross, J. J. (2013). There's more to anxiety than meets the eye: Isolating threat-related attentional engagement and disengagement biases. *Emotion*, *13*(3), 520–528. https://doi.org/10.1037/a0031236

Sheppes, G., Scheibe, S., Suri, G., & Gross, J. J. (2011). Emotion-regulation choice. *Psychological Science*, *22*(11), 1391–1396. https://doi.org/10.1177/0956797611418350

Sheppes, G., Scheibe, S., Suri, G., Radu, P., Blechert, J., & Gross, J. J. (2014). Emotion regulation choice: A conceptual framework and supporting evidence. *Journal of Experimental Psychology: General*, *143*(1), 163–181. https://doi.org/10.1037/a0030831

Shevchenko, Y. (2022). Open Lab: A web application for running and sharing online experiments. *Behavior Research Methods*. https://doi.org/10.3758/s13428-021-01776-2

Suri, G., Sheppes, G., Young, G., Abraham, D., McRae, K., & Gross, J. J. (2018). Emotion regulation choice: the role of environmental affordances. *Cognition and Emotion*, *32*(5), 963–971. https://doi.org/10.1080/02699931.2017.1371003

Thompson, M. M., & Zanna, M. P. (1995). The Conflicted Individual: Personality-Based and Domain Specific Antecedents of Ambivalent Social Attitudes. *Journal of Personality*, *63*(2), 259–288. https://doi.org/10.1111/j.1467-6494.1995.tb00810.x

Urry, H. L., & Gross, J. J. (2010). Emotion regulation in older age. *Current Directions in Psychological Science*, *19*(6), 352–357. https://doi.org/10.1177/0963721410388395 van Reekum, C. M., Johnstone, T., Urry, H. L., Thurow, M. E., Schaefer, H. S., Alexander, A. L., & Davidson, R. J. (2007). Gaze fixations predict brain activation during the voluntary regulation of picture-induced negative affect. *NeuroImage*, *36*(3), 1041–1055. https://doi.org/10.1016/j.neuroimage.2007.03.052

Chapter 3: Brain activity associated with emotion regulation predicts individual differences in working memory ability

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Abstract

Previous behavioral research has found that working memory is associated with emotion regulation efficacy. However, there has been mixed evidence as to whether the neural mechanisms between emotion regulation and working memory overlap. The present study tested the prediction that individual differences on the working memory subtest of the Weschler Adult Intelligence Scale (WAIS-IV) could be predicted from the pattern of brain activity produced during emotion regulation in regions typically associated with working memory such as the [dorsolateral prefrontal cortex (dlPFC)]. One-hundred-and-one participants completed an emotion regulation [functional magnetic resonance imaging (fMRI)] task in which they either viewed or reappraised negative images. Participants also completed working memory test outside the scanner. A whole brain covariate analysis contrasting the reappraise negative and view negative [blood-oxygen level dependent (BOLD)] response found that activity in the right dorsal lateral prefrontal cortex (dlPFC) positively related to working memory ability. Moreover, a multivoxel pattern analysis (MVPA) approach using 10-fold cross validated support vector regression in [regions of interest (ROIs)] associated with working memory, including bilateral dlPFC, demonstrated we could predict individual differences in working memory ability from the pattern of activity associated with emotion regulation. These findings support the idea that emotion regulation shares underlying cognitive processes and neural mechanisms with working memory, particularly in the dlPFC.

Introduction

The ability to change or maintain one's emotional state is critical to wellbeing (Gross, 1998). An example of this ability, referred to as emotion regulation, is reappraisal, which involves changing one's thoughts or interpretations of an emotional stimulus (Gross, 1998, 2002). The Selection, Optimization, and Compensation with Emotion Regulation (SOC-ER) model posits that certain cognitive processes are required to successfully regulate an emotional stimulus (Opitz et al., 2012; Urry & Gross, 2010), a skill also referred to as emotion regulation efficacy (Greening et al., 2014). Working memory, which involves the active maintenance, manipulation, and updating of information (Miyake et al., 2000) may be one of the key underlying cognitive process necessary for emotion regulation.

There have been several behavioral demonstrations of the association between working memory and emotion regulation, particularly for reappraisal. Research has found that executive function, and particularly working memory, is associated with behavioural emotion regulation efficacy (W. Hofmann et al., 2012; Schmeichel & Tang, 2015). In addition, people who reappraise more frequently have higher working memory capacity (Jasielska et al., 2015). Performance on working memory tasks has been shown to be positively associated with behavioural reappraisal efficacy, defined as the difference in performance between reappraisal and view trials (Hendricks & Buchanan, 2016; Opitz et al., 2014), and working memory training appears to increase emotion regulation success (Schmeichel & Tang, 2015; Schweizer et al., 2013). Such studies suggest a causal relationship between working memory and emotion regulation, with improved working memory leading to improved emotion regulation. Emotional stimuli can also disrupt performance on a task with high working memory load, while having no effect on a task with low working memory load (Tavares et al., 2016), which suggests that the same resources required for working memory are also involved in regulation of the emotional distractor. In addition, emotion dysregulation, such as people's experiences of post-traumatic stress disorder, is also associated with worse performance on working memory tasks (Morey et al., 2009). Together, these behavioral findings suggest that emotion regulation may depend on the same cognitive processes as working memory.

Nevertheless, findings from neuroimaging studies of emotion regulation are more uncertain as to whether the brain regions associated with emotion regulation overlap with those regions associated with working memory (Denny et al., 2015; Goldin et al., 2008; Kanske et al., 2011; Lee & Xue, 2018; Morawetz et al., 2016; Ochsner et al., 2004). This research suggests one of two possibilities. One possibility is that working memory and emotion regulation are influenced by the same neural processes. Research consistently finds that reappraisal of negative images is associated with greater activity in frontal regions associated with working memory, including the dorsolateral PFC (dlPFC) and the dorsomedial PFC (dmPFC) as compared to simply viewing negative images (Buhle et al., 2014; Ochsner et al., 2012). Individual differences in behavioural emotion regulation efficacy (i.e., trial-by-trial self-reported negative affect for reappraise versus attend negative trials) is positively correlated with dlPFC activity (Greening et al., 2014), though in that study no measure of working memory was conducted. Other research finds that working memory performance along with dlPFC activity can be disrupted by emotional distractors (Dolcos & McCarthy, 2006). Research has also implicated the dorsal anterior cingulate cortex (dACC) in reappraisal (Ochsner et al., 2012). Emotional working memory training affects activity in prefrontal areas, as well as activity in the anterior cingulate cortex (ACC) during emotion regulation (Schweizer et al., 2013) implying similar neural mechanisms. In a more recent demonstration of individual differences, dlPFC activity generated by a working memory task was positively correlated with self-reported use of emotional reappraisal (Scult et al., 2017). When reappraisal is compared directly to working memory tasks deployed during distraction-based emotion regulation, both reappraisal and working memory involve significant activation of dlPFC and dmPFC/dACC (Kanske et al., 2011; McRae et al., 2010). The dmPFC/dACC in particular seems to be involved in emotional working memory (Smith et al., 2018). However, this overlap in activation during working memory and reappraisal, and the inference of shared neural mechanisms, was derived from conjunction analyses. Unfortunately, it is possible to have overlapping brain activation from a conjunction analysis of two conditions despite distinct neural representations of the two conditions, as demonstrated using a multivoxel pattern analysis (MVPA) approach (Woo et al., 2014).

The preceding neuroimaging literature implies that one possibility is that the cognitive processes involved in working memory are likewise necessary for emotion regulation. However, a second possibility is that the overlap in brain regions engaged between working memory and emotion regulation efficacy is merely coincidental. For example, Lee and Xue (2018) argue that while there is overlap between emotion regulation and working memory in areas of the PFC, the distinct areas of the PFC associated solely with emotion regulation suggest emotion regulation and working memory do not use the same neural resources. One way to determine which of these possibilities is true is to evaluate whether MVPA of differential activity during reappraise versus look trials of an emotion regulation task (i.e., neural emotion regulation efficacy) can be used to predict individual differences in behavioural performance on a working memory task. MVPA with cross-validation offers one solution to the limitations of earlier univariate neuroimaging research (Gabrieli et al., 2015). Compared to univariate individual difference analyses, MVPA allows for greater power, meaning less participants are needed (Marek et al., 2022). It would allow for the unbiased evaluation of whether the task-relevant patterns of activation elicited during emotion regulation are specifically predictive (Poldrack, 2008; Wager et al., 2011) of individual differences in working memory performance, rather than simply a coincidence. Were this to be the case, it would provide unbiased and direct evidence that performance during emotion regulation is underpinned by working memory.

In general, we predicted that brain activity associated with emotion regulation efficacy (i.e., the differential brain activity of reappraise negative trials versus view negative trials) in frontoparietal areas would be predictive of individual differences in working memory. To test this prediction, we first evaluated whether a behavioural measure of working memory covaries with brain activity associated with emotion regulation efficacy using a whole-brain univariate analysis. Second, we used MVPA on regions-of- interest (ROIs) commonly implicated in working memory combined with ten-fold cross-validated support vector regression analysis (Gabrieli et al., 2015). This allowed us to test the novel hypothesis that individual differences in behavioural working memory can be predicted in an unbiased manner from the pattern of brain activity produced during emotion regulation in frontoparietal regions associated with working memory such as dlPFC.

Methods

Participants

One hundred and ten participants were recruited from the general population in the Los Angeles area. Of the participants, four were removed for not completing the emotion regulation task, and five were removed for not completing the [Weschler Adult Intelligence Scale-IV (WAIS-IV)]. As a result, 101 participants (62 female, 39 male) were included in the analysis. Participants were between the ages of 18 and 55 (mean age = 26.24 years, SD = 9.06).

Participants were English speakers, had normal or corrected-to-normal vision, and had no history of mental illness. Participants provided written informed consent and were screened for MRI safety prior to the experiment. All study protocols were approved in accordance with the Institutional Review Board approval guidelines provided by the University of Southern California.

Procedure

The data analyzed here are part of a larger study with independent research questions and hypotheses, which focus on the relationship between general intelligence and emotional intelligence. In the scanner, the emotion regulation task was one of four tasks relating to the [Four Component] model of emotional intelligence. However, the present work only focuses on the relationship between emotion regulation and working memory, so only those parts of the procedure will be discussed. Participants entered the MRI scanner and completed an emotion regulation task. Before the task, there was an initial fixation cross rest period of 6000 ms. In each trial, the image and an instruction below the image appeared on screen for 8000 ms. In the regulate negative condition, participants were instructed to down-regulate their emotional responses using reappraisal. In the regulate negative condition, the instruction read “Reduce,” while in the view negative and view neutral conditions, the instruction read “Look.” Instructions for the regulate negative condition were as followed: “When you are prompted to Reduce, you should try to change how you feel when you see each picture by searching for an alternative interpretation of what you see. For example, you might imagine ways the situation could improve for the better, or identify aspects of the situation that are not as bad as they seem, or possibly think of what you are seeing from another perspective. Please do not look away from the picture or try to distract yourself from it. We will now look at an example together and discuss how you might change your feelings about it.” In the view negative condition, participants passively viewed the negative images. In the view neutral condition, participants passively viewed the neutral images. Instructions for the view conditions were as follows: “When you are prompted to Look, you should simply take in the image and try to imagine how you would feel seeing it in real life.” Afterwards, the image disappeared, and they rated how negatively the image made them feel on a sliding Likert scale of 0-5 (0 being “not strong” and 5 being “very strong”), which remained on the screen for 5000 ms, or until participants locked in their responses. Then, there was a rest jitter period of 3000-5000 ms before the next trial. The main task block consisted of 40 trials, with 15 regulate negative trials, 15 view negative trials, and 10 view neutral trials (See Figure 1). There was also a practice block of four trials, in which participants were instructed to look during the first two trials and reappraise during the last two trials. Images were sourced from the internet (such as the r/mildlydisgusting subreddit on reddit.com) and included negative images meant to induce mild, but not strong, disgust and neutral images containing scenes and objects (behavioral results from this study will confirm that subjects were able to successfully regulate their emotional responses to the stimuli). Thumbnails and ratings of the images are included in the supplemental materials. Negative images were randomly assigned to regulate negative and view negative conditions for each participant.

The experiment was completed at the MRI facility at University of Southern California using a 3T Siemens scanner with a 32-channel head coil. A T1-weighted magnetization-prepared rapid gradient-echo whole brain was used to acquire anatomical images (repetition time: 2300 ms, echo time: 2.26 ms, voxel size 1-mm isotropic voxels, flip angle 9°). Functional images were acquired in one run with a T2*-weighted gradient-echo sequence (repetition time: 2000 ms, echo time: 25 ms, 41 transverse 3-mm slices, flip angle 90°).

To measure working memory, Participants completed the WAIS-IV (Wechsler, 2008) in a second session outside the scanner. The WAIS-IV measures cognitive control and consists of four [indices]: working memory, processing speed, verbal comprehension, and perceptual reasoning. Only the working memory [index] is utilized in present study. The working memory tasks included a digit span task and an arithmetic task. In the digit span task, participants were instructed to repeat a series of digit strings either forwards or backwards (digit span sequencing was not used). In the arithmetic task, the instructor read out a word problem that the participant then was asked to solve. Working memory performance was scored using the WAIS-IV protocol (Wechsler, 2008).

Figure 1: Typical experimental trial for the emotion regulation task.

Analysis

Behavioral Analyses

Behavioral analyses included a paired samples t-test, which was run to determine differences in a participants' ratings during the reappraise negative and view negative conditions. Additionally, a correlation analysis was run to show the association between the difference in ratings between reappraise negative and view negative conditions and working memory performance.

MRI [Preprocessing]

For each participants' emotion regulation run, fMRIPrep (version 1.1.22) was performed for preprocessing. What follows is a boilerplate from [fMRIPrep], distributed under the CC0 license:

> First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. A B0-nonuniformity map (or fieldmap) was estimated based on a phase-difference map calculated with a dual-echo GRE (gradient-recall echo) sequence, processed with a custom workflow of SDCFlows inspired by the epidewarp.fsl script and further improvements in HCP Pipelines (Glasser et al., 2013). The fieldmap was then co-registered to the target EPI (echo-planar imaging) reference run and converted to a displacements field map (amenable to registration tools such as ANTs) with FSL's fugue and other SDCflows tools. Based on the estimated susceptibility distortion, a corrected EPI (echo-planar imaging) reference was calculated for a more accurate co-registration with the anatomical reference. 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 six degrees of freedom. 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 et al., 2002). BOLD runs were slice-time corrected to 0.966s (0.5 of slice acquisition range 0s-1.93s) using 3dTshift from AFNI 20160207 (Cox & Hyde, 1997, RRID:SCR_005927). The BOLD time-series (including slice-timing correction

when applied) 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 time-series were resampled into standard space, generating a preprocessed BOLD run in MNI152NLin2009cAsym space. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. Automatic removal of motion artifacts using independent component analysis (ICA-AROMA) (Pruim et al., 2015) was performed on the preprocessed BOLD on MNI space time-series after removal of non-steady state volumes and spatial smoothing with an isotropic, Gaussian kernel of 6mm FWHM (full-width half-maximum). Corresponding “[non-aggressively]” denoised runs were produced after such smoothing. Additionally, the “aggressive” noise-regressors were collected and placed in the corresponding confounds file. Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power (absolute sum of relative motions (Power et al., 2014)) and Jenkinson (relative root mean square displacement between affines (Jenkinson et al., 2002)). 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 et al., 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). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, the aCompCor masks are subtracted a mask of pixels that likely contain a volume fraction of GM. This mask is obtained by dilating a GM mask extracted from the FreeSurfer's aseg segmentation, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the k components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al., 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardised DVARS were annotated as motion outliers. 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 output 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).

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Afterwards, spatial smoothing using a Gaussian kernel of [full width at half maximum (FWHM)] 5.0mm was applied, as smoothing does not negatively affect MVPA results (Op de Beeck, 2010) and may actually improve the sensitivity of multivariate analyses (Hendriks et al., 2017). Noise regressors were removed all at once using a level 1 general linear model on each participant in FSL (Woolrich et al., 2001). Specifically, this initial level 1 analysis regressed out noise by including the following nuisance regressors from the [fMRIPrep] preprocessing: six rigid-body motion regressors, every component identified as noise by ICA-AROMA, and the first [principal] component from the restricted white matter + grey matter mask created by compCor. The resulting cleaned residual file was used for the primary analysis described below.

Whole Brain Analysis

The cleaned residual data underwent time-series statistical analyses as carried out using [FMRIB’s Improved Linear Model (FILM)] with local autocorrelation correction (Woolrich et al., 2001). We ran a second level 1 analysis on the cleaned residual data that included three regressors of interest and three regressors of no interest. The regulate negative, view negative, and view neutral regressors were included as regressors of interest, which were event-related and lasted for [eight] seconds (i.e., the duration of the image presentation and the period during which participants carried out the instructed task condition). The regulate negative ratings, view negative ratings, and view neutral ratings regressors were included as regressors of no interest, which were event related and lasted up to five seconds, contingent on reaction time during the Likert epoch. The double gamma hemodynamic response function (HRF) was used to convolve the basic waveform for all regressors. Temporal derivatives of all task-related regressors were included. Contrasts measured were the regulate negative condition, the view negative condition, the view neutral condition, and a contrast of regulation efficacy, regulate negative – view negative difference.

The second-level analysis, which included one run for each subject, were carried out using a fixed effects model, by forcing the random effects variance to zero in FLAME (FMRIB's Local Analysis of Mixed Effects, Beckmann et al., 2003; Woolrich, 2008; Woolrich et al., 2004).

We then performed standard univariate and covariate group analyses using FLAME stage 1 (Beckmann et al., 2003; Woolrich, 2008; Woolrich et al., 2004). Z (Gaussianised T/F) statistic images were thresholded using clusters determined by $Z>3.1$ and a (corrected) cluster significance threshold of $p = 0.05$ (Worsley, 2001). In the whole-brain covariate analysis, WAIS-IV working memory scores were used as an additional predictor. The covariate analysis used WAIS-IV working memory scores to predict differences in BOLD activity between regulate negative and view negative conditions. In other words, the covariate analysis identified brain areas that responded during reappraising that are predictive of working memory performance. Further details of the univariate analyses can be found at https://neurovault.org/collections/IHXZNJXZ.

Multivariate Analysis

Next, we used multi-voxel pattern analysis (MVPA) with a continuous support vector regression (SVR) analysis using a linear kernel to determine if we could predict working memory performance on the WAIS-IV with the regulate negative – view negative BOLD contrast. SVR is a linear regression based on support vector machines, which performs well particularly with high dimensional data, such as datasets with a high voxel counts as features (Misaki et al., 2010), or data used to determine individual differences (Zhou et al., 2021). The SVR was implemented using a stratified 10-fold cross-validation scheme (Greening & Mitchell, 2015), where the test set included 10 participants (with the exception of one set which included 11) and no participant was removed more than once. The voxels for inclusion as features were from brain areas that were selected using an ROI approach based on independent components analysis (ICA). The use of ICA was a feature reduction step, as fMRI data is notoriously overdetermined in that the number features (i.e., voxels) greatly exceeds the number of examples (i.e., participants). In particular, we were interested in areas implicated in working memory, we used feature reduction to focus on those areas typically associated with working memory. Feature reduction is a common strategy for reducing problems commonly associated with highly overdetermined datasets such as overfitting (Hughes, 1968). The ICA was conducted at the group level with Regulate Negative – View Negative contrasts using MELODIC. Following this group ICA, we selected the Independent Components (ICs) that included brain regions commonly associated with working memory. We did this by using fslcc to evaluate the interclass correlation between each IC produced and a brain map associated with working memory based on the meta-analysis results found on Neurosynth.org (Yarkoni et al., 2011). It is worth noting that while we looked for ICs that correlated with meta-analytical working memory activity from

Neurosynth, our functional data was emotion regulation data and no working memory tasks were completed in the scanner. In other words, our feature reduction was blind to our primary outcome measure of the multivariate analysis, which was the WAIS working memory measure conducted outside the scanner. Using this approach, we identified two ICs correlated with working memory. These two ICs were then turned into binary masks by thresholding the maps at a voxel-level with a z-value of 3.1, and transformed into more discreet clusters using erosion and dilation. See the results section for details on the regions identified.

For each participant and each MVPA analysis (i.e., for each of the two ROI maps and for the whole-brain analysis below), a matrix of voxels containing the emotion regulation efficacy contrast parameter estimates was made. In each fold, the training data was used to train an SVR model on the emotion regulation efficacy voxel activity to predict the working memory WAIS-IV scores of the training data; after training, the trained model was tested on the held out set of test participant data to predict the working memory WAIS-IV score of each participant in the test set. After the ten-fold cross validation, we were left with one predicted working memory WAIS-IV score per participant, which we then compared to the known working memory WAIS-IV score using root mean square error (RMSE), or the empirical RMSE. To evaluate whether the empirical RMSE was significantly lower than chance, it was compared to permutation estimated RMSEs from 1000 permutation simulations in which the working memory scores randomly shuffled amongst the participants. Further details of the multivariate analysis can be found at https://neurovault.org/collections/IHXZNJXZ.

Results

Behavioral Results

Working memory scores as measured by the WAIS-IV ranged from 83 to 145 (M= 110.8, SD = 12.27) and were distributed normally. A paired samples t-test determined that there was a significant difference in ratings of negativity between the reappraise negative condition (M = 2.553, SD = 0.531) and the view negative condition (M = 3.237, SD = 0.567), t(100) = -11.287, $p < .001$, Cohen's d' = -1.245 (see Figure 2a). In addition, a Pearson's correlation analysis showed a negative correlation between reappraisal efficacy (defined as Reappraise Negative - View Negative) and working memory score, suggesting that a more negative difference between Reappraise Negative and View Negative is associated with greater working memory performance r(99) = -0.306, $p = .0018$ (see Figure 2b).

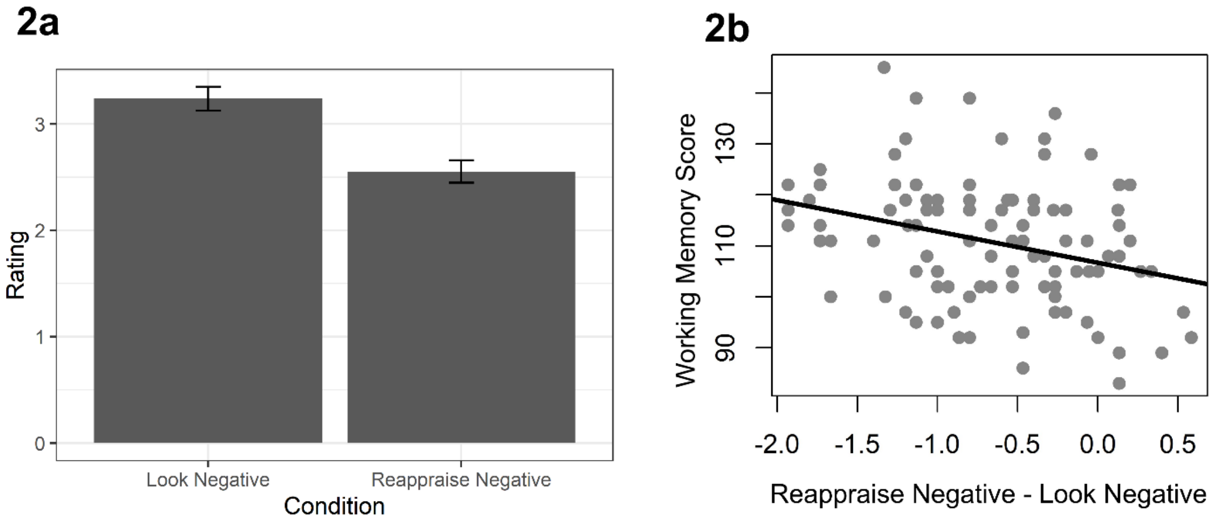

Figure 2: Behavioral results showing the difference in ratings of negativity between Look negative and Reappraise Negative conditions (Fig 2a) and correlation between Reappraise Negative – Look Negative Ratings and Working Memory score (Fig 2b)

Univariate Analysis

We found significantly greater activity to Regulate Negative compared to View Negative in bilateral aspects of the orbital frontal cortex, bilateral aspects of the ventrolateral prefrontal cortex, bilateral aspects of the frontal poles, the left superior frontal gyrus, the left middle frontal gyrus, the left inferior frontal gyrus, the left dorsal lateral prefrontal cortex, and aspects of the right middle temporal gyrus. We observed significantly greater activity to View Negative compared to Regulate Negative trials in aspects of the right premotor cortex, the right middle/inferior temporal gyrus, the right temporal lobe, and the left somatosensory cortex (Table 1).

Table 1: Significantly active clusters in differential [blood-oxygen-level-dependent] contrast between Reappraise Negative and View Negative conditions. Clusters organized by size. Voxels represents the number of contiguous voxels in a cluster. Z-MAX is the maximum Z-value of that cluster, and the coordinates are where Z-MAX is in MNI space.

Cluster Index	Voxels	Location	Z-MAX	Z-MAX X (mm)	Z-MAX Y (mm)	Z-MAX Z (mm)
Reappraise Negative – View Negative						
1	2545	L Superior Frontal Gyrus/Middle Frontal Gyrus (DLPFC)	5.63	-4	12	64
2	2148	L Inferior Frontal Gyrus/Frontal Orbital Cortex (VLPFC)	6.39	-48	22	-22
3	1581	L Lateral Occipital Cortex	5.52	-58	-62	30
4	986	R Orbital Frontal Cortex (VLPFC)	5.98	54	36	-12
5	222	R Middle Temporal Gyrus	5.11	56	-36	0
6	205	R Frontal Pole	4.38	14	58	28
7	111	L Frontal Pole	3.96	-20	52	20
View Negative – Reappraise Negative						
1	973	L Postcentral Gyrus (Primary Somatosensory Cortex)	5.23	-50	-30	50
2	193	R Planum Temporale	4.64	54	-28	12
3	100	R Precentral Gyrus (Premotor Cortex)	4.36	40	-10	68
4	77	R Middle Temporal Gyrus/Inferior Temporal Gyrus	4.11	56	-44	-12

Covariate Analysis

The results of the contrasts between Regulate Negative and View Negative with working memory WAIS score as a predictor above a threshold of 3.1 can be seen in Figure 3. Individual differences in working memory were positively associated with greater differential activity in the right dlPFC/right middle frontal gyrus during the Regulate versus View Negative condition (Table 2). A similar result was found when controlling for age and gender variables. Despite the circularity and non-independence of performing analysis on voxels already selected to show a correlation (Kriegeskorte et al., 2009), to understand whether the effect was being driven by the Reappraise Negative trials, the View Negative trials, or [both,] we created scatterplots and performed follow-up correlational analysis on the dlPFC cluster to visualize the effect (Middle of Figure 3). This visualization suggested that whereas greater activity during the regulate negative condition was associated with greater working memory scores ($p = .007$), greater activity in the view negative condition was not associated with working memory scores ($p = .945$).

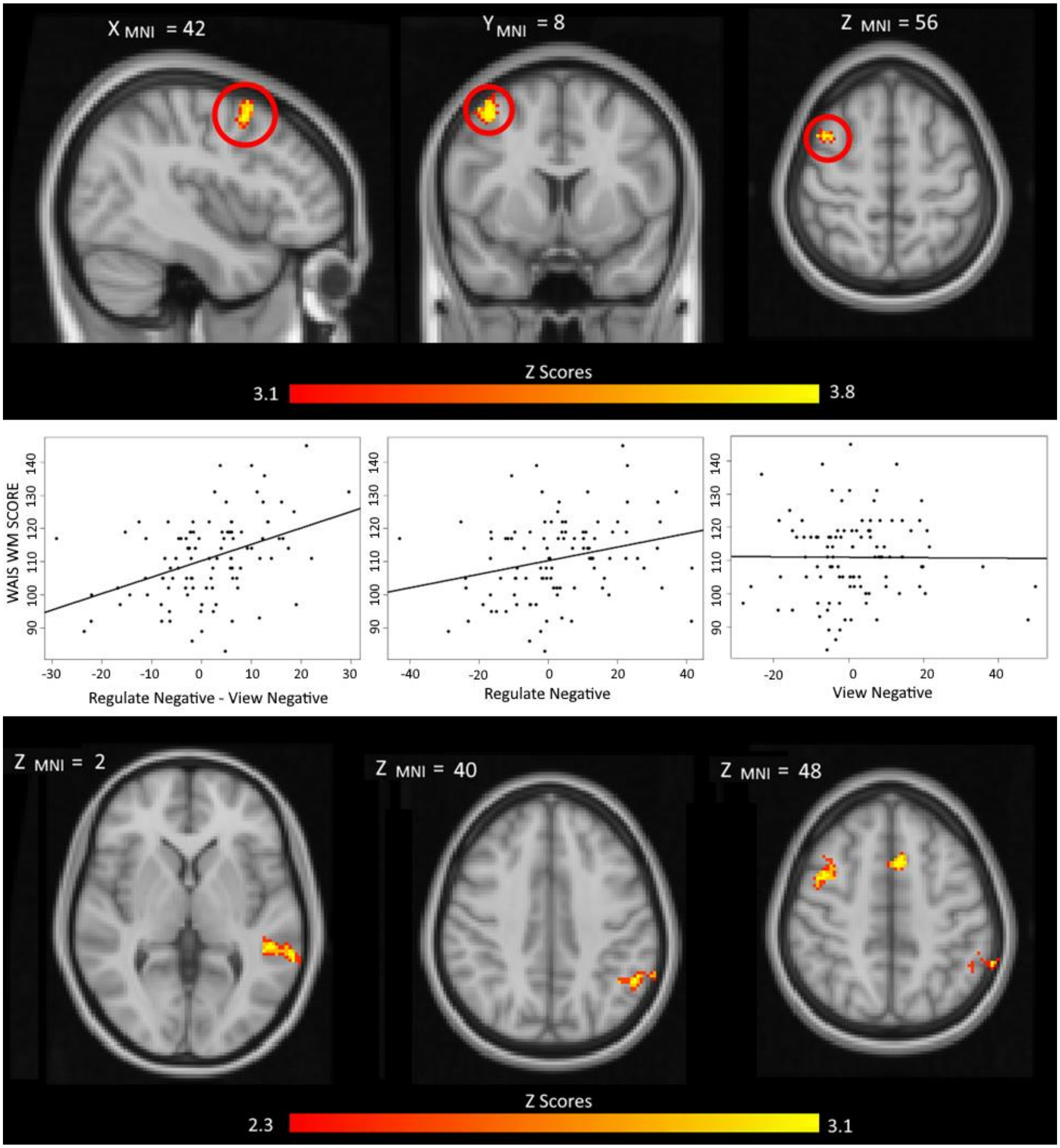

Figure 3: [Blood-oxygen-level-dependent] (BOLD) response of prefrontal activation predicted by working memory at a z-threshold of 3.1 (TOP), scatter plots displaying the relationship between working memory score and BOLD signal extracted from the [dorsolateral prefrontal cortex] cluster circled in red (MIDDLE), and activation predicted by working memory at a z-threshold of 2.3 (BOTTOM). Active brain clusters are displayed on MNI 2mm brain images.

As an exploratory analysis, we also re-ran the covariate analysis with the initial cluster threshold reduced to 2.3. As the primary covariate analysis revealed, working memory was associated again with greater differential [activity] in the right dlPFC. However, we also observed that the left angular gyrus, the bilateral dorsomedial prefrontal cortex (Paracingulate Gyrus), and the left middle temporal gyrus (see Figure 3) were all positively associated with working memory WAIS-IV scores.

Lastly, we also conducted exploratory covariate analyses on each condition independently to follow up on the above with a cluster threshold of 3.1. This revealed a significant positive association between working memory and the regulate negative condition, such that greater working memory [predicted] greater activity in the right dlPFC and bilateral occipital cortex (Table 2). There was no negative association between working memory and activity during regulate negative. There were also no significant clusters for either positive or negative associations between working memory and activity in the view negative condition.

Table 2: Significantly active clusters in differential [blood-oxygen-level-dependent] contrast between Reappraise Negative and View Negative conditions and in the Reappraise Negative condition using working memory as a predictor. Clusters noted here were based on an initial cluster threshold of 3.1 and organized by size. Voxels represents the number of contiguous voxels in a cluster. Z-MAX is the maximum Z-value of that cluster, and the coordinates are where Z-MAX is in MNI space.

Cluster Index	Voxels	Location	Z-MAX	Z-MAX X (mm)	Z-MAX Y (mm)	Z-MAX Z (mm)
Reappraise Negative – View Negative						
1	109	R Middle Frontal Gyrus (DLPFC)	4.22	42	8	56
Reappraise Negative						
1	341	L Posterior Supramarginal Gyrus	4.28	-42	-52	36
2	191	R Posterior Supramarginal Gyrus	4.67	58	-36	42
3	141	L Inferior Frontal Gyrus (DLPFC)	4.23	50	8	12

Multivariate Analysis

The group ICA analysis produced two ICs that were most implicated in working memory. The first IC (ROI 1, Pearson's r = .28) included bilateral frontoparietal regions associated with working memory, including bilateral dlPFC, dmPFC, and dACC, and areas of the superior and inferior parietal cortex. The second IC (ROI 2, Pearson's r = .30) also included aspects of the bilateral dlPFC as well as parts of the lateral occipital cortex. See Figure 4 for detailed ROI maps.

For the MVPA, we completed no feature selection other than using the masks containing the ROIs (See Figure 4 for anatomical extent of the mask and the resulting weights from the analysis; further details regarding linear weights can be found at https://neurovault.org/collections/IHXZNJXZ). Using ROI 1, we found that differential brain activity associated with emotion regulation efficacy was able to predict individual working memory scores significantly better than chance (RMSE = 11.893, *p* = .014). In addition, we found that differential brain activity associated with emotion regulation efficacy was able to predict individual working memory scores significantly better than chance using ROI 2 (RMSE = 12.098, *p* = .042). We found a similar pattern of results after combining both ROIs into a single mask (RMSE = 11.954, *p* = .034) (See Figure 5). However, when performing a whole brain analysis with 10% feature selection, our results were only marginally significant (RMSE = 12.079, *p* = .079).

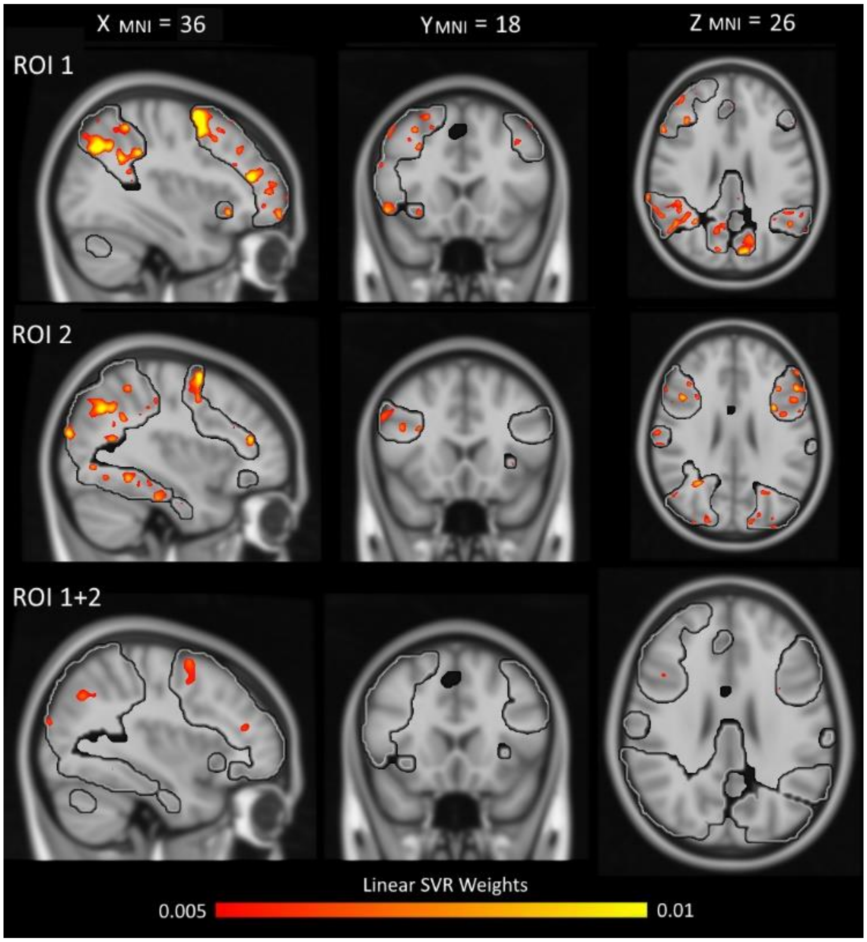

Figure 4: Weighted [multivoxel pattern analysis] maps for [Region of interest (ROI)] 1, ROI 2, and combined ROI maps used in multivariate analyses. The black outline denotes the area of each ROI map. Red and yellow clusters are the areas with the greatest linear weights when

predicting working memory scores. Active brain clusters are displayed on MNI 2mm brain images.

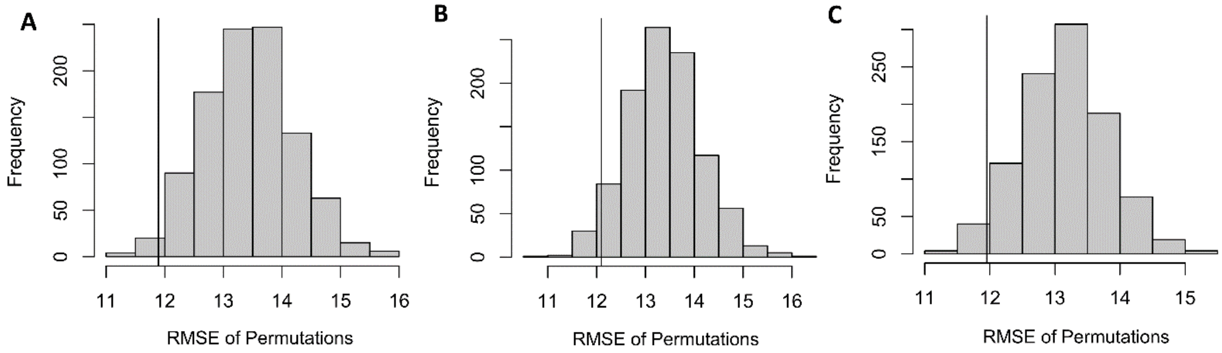

Figure 5: Histograms showing the range of permutation [root mean square errors] for [Region of interest (ROI)] 1 (A), ROI 2 (B), and the combined ROI 1 and 2 mask (C). The solid line on each histogram represents the actual [root mean square error] of the original analysis.

Discussion

The purpose of this study was to determine if working memory and emotion regulation share similar underlying neurocognitive processes. To test this possibility, differential brain activity during reappraisal versus viewing of negative images was used to predict individual differences in working memory ability. First, we conducted an analysis which revealed that working memory significantly covaried with brain activity resulting from the contrast between reappraising images and viewing negative images in the right dorsolateral prefrontal cortex. We also completed an ROI-based MVPA analysis to determine whether activity during emotion regulation predicted working memory ability using stratified 10-fold cross validation. This analysis demonstrated that ROI 1, which included bilateral dlFPC, dmPFC/dACC, and parietal regions, and ROI 2, which included bilateral dlPFC and occipital regions, both predicted working memory ability above chance.

The behavioral results of the presented study demonstrated that working memory performance, as measured using the WAIS-IV score, is positively correlated with emotion regulation efficacy as measured with average self-reported reappraise negative ratings minus average view negative ratings. Specifically, emotion regulation efficacy was positively correlated with working memory performance. The behavioral findings replicate previous research showing that working memory predicts reappraisal performance when measured by a keep track task (Hendricks & Buchanan, 2016) as well as the digit span portion of the WAIS-IV (Opitz et al., 2014). By having participants complete all working memory components of the WAIS-IV (i.e. digit span and arithmetic task), we replicate and further [generalize the] association between reappraisal efficacy and working memory.

The first important finding of the present study is the covariate analysis demonstrating that the differential activity between reappraising and viewing negative images in the right dlPFC positively covaried with individual working memory scores. Although to our knowledge this is a novel finding not previously reported in the literature, it corroborates previous research that the dlPFC is an area of interest in both reappraisal and working memory tasks (Kanske et al., 2011; McRae et al., 2010; Ochsner et al., 2012). Previous research has also shown that dlPFC activity [during] a working memory task predicts self-reported reappraisal frequency (Scult et al., 2017). Moreover, other research has observed that differential dlPFC activity associated with reappraising negative versus looking at negative stimuli is positively correlated with emotion regulation success (Kanske et al., 2011; McRae et al., 2010). Together with the previous literature, the present results support the idea of the right dlPFC being implicated in both emotional reappraisal and working memory, but also further suggests that the neural mechanisms associated with successful emotion regulation are at least correlated with working memory.

We also observed that activity in additional fronto-parietal regions (bilateral dmPFC and angular gyrus) positively covaried with working memory. Although these findings were the result of the more liberal exploratory analysis using a cluster forming threshold of Z=2.3, they are consistent with the inference that brain regions commonly associated with working memory ability (Curtis & D'Esposito, 2003; Dolcos et al., 2013) are contributing to the process of emotion regulation. Likewise, previous research comparing brain activity elicited during reappraisal versus working memory-based distraction of emotional pictures found similar activity in the dmPFC and lateral parietal regions (Kanske et al., 2011; McRae et al., 2010).

Extending beyond the covariate [analysis, we] also observed that MVPA with stratified 10-fold cross validation using the pattern of brain activity in our two ROIs on the differences between reappraising and viewing negative images could be used to predict working memory performance on the WAIS-IV significantly above chance. Differential brain activity while reappraising and viewing negative images predicted working memory when using ROI 1, ROI 2, and a combined mask of ROIs 1 and 2. Both ROI 1 and 2 included bilateral [aspects] of dlPFC and aspects of dmPFC/dACC. This pattern is in line with previous research showing that brain activity during a working memory task is correlated with how often one used reappraisal (Scult et al., 2017). Rather than simply demonstrating the reverse of Scult et al. (2017), our finding further contributes to the research by including a biological measure of reappraisal efficacy (i.e., fMRI activity) rather than self-reported questionnaire data. More broadly, our novel findings extend beyond the previous correlational research by demonstrating that individual differences in working memory can be predicted in an unbiased manner from the neural representation pattern elicited by emotion regulation.

In terms of the brain regions associated with emotion regulation and working memory, the involvement of the dlPFC was observed in both the covariate and MVPA analyses, which is consistent with previous literature (Kanske et al., 2011; McRae et al., 2010). Activity in the dlPFC is also associated with top-down processing (Blair & Mitchell, 2009), which may explain its role in the cognition-driven reappraisal. The present results implicating the dmPFC/dACC in addition to the dlPFC also coincides with previous research. For example, Schweizer et al. (2013) found that working memory training was able to improve emotion regulation as well as increase recruitment of both medial (i.e., dmPFC/dACC) and lateral areas of the prefrontal cortex during activation emotion regulation (Schweizer et al., 2013). While there is no consensus on whether the dlPFC versus the dmPFC/dACC make unique contributions to working memory and emotion regulation, there are several theories about their roles. One theory is that the dmPFC/dACC is associated with emotional appraisals (Maier et al., 2012) and emotion regulation (Greening et al., 2013; Silvers et al., 2015) alongside working memory. Alternatively, the medial prefrontal areas are associated with emotional attention and pulling resources from prefrontal areas (Pessoa, 2009). Therefore, emotional stimuli pull resources from the dlPFC typically associated with working memory, thus impairing working memory performance. Alternatively, the dmPFC/dACC may signal to the dlPFC when cognitive control or emotion regulation is necessary (Mitchell, 2011). Therefore, it is possible that emotion regulation and working memory compete for the same resources, likely those within the central executive. The central executive system plays a role in attention and performance involved in working memory (Baddeley, 2003). However, in the presence of an emotional stimulus, attention and working memory are required in order to regulate that stimulus (Pessoa, 2009), taking from those resources. The MVPA analysis also found evidence of bilateral inferior parietal lobe being involved in working memory and emotion regulation. Prior research has found the inferior parietal lobe to be implicated in networks associated with neural emotion regulation efficacy (Morawetz et al., 2016) and but also necessary for working memory performance (Alain et al., 2008; Olson & Berryhill, 2009).

The present study is the first of our knowledge to use MVPA on emotion regulation data to predict individual differences in working memory. MVPA with cross-validation advances our knowledge of emotion regulation and working memory as it serves as a robust unbiased approach for measuring the predictive effect size of brain activity on behaviour, and therefore the generalizability of the prediction model to individual differences (Gabrieli et al., 2015; Zhou et al., 2021). It has also proved to be useful for uncovering the neurocognitive mechanisms of emotion regulation in other contexts. For example, MVPA has been used to differentiate brain activity during reappraisal from brain activity during distraction (Martins et al., 2014). MVPA has also been used to determine whether emotions were being up-regulated or down-regulated (Morawetz et al., 2016). While Martins et al. (2014) and Morawetz et al. (2016) used support vector [classification], which is appropriate for categorical data, SVR is a useful tool for predicting continuous data such as individual differences. For example, SVR has been used previously to predict individual differences in working memory capacity (Ullman et al., 2014). By moving beyond a simple correlational or covariate [analysis and] using the more robust method of MVPA with cross-validation, this study further supports the role of prefrontal areas in emotion regulation being predictive of working memory ability. In addition, our findings support the idea that the neural mechanisms involved in working memory are quantitatively similar to those mechanisms associated with emotion regulation.

According to the modal model of emotion regulation, emotion regulation consists of situation focused, attention focused, cognition focused, and response focused stages (Gross, 2002, 2014). The cognition stage of emotion regulation is particularly important as it is the phase during which reappraisal takes place (Gross, 2002). The SOC-ER model posits that to successfully regulate emotions, cognitive processes are required to select an emotion regulation method, optimize it, and compensate for any emotion regulation failures (Opitz et al., 2012; Urry & Gross, 2010). As our findings support the notion that emotion regulation, particularly reappraisal, is underpinned by a cognitive process shared with working memory, it implies that if a person does not have the proper working memory resources, their reappraisal of the stimulus is less likely to be successful. This is of interest as cognition-based methods of emotion regulation, such as reappraisal, are considered very effective forms of emotion regulation (Gross & John, 2003). If someone is unable to properly reappraise, they may have a difficult time decreasing negative emotion and struggle with coping strategies. This emotion regulation failure, or emotion dysregulation, can occur when cognitive processes, such as working memory, are impaired. Emotion dysregulation is a cornerstone of several mental illnesses, particularly anxiety and mood disorders (S. G. Hofmann et al., 2012). In a similar vein, impaired executive function, including working memory, is associated with similar mental illnesses (Snyder et al., 2015). According to the SOC-ER model, these issues with executive dysfunction would mean a person lacks the necessary cognitive resources to regulate their emotions properly (Opitz et al., 2012), which in turn causes anxiety and mood disorders to form (S. G. Hofmann et al., 2012).

As [the] present study was not [preregistered], a preregistered replication is needed to determine if this finding can be found in confirmatory contexts. Different settings and participant populations will also help identify if the findings generalize. Another limitation to the study is that it is possible participants were regulating the image in the view condition, as they were instructed to respond naturally to the image, which may imply regulation, though the self-reported rating suggest otherwise. Future research could focus on whether brain activity during reappraisal affects other aspects of executive function. Aside from working memory, executive function also consists of inhibition and shifting attention, and these three aspects of executive function share some overlap (Friedman & Miyake, 2017; Miyake et al., 2000). Executive function is driven by activity in the prefrontal cortex (Friedman & Miyake, 2017), and activation in the dmPFC/dACC from emotional attention pulls prefrontal resources associated with executive function (Pessoa, 2009). This suggests that other forms of executive function (i.e. inhibition and shifting) may impact emotion regulation as well. Executive function is necessary to maintain, monitor, switch, and stop emotion regulation methods (Pruessner et al., 2020). In addition, there is evidence that other forms of executive function, inhibition and shifting, have behavioral associations with working memory (Schmeichel & Tang, 2015). Therefore, it is possible that differential emotion regulation activity may predict inhibition and switching performance. Future research could also look at the role the dlPFC plays in emotion regulation during high intensity or stressful situations, or how the dlPFC mediates the role adversity plays in emotion regulation efficacy. Previous research has found the left dlPFC is implicated in resilience in the face of adversity (Brosch et al., 2022; Cisler et al., 2013). Considering the role of the dlPFC during both reappraisal and working memory, as well as the lack of activity in the dlPFC when looking at an emotional [image,] it may be possible that intense negative emotions may inhibit the dlPFC, leading to poorer emotion regulation efficacy and worse resilience.

In summary, our study supports the notion that emotion regulation and working memory performance are supported by at least partially shared neurocognitive processes. This study not only further solidifies existing work by showing that working memory ability is a cognitive resource which drives instructed emotion regulation efficacy correlationally, but it also demonstrated that individual differences in working memory performance can be predicted from neural activity during emotion regulation using MVPA and cross-validation. Therefore, working memory capacity may serve as a cognitive resource necessary for emotion regulation success. This is of importance because successful emotion regulation is necessary for wellbeing.

Declarations

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Conflict of Interest

None of the authors have any conflicts of interest to declare.

Ethics Approval

This work was approved by the University of Southern California IRB and University of Manitoba REB.

Consent to participate and Consent to publication

Informed consent was received for all participants in this study.

Availability of data and materials

N/A

Code availability

N/A

[Chapter 3] References

Alain, C., He, Y., & Grady, C. (2008). The Contribution of the Inferior Parietal Lobe to Auditory Spatial Working Memory. *Journal of Cognitive Neuroscience*, *20*(2), 285–295. https://doi.org/10.1162/jocn.2008.20014

Baddeley, A. (2003). Working memory and language: An overview. *Journal of Communication Disorders*, *36*(3), 189–208. https://doi.org/10.1016/S0021-9924(03)00019-4

Beckmann, C. F., Jenkinson, M., & Smith, S. M. (2003). General multilevel linear modeling for group analysis in FMRI. *NeuroImage*, *20*(2), 1052–1063. https://doi.org/10.1016/S1053-8119(03)00435-X

Behzadi, Y., Restom, K., Liau, J., & Liu, T. T. (2007). A component based noise correction method (CompCor) for BOLD and perfusion based fMRI. *NeuroImage*, *37*(1), 90–101. https://doi.org/10.1016/j.neuroimage.2007.04.042

Blair, R. J. R., & Mitchell, D. G. V. (2009). Psychopathy, attention and emotion. *Psychological Medicine*, *39*(4), 543–555. https://doi.org/10.1017/S0033291708003991

Brosch, K., Stein, F., Meller, T., Schmitt, S., Yuksel, D., Ringwald, K. G., Pfarr, J. K., Waltemate, L., Lemke, H., Opel, N., Meinert, S., Dohm, K., Grotegerd, D., Goltermann, J., Repple, J., Winter, A., Jansen, A., Dannlowski, U., Nenadić, I., … Krug, A. (2022). DLPFC volume is a neural correlate of resilience in healthy high-risk individuals with both childhood maltreatment and familial risk for depression. *Psychological Medicine, 52*(16), 4139–4145. https://doi.org/10.1017/S0033291721001094

Buhle, J. T., Silvers, J. A., Wager, T. D., Lopez, R., Onyemekwu, C., Kober, H., Weber, J., & Ochsner, K. N. (2014). Cognitive Reappraisal of Emotion: A Meta-Analysis of Human

Neuroimaging Studies. *Cerebral Cortex*, *24*(11), 2981–2990. https://doi.org/10.1093/cercor/bht154

Cisler, J. M., James, G. A., Tripathi, S., Mletzko, T., Heim, C., Hu, X. P., Mayberg, H. S., Nemeroff, C. B., & Kilts, C. D. (2013). Differential functional connectivity within an emotion regulation neural network among individuals resilient and susceptible to the depressogenic effects of early life stress. *Psychological Medicine*, *43*(3), 507–518. https://doi.org/10.1017/S0033291712001390

Cox, R. W., & Hyde, J. S. (1997). Software tools for analysis and visualization of fMRI data. *NMR in Biomedicine*, *10*(4–5), 171–178. https://doi.org/10.1002/(SICI)1099-1492(199706/08)10:4/5<171::AID-NBM453>3.0.CO;2-L

Curtis, C. E., & D’Esposito, M. (2003). Persistent activity in the prefrontal cortex during working memory. In *Trends in Cognitive Sciences* (Vol. 7, Issue 9, pp. 415–423). Elsevier Ltd. https://doi.org/10.1016/S1364-6613(03)00197-9

Denny, B. T., Inhoff, M. C., Zerubavel, N., Davachi, L., & Ochsner, K. N. (2015). Getting over it: Long-lasting effects of emotion regulation on amygdala response. *Psychological Science, 26*(9), 1377–1388. https://doi.org/10.1177/0956797615578863

Dolcos, F., Iordan, A. D., Kragel, J., Stokes, J., Campbell, R., McCarthy, G., & Cabeza, R. (2013). Neural correlates of opposing effects of emotional distraction on working memory and episodic memory: An event-related fMRI investigation. *Frontiers in Psychology*, *4*(JUN), 1–16. https://doi.org/10.3389/fpsyg.2013.00293

Dolcos, F., & McCarthy, G. (2006). Brain systems mediating cognitive interference by emotional distraction. *Journal of Neuroscience*, *26*(7), 2072–2079. https://doi.org/10.1523/JNEUROSCI.5042-05.2006

Friedman, N. P., & Miyake, A. (2017). Unity and diversity of executive functions: Individual differences as a window on cognitive structure. *Cortex*, *86*, 186–204. https://doi.org/10.1016/j.cortex.2016.04.023

Gabrieli, J. D. E., Ghosh, S. S., & Whitfield-Gabrieli, S. (2015). Prediction as a humanitarian and pragmatic contribution from human cognitive neuroscience. *Neuron, 85*(1), 11–26. https://doi.org/10.1016/j.neuron.2014.10.047

Glasser, M. F., Sotiropoulos, S. N., Wilson, J. A., Coalson, T. S., Fischl, B., Andersson, J. L., Xu, J., Jbabdi, S., Webster, M., Polimeni, J. R., Van Essen, D. C., & Jenkinson, M. (2013). The minimal preprocessing pipelines for the Human Connectome Project. *NeuroImage, 80*, 105–124. https://doi.org/10.1016/j.neuroimage.2013.04.127

Goldin, P. R., McRae, K., Ramel, W., & Gross, J. J. (2008). The neural bases of emotion regulation: Reappraisal and suppression of negative emotion. *Biological Psychiatry*, *63*(6), 577–586. https://doi.org/10.1016/j.biopsych.2007.05.031

Greening, S. G., & Mitchell, D. G. V. (2015). A network of amygdala connections predict individual differences in trait anxiety. *Human Brain Mapping*, *36*(12), 4819–4830. https://doi.org/10.1002/hbm.22952

Greening, S. G., Osuch, E. A., Williamson, P. C., & Mitchell, D. G. V. (2013). Emotion-related brain activity to conflicting socio-emotional cues in unmedicated depression. *Journal of Affective Disorders*, *150*(3), 1136–1141. https://doi.org/10.1016/j.jad.2013.05.053

Greening, S. G., Osuch, E. A., Williamson, P. C., & Mitchell, D. G. V. (2014). The neural correlates of regulating positive and negative emotions in medication-free major depression. *Social Cognitive and Affective Neuroscience*, *9*(5), 628–637. https://doi.org/10.1093/scan/nst027

Greve, D. N., & Fischl, B. (2009). Accurate and robust brain image alignment using boundary-based registration. *NeuroImage*, *48*(1), 63–72. https://doi.org/10.1016/j.neuroimage.2009.06.060

Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. *Review of General Psychology*, *2*(3), 271–299. https://doi.org/https://doi.org/10.1037/1089-2680.2.3.271

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology*, *39*, 281–291. https://doi.org/10.1002/9780470177334.ch3

Gross, J. J. (2014). *Emotion regulation: Conceptual and empirical foundations*.

Gross, J. J., & John, O. P. (2003). Individual Differences in Two Emotion Regulation Processes: Implications for Affect, Relationships, and Well-Being. *Journal of Personality and Social Psychology*, *85*(2), 348–362. https://doi.org/10.1037/0022-3514.85.2.348

Hendricks, M. A., & Buchanan, T. W. (2016). Individual differences in cognitive control processes and their relationship to emotion regulation. *Cognition and Emotion*, *30*(5), 912–924. https://doi.org/10.1080/02699931.2015.1032893

Hendriks, M. H. A., Daniels, N., Pegado, F., & Op de Beeck, H. P. (2017). The Effect of Spatial Smoothing on Representational Similarity in a Simple Motor Paradigm. *Frontiers in Neurology*, *8*. https://doi.org/10.3389/fneur.2017.00222

Hofmann, S. G., Sawyer, A. T., Fang, A., & Asnaani, A. (2012). Emotion dysregulation model of mood and anxiety disorders. *Depression and Anxiety*, *29*(5), 409–416. https://doi.org/10.1002/da.21888

Hofmann, W., Schmeichel, B. J., & Baddeley, A. D. (2012). Executive functions and self-regulation. *Trends in Cognitive Sciences*, *16*(3), 174–180. https://doi.org/10.1016/j.tics.2012.01.006

Hughes, G. (1968). On the mean accuracy of statistical pattern recognizers. *IEEE Transactions on Information Theory*, *14*(1), 55–63. https://doi.org/10.1109/TIT.1968.1054102

Jasielska, A., Kaczmarek, L., Brońska, A., Dominiak, M., Niemier, K., Patalas, D., Sokołowski, A., & Tomczak, M. (2015). The relationship between working memory and emotion regulation strategies. *Annals of Psychology*, *18*(4), 567–578.

Jenkinson, M., Bannister, P., Brady, M., & Smith, S. (2002). Improved optimization for the robust and accurate linear registration and motion correction of brain images. *NeuroImage*, *17*(2), 825–841. https://doi.org/10.1006/nimg.2002.1132

Kanske, P., Heissler, J., Schönfelder, S., Bongers, A., & Wessa, M. (2011). How to regulate emotion? Neural networks for reappraisal and distraction. *Cerebral Cortex*, *21*(6), 1379–1388. https://doi.org/10.1093/cercor/bhq216

Kriegeskorte, N., Simmons, W. K., Bellgowan, P. S., & Baker, C. I. (2009). Circular analysis in systems neuroscience: The dangers of double dipping. *Nature Neuroscience*, *12*(5), 535–540. https://doi.org/10.1038/nn.2303

Lanczos, C. (1964). Evaluation of Noisy Data. *Journal of the Society for Industrial and Applied Mathematics Series B Numerical Analysis*, *1*(1), 76–85. https://doi.org/10.1137/0701007

Lee, T. W., & Xue, S. W. (2018). Does emotion regulation engage the same neural circuit as working memory? A meta-analytical comparison between cognitive reappraisal of negative emotion and 2-back working memory task. *PLoS ONE*, *13*(9). https://doi.org/10.1371/journal.pone.0203753

Maier, S., Szalkowski, A., Kamphausen, S., Perlov, E., Feige, B., Blechert, J., Philipsen, A., van Elst, L. T., Kalisch, R., & Tüscher, O. (2012). Clarifying the Role of the Rostral dmPFC/dACC in Fear/Anxiety: Learning, Appraisal or Expression? *PLoS ONE*, *7*(11). https://doi.org/10.1371/journal.pone.0050120

Marek, S., Tervo-Clemmens, B., Calabro, F. J., Montez, D. F., Kay, B. P., Hatoum, A. S., Donohue, M. R., Foran, W., Miller, R. L., Hendrickson, T. J., Malone, S. M., Kandala, S., Feczko, E., Miranda-Dominguez, O., Graham, A. M., Earl, E. A., Perrone, A. J., Cordova, M., Doyle, O., … Dosenbach, N. U. F. (2022). Reproducible brain-wide association studies require thousands of individuals. *Nature*, *603*(7902), 654–660. https://doi.org/10.1038/s41586-022-04492-9

Martins, B., Ponzio, A., Velasco, R., Kaplan, J., & Mather, M. (2014). Dedifferentiation of emotion regulation strategies in the aging brain. *Social Cognitive and Affective Neuroscience*, *10*(6), 840–847. https://doi.org/10.1093/scan/nsu129

McRae, K., Hughes, B., Chopra, S., Gabrieli, J. D. E., Gross, J. J., & Ochsner, K. N. (2010). The neural bases of distraction and reappraisal. *Journal of Cognitive Neuroscience*, *22*(2), 248–262. https://doi.org/10.1162/jocn.2009.21243

Misaki, M., Kim, Y., Bandettini, P. A., & Kriegeskorte, N. (2010). Comparison of multivariate classifiers and response normalizations for pattern-information fMRI. *NeuroImage*, *53*(1), 103–118. https://doi.org/10.1016/j.neuroimage.2010.05.051

Mitchell, D. G. V. (2011). The nexus between decision making and emotion regulation: A review of convergent neurocognitive substrates. *Behavioural Brain Research*, *217*(1), 215–231. https://doi.org/10.1016/j.bbr.2010.10.030

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex “frontal lobe” tasks: A latent variable analysis. *Cognitive Psychology*, *41*(1), 49–100. https://doi.org/10.1006/cogp.1999.0734

Morawetz, C., Bode, S., Baudewig, J., Jacobs, A. M., & Heekeren, H. R. (2016). Neural representation of emotion regulation goals. *Human Brain Mapping*, *37*(2), 600–620. https://doi.org/10.1002/hbm.23053

Morey, R. A., Dolcos, F., Petty, C. M., Cooper, D. A., Hayes, J. P., LaBar, K. S., & McCarthy, G. (2009). The role of trauma-related distractors on neural systems for working memory and emotion processing in posttraumatic stress disorder. *Journal of Psyciatric Resilience*, *43*(8), 809–817. https://doi.org/10.1016/j.jpsychires.2008.10.014.The

Ochsner, K. N., Ray, R. D., Cooper, J. C., Robertson, E. R., Chopra, S., Gabrieli, J. D. E., & Gross, J. J. (2004). For better or for worse: Neural systems supporting the cognitive down- and up-regulation of negative emotion. *NeuroImage*, *23*(2), 483–499. https://doi.org/10.1016/j.neuroimage.2004.06.030

Ochsner, K. N., Silvers, J. A., & Buhle, J. T. (2012). Functional imaging studies of emotion regulation: A synthetic review and evolving model of the cognitive control of emotion. *Annals of the New York Academy of Sciences*, *1251*, 1–24. https://doi.org/10.1111/j.1749-6632.2012.06751.x.Functional

Olson, I. R., & Berryhill, M. (2009). Some surprising findings on the involvement of the parietal lobe in human memory. *Neurobiology of Learning and Memory*, *91*(2), 155–165. https://doi.org/10.1016/j.nlm.2008.09.006

Op de Beeck, H. P. (2010). Against hyperacuity in brain reading: Spatial smoothing does not hurt multivariate fMRI analyses? *NeuroImage*, *49*(3), 1943–1948. https://doi.org/10.1016/j.neuroimage.2009.02.047

Opitz, P. C., Gross, J. J., & Urry, H. L. (2012). Selection, optimization, and compensation in the domain of emotion regulation: Applications to adolescence, older age, and major depressive disorder. *Social and Personality Psychology Compass*, *6*(2), 142–155. https://doi.org/10.1111/j.1751-9004.2011.00413.x

Opitz, P. C., Lee, I. A., Gross, J. J., & Urry, H. L. (2014). Fluid cognitive ability is a resource for successful emotion regulation in older and younger adults. *Frontiers in Psychology*, *5*(JUN), 1–13. https://doi.org/10.3389/fpsyg.2014.00609

Pessoa, L. (2009). How do emotion and motivation direct executive control? *Trends in Cognitive Sciences*, *13*(4), 160–166. https://doi.org/10.1016/j.tics.2009.01.006

Poldrack, R. A. (2008). The role of fMRI in Cognitive Neuroscience: where do we stand? In *Current Opinion in Neurobiology* (Vol. 18, Issue 2, pp. 223–227). https://doi.org/10.1016/j.conb.2008.07.006

Power, J. D., Mitra, A., Laumann, T. O., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2014). Methods to detect, characterize, and remove motion artifact in resting state fMRI. *NeuroImage*, *84*, 320–341. https://doi.org/10.1016/j.neuroimage.2013.08.048

Pruessner, L., Barnow, S., & Holt, D. V. (2020). A cognitive control framework for understanding emotion regulation flexibility. *Emotion*, *20*(1), 21–29. https://doi.org/10.1037/emo0000658.supp

Pruim, R. H. R., Mennes, M., Buitelaar, J. K., & Beckmann, C. F. (2015). Evaluation of ICA-AROMA and alternative strategies for motion artifact removal in resting state fMRI. *NeuroImage*, *112*, 278–287. https://doi.org/10.1016/j.neuroimage.2015.02.063

Satterthwaite, T. D., Elliott, M. A., Gerraty, R. T., Ruparel, K., Loughead, J., Calkins, M. E., Eickhoff, S. B., Hakonarson, H., Gur, R. C., Gur, R. E., & Wolf, D. H. (2013). An improved framework for confound regression and filtering for control of motion artifact in the preprocessing of resting-state functional connectivity data. *NeuroImage*, *64*, 240–256. https://doi.org/10.1016/j.neuroimage.2012.08.052

Schmeichel, B. J., & Tang, D. (2015). Individual differences in executive functioning and their relationship to emotional processes and responses. *Current Directions in Psychological Science*, *24*(2), 93–98. https://doi.org/10.1177/0963721414555178

Schweizer, S., Grahn, J., Hampshire, A., Mobbs, D., & Dalgleish, T. (2013). Training the emotional brain: Improving affective control through emotional working memory training. *Journal of Neuroscience*, *33*(12), 5301–5311. https://doi.org/10.1523/JNEUROSCI.2593-12.2013

Scult, M. A., Knodt, A. R., Swartz, J. R., Brigidi, B. D., & Hariri, A. R. (2017). Thinking and Feeling: Individual Differences in Habitual Emotion Regulation and Stress-Related Mood Are Associated With Prefrontal Executive Control. *Clinical Psychological Science*, *5*(1), 150–157. https://doi.org/10.1177/2167702616654688

Silvers, J. A., Weber, J., Wager, T. D., & Ochsner, K. N. (2015). Bad and worse: Neural systems underlying reappraisal of high-and low-intensity negative emotions. *Social Cognitive and Affective Neuroscience*, *10*(2), 172–179. https://doi.org/10.1093/scan/nsu043

Smith, R., Lane, R. D., Alkozei, A., Bao, J., Smith, C., Sanova, A., Nettles, M., & Killgore, W. D. S. (2018). The role of medial prefrontal cortex in the working memory maintenance of one's own emotional responses. *Scientific Reports*, *8*(1). https://doi.org/10.1038/s41598-018-21896-8

Snyder, H. R., Miyake, A., & Hankin, B. L. (2015). Advancing understanding of executive function impairments and psychopathology: Bridging the gap between clinical and cognitive approaches. *Frontiers in Psychology*, *6*(MAR). https://doi.org/10.3389/fpsyg.2015.00328

Tavares, T. P., Logie, K., & Mitchell, D. G. V. (2016). Opposing effects of perceptual versus working memory load on emotional distraction. *Experimental Brain Research*, *234*(10), 2945–2956. https://doi.org/10.1007/s00221-016-4697-2

Ullman, H., Almeida, R., & Klingberg, T. (2014). Structural maturation and brain activity predict future working memory capacity during childhood development. *Journal of Neuroscience*, *34*(5), 1592–1598. https://doi.org/10.1523/JNEUROSCI.0842-13.2014

Urry, H. L., & Gross, J. J. (2010). Emotion regulation in older age. *Current Directions in Psychological Science*, *19*(6), 352–357. https://doi.org/10.1177/0963721410388395

Wager, T. D., Atlas, L. Y., Leotti, L. A., & Rilling, J. K. (2011). Predicting individual differences in placebo analgesia: Contributions of brain activity during anticipation and pain experience. *Journal of Neuroscience*, *31*(2), 439–452. https://doi.org/10.1523/JNEUROSCI.3420-10.2011

Wechsler, D. (2008). *Wechsler Adult Intelligence Scale--Fourth Edition (WAIS-IV) [Database record].*

Woo, C.-W., Koban, L., Kross, E., Lindquist, M. A., Banich, M. T., Ruzic, L., Andrews-Hanna, J. R., & Wager, T. D. (2014). Separate neural representations for physical pain and social rejection. *Nature Communications*, *5*(1), 5380. https://doi.org/10.1038/ncomms6380

Woolrich, M. (2008). Robust group analysis using outlier inference. *NeuroImage*, *41*(2), 286–301. https://doi.org/10.1016/j.neuroimage.2008.02.042

Woolrich, M., Behrens, T. E. J., Beckmann, C. F., Jenkinson, M., & Smith, S. M. (2004). Multilevel linear modelling for FMRI group analysis using Bayesian inference. *NeuroImage*, *21*(4), 1732–1747. https://doi.org/10.1016/j.neuroimage.2003.12.023

Woolrich, M., Ripley, B. D., Brady, M., & Smith, S. M. (2001). Temporal Autocorrelation in Univariate Linear Modeling of FMRI Data. *NeuroImage*, *14*(6), 1370–1386. https://doi.org/10.1006/nimg.2001.0931

Worsley, K. J. (2001). Statistical analysis of activation images. *Functional MRI: An Introduction to Methods* , *14*(1), 251–270.

Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. *Nature Methods*, *8*(8), 665–670. https://doi.org/10.1038/nmeth.1635

Zhou, F., Zhao, W., Qi, Z., Geng, Y., Yao, S., Kendrick, K. M., Wager, T. D., & Becker, B. (2021). A distributed fMRI-based signature for the subjective experience of fear. *Nature Communications*, *12*(1). https://doi.org/10.1038/s41467-021-26977-3

Chapter 4: It's all connected! Multivariate pattern analysis of inter-network connectivity distinguishes between reappraisal and passive viewing of emotional scenes

Abstract

Down-regulation using reappraisal is typically associated with negative connectivity between prefrontal areas such as the dorsolateral prefrontal cortex (dlPFC) and salient areas like the insula and the amygdala. The former areas are associated with cognitive networks such as the frontoparietal networks and the attentional control network (ACN), while the latter is associated with emotional networks such as the salience network (SN) and the limbic network. In addition, the default mode network (DMN) has been shown to contribute to emotion regulation. The purpose of this study was to determine using multivariate pattern analysis (MVPA) if inter-network functional connectivity could predict whether a person was reappraising or passively viewing a negative image. Thirty-one participants completed a magnetic resonance imaging (MRI) task in which they viewed and reappraised series of images. Using independent component derived networks and dual regression, we determined functional connectivity between each network during the reappraisal and viewing tasks. A univariate analysis determined that connections between aspects of the DMN and ACN differed between reappraisal and view conditions. The MVPA determined whether someone was reappraising or viewing an image could be predicted better than task, with connections involving the above networks being reliable contributors to the model. These findings support the idea that multiple networks contribute to the emotion regulation process.

Introduction

Reappraisal is a form of emotion regulation in which one changes one's thoughts or interpretations of an emotional stimulus to change or maintain their emotional state (Gross, 1998, 2002). The Selection, Optimization, and Compensation with Emotion Regulation (SOC-ER) model states that the success of emotion regulation, including reappraisal, hinges on available internal resources (Opitz et al., 2012; Urry & Gross, 2010). Internal resources refer to an umbrella term that includes task-based measures of executive function or the magnitude of brain activity in regions such as the dorsolateral prefrontal cortex (dlPFC), ventrolateral prefrontal cortex (vlPFC), and the ventromedial prefrontal cortex (vmPFC) (Goldin et al., 2008; McRae et al., 2010). However, another potential internal resource that has received much less consideration is functional connectivity between canonical intrinsic brain networks such as the attention control network (ACN), the salience network (SN) or the default mode network (DMN). Previous research has shown that differences in inter-network connectivity in the brain may be associated with reappraising versus viewing emotional scenes (Sripada et al., 2014). However, there is no research regarding the individual contributions of connections between intrinsic functional networks in emotion regulation.

On a univariate level, reappraisal is generally associated with greater activation of lateral frontoparietal networks, which include aspects of the dlPFC and vlPFC (McRae et al., 2010; Ochsner et al., 2012). A recurring finding is that the dlPFC is associated with reappraisal as well as several other forms of emotion regulation including distraction (Buhle et al., 2014; Kanske et al., 2011; McRae et al., 2010; Ochsner et al., 2012; Silvers et al., 2015). Individual difference research has found greater activity in the dlPFC to be associated with greater regulation ability (Drabant et al., 2009; Greening et al., 2014; Horner et al., 2024). Univariate research has also implicated the vlPFC (Buhle et al., 2014; Goldin et al., 2008; Silvers et al., 2015; Wager et al., 2008) in emotion regulation. In addition, aspects of the parietal lobe are also activated in some reappraisal studies (Buhle et al., 2014; Kanske et al., 2011; McRae et al., 2010). While many of the previous univariate findings do not evaluate functional connectivity differences, they allude to the potential networks involved in emotion regulation, in particular, the frontoparietal networks and the attention control network (ACN). The left frontoparietal network is believed to be involved in language and working memory performance, while the right frontoparietal network is associated with memory, including working memory, divided attention, and inhibition (Laird et al., 2011). Previous research has also shown that the frontoparietal network contributes to emotion regulation performance (Moreira et al., 2021; Schweizer et al., 2013; Wessing et al., 2015). Additionally, the ACN is associated with attentional orienting, and attention and cognitive control (Roye et al., 2020). Moreover, the ACN is implicated in reappraisal (Sripada et al., 2014; Viviani, 2013).

Reappraisal is also associated with the suppression or inhibition of areas such as the insula and amygdala. Univariate analyses find decreases in insula activity during the down-regulation of emotion (Goldin et al., 2008; Min et al., 2022). The insula is commonly associated with the salience network (SN), which is associated with attention to emotional stimuli (Menon & Uddin, 2010) and emotion regulation (Denny et al., 2018; Morawetz, Kellermann, et al., 2016). In addition, in univariate studies the down-regulation of negative emotions by reappraisal is associated with the down-regulation of the amygdala (Buhle et al., 2014; Goldin et al., 2008; Kanske et al., 2011; McRae et al., 2010; Ochsner et al., 2012). The amygdala is typically associated with the limbic network, which plays a role in emotional responses (Laird et al., 2011;

Lee & Telzer, 2016). The limbic network also decreases in activity during emotional down-regulation (Moreira et al., 2021).

The ventromedial PFC (vmPFC) is another important region in either the down-regulation of the amygdala (Hermann et al., 2021; Johnstone et al., 2007) or the up-regulation of positive affect (Greening et al., 2014), especially owing to its robust and direct connections to the amygdala unlike aspects of the lateral frontoparietal lobes (Mitchell, 2011). Additionally, the posterior medial cortex (PMC) can be more active during reappraisal (McRae et al., 2010). From an intrinsic network perspective, the vmPFC and PMC are core aspects of the default mode network (DMN). The DMN also includes secondary aspects such as the angular gyrus and hippocampus (Buckner et al., 2008; Laird et al., 2011). It is implicated in mind wandering (K. C. R. Fox et al., 2015), self-referential processing (Finn, 2021; Gusnard et al., 2001), episodic memory, and imagining the future (Buckner et al., 2008). The DMN is also associated with the processing of emotion (Saarimäki et al., 2022), with weaker connectivity within the DMN associated with less emotionality during habituation (Min et al., 2024). With respect to emotion regulation, greater emotion regulation ability is associated with less positive connectivity between the PMC and the vmPFC (Fresco et al., 2017; Lieberman et al., 2023). Moreover, resting-state functional connectivity within the DMN has also been associated with greater self-reported reappraisal and suppression (Chen et al., 2024). While these results may seem mixed, they suggest that the DMN may play a nuanced and underappreciated role in emotion regulation.

As these networks all seem to contribute to emotion regulation, it is possible that the pattern of connections between networks also contribute to emotion regulation. For example, task-based connectivity analyses during emotion regulation have found negative connectivity between lateral and medial prefrontal areas and the amygdala (Kanske et al., 2011) as well as the insula (Li et al., 2021), such that when activity in prefrontal areas increases, activity in the amygdala and insula decreases. Thus, the negative (i.e., anticorrelated) connectivity between the frontoparietal networks and emotion-focused networks such as the SN and the limbic network may contribute to emotion regulation ability. Previous research has also found that connections between the SN and DMN are associated with emotion regulation in the context of anxiety and trauma (Fresco et al., 2017; Lieberman et al., 2023). Moreover, frontoparietal networks and the DMN tend to have negative connectivity during externally-oriented cognitive tasks (M. D. Fox et al., 2005). As reappraisal is a cognition-based form of emotion regulation (Gross, 2002), reappraisal may serve as an internal cognition-based task while viewing is an external task which does not require cognition. Furthermore, greater negative correlation between the ACN and DMN is also associated with distractor suppression (Rosenberg et al., 2017). Together, these findings imply that there may be a reliable pattern of inter-network connectivity of the intrinsic functional networks during reappraisal versus the passive viewing of emotional scenes.

The networks illustrated in the previous paragraphs provide evidence that multiple networks may be involved in emotion regulation. Intrinsic network functional connectivity analyses provide a holistic method of determining contributions between networks that might not be seen with a univariate analysis of brain activity, or in seed-based psychophysiological interaction (PPI) connectivity analyses between pairs of networks. One recent study has shown evidence that network connectivity differs between networks in emotion regulation compared to passive viewing, involving visual networks, frontoparietal networks, the ACN, and the DMN (Sripada et al., 2014). However, Sripada et al. (2014) focused on the univariate differences of each functional connection, rather than consider how the pattern of connections might together be related to emotion regulation.

Multivariate pattern analysis (MVPA) is an analytic approach that serves as a robust method of quantifying the contribution of multiple explanatory variables (e.g., brain regions or voxels) to a given cognitive process (Gabrieli et al., 2015; Norman et al., 2006). This approach has been helpful in the emotion regulation literature to determine brain activity patterns of emotion regulation (Horner et al., 2024; Morawetz, Bode, et al., 2016), and to differentiate between reappraisal and distraction (Martins et al., 2014). In addition, MVPA can also be used to elucidate whether the pattern of inter-network functional connectivity is predictive of distinct cognitive processes (Heinzle et al., 2012). However, to our knowledge, no research to date has evaluated whether the cognitive reappraisal of negative scenes can be distinguished from the passive viewing of negative scenes using MVPA on inter-network functional connectivity data.

The purpose of the present study was to test the hypothesis that moving beyond studies of activation, task-based inter-network functional connectivity between the intrinsic canonical networks can be used to predict whether participants are reappraising versus attending to negative scenes. To address our primary hypothesis, we pursued two specific network-based analyses. First, we investigated univariate connectivity differences in between the canonical intrinsic networks as identified using a group independent components analysis (ICA) with a specific interest in the ACN, frontoparietal networks, SN, limbic network and DMN. We expected that during reappraisal greater negative connectivity (i.e., greater anticorrelation) would be observed between the emotion-focused networks (i.e. the SN and the limbic network) and attentional and cognitive control networks (i.e. the ACN and the frontoparietal networks) compared to the view condition. We also expected that during reappraisal, greater positive connectivity between the ACN and DMN would be observed compared to the view condition due to its role as an internally directed cognitive process. Second, and most importantly, using

MVPA and leave-one-subject-out cross-validation, we tested the prediction that the patterns of inter-network task-based functional connectivity could predict whether participants were reappraising versus passively viewing negative scenes. We expect the most consistently reliable connections in this model will include the ones listed above.

Methods

Participants

33 participants were recruited from the community in and around York University, Toronto, CA. Of the participants, one participant was removed from the study due to an incidental finding in the anatomical scan, while one participant was removed for not completing the emotion regulation task, leaving the study with 31 participants (21 Female, nine Male, one unspecified, Age 18-36, M = 21.03, one participant did not specify age). The sample size was selected based on previous research that sought to identify independent components (Lee et al., 2017), create connectivity matrices to determine differences in functional states (Rosenberg et al., 2015), and use linear support vector machine (SVM) classification (Pariyadath et al., 2014). Participants were screened to ensure that they could safely enter the magnetic resonance imaging (MRI) scanner. All participants gave informed consent, and the experiment was approved by the University of Manitoba Research Ethics Board.

Procedure

Participants completed a modified emotion regulation task optimized to measure task-based functional connectivity using tools more commonly associated with resting-state functional magnetic resonance imaging (fMRI) analysis, as recommend by Finn (2021). We used an exaggerated block design in which participants spent one 284s block passively viewing negative images, followed by one 284s block down-regulating images using reappraisal. We chose this method despite order effects because if the reappraise block was first, participants would be more likely to implement that strategy during the view block. At the beginning of the block, participants were given an instruction to view or reappraise the images. The view instruction read as follows: “In a moment, you will see some photos on the screen. Please pay close attention to the photos. On these trials, you will simply view the images, without performing any method of regulation.” The reappraise instruction read as follows: “In a moment, you will see some photos on the screen. Please pay close attention to the photos. On these trials, you will reappraise your interpretation of the images. Reappraisal is a form of emotion regulation in which you attempt to reinterpret an emotional stimulus. When instructed to reappraise, try to view the image in a way that makes it seem less negative. This may include constructing a positive outcome (a person injured soon received medical help and made a full recovery, OR this person sacrificed themselves to save other people). You may also focus on an aspect of the image that may not be as bad as it initially seemed. It is important that you do not look away from the image on the screen.” Before each image, a fixation of variable duration (i.e., jittered) between 8000-10000 ms appeared. Then each image appeared on screen for 8000 ms. Each block ended with a final 10-second fixation. See Figure 1 for a typical trial. To avoid confounding the signal with movement or response, there were no other trial phases. This task design did not include any trial-by-trial instructions or behavioural responses (e.g., Likert responses). This was to avoid motion-related confounds in our conditions. However, we collected behavioural responses outside the MRI, as emotional responses to regulated stimuli are sustained afterwards (Erk et al., 2010).

Once outside the scanner, a behavioural task was conducted to evaluate self-reported affect and recognition memory for the previously presented images. This allowed for the evaluation of the success of reappraisal and allowed for the quantification of how well participants followed instructions to View and Reappraise. Specifically, participants completed a self-paced affect rating and recognition memory test in which they viewed all 32 of the previously seen images as well as 32 new images (see Figure 1). On each trial, participants saw one of the images followed by a series of questions relating to the image. First, they rated how positive and how negative each image made them feel on a 1-7 Likert scale for all images. Next, recognition memory of participants was determined by having participants first judge whether the image was old or new. Then, for all old images, participants were asked to make a source decision judgment to evaluate their degree of memory recollection. Specifically, participants indicated whether the old image was shown in the view block or the reappraise block. Previous research finds that reappraisal effects are sustained (Denny et al., 2015; Erk et al., 2010; Hermann et al., 2021), meaning ratings outside the scanner can be used as an indirect measure of subjective feelings while in the scanner.

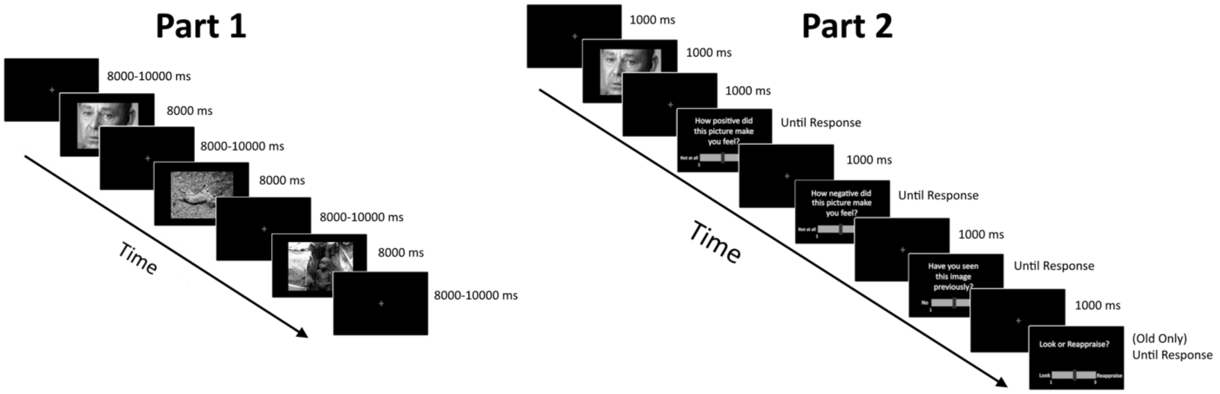

Figure 1: Typical experimental trial for parts 1 and 2 the emotion regulation task

Stimuli

64 images were selected from the International Affective Picture System (IAPS), the Nencki Affective Picture System (NAPS), and the Geneva Affective Picture Database (GAPED) datasets (Dan-Glauser & Scherer, 2011; Lang et al., 1997; Marchewka et al., 2014). Of the 64

images, 32 were high intensity, half of which had high affordances for reappraisal, and the other half had low affordances for reappraisal. The remaining 32 images were low intensity, half of which had high affordances for reappraisal, and the other half had low affordances for reappraisal. Images were randomly assigned to the view, reappraise, and new conditions, with 16 images being in the view and reappraise conditions each, and 32 images being in the new condition. We selected the images from a range of affordances and intensity to show effects in a wide range of negative emotionality and emotion regulation performance (Horner et al., 2023; Suri et al., 2018). Images were randomly assigned to matched sets so that an equal number of images of each of the four types was in each group.

Skin Conductance Response

As we did not have participants complete Likert ratings in the MRI scanner, we opted to measure skin conductance response (SCR), an indirect measure of emotional arousal found when looking at emotional images (Lang et al., 1998; Wood et al., 2014) that does not confound our blood-oxygen level dependent (BOLD) recordings. Similar to previous research in the lab combining concurrent psychophysiology and fMRI (Burleigh & Greening, 2023; Greening et al., 2022), electrodermal activity was recorded with the Biopac MP-150 system and AcqKnowledge software (BIOPAC systems, Goleta, CA, USA) and was sampled at 1000 Hz. Two Ag/AgCl laminated, carbon composition contact electrodes with a conductive saline-based gel (BIOPAC GEL101) were placed on the fingertips of the fourth and fifth fingers of the non-dominant hand. Analyses were carried out in MATLAB R2018a (Version 9.4) on skin conductance response (SCR) signals. A first-order Butterworth bandpass filter was applied with cut-off frequencies of .01 and 5 Hz (Bach, Flandin, Friston, & Dolan, 2010). Time series were then down-sampled to 100 Hz. Trial-wise baseline detrending was conducted by subtracting the baseline (mean electrodermal activity recorded one second prior to image onset) from the rest of the trial segment. Next, SCRs were calculated through a trough-to-peak analysis strategy. Specifically, a minimum SCR value was identified in the first second after image onset. The maximum SCR value was identified between the 1-8s time window after stimulus onset. An SCR that did not cross a 0.02 μS threshold was set to zero (Boucsein et al., 2012). To increase normality, the difference scores were then square root transformed (Burleigh et al., 2022).

Brain Imaging Acquisition

The experiment was completed at the MRI facility at York University using a 3T Siemens PrismaFit scanner with a 32-channel head coil. A T1-weighted magnetization-prepared rapid gradient-echo whole brain sequence was used to acquire anatomical images (repetition time: 2300 ms, echo time: 2.26 ms, voxel size 1x1x1-mm, slices, 192, flip angle 8°). Functional images were acquired with two runs using a T2*-weighted multi-echo planar imaging sequence for each run (repetition time: 1000 ms, echo time: 12 ms, 30 ms, and 48 ms, voxel size 3x3x3 mm, slices: 52, flip angle 50°, multi-band acceleration factor: 4).

Analysis

For each participants' emotion regulation runs, fMRIPrep (version 1.1.22) was performed for preprocessing. What follows is a boilerplate from [fMRIPrep], distributed under the CC0 license:

> Results included in this manuscript come from preprocessing performed using fMRIPrep 23.2.2 (Esteban et al., 2018, 2019; RRID:SCR_016216), which is based on Nipype 1.8.6 (Gorgolewski et al., 2011; 2018; RRID:SCR_002502)
>
> ### *Anatomical data preprocessing*

A total of 1 T1-weighted (T1w) images were found within the input BIDS dataset. The T1w image was corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al., 2010), distributed with ANTs 2.5.0 (Avants et al., 2008; RRID:SCR_004757), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a Nipype implementation of the antsBrainExtraction.sh workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and grey-matter (GM) was performed on the brain-extracted T1w using fast (FSL (version unknown), RRID:SCR_002823, Zhang et al., 2001). Brain surfaces were reconstructed using recon-all (FreeSurfer 7.3.2, RRID:SCR_001847, Dale et al., 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 grey-matter of Mindboggle (RRID:SCR_002438, Klein et al., 2017). Volume-based spatial normalization to one standard space (MNI152NLin2009cAsym) was performed through nonlinear registration with antsRegistration (ANTs 2.5.0), using brain-extracted versions of both T1w reference and the T1w template. The following template was selected for spatial normalization and accessed with TemplateFlow (23.1.0, Ciric et al., 2022): ICBM 152 Nonlinear Asymmetrical template version 2009c [Fonov et al. (2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym].

Functional data preprocessing

For each of the 2 BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume was generated from the shortest echo of the BOLD run, using a custom methodology of fMRIPrep, for use in head motion correction. 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, Jenkinson et al., 2002). 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 six degrees of freedom. Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power (absolute sum of relative motions (Power et al., 2014)) and Jenkinson (relative root mean square displacement between affines, (Jenkinson et al., 2002)). 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 et al., 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). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, a mask of pixels that likely contain a volume fraction of GM is subtracted from the aCompCor masks. This mask is obtained by dilating a GM mask extracted from the FreeSurfer's aseg segmentation, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the k components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al., 2013). Frames that exceeded a threshold of 0.9 mm FD or 1.5 standardized DVARS were annotated as motion outliers. Additional nuisance timeseries are calculated by means of principal components analysis of the signal found within a thin band (crown) of voxels around the edge of the brain (Patriat et al., 2017). 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 output spaces). Gridded (volumetric) resamplings were performed using nitransforms, configured with cubic B-spline interpolation.

> Many internal operations of fMRIPrep use Nilearn 0.10.2 (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.

The above boilerplate text was automatically generated by fMRIPrep with the express intention that users should copy and paste this text into their manuscripts unchanged. It is released under the CC0 license. Although excluded from the boilerplate, our fMRIPrep pipeline also employed the optimally weighted combination of the multi-echo data using tedana (Ahmed et al., 2023).

Univariate Whole Brain Analysis

To determine the univariate effects of our analysis, we performed some additional preprocessing and analyses using FEAT (FMRI Expert Analysis Tool) Version 6.00, part of FSL (FMRIB's Software Library, www.fmrib.ox.ac.uk/fsl). The analyses in this section were only used to determine univariate effects and were not used for the network connectivity analyses. Spatial smoothing was carried out using a Gaussian kernel of FWHM 6.0mm, and time-series statistical analysis were carried out using FILM with local autocorrelation correction (Woolrich et al., 2001). We denoised the data using reg_filt by regressing out the first five components of aCompCor (Muschelli et al., 2014), the cosine, the three translations and three rotations, and all motion outliers using an outlier detection of 0.9mm.

We then performed a standard univariate analysis using FLAME stage 1 (Beckmann et al., 2003; Woolrich, 2008; Woolrich et al., 2004). Z (Gaussianised T/F) statistic images were thresholded using clusters determined by $Z>3.1$ and a (corrected) cluster significance threshold of $p = 0.05$ (Worsley, 2001). The whole-brain univariate analysis looked at differences in BOLD activity between reappraise and view conditions. Further details of the univariate analysis can be found at https://neurovault.org/collections/VFVNUBCU.

Network Connectivity Analyses

The present study focused on task related functional connectivity, which has been found to be similar to resting state functional connectivity (Finn, 2021). The FMRI connectivity analysis was completed using a method previously used by our lab (Roye et al., 2020). For the network connectivity analyses, we used the optimally weighted data preprocessed by fMRIPrep. We smoothed the filtered data using a Gaussian kernel of FWHM 6.0mm. We corrected for motion using reg_filt by regressing out the first five components of aCompCor (Muschelli et al., 2014), the cosine, the three translations and three rotations, and all motion outliers using an outlier detection of 0.9mm. Then, we concatenated the participant-denoised data into a 4D file and used MELODIC-ICA to perform a group-wise independent components analysis (ICA) for 25 components. We opted to use ICA instead of seed-based PPI analyses in order to drastically decrease the number of connections tested (Laird et al., 2011; Lee et al., 2017; Roye et al., 2020). Next, we identified canonical networks by comparing our MELODIC file to intrinsic connectivity networks from previous research (Laird et al., 2011). We then used fslcc to select 17 independent components (ICs) that correlated with canonical networks (Laird et al., 2011) with an r value of .3 or greater. Networks selected were three default mode networks (DMN1, DMN2, and DMN3), the left and right frontoparietal network (Left FP and Right FP), two attention control networks (ACN1 and ACN2), the salience network (SN), the limbic network (LIMB), two reward networks (REW1 and REW2), the cerebellum basal ganglia network (CBG), the higher visual network (HVIS), the visual network (VIS), the sensorimotor language network (SML) and two somatosensory networks (SSN1 and SSN2) (See Figure 2 for selected networks). Further details of the independent components, including r-values, can be found at https://neurovault.org/collections/VFVNUBCU. Next, we used dual regression (Beckmann et al., 2009) to generate subject-specific versions of the spatial maps, and associated timeseries based on the results of the ICA (See Figure 2 for steps to this process).

With the time series maps for each participant, we next used FSLNets to create a partial correlation matrix (Lee et al., 2017) for the view and reappraise conditions. We opted to use partial correlation instead of full correlations because partial correlations show direct connections between networks (Smith et al., 2011, 2013). We converted the correlations using Fisher's R-to-Z transformation. We used scikit-learn (Pedregosa et al., 2011) to conduct a connectivity based MVPA and leave-one-subject-out cross-validation on the Fisher z-values of the partial correlation to determine if we can predict whether a participant is passively viewing or reappraising an image based on one's flattened connectivity matrix (Ullman et al., 2014). To determine if our classification accuracy was significantly greater than chance, 5000 permutations were run varying the view and reappraise labels.

To determine the most consistently meaningful contributors to the model, we performed feature selection by extracting the top 10% of the connections with the greatest linear coefficients across each fold, with fourteen connections being chosen for each fold (Pariyadath et al., 2014). The odds of being selected for each fold are 10.29%. Edges that appeared in the top edges at least eleven times were considered consistently meaningful linear coefficients, as they appeared in the top more often than chance ($p < 0.000005$).

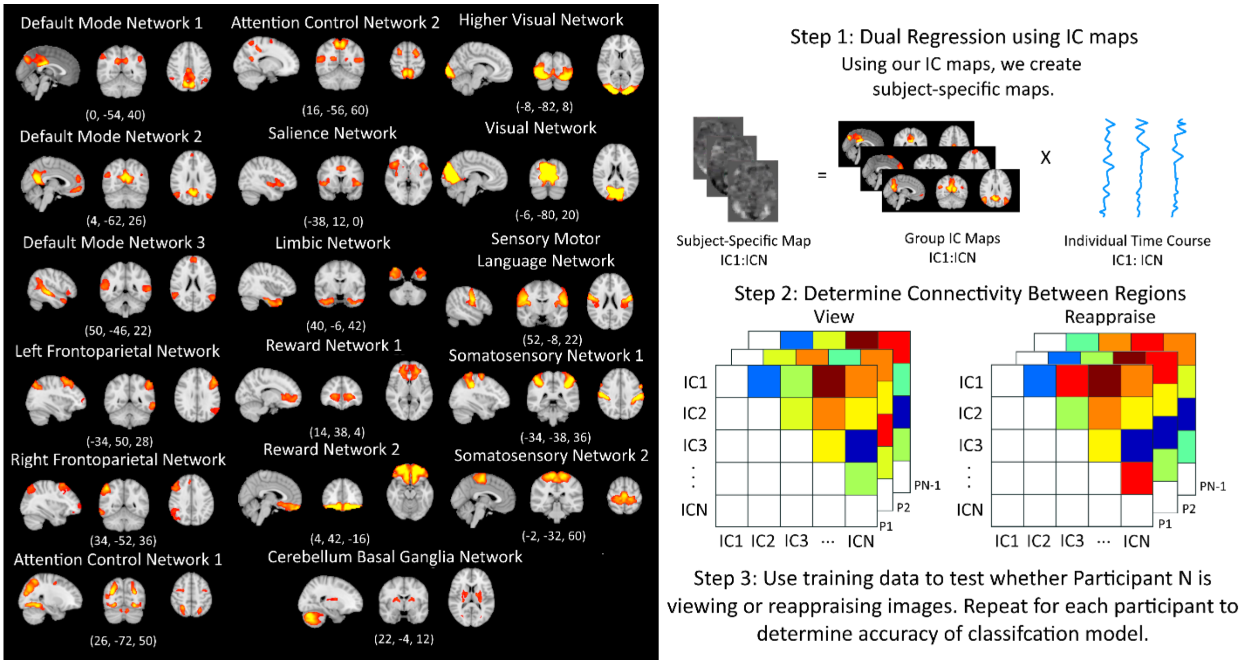

Figure 2: Left: Canonical networks derived from our independent components analysis with z thresholds of 5<z<10. Right: Steps to how we completed our connectivity analysis.

Results

Behavioural Results

Self-reported ratings of affect: Using a paired samples t-test, we found a significant effect of instruction on negative ratings, such that images that were passively viewed (M = 4.516, SD = 0.724) were rated as more negative than images that were reappraised (M = 4.258, SD = 0.974), t(30) = 2.252, *p* = .032, d' = 0.301 (See Figure 3a). We also found a significant effect of instruction on positive ratings, such that images that were passively viewed (M = 2.726, SD = 0.567) were rated as less positive than images that were reappraised (M = 3.006, SD = 0.892), t(30) = -2.221, *p* = .034, d' = 0.374 (See Figure 3b).

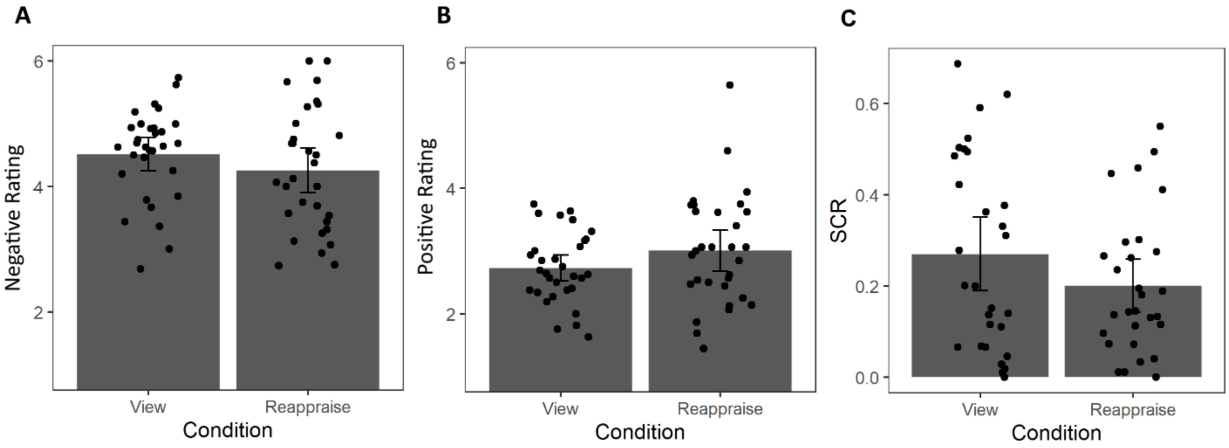

Figure 3: Differences in (a) negative rating, (b) positive rating, and (c) skin conductance response between reappraise and view conditions. Error bars represent 95% confidence intervals.

Memory measures: Overall accuracy on the memory task was 94.10%. A paired samples t-test showed no significant differences in accuracy between old images (M = 95.16%, SD = 7.07%) and new images (M = 93.04%, SD = 10.70%), t(30) = 1.079, *p* = .289, d' = 0.233. We found a significant effect of instruction on memory, such that images that were passively viewed (M = 93.35%, SD = 9.54%) were remembered with worse accuracy than images that were reappraised (M = 96.98%, SD = 5.56%), t(30) = -3.0571, *p* = .0047, d' = 0.465. Overall source decision accuracy was 77.79%, and a paired samples t-test found no significant differences in source decisions between viewing (M = 79.18%, SD = 23.69%) and reappraisal (M = 76.46%, SD = 28.47%), t(30) = 0.2976, *p* = .7681, d' = 0.104.

Skin Conductance Results

Using a paired samples t-test, we found a significant reduction of SCR to the negative images when reappraising (M = 0.20, SD = 0.15) compared to passive viewing of the images (M = 0.27, SD = 0.21), t(28) = 2.24, *p* = .034, d' = 0.415 (See Figure 3c).

Univariate Brain Imaging Results

Activation Results: See Figure 4 and Table 1 for the full univariate activation results. Notably, we found significantly greater activity for Reappraise compared to View in bilateral aspects of the dorsolateral prefrontal cortex, bilateral aspects of the occipital cortex, the left dorsomedial prefrontal cortex, and right aspects of the cerebellum. Conversely, we observed significant reductions in activation during Reappraise versus View in aspects of the bilateral hippocampus, amygdala, and insula.

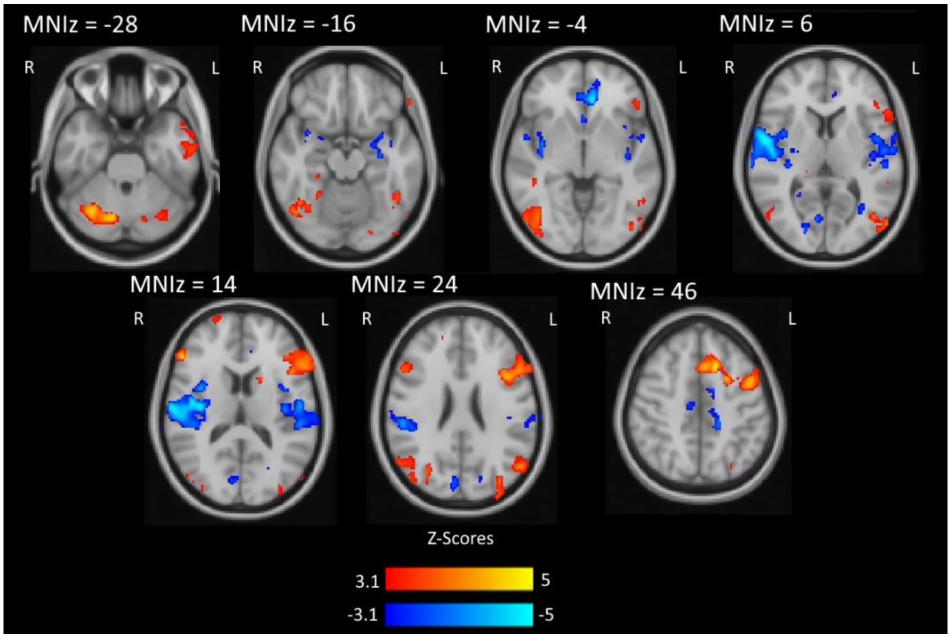

Figure 4: Blood-oxygen-level-dependent response for the whole brain analysis of differences between reappraise negative and view negative trials. Red-Yellow clusters show positive activation (reappraise-view) while blue clusters show negative activation (view-reappraise). Active clusters are displayed on MNI 2mm brain images (displayed at a threshold of z< 3.1, one-tailed, corrected)

Table 1: Significantly active clusters in differential blood-oxygen-level-dependent contrast between Reappraise and View conditions. Clusters organized by size. Voxels represents the number of contiguous voxels in a cluster. Z-MAX is the maximum Z-value of that cluster, and the coordinates are where Z-MAX is in MNI space.

Cluster Index	Voxels	Location	Z-MAX	Z-MAX X (mm)	Z-MAX Y (mm)	Z-MAX Z (mm)
Reappraise – View						
1	4630	L Superior Frontal Gyrus/L Middle Frontal Gyrus/L Inferior Frontal Gyrus (dlPFC/vlPFC)	5.05	-14	18	46
2	1373	R Cerebellum/R Lateral Occipital Cortex (inferior)	4.79	34	-64	-32
3	686	R Lateral Occipital Cortex (superior)	4.86	26	-72	32
4	522	L Lateral Occipital Cortex (superior)	4.32	-36	-76	32
5	314	L Lateral Occipital Cortex (inferior)	4.05	-54	-78	6
6	264	R Inferior Frontal Gyrus (vlPFC)	4.82	54	32	14
7	201	L Lateral Occipital Cortex (superior)	4.21	-54	-68	24
8	188	L Middle Temporal Gyrus (anterior)	4.94	-50	-8	-22
9	169	L Cerebellum	3.93	-28	-68	-34
View – Reappraise						
1	2769	R Central Operculum Cortex/R Parietal Opercular Cortex/R Insula/R Supramarginal Gyrus/R Precentral Gyrus	5.47	56	0	4
2	1527	L Central Operculum Cortex/L Parietal Opercular Cortex/L Insula/L Supramarginal Gyrus/L Amygdala	4.63	-72	-24	28
3	299	L Paracingulate Gyrus/L Anterior Cingulate Gyrus	5.15	-8	36	-6
4	186	R Intracalcine Cortex/R Cuneal Cortex	3.98	8	-72	6

Multivariate Brain Imaging Results

Fisher transformed z-values of partial correlations for reappraise and view conditions can be seen in Figure 5a. A 5000-permutation support vector classification with leave-one-subject out cross-validation found that connectivity between the 17 canonical brain networks predicted whether a participant was viewing or reappraising an image better than chance, accuracy = 70.97%, *p* = .0040 (Figure 6a). When 10% feature selection was performed with the most consistently meaningful linear coefficients, prediction accuracy improved, accuracy = 79.03%, *p* = .0004.

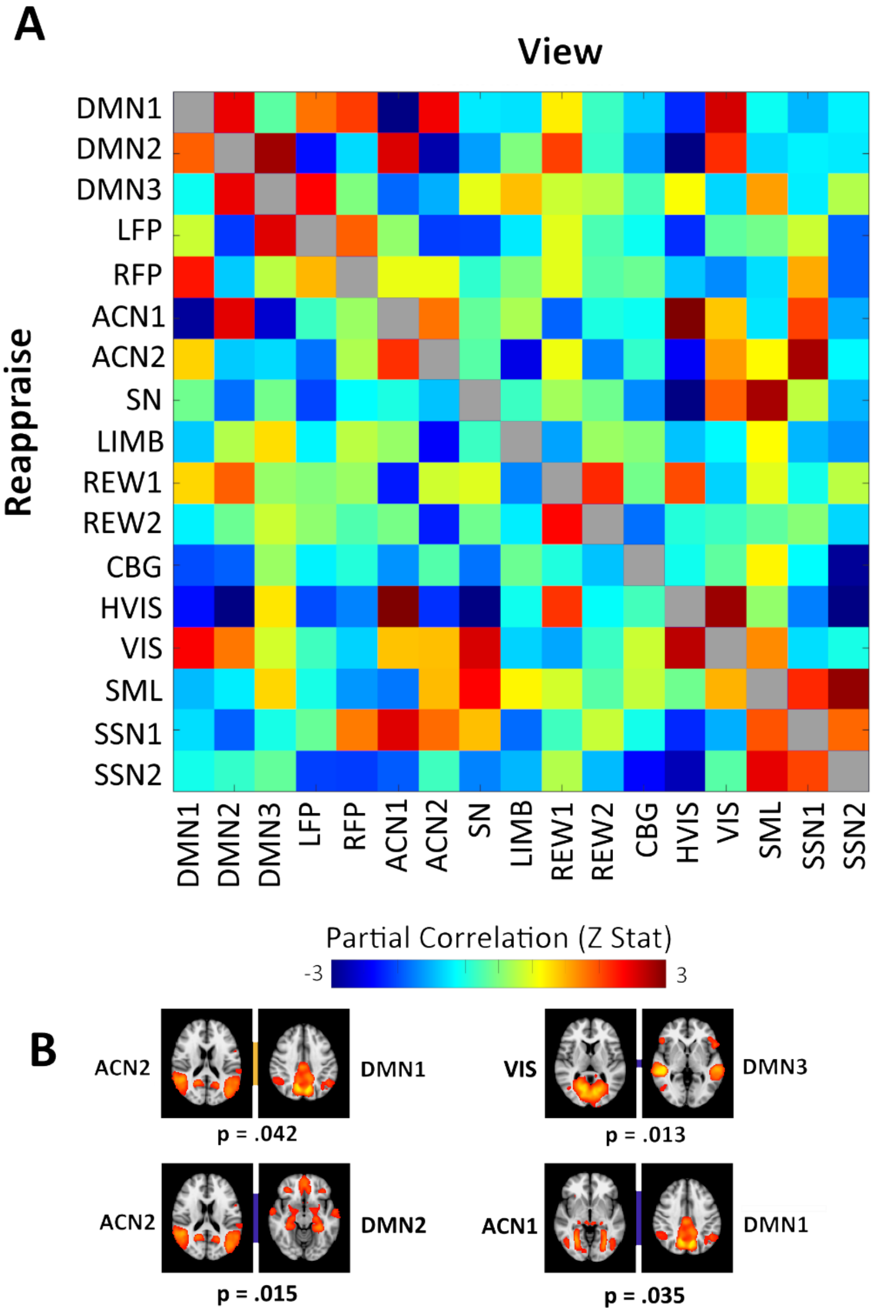

Figure 5: A) Z-stats of partial correlations between canonical networks in the view (top triangle) and reappraise (bottom triangle) conditions and B) Most significant edges in linear model for view-reappraise. The orange line means that the correlation between the networks is reduced in the reappraise condition. The blue line means that the anticorrelation between the networks is reduced in the reappraise condition.

Functional Connectivity Results: A cross-subject general linear model was performed within subjects with contrasts reappraise – view and view – reappraise and were corrected using FDR correction across the 136 connections, and corrected p-values were determined using 5000 permutations. DMN2 and ACN2 were more anticorrelated in the view condition than the reappraise condition $p_{corr} = .0150$. DMN1 and ACN1 were more anticorrelated in the view condition than the reappraise condition $p_{corr} = .0354$. DMN3 and the visual network were more anticorrelated in the view condition than the reappraise condition $p_{corr} = .0128$. DMN1 and ACN2 had greater correlation in the view condition than the reappraise condition $p_{corr} = .042$ (see Figure 5b).

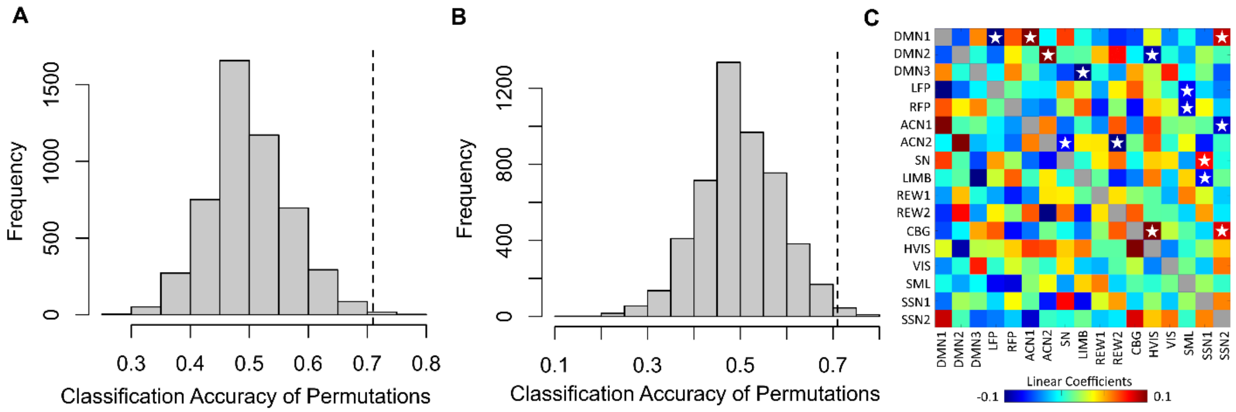

Figure 6: (A-B) Histogram comparing our observed classification accuracy (dashed line) to the null distribution of accuracies produced from the permutation test using all edges (A), and most consistently meaningful edges (B). (C) Linear coefficients of the support vector classification of the 17 canonical networks. Positive linear coefficients are associated with larger z-values during the reappraisal condition while negative linear coefficients are associated with larger z-values during the view condition. In the upper triangle, the most reliable features are labelled with a white star.

Linear coefficients can be seen in Figure 6c, with the extracted edges that contribute most to the model being shown in Table 2. Edges positively predictive of reappraisal, were those connections that resulted in greater positive weights, either due to greater correlation or less anticorrelation in the reappraise condition compared to view. Of note, we found lesser inter-network anticorrelations between DMN1 and ACN1, as well as DMN2 and ACN2 in the reappraise condition compared to the view condition. Likewise, edges negatively predictive of reappraisal entailed connections that resulted in greater negative weights, either due to lesser inter-network correlation or greater inter-network anticorrelation in reappraisal versus view. Notably, we observed greater inter-network anticorrelation between ACN2 and SN, as well as greater inter-network anticorrelation between ACN2 and REW2 in the reappraise condition compared to the view condition.

Table 2: Functional connectivity edges that make a consistently meaningful contribution to the full model predicting reappraise vs view.

Edge	Linear Coefficient	Mean Z (View)	Mean Z (Reappraisal)
Edges that suggest greater correlation in the view condition			
DMN3+LIMB	-0.109	1.114	0.928
DMN1+Left FP	-0.104	1.555	0.424
Edges that suggest greater correlation in the reappraise condition			
SN+SSN1	0.075	0.364	1.118
Edges that suggest greater anticorrelation in the view condition			
DMN2+ACN2	0.126	-2.751	-1.067
DMN1+ACN1	0.114	-4.098	-2.857
CBG+HVIS	0.113	-0.667	-0.359
DMN1+SSN2	0.086	-0.835	-0.647
CBG+SSN2	0.082	-2.867	-2.236
Edges that suggest greater anticorrelation in the reappraise condition			
ACN2+REW2	-0.135	-1.490	-2.106
DMN2+HVIS	-0.092	-3.220	-3.558
ACN1+SSN2	-0.085	-1.253	-1.713
RFP+SML	-0.082	-0.958	-1.360
LIMB+SSN1	-0.078	-1.191	-1.623
LFP+SML	-0.077	-0.087	-0.620
ACN2+SN	-0.076	-0.253	-1.108

Discussion

The purpose of this study was to test the general hypothesis that differences in inter-network connectivity are predictive of the reappraisal versus passive viewing of negative scenes. We expected inter-network connectivity differences between emotional networks (i.e., SN and limbic network), cognitive networks (i.e., ACN and frontoparietal networks), and the DMN. Broadly, our findings support this general hypothesis. First, using a cross-section general linear model, we observed differences in connectivity between aspects of the DMN and aspects of the ACN, as well as between aspects of the DMN and the visual network, during passive viewing versus reappraisal, showing partial support for our hypothesis that reappraisal would be associated with greater positive connectivity between the ACN and DMN. Second, we demonstrated that we could predict whether someone was reappraising or passively viewing an image based on the pattern of inter-network connectivity, as was hypothesized. We found that a multivariate pattern analysis of inter-network connections between 17 canonical networks (136 edges) using support vector classification predicted whether one was reappraising or viewing a negative image greater than chance, with connections involving frontoparietal networks, ACN, SN, limbic network, and the DMN, as well as several other networks contributing to the model.

The behavioural task and SCR results confirmed the effectiveness of the reappraisal manipulation. We found that images were rated as more negative and less positive in the view condition compared to the reappraisal condition, which is consistent with much of the previous literature. Moreover, this suggests that our use of a longer block design in which participants receive the regulation instruction only once at the start of the block of trials did not meaningfully affect the emotion regulation task. Our findings are also consistent with previous research showing that reappraisal is effective and that the effects of regulation are sustained over time

(Denny et al., 2015; Erk et al., 2010; Hermann et al., 2021). The behavioural results also revealed that memory for reappraised images was greater than memory for viewed images, which is consistent with previous literature (Dillon et al., 2007; Wang et al., 2017; Yeh et al., 2020). One possible explanation for this is that reappraisal requires greater attentional control compared to passive viewing, which in turn could lead to improved memory encoding and later retrieval of the reappraised emotional information (Dillon et al., 2007). There were no significant differences in source monitoring accuracy between the view condition and the reappraise condition, suggesting that participants remembered the conditions in which they saw the images. There was, however, also a significant reduction in SCR when reappraising versus viewing the negative stimuli. This is consistent with emotion regulation successfully down-regulating SCR activity in studies involved fear-related stimuli (Delgado et al., 2008; Greening et al., 2022) and is consistent with previous observations that reappraisal can reduce the magnitude of SCRs to negative images (Driscoll et al., 2009; Urry et al., 2009). Additionally, behavioural ratings and brain activity were indeed affected by our emotion regulation paradigm, suggesting that our emotion regulation paradigm was effective.

Consistent with meta-analyses of reappraisal and emotion regulation (Buhle et al., 2014), the univariate data found increased activation in bilateral frontoparietal regions including dlPFC and vlPFC, and decreased activation in the amygdala, insula, vmPFC and hippocampus. These findings confirmed that our unique emotion regulation task was consistent with previous emotion regulation tasks and that areas associated with various intrinsic networks are differentially recruited during emotion regulation by reappraisal versus passive viewing.

Our network results revealed several inter-network connections that were negative predictors of reappraisal. In other words, connections in which greater anticorrelations, or lesser positive correlations, were observed during reappraisal versus viewing negative images. Importantly, these results provided partial support for our first specific prediction that the ACN and frontoparietal (FP) networks would be more anticorrelated with the SN and limbic networks during reappraisal versus viewing negative images. Specifically, the MVPA analysis demonstrated that the edge between the ACN2 and SN was a reliable negative predictor of reappraisal (i.e., a positive predictor of view), in which there was a larger anticorrelation between these networks during reappraisal compared to view, partially supporting our hypothesis. The ACN2 in the present study included frontoparietal areas previously associated with emotion regulation such as the bilateral dlPFC and temporoparietal junction (Buhle et al., 2014). Moreover, the anticorrelation of the SN with ACN2 in the present study is consistent with previous findings of reduced anterior insula activity during reappraisal of negative stimuli (Goldin et al., 2008). From a network perspective, the present findings involving ACN2 are consistent with previous descriptions of the ACN being associated with attention selection and inhibition (Laird et al., 2011), both of which can decrease emotional responses when necessary (Schmeichel & Tang, 2015; Tabibnia et al., 2011).

However, inconsistent with our predictions, we found no evidence for greater anticorrelations or lesser positive correlations during reappraisal between the FP networks and either the SN or limbic networks, nor between the ACN and the limbic network. Regarding the lack of findings between the frontoparietal networks and both the SN and limbic network, there is at least two potential considerations. First, the connections between emotion-focused networks (i.e. the limbic network and SN) and the frontoparietal network may be indirect, working through other networks. This may likewise explain the lack of significant findings between the ACN and limbic network. Second, and more broadly for the inter-network analyses, our study used the intrinsic networks and allowed for relatively fewer total pairwise comparisons in our connectivity networks, though we are not able to separate the intrinsic networks into their constituent subregions or sub-nodes as others have done (Sripada et al., 2014). Separating out the subregions of each network may show more nuanced connectivity between regions, though it would come at the cost of more edges to consider.

The MVPA on inter-network connectivity also found some unpredicted, but still interesting network relationships which were reliable negative predictors with reappraisal. Notably, the connection between the ACN2 and the reward network 2 (REW2) had a greater anticorrelation during reappraisal compared to view. REW2 contained aspects of the ventral orbital frontal cortex (vOFC), which is sensitive to both negative valence (Chikazoe et al., 2014) and punishment (O'Doherty et al., 2001; Remijnse et al., 2005), rather than simply rewards. Thus, it is possible that during reappraisal, the ACN inhibits activity in the reward network, resulting in a greater anticorrelation. In addition, the connection between the DMN3 and limbic network had a reduced correlation during reappraisal. One possible explanation for this finding is that regions contributing to our DMN3, including lateral temporal lobe and temporoparietal junction, are also associated with theory of mind and perspective-taking (Buckner & Carroll, 2007; Spreng & Grady, 2009). As the limbic network is associated with emotional responses (Laird et al., 2011; Lee & Telzer, 2016), it may be that when exposed to emotional images participants are considering the emotional viewpoint displayed in the emotional image more so in the look compared to reappraise condition. The difference being that with reappraisal, people reorient their perspective to decrease emotional responding, resulting in lesser connectivity between these two networks during the reappraisal condition.

Related to our second prediction, the present study also found inter-network connections that were positive predictors of reappraisal versus viewing negative images. These were connections in which greater positive correlations, or lesser anticorrelations, were observed during reappraisal versus viewing negative images. Notably, the results were consistent with our prediction that a more positive correlation would be observed between the ACN and DMN during reappraisal versus viewing. Specifically, both the general linear model and the MVPA analysis found that the edge between DMN1 and ACN1 and the edge between DMN2 and ACN2 had a greater anticorrelation during view compared to reappraisal. Connectivity between the ACN and the DMN has been shown previously to increase during reappraisal (Sripada et al., 2014), similar to our findings of reduced anticorrelation during reappraisal. More generally, the pattern of connectivity we observed between the DMN and ACN, particular in the look negative condition, was the typical anticorrelated connectivity reported in the literature (Menon & Uddin, 2010), especially during external attention-focused tasks (Kelly et al., 2008). Moreover, the relative reduction in this anticorrelation between the ACN and DMN during reappraisal was consistent with the results of Sripada et al. (2014). Regarding the reduced anticorrelations between the DMN and ACN during reappraisal, one potential explanation is that reappraisal involves a relative reduction in externally-direct processing along with a commensurate redirection of attention inwards (Buckner et al., 2008). Additionally, both the ACN1 and ACN2 of the present study included aspects of the dlPFC and of the lateral parietal lobes, which are commonly discussed in activations studies of emotion regulation (Buhle et al., 2014; Kanske et al., 2011; McRae et al., 2010; Ochsner et al., 2012; Silvers et al., 2015). On the other hand, much of the classic activation studies of emotional reappraisal do not emphasize the potential involvement of the DMN. Nevertheless, several studies have observed greater activity in the

PMC during emotion regulation compared to passive viewing of emotional materials (Berboth et al., 2021; McRae et al., 2010) which is a prominent region in both the DMN1 and DMN2 of the current study. Taken together, the network perspective presented here brings new insights to a potential role of the DMN in emotion regulation that has previously been under-emphasized.

Another noteworthy finding was that compared to viewing negative images, reappraising images was associated with reduced negative connectivity between DMN3 and the visual network in the general linear model. This supports previous research, which has shown that greater positive connectivity between the DMN and visual network was associated with reappraisal (Sripada et al., 2014). It might be the case that the regions implicated in our DMN3 are those associated with theory of mind. Thus, looking at an image during reappraisal results may involve reorienting one’s perspective such that the image can be viewed as less negative (Buckner & Carroll, 2007; Sripada et al., 2014).

A general observation regarding our two network analysis strategies is that the univariate connectivity analysis revealed fewer significant or reliable edges (i.e., inter-network connections) than the multivariate analysis. One possible explanation for this is that we looked for significant differences in connectivity between 136 edges and correction for that many comparisons overshadowed noteworthy effects. Thus, small differences in connections that can also contribute to regulation may have gone unremarked upon using the univariate connectivity method. However, by using a multivariate classifier, all pair-wise combinations of network connections can provide contributions to a single model, allowing us to consider small changes in the strength of connectivity between any given two networks which may play a role in dissociating reappraisal from passive viewing (Heinzle et al., 2012). While we performed feature selection with our most reliable connections, it is worth noting that even in the analysis with all connections, the combined influence of all networks contributed to the significant full model (Greening & Mitchell, 2015).

Taken together, the present study determined that in accordance with the SOC-ER model (Opitz et al., 2012; Urry & Gross, 2010), inter-network connectivity serves as an internal factor that affects emotion regulation. The present study is the first to our knowledge to use MVPA with cross-validation to evaluate whether the broad-scale pattern of intrinsic network functional connectivity is associated with emotion regulation. Moreover, we found that inter-network connectivity can be used to predict whether someone is viewing or reappraising an image, which supports the idea that a distinct pattern of functional connectivity between the intrinsic networks is indicative of reappraisal. In addition, areas such as the default mode network, emotional networks, and networks associated with executive function all played a role in reliably distinguishing between states of reappraisal versus passive viewing of negative scenes. Thus, emotion regulation may have a more holistic role in the brain than once thought.

Chapter 4 References

Abraham, A., Pedregosa, F., Eickenberg, M., Gervais, P., Mueller, A., Kossaifi, J., Gramfort, A., Thirion, B., & Varoquaux, G. (2014). Machine learning for neuroimaging with scikit-learn. Frontiers in Neuroinformatics, 8. https://doi.org/10.3389/fninf.2014.00014

Ahmed, Z., Bandettini, P. A., Bottenhorn, K. L., Caballero-Gaudes, C., Dowdle, L. T., DuPre, E., Gonzalez-Castillo, J., Handwerker, D., Heunis, S., Kundu, P., Laird, A. R., Markello, R., Markiewicz, C. J., Maullin-Sapey, T., Moia, S., Molfese, P., Salo, T., Staden, I., Teves, J., … Whitaker, K. (2023). ME-ICA/tedana: 23.0.1.

Avants, B., Epstein, C., Grossman, M., & Gee, J. (2008). Symmetric diffeomorphic image registration with cross-correlation: Evaluating automated labeling of elderly and neurodegenerative brain. Medical Image Analysis, 12(1), 26–41. https://doi.org/10.1016/j.media.2007.06.004

Beckmann, C. F., Jenkinson, M., & Smith, S. M. (2003). General multilevel linear modeling for group analysis in FMRI. NeuroImage, 20(2), 1052–1063. https://doi.org/10.1016/S1053-8119(03)00435-X

Beckmann, C. F., Mackay, C. E., Filippini, N., & Smith, S. M. (2009). Group comparison of resting-state FMRI data using multi-subject ICA and dual regression. Neuroimage, 47(Suppl 1), S148.

Behzadi, Y., Restom, K., Liau, J., & Liu, T. T. (2007). A component based noise correction method (CompCor) for BOLD and perfusion based fMRI. NeuroImage, 37(1), 90–101. https://doi.org/10.1016/j.neuroimage.2007.04.042

Berboth, S., Windischberger, C., Kohn, N., & Morawetz, C. (2021). Test-retest reliability of emotion regulation networks using fMRI at ultra-high magnetic field. NeuroImage, 232, 117917. https://doi.org/10.1016/j.neuroimage.2021.117917

Buckner, R. L., Andrews-Hanna, J. R., & Schacter, D. L. (2008). The brain's default network: Anatomy, function, and relevance to disease. Annals of the New York Academy of Sciences, 1124(1), 1–38. https://doi.org/10.1196/annals.1440.011

Buckner, R. L., & Carroll, D. C. (2007). Self-projection and the brain. Trends in Cognitive Sciences, 11(2), 49–57. https://doi.org/10.1016/j.tics.2006.11.004

Buhle, J. T., Silvers, J. A., Wager, T. D., Lopez, R., Onyemekwu, C., Kober, H., Weber, J., & Ochsner, K. N. (2014). Cognitive Reappraisal of Emotion: A Meta-Analysis of Human Neuroimaging Studies. Cerebral Cortex, 24(11), 2981–2990. https://doi.org/10.1093/cercor/bht154

Burleigh, L., & Greening, S. G. (2023). Fear in the mind's eye: the neural correlates of differential fear acquisition to imagined conditioned stimuli. Social Cognitive and Affective Neuroscience, 18(1), 1–13. https://academic.oup.com/scan/article/18/1/nsac063/6984812

Chen, Y., Zhang, L., & Yin, H. (2024). Different emotion regulation strategies mediate the relations of corresponding connections within the default-mode network to sleep quality. Brain Imaging and Behavior, 18(2), 302–314. https://doi.org/10.1007/s11682-023-00828-9

Chikazoe, J., Lee, D. H., Kriegeskorte, N., & Anderson, A. K. (2014). Population coding of affect across stimuli, modalities and individuals. Nature Neuroscience, 17(8), 1114–1122. https://doi.org/10.1038/nn.3749

Ciric, R., Thompson, W. H., Lorenz, R., Goncalves, M., MacNicol, E. E., Markiewicz, C. J., Halchenko, Y. O., Ghosh, S. S., Gorgolewski, K. J., Poldrack, R. A., & Esteban, O. (2022).

TemplateFlow: FAIR-sharing of multi-scale, multi-species brain models. Nature Methods, 19(12), 1568–1571. https://doi.org/10.1038/s41592-022-01681-2

Dale, A. M., Fischl, B., & Sereno, M. I. (1999). Cortical Surface-Based Analysis. NeuroImage, 9(2), 179–194. https://doi.org/10.1006/nimg.1998.0395

Dan-Glauser, E. S., & Scherer, K. R. (2011). The Geneva affective picture database (GAPED): a new 730-picture database focusing on valence and normative significance. Behavior Research Methods, 43(2), 468–477. https://doi.org/10.3758/s13428-011-0064-1

Delgado, M. R., Nearing, K. I., LeDoux, J. E., & Phelps, E. A. (2008). Neural Circuitry Underlying the Regulation of Conditioned Fear and Its Relation to Extinction. Neuron, 59(5), 829–838. https://doi.org/10.1016/j.neuron.2008.06.029

Denny, B. T., Fan, J., Fels, S., Galitzer, H., Schiller, D., & Koenigsberg, H. W. (2018). Sensitization of the neural salience network to repeated emotional stimuli following initial habituation in patients with borderline personality disorder. American Journal of Psychiatry, 175(7), 657–664. https://doi.org/10.1176/appi.ajp.2018.17030367

Denny, B. T., Inhoff, M. C., Zerubavel, N., Davachi, L., & Ochsner, K. N. (2015). Getting over it: Long-lasting effects of emotion regulation on amygdala response. Psychological Science, 26(9), 1377–1388. https://doi.org/10.1177/0956797615578863

Dillon, D. G., Ritchey, M., Johnson, B. D., & LaBar, K. S. (2007). Dissociable effects of conscious emotion regulation strategies on explicit and implicit memory. Emotion, 7(2), 354–365. https://doi.org/10.1037/1528-3542.7.2.354

Drabant, E. M., McRae, K., Manuck, S. B., Hariri, A. R., & Gross, J. J. (2009). Individual Differences in Typical Reappraisal Use Predict Amygdala and Prefrontal Responses. Biological Psychiatry, 65(5), 367–373. https://doi.org/10.1016/j.biopsych.2008.09.007

Erk, S., Mikschl, A., Stier, S., Ciaramidaro, A., Gapp, V., Weber, B., & Walter, H. (2010). Acute and sustained effects of cognitive emotion regulation in major depression. Journal of Neuroscience, 30(47), 15726–15734. https://doi.org/10.1523/JNEUROSCI.1856-10.2010

Esteban, O., Blair, R., Markiewicz, C. J., Berleant, S. L., Moodie, C., Ma, F., & Ilkay Isik, A. (2018). fMRIPrep 23.2.2.

Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., Kent, J. D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S. S., Wright, J., Durnez, J., Poldrack, R. A., & Gorgolewski, K. J. (2019). fMRIPrep: a robust preprocessing pipeline for functional MRI. Nature Methods, 16(1), 111–116. https://doi.org/10.1038/s41592-018-0235-4

Finn, E. S. (2021). Is it time to put rest to rest? Trends in Cognitive Sciences, 25(12), 1021–1032. https://doi.org/10.1016/j.tics.2021.09.005

Fox, K. C. R., Spreng, R. N., Ellamil, M., Andrews-Hanna, J. R., & Christoff, K. (2015). The wandering brain: Meta-analysis of functional neuroimaging studies of mind-wandering and related spontaneous thought processes. NeuroImage, 111, 611–621. https://doi.org/10.1016/j.neuroimage.2015.02.039

Fox, M. D., Snyder, A. Z., Vincent, J. L., Corbetta, M., Van Essen, D. C., & Raichle, M. E. (2005). The human brain is intrinsically organized into dynamic, anticorrelated functional networks. In PNAS July (Vol. 5). www.pnas.orgcgidoi10.1073pnas.0504136102

Fresco, D. M., Roy, A. K., Adelsberg, S., Seeley, S., García-Lesy, E., Liston, C., & Mennin, D. S. (2017). Distinct functional connectivities predict clinical response with emotion regulation therapy. Frontiers in Human Neuroscience, 11. https://doi.org/10.3389/fnhum.2017.00086

Gabrieli, J. D. E., Ghosh, S. S., & Whitfield-Gabrieli, S. (2015). Prediction as a humanitarian and pragmatic contribution from human cognitive neuroscience. Neuron, 85(1), 11–26. https://doi.org/10.1016/j.neuron.2014.10.047

Goldin, P. R., McRae, K., Ramel, W., & Gross, J. J. (2008). The neural bases of emotion regulation: Reappraisal and suppression of negative emotion. Biological Psychiatry, 63(6), 577–586. https://doi.org/10.1016/j.biopsych.2007.05.031

Goldin, P. R., Moodie, C. A., & Gross, J. J. (2019). Acceptance versus reappraisal: Behavioral, autonomic, and neural effects. Cognitive, Affective and Behavioral Neuroscience, 19(4), 927–944. https://doi.org/10.3758/s13415-019-00690-7

Gorgolewski, K., Burns, C. D., Madison, C., Clark, D., Halchenko, Y. O., Waskom, M. L., & Ghosh, S. S. (2011). Nipype: A Flexible, Lightweight and Extensible Neuroimaging Data Processing Framework in Python. Frontiers in Neuroinformatics, 5. https://doi.org/10.3389/fninf.2011.00013

Gorgolewski, K. J., Esteban, O., Markiewicz, C. J., Ziegler, E., Ellis, D. G., Notter, M. P., & Jarecka, D. (2018). Nipype.

Greening, S. G., Lee, T. H., Burleigh, L., Grégoire, L., Robinson, T., Jiang, X., Mather, M., & Kaplan, J. (2022). Mental imagery can generate and regulate acquired differential fear conditioned reactivity. Scientific Reports, 12(1), 1–23. https://doi.org/10.1038/s41598-022-05019-y

Greening, S. G., & Mitchell, D. G. V. (2015). A network of amygdala connections predict individual differences in trait anxiety. Human Brain Mapping, 36(12), 4819–4830. https://doi.org/10.1002/hbm.22952

Greening, S. G., Osuch, E. A., Williamson, P. C., & Mitchell, D. G. V. (2014). The neural correlates of regulating positive and negative emotions in medication-free major depression. Social Cognitive and Affective Neuroscience, 9(5), 628–637. https://doi.org/10.1093/scan/nst027

Greve, D. N., & Fischl, B. (2009). Accurate and robust brain image alignment using boundary-based registration. NeuroImage, 48(1), 63–72. https://doi.org/10.1016/j.neuroimage.2009.06.060

Gross, J. J. (1998). The emerging field of emotion regulation: An integrative review. Review of General Psychology, 2(3), 271–299. https://doi.org/https://doi.org/10.1037/1089-2680.2.3.271

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. Psychophysiology, 39, 281–291. https://doi.org/10.1002/9780470177334.ch3

Gusnard, D. A., Akbudak, E., Shulman, G. L., & Raichle, M. E. (2001). Medial prefrontal cortex and self-referential mental activity: Relation to a default mode of brain function. Proceedings of the National Academy of Sciences, 98(7), 4259–4264. https://doi.org/10.1073/pnas.071043098

Heinzle, J., Wenzel, M. A., & Haynes, J.-D. (2012). Visuomotor Functional Network Topology Predicts Upcoming Tasks. Journal of Neuroscience, 32(29), 9960–9968. https://doi.org/10.1523/JNEUROSCI.1604-12.2012

Hermann, A., Neudert, M. K., Schäfer, A., Zehtner, R. I., Fricke, S., Seinsche, R. J., & Stark, R. (2021). Lasting effects of cognitive emotion regulation: neural correlates of reinterpretation and distancing. Social Cognitive and Affective Neuroscience, 16(3), 268–279. https://doi.org/10.1093/scan/nsaa159

Horner, S. B., Lulla, R., Wu, H., Shaktivel, S., Vaccaro, A., Herschel, E., Christov-Moore, L., McDaniel, C., Kaplan, J. T., & Greening, S. G. (2024). Brain activity associated with emotion regulation predicts individual differences in working memory ability. Cognitive, Affective, & Behavioral Neuroscience. https://doi.org/10.3758/s13415-024-01232-6

Horner, S., Burleigh, L., Traylor, Z., & Greening, S. G. (2023). Looking on the bright side: the impact of ambivalent images on emotion regulation choice. Cognition and Emotion, 37(7), 1213–1229. https://doi.org/10.1080/02699931.2023.2256056

Jenkinson, M., Bannister, P., Brady, M., & Smith, S. (2002). Improved optimization for the robust and accurate linear registration and motion correction of brain images. NeuroImage, 17(2), 825–841. https://doi.org/10.1006/nimg.2002.1132

Johnstone, T., van Reekum, C. M., Urry, H. L., Kalin, N. H., & Davidson, R. J. (2007). Failure to Regulate: Counterproductive Recruitment of Top-Down Prefrontal-Subcortical Circuitry in Major Depression. The Journal of Neuroscience, 27(33), 8877–8884. https://doi.org/10.1523/JNEUROSCI.2063-07.2007

Kanske, P., Heissler, J., Schönfelder, S., Bongers, A., & Wessa, M. (2011). How to regulate emotion? Neural networks for reappraisal and distraction. Cerebral Cortex, 21(6), 1379–1388. https://doi.org/10.1093/cercor/bhq216

Kelly, A. M. C., Uddin, L. Q., Biswal, B. B., Castellanos, F. X., & Milham, M. P. (2008). Competition between functional brain networks mediates behavioral variability. NeuroImage, 39(1), 527–537. https://doi.org/10.1016/j.neuroimage.2007.08.008

Kim, S. H., & Hamann, S. (2012). The effect of cognitive reappraisal on physiological reactivity and emotional memory. International Journal of Psychophysiology, 83(3), 348–356. https://doi.org/10.1016/j.ijpsycho.2011.12.001

Klein, A., Ghosh, S. S., Bao, F. S., Giard, J., Häme, Y., Stavsky, E., Lee, N., Rossa, B., Reuter, M., Chaibub Neto, E., & Keshavan, A. (2017). Mindboggling morphometry of human brains. PLOS Computational Biology, 13(2), e1005350. https://doi.org/10.1371/journal.pcbi.1005350

Laird, A. R., Fox, P. M., Eickhoff, S. B., Turner, J. A., Ray, K. L., Mckay, D. R., Glahn, D. C., Beckmann, C. F., Smith, S. M., & Fox, P. T. (2011). Behavioral interpretations of intrinsic connectivity networks. Journal of Cognitive Neuroscience, 23(12), 4022–4037. https://doi.org/10.1162/jocn_a_00077

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). International affective picture system (IAPS): Technical manual and affective ratings. NIMH Center for the Study of Emotion and Attention, 39–58.

Lang, P. J., Bradley, M. M., Fitzsimmons, J. R., Cuthbert, B. N., Scott, J. D., Moulder, B., & Nangia, V. (1998). Emotional arousal and activation of the visual cortex: An fMRI analysis.

Lee, T. H., Miernicki, M. E., & Telzer, E. H. (2017). Families that fire together smile together: Resting state connectome similarity and daily emotional synchrony in parent-child dyads. NeuroImage, 152, 31–37. https://doi.org/10.1016/j.neuroimage.2017.02.078

Lee, T. H., & Telzer, E. H. (2016). Negative functional coupling between the right fronto-parietal and limbic resting state networks predicts increased self-control and later substance use onset in adolescence. Developmental Cognitive Neuroscience, 20, 35–42. https://doi.org/10.1016/j.dcn.2016.06.002

Li, W., Yang, P., Ngetich, R. K., Zhang, J., Jin, Z., & Li, L. (2021). Differential involvement of frontoparietal network and insula cortex in emotion regulation. Neuropsychologia, 161. https://doi.org/10.1016/j.neuropsychologia.2021.107991

Lieberman, J. M., Rabellino, D., Densmore, M., Frewen, P. A., Steyrl, D., Scharnowski, F., Théberge, J., Neufeld, R. W. J., Schmahl, C., Jetly, R., Narikuzhy, S., Lanius, R. A., & Nicholson, A. A. (2023). Posterior cingulate cortex targeted real-time fMRI neurofeedback recalibrates functional connectivity with the amygdala, posterior insula, and default-mode network in PTSD. Brain and Behavior, 13(3). https://doi.org/10.1002/brb3.2883

Marchewka, A., Żurawski, Ł., Jednoróg, K., & Grabowska, A. (2014). The Nencki Affective Picture System (NAPS): Introduction to a novel, standardized, wide-range, high-quality, realistic picture database. Behavior Research Methods, 46(2), 596–610. https://doi.org/10.3758/s13428-013-0379-1

Martins, B., Ponzio, A., Velasco, R., Kaplan, J., & Mather, M. (2014). Dedifferentiation of emotion regulation strategies in the aging brain. Social Cognitive and Affective Neuroscience, 10(6), 840–847. https://doi.org/10.1093/scan/nsu129

McRae, K., Hughes, B., Chopra, S., Gabrieli, J. D. E., Gross, J. J., & Ochsner, K. N. (2010). The neural bases of distraction and reappraisal. Journal of Cognitive Neuroscience, 22(2), 248–262. https://doi.org/10.1162/jocn.2009.21243

Menon, V., & Uddin, L. Q. (2010). Saliency, switching, attention and control: a network model of insula function. Brain Structure & Function, 214(5–6), 655–667. https://doi.org/10.1007/s00429-010-0262-0

Min, J., Koenig, J., Nashiro, K., Yoo, H. J., Cho, C., Thayer, J. F., & Mather, M. (2024). Resting heart rate variability is associated with neural adaptation when repeatedly exposed to emotional stimuli. Neuropsychologia, 196. https://doi.org/10.1016/j.neuropsychologia.2024.108819

Min, J., Nashiro, K., Yoo, H. J., Cho, C., Nasseri, P., Bachman, S. L., Porat, S., Thayer, J. F., Chang, C., Lee, T. H., & Mather, M. (2022). Emotion Downregulation Targets Interoceptive Brain Regions While Emotion Upregulation Targets Other Affective Brain Regions. Journal of Neuroscience, 42(14), 2973–2985. https://doi.org/10.1523/JNEUROSCI.1865-21.2022

Mitchell, D. G. V. (2011). The nexus between decision making and emotion regulation: A review of convergent neurocognitive substrates. Behavioural Brain Research, 217(1), 215–231. https://doi.org/10.1016/j.bbr.2010.10.030

Morawetz, C., Bode, S., Baudewig, J., Jacobs, A. M., & Heekeren, H. R. (2016). Neural representation of emotion regulation goals. Human Brain Mapping, 37(2), 600–620. https://doi.org/10.1002/hbm.23053

Morawetz, C., Kellermann, T., Kogler, L., Radke, S., Blechert, J., & Derntl, B. (2016). Intrinsic functional connectivity underlying successful emotion regulation of angry faces. Social Cognitive and Affective Neuroscience, 11(12), 1980–1991. https://doi.org/10.1093/scan/nsw107

Moreira, J. F. G., Mclaughlin, K. A., & Silvers, J. A. (2021). Characterizing the Network Architecture of Emotion Regulation Neurodevelopment. Cerebral Cortex, 31(9), 4140–4150. https://doi.org/10.1093/cercor/bhab074

Muschelli, J., Nebel, M. B., Caffo, B. S., Barber, A. D., Pekar, J. J., & Mostofsky, S. H. (2014). Reduction of motion-related artifacts in resting state fMRI using aCompCor. NeuroImage, 96, 22–35. https://doi.org/10.1016/j.neuroimage.2014.03.028

Norman, K. A., Polyn, S. M., Detre, G. J., & Haxby, J. V. (2006). Beyond mind-reading: multi-voxel pattern analysis of fMRI data. Trends in Cognitive Sciences, 10(9), 424–430. https://doi.org/10.1016/j.tics.2006.07.005

Ochsner, K. N., Silvers, J. A., & Buhle, J. T. (2012). Functional imaging studies of emotion regulation: A synthetic review and evolving model of the cognitive control of emotion. Annals of the New York Academy of Sciences, 1251, 1–24. https://doi.org/10.1111/j.1749-6632.2012.06751.x.Functional

O'Doherty, J., Kringelbach, M. L., Rolls, E. T., Hornak, J., & Andrews, C. (2001). Abstract reward and punishment representations in the human orbitofrontal cortex. Nature Neuroscience, 4(1), 95–102. https://doi.org/10.1038/82959

Opitz, P. C., Gross, J. J., & Urry, H. L. (2012). Selection, optimization, and compensation in the domain of emotion regulation: Applications to adolescence, older age, and major depressive disorder. Social and Personality Psychology Compass, 6(2), 142–155. https://doi.org/10.1111/j.1751-9004.2011.00413.x

Pariyadath, V., Stein, E. A., & Ross, T. J. (2014). Machine learning classification of resting state functional connectivity predicts smoking status. Frontiers in Human Neuroscience, 8(JUNE). https://doi.org/10.3389/fnhum.2014.00425

Patriat, R., Reynolds, R. C., & Birn, R. M. (2017). An improved model of motion-related signal changes in fMRI. NeuroImage, 144, 74–82. https://doi.org/10.1016/j.neuroimage.2016.08.051

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825–2830.

Power, J. D., Mitra, A., Laumann, T. O., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2014). Methods to detect, characterize, and remove motion artifact in resting state fMRI. NeuroImage, 84, 320–341. https://doi.org/10.1016/j.neuroimage.2013.08.048

Remijnse, P. L., Nielen, M. M. A., Uylings, H. B. M., & Veltman, D. J. (2005). Neural correlates of a reversal learning task with an affectively neutral baseline: An event-related fMRI study. NeuroImage, 26(2), 609–618. https://doi.org/10.1016/j.neuroimage.2005.02.009

Rosenberg, M. D., Finn, E. S., Scheinost, D., Constable, R. T., & Chun, M. M. (2017). Characterizing attention with predictive network models. Trends in Cognitive Sciences, 21(4), 290–302. https://doi.org/10.1016/j.tics.2017.01.011

Rosenberg, M. D., Finn, E. S., Scheinost, D., Papademetris, X., Shen, X., Constable, R. T., & Chun, M. M. (2015). A neuromarker of sustained attention from whole-brain functional connectivity. Nature Neuroscience, 19(1), 165–171. https://doi.org/10.1038/nn.4179

Roye, S., Castagna, P. J., Calamia, M., De Vito, A. N., Lee, T. H., & Greening, S. G. (2020). Relationships between multiple dimensions of executive functioning and resting-state networks in adults. Neuropsychologia, 141, 1–9. https://doi.org/10.1016/j.neuropsychologia.2020.107418

Saarimäki, H., Glerean, E., Smirnov, D., Mynttinen, H., Jääskeläinen, I. P., Sams, M., & Nummenmaa, L. (2022). Classification of emotion categories based on functional connectivity patterns of the human brain. NeuroImage, 247. https://doi.org/10.1016/j.neuroimage.2021.118800

Satterthwaite, T. D., Elliott, M. A., Gerraty, R. T., Ruparel, K., Loughead, J., Calkins, M. E., Eickhoff, S. B., Hakonarson, H., Gur, R. C., Gur, R. E., & Wolf, D. H. (2013). An improved framework for confound regression and filtering for control of motion artifact in the preprocessing of resting-state functional connectivity data. NeuroImage, 64, 240–256. https://doi.org/10.1016/j.neuroimage.2012.08.052

Schmeichel, B. J., & Tang, D. (2015). Individual differences in executive functioning and their relationship to emotional processes and responses. Current Directions in Psychological Science, 24(2), 93–98. https://doi.org/10.1177/0963721414555178

Schweizer, S., Grahn, J., Hampshire, A., Mobbs, D., & Dalgleish, T. (2013). Training the emotional brain: Improving affective control through emotional working memory training. Journal of Neuroscience, 33(12), 5301–5311. https://doi.org/10.1523/JNEUROSCI.2593-12.2013

Silvers, J. A., Weber, J., Wager, T. D., & Ochsner, K. N. (2015). Bad and worse: Neural systems underlying reappraisal of high-and low-intensity negative emotions. Social Cognitive and Affective Neuroscience, 10(2), 172–179. https://doi.org/10.1093/scan/nsu043

Smith, S. M., Beckmann, C. F., Andersson, J., Auerbach, E. J., Bijsterbosch, J., Douaud, G., Duff, E., Feinberg, D. A., Griffanti, L., Harms, M. P., Kelly, M., Laumann, T., Miller, K. L., Moeller, S., Petersen, S., Power, J., Salimi-Khorshidi, G., Snyder, A. Z., Vu, A. T., … Glasser, M. F. (2013). Resting-state fMRI in the Human Connectome Project. NeuroImage, 80, 144–168. https://doi.org/10.1016/j.neuroimage.2013.05.039

Smith, S. M., Miller, K. L., Salimi-Khorshidi, G., Webster, M., Beckmann, C. F., Nichols, T. E., Ramsey, J. D., & Woolrich, M. W. (2011). Network modelling methods for FMRI. NeuroImage, 54(2), 875–891. https://doi.org/10.1016/j.neuroimage.2010.08.063

Spreng, R. N., & Grady, C. L. (2009). Patterns of Brain Activity Supporting Autobiographical Memory, Prospection, and Theory of Mind, and Their Relationship to the Default Mode Network. http://direct.mit.edu/jocn/article-pdf/22/6/1112/1939584/jocn.2009.21282.pdf

Sripada, C., Angstadt, M., Kessler, D., Phan, K. L., Liberzon, I., Evans, G. W., Welsh, R. C., Kim, P., & Swain, J. E. (2014). Volitional regulation of emotions produces distributed alterations in connectivity between visual, attention control, and default networks. NeuroImage, 89, 110–121. https://doi.org/10.1016/j.neuroimage.2013.11.006

Suri, G., Sheppes, G., Young, G., Abraham, D., McRae, K., & Gross, J. J. (2018). Emotion regulation choice: the role of environmental affordances. Cognition and Emotion, 32(5), 963–971. https://doi.org/10.1080/02699931.2017.1371003

Tabibnia, G., Monterosso, J. R., Baicy, K., Aron, A. R., Poldrack, R. A., Chakrapani, S., Lee, B., & London, E. D. (2011). Different forms of self-control share a neurocognitive substrate. Journal of Neuroscience, 31(13), 4805–4810. https://doi.org/10.1523/JNEUROSCI.2859-10.2011

Tustison, N. J., Avants, B. B., Cook, P. A., Yuanjie Zheng, Egan, A., Yushkevich, P. A., & Gee, J. C. (2010). N4ITK: Improved N3 Bias Correction. IEEE Transactions on Medical Imaging, 29(6), 1310–1320. https://doi.org/10.1109/TMI.2010.2046908

Ullman, H., Almeida, R., & Klingberg, T. (2014). Structural maturation and brain activity predict future working memory capacity during childhood development. Journal of Neuroscience, 34(5), 1592–1598. https://doi.org/10.1523/JNEUROSCI.0842-13.2014

Urry, H. L., & Gross, J. J. (2010). Emotion regulation in older age. Current Directions in Psychological Science, 19(6), 352–357. https://doi.org/10.1177/0963721410388395

Viviani, R. (2013). Emotion regulation, attention to emotion, and the ventral attentional network. Frontiers in Human Neuroscience, 7(NOV), 1–24. https://doi.org/10.3389/fnhum.2013.00746

Wager, T. D., Davidson, M. L., Hughes, B. L., Lindquist, M. A., & Ochsner, K. N. (2008). Prefrontal-Subcortical Pathways Mediating Successful Emotion Regulation. Neuron, 59(6), 1037–1050. https://doi.org/10.1016/j.neuron.2008.09.006

Wang, Y. M., Chen, J., & Han, B. Y. (2017). The Effects of Cognitive Reappraisal and Expressive Suppression on Memory of Emotional Pictures. Frontiers in Psychology, 8. https://doi.org/10.3389/fpsyg.2017.01921

Wessing, I., Rehbein, M. A., Romer, G., Achtergarde, S., Dobel, C., Zwitserlood, P., Fürniss, T., & Junghöfer, M. (2015). Cognitive emotion regulation in children: Reappraisal of emotional faces modulates neural source activity in a frontoparietal network. Developmental Cognitive Neuroscience, 13, 1–10. https://doi.org/10.1016/j.dcn.2015.01.012

Wood, K. H., Ver Hoef, L. W., & Knight, D. C. (2014). The amygdala mediates the emotional modulation of threat-elicited skin conductance response. Emotion, 14(4), 693–700. https://doi.org/10.1037/a0036636

Woolrich, M. (2008). Robust group analysis using outlier inference. NeuroImage, 41(2), 286–301. https://doi.org/10.1016/j.neuroimage.2008.02.042

Woolrich, M., Behrens, T. E. J., Beckmann, C. F., Jenkinson, M., & Smith, S. M. (2004). Multilevel linear modelling for FMRI group analysis using Bayesian inference. NeuroImage, 21(4), 1732–1747. https://doi.org/10.1016/j.neuroimage.2003.12.023

Woolrich, M., Ripley, B. D., Brady, M., & Smith, S. M. (2001). Temporal Autocorrelation in Univariate Linear Modeling of FMRI Data. NeuroImage, 14(6), 1370–1386. https://doi.org/10.1006/nimg.2001.0931

Worsley, K. J. (2001). Statistical analysis of activation images. Functional MRI: An Introduction to Methods , 14(1), 251–270.

Yeh, N., Barber, S. J., Suri, G., & Opitz, P. (2020). The role of reappraisal success in emotional and memory outcomes. Emotion, 20(6), 939–950. https://doi.org/10.1037/emo0000575

Zhang, Y., Brady, M., & Smith, S. (2001). Segmentation of brain MR images through a hidden Markov random field model and the expectation-maximization algorithm. IEEE Transactions on Medical Imaging, 20(1), 45–57. https://doi.org/10.1109/42.906424

Chapter 5: General Discussion and Future Directions

The SOC-ER model posits that both external and internal factors can affect emotion regulation (Opitz et al., 2012; Urry & Gross, 2010). The series of studies presented herein expanded upon the implications of the SOC-ER model and identified external factors (ambivalence, intensity) and internal factors (working memory, brain activity, network connectivity) that influence emotion regulation selection and performance. These findings can help us determine why people choose certain emotion regulation methods, and why some people may not be as successful at regulating emotions as others. Furthermore, these findings can help people determine their needs in order to properly regulate emotions.

The purpose of this series of studies was to determine external and internal factors that affect emotion regulation selection and performance. In Study 1, I determined that in addition to intensity, the ambivalence of a stimulus impacts emotion regulation choice, with participants being more likely to reappraise ambivalent images, showing that ambivalence serves as an external factor in emotion regulation selection. In Study 2, I found that differential brain activity during an emotion regulation task predicts working memory ability greater than chance, particularly in brain regions that are correlated with working memory such as the dlPFC. This suggests that emotion regulation and working memory are underpinned by the same mechanism of cognitive control and that working memory serves as an internal resource that affects emotion regulation ability. In addition, Study 2 shows how brain activity plays a role in emotion regulation. In Study 3, I found that differences in connectivity between different networks in the brain can predict whether one is regulating or viewing an image above chance, further supporting the idea that brain activity, and specifically inter-network functional connectivity, serves as an internal factor that influences emotion regulation.

External Factors of Emotion Regulation

Study 1 focused primarily on external factors of emotion regulation, particularly intensity and ambivalence of a stimulus, which were shown to have independent effects on emotion regulation choice. Previous research had indeed found that intensity impacted emotion regulation selection (Sheppes, 2014; Sheppes et al., 2011, 2014). However, in Study 1, I determined that the high intensity images used by Sheppes and colleagues (2011) were less ambivalent than the low intensity images. Therefore, I created a paradigm to determine how ambivalence and intensity each contributed to emotion regulation choice. I then found that not only were participants more likely to choose to reappraise low intensity compared to high intensity images, but also that participants were more likely to choose to reappraise ambivalent images compared to non-ambivalent images. Thus, study 1 found ambivalence to be an external factor dissociable from intensity that impacted emotion regulation selection. As reappraisal serves as an effective form of emotion regulation (Gross & John, 2003), having a wider knowledge of external factors which impact reappraisal can help determine the environmental settings in which effective emotion regulation is easier.

In addition, Study 1 looked at how ambivalence may impact emotion regulation choice. Ambivalence of an image serves as a reappraisal affordance. This contributes to the literature of SOC-ER by more clearly defining reappraisal affordance, which can make it easier to identify additional factors that increase reappraisal affordance. Notably, ease of reappraisal is important for emotion regulation choice, making it more likely for a participant to choose reappraisal (Sheppes et al., 2014; Suri et al., 2018). It is likely the case that this ease of reappraisal influences selection of an emotion regulation method, because a person understands that choosing reappraisal when it is easier may lead to more successful downregulation of emotion (Opitz et al., 2012; Suri et al., 2018; Urry & Gross, 2010).

While this study has clarified that ambivalence of an image impacts emotion regulation choice due to its role as a reappraisal affordance, it is still unclear what mechanism of ambivalent stimuli serves as a reappraisal affordance. This would be important to expand upon in future research, as external factors that share this mechanism with ambivalence may also serve as external factors of emotion regulation. The most obvious mechanism by which ambivalence causes easier reappraisal is through the use of positive cues. The positive cues may inherently exist as a reappraisal affordance, thus leading to participants being more likely to reappraise ambivalent images compared to non-ambivalent images. Were reappraisal chosen due to the ease of down-regulating negative emotions with positive cues, one may expect similar results when down-regulating positive emotion using positive and ambivalent stimuli, as negative cues could help one down-regulate emotion. Alternatively, it is possible that less creativity is required to reappraise an image when positive cues are present. Indeed, future research can determine if cues that increase creativity can impact emotion regulation choice. Another option is that positive cues can facilitate attention (Fink et al., 2017). Future research can investigate whether attentional biases moderate the role ambivalence plays in emotion regulation choice. Alternatively, eye tracking can be used to investigate if looking at positive cues impacts emotion regulation choice.

Study 1 provides evidence that ambivalence impacts effective emotion regulation. However, many other environmental factors may contribute to effective emotion regulation as well. First of all, while I looked at external factors of emotion regulation selection in this series of experiments in Study 1, I did not directly focus on external factors of emotion regulation performance. If participants choose to reappraise an ambivalent image more often than a non-ambivalent image because it is easier, I would expect more optimized emotion regulation according to the SOC-ER model (Opitz et al., 2012; Urry & Gross, 2010). In this case, I would expect to see greater performance when down-regulating ambivalent images compared to non-ambivalent images using reappraisal. Similarly, I would expect to see greater performance down-regulating ambivalent images using reappraisal compared to distraction. Future research could also focus on external factors such as content present in the stimulus (i.e. humans, animals, etc.) or personal significance, and how that impacts emotion regulation choice. Similarly, future research could expand the methods of emotion regulation that are undertaken, including suppression and acceptance.

Internal Factors of Emotion Regulation

Studies 2 and 3 looked at internal factors implicated in emotion regulation efficacy, notably working memory, cognitive control, brain activity, and inter-network functional connectivity. These studies supported our hypothesis in that the neural mechanisms of reappraisal were associated with working memory, cognitive control, and attention. This in turn supports the idea that according to the SOC-ER theory, working memory and cognitive control serve as internal factors in emotion regulation performance, which serve to optimize reappraisal performance. Thus, it is evident that those who have better working memory and cognitive control abilities have greater reappraisal efficacy, which may translate to overall stronger emotion regulation skills. Studies 2 and 3 also showed that neural activity impact emotion regulation, suggesting that brain activity and inter-network brain connectivity serve as internal factors in the optimization of reappraisal. Whereas Study 2 focused on the relationship between reappraisal induced brain activity and behavioural working memory, Study 3 looked at whole brain network connectivity across the brain, particularly networks that are implicated in attentional and cognitive control, and emotion.

Both studies also used multivariate analyses to determine their results. Multivariate analyses are more robust than univariate analyses (Gabrieli et al., 2015; Zhou et al., 2021), making them useful to predict individual differences and binary dependent variables. I also used permutation testing to make sure the results were not achievable using random data, making the results stronger. Study 2 used MVPA in regions of interest with SVR to predict individual differences in brain activity and how they affected working memory. Meanwhile, Study 3 used a multivariate analysis across network edges in the whole brain with SVC to predict if differences between networks would predict whether someone was viewing or reappraising an image. Both studies used ICA in order to complete analyses. Study 2 did an ICA to select ROIs that correlated with working memory, while Study 3 used ICA to determine canonical brain networks (Laird et al., 2011). In addition, Study 3 used dual regression in order to determine the correlations between those canonical brain networks (T. H. Lee et al., 2017b; Roye et al., 2020).

Working Memory and Cognitive Control

This series of studies provided evidence that working memory serves as an internal factor of emotion regulation. Univariate analyses in studies 2 and 3 both showed greater dlPFC and vlPFC activity during reappraisal compared to view, which are common areas of activation in both reappraisal and cognitive control, particularly working memory (Kanske et al., 2011; McRae et al., 2010; Ochsner et al., 2012). While this alone does not confirm the relationship between working memory and emotion regulation, this finding was supported by the univariate analysis of Study 2, which found greater activity in the dlPFC during reappraise compared to view when working memory performance was a predictor. Study 2 also found that differential brain activity while regulating and viewing images predicted working memory ability at a rate greater than chance, with strong contributions to the model found in frontoparietal areas, particularly the dlPFC. Thus, it is likely that emotion regulation and working memory are driven by a shared mechanism, likely cognitive control. Within the context of the SOC-ER model, this would suggest that improved working memory would provide improved optimization of reappraisal, resulting in greater reappraisal efficacy.

Furthermore, due to overlap with areas associated with cognitive control and attention, I can speculate the role of attention and cognitive control on emotion regulation. Study 3 found that connections from the ACN were important in determining the difference between viewing and reappraising an image. The general linear model and MVPA model found that connections between the ACN and the DMN had reduced negative connectivity in the reappraise condition compared to the view condition. In addition, the MVPA found that the anticorrelation between the ACN and the SN was greater in the reappraise condition compared to the view condition. The ACN plays a role in attention and cognitive control (Roye et al., 2020). While this does not directly entail that attention and cognitive control are internal factors in emotion regulation, one can speculate that similarly to the overlap in activity in the dlPFC in emotion regulation and working memory, emotion regulation pulls cognitive and attentional resources from the ACN in order to effectively regulate emotions, implying that attentional and cognitive control skills are required in order to properly regulate emotions.

There are many potential explanations for the overlap between emotion regulation and cognitive control. The dual competition model posits that attending to an emotional stimulus draws resources from cognitive control processes (Pessoa, 2009). Perhaps it is possible that when one sees an emotional stimulus, it requires cognitive control resources in order to reappraise the image. One could in fact argue that improved working memory and cognitive control lead to improved reappraisal efficacy. This is indeed illustrated in Study 2, as differential brain activity predicted working memory performance. One potential implication for the role of cognitive control on reappraisal is that of mental illness. Depression and anxiety are associated with both poor cognitive control (Snyder et al., 2015) and emotion dysregulation (S. G. Hofmann et al., 2012). According to the findings from this study, it is possible that these deficits come from the same mechanism. In that case, it is possible that improvements in working memory and cognitive control may lead to improved emotion regulation ability. Future research can look at causal effects of cognitive control and working memory training on emotion regulation efficacy.

Within the context of the SOC-ER model, I have found that internal factors of cognitive control, particularly working memory, led to greater optimization of reappraisal, leading to improved reappraisal ability. Due to reappraisal serving as a more effective method of emotion regulation in those with greater working memory ability, cognitive control may also facilitate selection of reappraisal. However, I did not focus on internal factors of emotion regulation selection. Future research can focus on individual differences in internal factors in working memory and cognitive control ability and how they may impact emotion regulation choice. One limitation of Study 2 is the use of the WAIS-WM as a working memory measure. Future research could replicate this study with other working memory tasks to make sure the finding generalizes to other types of working memory performance, such as n-back tasks and complex span tasks.

Functional Connectivity

In Study 3, the univariate model found differences in connectivity between the DMN and ACN, as well as the DMN and visual network during reappraisal and distraction. In addition, inter-network functional connectivity was able to predict whether one was reappraising or viewing an image greater than chance, with connections involving the DMN, ACN, and SN reliably contributing to the model. These findings suggest that functional connectivity between brain networks also serves as an internal factor which influences emotion regulation.

As stated previously, connections with the DMN and ACN were implicated in reappraisal, such that the DMN and ACN had reduced negative connectivity during reappraisal compared to viewing. While previous research has found greater connectivity between the DMN and ACN during reappraisal (Sripada et al., 2014), it is possible that the reduced negative connectivity during reappraisal is indicative of reappraisal’s role as an internal attention task, which may suggest that internal attention is required for reappraisal according to the SOC-ER model, I see a nuanced dynamic between the DMN and ACN.

In regard to networks associated with cognition and emotion, the connection between ACN and the SN was associated with greater anticorrelation during the reappraise condition in the MVPA model. As discussed in the previous section, the dynamic between the ACN and emotional driven networks such as the SN and the reward network imply that activation in lateral prefrontal networks and parietal networks deactivate emotionally driven networks such as the vmPFC and insula. In addition, the connection between the ACN and the reward network was associated with greater anticorrelation during the reappraise condition in the MVPA model. In a similar vein it is likely that during reappraisal, the ACN inhibits the orbitofrontal cortex, which is sensitive to negative stimuli (Chikazoe et al., 2014). These findings suggest that as participants inhibit the emotional stimuli to reappraise it, further implying that cognitive control, or at least the brain networks implicated in cognitive control, serve as an internal resource in emotion regulation. Future research could look at the impact of network connectivity during reappraisal and determine whether it affects cognitive control ability, perhaps looking at inhibition ability.

Inter-network functional connectivity serving as an internal resource of emotion regulation optimization in the SOC-ER model can provide a fuller description of internal resources which affect emotion regulation than brain activity alone. While brain activity can provide context as to areas required for emotion regulation, as well as potential internal factors of emotion regulation selection and optimization, inter-network functional connectivity analyses can provide a holistic approach to emotion regulation, which may involve not only multiple regions, but also multiple networks. The overlap between cognitive control and emotion regulation may be one way in which emotion dysregulation manifests. However, dysfunction in other areas, or weaker connections between networks may also influence emotion regulation ability. Determining the contributions of network connection to emotion regulation provides a starting point for additional internal factors of emotion regulation.

While I cannot downplay the roles regions such as the dlPFC and amygdala play in emotion regulation, particularly down-regulation of emotion using reappraisal, taking a holistic network approach can provide context into general network dynamics during regulation. As different forms of emotion regulation affect different regions of the brain (McRae et al., 2010; Min et al., 2022) and discrete emotion models show activity across the brain in emotion (Kragel & LaBar, 2016), it is possible that inter-network connectivity could give a more general picture of emotion regulation. Future research can focus on other types of regulation such as distraction, as well as looking at regulation of positive emotions and upregulation of emotions.

Furthermore, as Study 3 was exploratory, it can lead the way for future research focused on connectivity between specific networks. For example, future research can look at individual differences in network connectivity between two networks (such as the default mode and left frontoparietal network) and determine if differences in connectivity between those networks predicts emotion regulation performance. In addition, this study shines light on networks that may not have been expected to be involved in reappraisal and may lead to studies on connectivity between and within those networks during reappraisal, such as the DMN and visual network. Looking at the network connectivity patterns in emotion regulation, particularly in frontoparietal and attention control networks illuminates the relationship between emotion regulation and cognitive control.

Conclusion

On the whole, this series of studies has made it evident that effective emotion regulation requires a mixture of external cues and internal skill sets. Ambivalence of a stimulus was found to be an external factor that affected emotion regulation choice independent of intensity of a stimulus. Working memory was found to be an internal factor implicated in emotion regulation ability. Finally, functional connectivity between networks was found to be an internal factor involved in emotion regulation.

While this series of studies only focused on external and internal factors that affect emotion regulation separately, many of these factors can come together to affect emotion regulation selection and performance. Contributing to research by identifying what factors affect emotion regulation can also help identify why people struggle with emotion dysregulation and identify how to improve emotion regulation. Improving general working memory and plasticity between relevant areas associated with emotion regulation could improve emotion regulation ability. Future research could also investigate the role of executive dysfunction and emotion regulation failure in mood disorders. Overall, research on internal and external factors of emotion regulation can have great implications for mental health and improving wellbeing in general.

Chapter 5 References

Chikazoe, J., Lee, D. H., Kriegeskorte, N., & Anderson, A. K. (2014). Population coding of affect across stimuli, modalities and individuals. Nature Neuroscience, 17(8), 1114–1122. https://doi.org/10.1038/nn.3749

Fink, A., Weiss, E. M., Schwarzl, U., Weber, H., de Assunção, V. L., Rominger, C., Schulter, G., Lackner, H. K., & Papousek, I. (2017). Creative ways to well-being: Reappraisal inventiveness in the context of anger-evoking situations. *Cognitive, Affective and Behavioral Neuroscience*, *17*(1), 94–105. https://doi.org/10.3758/s13415-016-0465-9

Fox, E., Russo, R., & Dutton, K. (2002). Attentional bias for threat: Evidence for delayed disengagement from emotional faces. *Cognition and Emotion*, *16*(3), 355–379. https://doi.org/10.1080/02699930143000527

Gabrieli, J. D. E., Ghosh, S. S., & Whitfield-Gabrieli, S. (2015). Prediction as a humanitarian and pragmatic contribution from human cognitive neuroscience. *Neuron*, *85*(1), 11–26. https://doi.org/10.1016/j.neuron.2014.10.047

Gross, J. J., & John, O. P. (2003). Individual Differences in Two Emotion Regulation Processes: Implications for Affect, Relationships, and Well-Being. *Journal of Personality and Social Psychology*, *85*(2), 348–362. https://doi.org/10.1037/0022-3514.85.2.348

Hofmann, S. G., Sawyer, A. T., Fang, A., & Asnaani, A. (2012). Emotion dysregulation model of mood and anxiety disorders. *Depression and Anxiety*, *29*(5), 409–416. https://doi.org/10.1002/da.21888

Kanske, P., Heissler, J., Schönfelder, S., Bongers, A., & Wessa, M. (2011). How to regulate emotion? Neural networks for reappraisal and distraction. *Cerebral Cortex*, *21*(6), 1379–1388. https://doi.org/10.1093/cercor/bhq216

Kragel, P. A., & LaBar, K. S. (2016). Decoding the Nature of Emotion in the Brain. *Trends in Cognitive Sciences*, *20*(6), 444–455. https://doi.org/10.1016/j.tics.2016.03.011

Laird, A. R., Fox, P. M., Eickhoff, S. B., Turner, J. A., Ray, K. L., Mckay, D. R., Glahn, D. C., Beckmann, C. F., Smith, S. M., & Fox, P. T. (2011). Behavioral interpretations of intrinsic connectivity networks. *Journal of Cognitive Neuroscience*, *23*(12), 4022–4037. https://doi.org/10.1162/jocn_a_00077

Lee, T. H., Miernicki, M. E., & Telzer, E. H. (2017). Families that fire together smile together: Resting state connectome similarity and daily emotional synchrony in parent-child dyads. *NeuroImage*, *152*, 31–37. https://doi.org/10.1016/j.neuroimage.2017.02.078

McRae, K., Hughes, B., Chopra, S., Gabrieli, J. D. E., Gross, J. J., & Ochsner, K. N. (2010). The neural bases of distraction and reappraisal. *Journal of Cognitive Neuroscience*, *22*(2), 248–262. https://doi.org/10.1162/jocn.2009.21243

Min, J., Nashiro, K., Yoo, H. J., Cho, C., Nasseri, P., Bachman, S. L., Porat, S., Thayer, J. F., Chang, C., Lee, T. H., & Mather, M. (2022). Emotion Downregulation Targets Interoceptive Brain Regions While Emotion Upregulation Targets Other Affective Brain Regions. *Journal of Neuroscience, 42*(14), 2973–2985. https://doi.org/10.1523/JNEUROSCI.1865-21.2022

Ochsner, K. N., Silvers, J. A., & Buhle, J. T. (2012). Functional imaging studies of emotion regulation: A synthetic review and evolving model of the cognitive control of emotion. *Annals of the New York Academy of Sciences*, *1251*, 1–24. https://doi.org/10.1111/j.1749-6632.2012.06751.x.Functional

Opitz, P. C., Gross, J. J., & Urry, H. L. (2012). Selection, optimization, and compensation in the domain of emotion regulation: Applications to adolescence, older age, and major depressive disorder. *Social and Personality Psychology Compass*, *6*(2), 142–155. https://doi.org/10.1111/j.1751-9004.2011.00413.x

Pessoa, L. (2009). How do emotion and motivation direct executive control? *Trends in Cognitive Sciences*, *13*(4), 160–166. https://doi.org/10.1016/j.tics.2009.01.006

Rosenberg, M. D., Finn, E. S., Scheinost, D., Constable, R. T., & Chun, M. M. (2017). Characterizing attention with predictive network models. *Trends in Cognitive Sciences*, *21*(4), 290–302. https://doi.org/10.1016/j.tics.2017.01.011

Rosenberg, M. D., Finn, E. S., Scheinost, D., Papademetris, X., Shen, X., Constable, R. T., & Chun, M. M. (2015). A neuromarker of sustained attention from whole-brain functional connectivity. *Nature Neuroscience*, *19*(1), 165–171. https://doi.org/10.1038/nn.4179

Roye, S., Castagna, P. J., Calamia, M., De Vito, A. N., Lee, T. H., & Greening, S. G. (2020). Relationships between multiple dimensions of executive functioning and resting-state networks in adults. *Neuropsychologia*, *141*, 1–9. https://doi.org/10.1016/j.neuropsychologia.2020.107418

Sheppes, G. (2014). Emotion regulation choice: Theory and findings. In J. J. Gross (Ed.), *Handbook of Emotion Regulation* (pp. 126–139). The Guilford Press.

Sheppes, G., Scheibe, S., Suri, G., & Gross, J. J. (2011). Emotion-regulation choice. *Psychological Science*, *22*(11), 1391–1396. https://doi.org/10.1177/0956797611418350

Sheppes, G., Scheibe, S., Suri, G., Radu, P., Blechert, J., & Gross, J. J. (2014). Emotion regulation choice: A conceptual framework and supporting evidence. *Journal of Experimental Psychology: General*, *143*(1), 163–181. https://doi.org/10.1037/a0030831

Snyder, H. R., Miyake, A., & Hankin, B. L. (2015). Advancing understanding of executive function impairments and psychopathology: Bridging the gap between clinical and cognitive approaches. *Frontiers in Psychology*, *6*(MAR). https://doi.org/10.3389/fpsyg.2015.00328

Sripada, C., Angstadt, M., Kessler, D., Phan, K. L., Liberzon, I., Evans, G. W., Welsh, R. C., Kim, P., & Swain, J. E. (2014). Volitional regulation of emotions produces distributed alterations in connectivity between visual, attention control, and default networks. *NeuroImage*, *89*, 110–121. https://doi.org/10.1016/j.neuroimage.2013.11.006

Suri, G., Sheppes, G., Young, G., Abraham, D., McRae, K., & Gross, J. J. (2018). Emotion regulation choice: the role of environmental affordances. *Cognition and Emotion*, *32*(5), 963–971. https://doi.org/10.1080/02699931.2017.1371003

Urry, H. L., & Gross, J. J. (2010). Emotion regulation in older age. *Current Directions in Psychological Science*, *19*(6), 352–357. https://doi.org/10.1177/0963721410388395

Vatansever, D., Menon, D. K., Manktelow, A. E., Sahakian, B. J., & Stamatakis, E. A. (2015). Default mode network connectivity during task execution. *NeuroImage*, *122*, 96–104. https://doi.org/10.1016/j.neuroimage.2015.07.053

Zhou, F., Zhao, W., Qi, Z., Geng, Y., Yao, S., Kendrick, K. M., Wager, T. D., & Becker, B. (2021). A distributed fMRI-based signature for the subjective experience of fear. *Nature Communications*, *12*(1). https://doi.org/10.1038/s41467-021-26977-3