Integrating Channels of Emotion:
Individual Differences in Subjective Experience, Psychophysiology and Neural Activity

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
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ABSTRACT

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Abstract

Emotions infuse individuals' lives with meaning, informing their memories and guiding future decisions. Previous research has emphasized three important channels of emotion: subjective experience, psychophysiology and neural activity. In addition, research has found that individuals manage their emotions across channels in a diversity of ways. However, most of this research narrowly focuses on a single channel of emotion and misses key aspects of these individual differences. Across 4 studies, this dissertation highlights the immense variability in emotional experiences by integrating channels of emotion.

The first empirical chapter (Chapter 2) focuses on subjective channels of emotion and reveals a fundamental aspect of emotion previously unknown—that positive events are actually less complex than negative events, and that individuals evaluate positive events more similarly than negative events. The next chapter (Chapter 3) uses a novel computational approach to identify a whole-brain biomarker of the tendency to suppress negative emotion. The following chapter (Chapter 4) focuses on psychophysiological channels of emotion and investigates the effect of anxiety on how individuals manage their emotions naturally versus when following instructions in the laboratory. Participants report managing their emotions in ways that did not did not reflect how they regulated in the lab—highlighting the importance of conducting research outside the laboratory. Based on this, the final empirical chapter (Chapter 5) uses experience sampling to leave the confines of the laboratory and study people in the wild. Participant responses show that multiple components of emotional health improve with age, including emotional

stability, affect, and the ability to resist desire—a finding missing from laboratory-based research.

No two individuals are alike in how they experience and manage their emotions. This research emphasizes the vast variability in how individuals experience and manage emotion depending on their goals and the larger context. This holistic framework enhances our understanding of the full spectrum of emotional functioning and brings the field closer to a personalized account of emotion.

Contents

List of Tables

List of Figures

1. Introduction

Researchers from various fields have been debating what constitutes an emotion for centuries (Bonar, 1926; Darwin, 1998; Descartes & Voss, 1989; Dixon, 2012; James, 1884; Lieberman, 2019; Smith, 1759; Soloman, 2008). Despite continued controversy over the definition of an emotion, there is widespread agreement that emotions play a fundamental role in individuals' lives. Emotions infuse experiences with meaning and provide the building blocks to the memories that punctuate individuals' lives—they motivate behavior and provide a roadmap to guide future decisions (Ekman & Davidson, 1984).

The importance of emotion has long been recognized by psychologists and neuroscientists, who often aim to understand where emotions come from, how individuals subjectively experience emotions and how emotions are represented in the brain and body (Barret, 2017; Barret & Russel, 2015; Gross, 2014; MacCormack & Lindquist, 2017; Ochsner & Lieberman, 2001). Empirical research has characterized and quantified emotions with a litany of measures, such as self-report, experience sampling, behavioral performance, psychophysiological activity and neural activity. Although each measure may only capture a specific correlate or channel of emotion, collectively these measures offer a more complete and nuanced account of an emotion.

Appraisal theories dominate the literature on emotion and guide numerous related lines of research, such as how individuals try to manage their emotions. In general, appraisal theories diverge from basic models of emotion, which purport that there are a limited and distinct number of emotions that are represented by unique and dedicated biological states (Gross & Barrett, 2011). In contrast, appraisal models of emotion emphasize that emotions are driven by (either exogenous or endogenous) events that are *appraised* on numerous dimensions, such as relevance, pleasantness and novelty. Once an event is imbued with meaning and relevance from these more primary appraisals, the process of an emotion is instantiated and an impressive synchronization of multiple systems occurs (Scherer, 2005). Specifically, psychophysiological, neural, behavioral and subjective components coalesce into the overarching emotion.

Appraisal theories of emotion, and specifically componential-appraisal theories, argue that emotions are better organized along appraisal dimensions—as opposed to basic categories—and individuals experience emotions based on how they appraise an event. This multidimensional pattern of appraisals affords tremendous variability within and between emotion states. For example, not all anger is created equal. Anger in response to an event may differ based on this pattern of appraisals, both over time within the same individual and between individuals in response to the same event (Kuppens, Stouten, Jeroen, & Mesquita, 2009; Scherer, 2005; Scherer & Moors, 2019). Appraisal theories purport that emotions are adaptive responses to the world, not abstract sensations, and allow for an infinite number of emotional states.

By emphasizing the dynamic and dimensional aspects of emotion, appraisal theories offer a wide net of possibilities for how individuals can manage their emotions. For example, based on the initial appraisals that inform an emotion, individuals can modify their emotional experiences in numerous ways, including by re-evaluating their initial appraisals. Indeed, appraisal theory is the foundation of the most popular model of emotion regulation—the process model of emotion regulation (Gross, 1998; Gross, 2015).

Just as there is significant variability in how individuals experience emotions, there is similar variability in how individuals regulate their emotions. These regulation choices inform larger health outcomes, such as psychological health and well-being. To aid in the investigation of these individual differences, the process model of emotion regulation has outlined the various strategies that exist for trying to change the intensity, duration, and quality of emotional experiences, collectively referred to as emotion regulation (Gross, 1998; Gross, 2015). The process model offers a helpful taxonomy for organizing the various ways in which individuals regulate their emotions into categories based on the regulatory goal and when it occurs in the lifecycle of an emotional experience (Figure 1). This foundational model has provided a common framework and vocabulary for emotion researchers to examine the experiential, behavioral, psychophysiological and neural representations of emotion regulation, and has been a catalyst to a catalog of groundbreaking studies (Buhle et al., 2014).

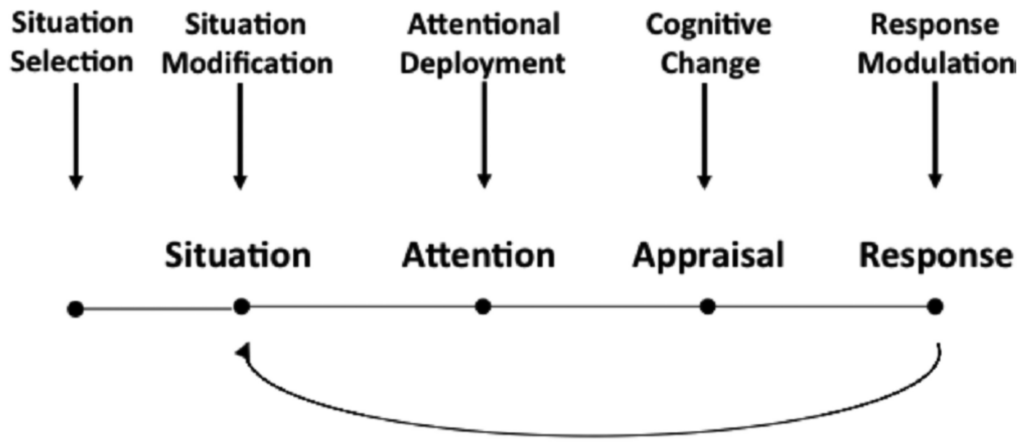

Figure 1: The Process Model of Emotion Regulation.

Taxonomy capturing how an individual may choose to regulate emotion at various stages in the lifecycle of an emotion lifecycle (Gross, 2015).

Although individuals may choose to regulate in different ways depending on the situation, each choice fits somewhere in this process model. Individuals trying to alter their emotional experiences may choose to not attend an event they think will elicit an unwanted emotion (situation selection). However, if they are already at the event and are experiencing an undesirable emotion, they may go into another room to change their surroundings (situation modification). Situation selection and modification are antecedent-focused strategies that target the external situation. Alternatively, individuals may stay in the room but pay attention to something else (attentional deployment) or reinterpret their surroundings to mean something else in an effort to change what they are feeling (cognitive change). Attentional deployment and cognitive change are both antecedent-focused strategies, but instead of targeting changing the emotional experience by altering the external situation, they change it by altering the internal situation within the individual. Finally, an individual may alter their response to the situation by masking their emotional response (response modulation), which attempts to alter the emotional experience by targeting the response instead of the anteceding emotion (Gross, 1998; Gross, 2015).

This foundational research on what emotions are and the various ways to regulate them laid the groundwork for research investigating individual differences in emotion regulation. Instead of delineating the representation of an emotional state or regulatory state, such research has focused on variability in how individuals experience and regulate their emotions; this transition has emphasized how deeply consequential variability in emotion and emotion regulation is for larger health outcomes. For examples, individuals who tend to rigidly regulate in the same ways across contexts (Blanke et al., 2019) and regulate using passive strategies such as suppression (Grommisch et al., 2019) tend to experience more negative emotions and heightened anxiety (Amstadter, 2008; Cisler & Olatunji, 2012; Denny, Inhoff, Zerubavel, Davachi, & Ochsner, 2015; Gross, 2002; Gross & Levenson, 1997; Jamieson, Mendes, Blackstock, & Schmader, 2010; Troy, Wilhelm, Shallcross, & Mauss, 2010).

Research investigating individual differences in emotion regulation has blossomed in recent years (Koval, Sütterlin, & Kuppens, 2016; Sheppes, Suri, & Gross, 2015) revealing important discoveries about how regulation choices are associated with larger health outcomes. However, a major limitation of existing research characterizing differences in how individuals experience and regulate emotion is an overly narrow focus on single channels of emotion. Though incremental discovery about a distinct emotional facet, such as psychophysiology, is valuable, research should aim to characterize multiple channels of emotion to comprehensively identify and explore the endless possibilities of individual differences that exist. Moreover, a complete characterization of individual differences in emotion requires understanding the relationship *among* channels of emotion. Indeed, a core component of emotion is the synchronization of multiple systems (Scherer, 1984a; 2009). How systems cohere is yet another biomarker of larger health outcomes—individuals suppressing negative emotion tend to also exhibit a disorganized divergence among emotion channels (Brown et al., 2019). Taken together, this suggests that narrowly focusing on a single channel of emotion may overlook key differences that unlock the door to important signatures of psychological health outcomes.

Innumerable mysteries about the consequences of regulation choices and how those choices dynamically evolve remain unexplored. These research inquiries will continue to shape the future of affective science and inform clinical interventions. Over the next four chapters, I will explore the myriad ways individuals differ in their affective experiences. I will present evidence from multiple levels of analysis to demonstrate variability in how individuals appraise, experience and regulate emotions. Specifically, I will present research from behavioral, neural, psychophysiological and experience-sampling studies that collectively demonstrate the value in understanding emotional experiences from multiple perspectives.

Chapter 2 investigates whether emotional valence (positivity and negativity) can help explain how individuals differ in their emotional experiences. Chapter 2 presents behavioral evidence that individuals experience positive stimuli relatively similarly, though there is broader variation between individuals in the experience of negative stimuli. Furthermore, positive stimuli are less complex than negative. This work uses a novel method for investigating emotion across individuals and provides new insight into characterizing individual variation in emotional experiences.

Chapter 3 investigates if there is a multivariate neural signature that captures individual differences in the tendency to reappraise and suppress. Chapter 3 uses connectome-based predictive modeling to demonstrate that a pattern of distributed functional connectivity in the brain predicts the tendency to suppress, but not reappraise. These findings help inform how whole-brain networks of functional connectivity characterize how people tend to regulate emotion outside the laboratory.

Chapter 4 investigates the relationship between self-report and psychophysiological measures of emotion and emotion regulation. Chapter 4 introduces a multivariate psychophysiological signature of reappraisal and suppression. Based on this signature, chapter 3 illustrates that individual differences in trait anxiety, but not regulation tendency, predict how individuals regulate emotion in the laboratory. These findings suggest that how individuals report regulating in everyday life is not a robust predictor of how they regulate in the laboratory.

Chapter 5 summarizes the benefit of leaving the laboratory and using experience sampling to investigate how individuals experience and regulate emotions in everyday life. This approach also allows researchers to study a broader population that may not always be represented in laboratory studies. For examples, though previous research has identified important differences in emotion across adulthood, it can be challenging and unrealistic to study aging populations in the laboratory. Studying emotion in the wild may provide a more generalizable and valid perspective. Chapter 5 then empirically demonstrates, using experience sampling, that older adults experience increased positive affect, decreased negative affect, are more stable in their affective experiences and better at resisting desires. These results demonstrate how emotional experience is related to more successful emotion regulation in everyday life and provide unique evidence that emotional health and regulation improve with age.

2. Individual Differences in Emotion

2.1 Abstract

Prior research demonstrates that individuals experience an emotion based on how they appraise the event on a number of dimensions. This unique pattern of appraisals informs the resulting emotion and allows for significant differences in emotional experiences between individuals (Scherer, 2005). Evaluating valence (the extent to which a stimulus is positive or negative) occurs early on in the appraisal process and is one of the most basic appraisal dimensions, yet it remains unclear how individuals subsequently evaluate events and experience emotions following this judgment. In addition, most existing emotion research has relied on individuals recalling previous memories rather than assessing high-dimensional appraisals and emotions in the moment. In the current study, we sought to examine how individual differences in emotion vary based on valence and how valence informs the complexity of appraisals. We explored the similarity of participants' self-reported appraisals and emotional experiences in response to 136 different emotional-eliciting static images. To acquire high-dimensional appraisal ratings for each stimulus, we used a sparse sampling strategy combined with non-negative matrix factorization, then computed the representational space of appraisals by computing the pairwise distance of appraisal ratings for each image between participants. We replicated these methods in a separate dataset of emotion-eliciting videos. In study 1, we demonstrated that individuals appraise positive images more similarly to each other than negative images. We replicated these effects in an independent dataset and found that individuals appraise and experience positive videos more similarly than negative videos. In addition, we investigated how valence informs the complexity of emotions

with Principal Components Analysis and determined that it takes fewer components to explain 90% of the variance in positive, compared to negative, appraisal ratings. Collectively, these findings illustrate that there are differences in how people conceptualize emotion based on valence and provide new insight into characterizing individual variation in emotional experiences.

2.2 Introduction

Decades of research have been dedicated to understanding fundamental questions about what emotions are, how people experience them, and how they inform decision making. Yet, there is still controversy over the basic ingredients of emotion, as well as individual differences in emotion and the crucial role they play in individuals' lives. Appraisal theories, in particular, dominate the literature on emotion and guide numerous related lines of research. Appraisal models of emotion emphasize that emotions are driven by (either exogenous or endogenous) events that are *appraised* on numerous dimensions, such as relevance, pleasantness and novelty. Once an event is imbued with meaning and relevance from these more primary appraisals, the process of an emotion is instantiated and an impressive synchronization of multiple systems occurs (Scherer, 2005). Specifically, psychophysiological, neural, behavioral and subjective components coalesce into the overarching emotion.

Appraisal theories of emotion argue that emotions are organized along appraisal dimensions and individuals experience emotions based on how they appraise an event. This multidimensional pattern of appraisal affords tremendous variability within and between emotion states (Fontaine, Scherer, Roesch, & Ellsworth, 2007; Scherer, 1984a; Scherer, 1984b; 2003; 2007; 2009). For example, not all anger is created equal. Anger in response to an event may differ based on this pattern of appraisals, both over time within the same individual and between people in response to the same event (Kuppens, Stouten, Jeroen, & Mesquita, 2009; Scherer, 2005; Scherer & Moors, 2019).

One core dimension of emotion is valence. Previous research spanning different schools of thought argues that valence is a fundamental building block of emotion (Barrett, 2006a; 2006b; Kuppens, Van Mechelen, Nezlek, Dossche, & Timmermans, 2007; Russell, 2003). Valence is an informative and primary dimension of emotion that distinguishes some states from others. However, emotional experiences vary along important dimensions beyond valence. Positive and negative emotions are not monolithic—they vary on dimensions other than valence. There is variety within positive and negative emotions, determined by additional appraisal dimensions. Yet, it is remains unknown how individuals vary in their emotional experiences based on valence. More research is needed to understand if individuals are more or less similar in their positive or negative emotional experiences. Uncovering these differences will help reveal fundamental aspects of and individual differences in how people evaluate and experience emotion.

2.3 Materials and Methods

For study 1, 201 participants viewed 136 static emotion-eliciting images from the International Affective Picture System (Bradley & Lang, 2007) using Amazon Mechanical Turk. Each participant rated a portion of images on 6 emotions (disgust anger, sadness, fear, joy, surprise) and 13 appraisals (suffering, avoid, contamination, narrative, immoral, pleasant, socially acceptable, threatened, relate, affection, desire, astonished, interact). The emotion questions were phrased as "How much does this image make you feel [INSERT EMOTION]?". The appraisal questions were phrased as follows: "Rate the degree to which someone or something is SUFFERING in this image.", "How strongly do you want to AVOID seeing this image?", "How much does this image make you think of CONTAMINATION or DISEASE?", "How much do you sense that a STORY is beginning to unfold in this image?", "How IMMORAL are the events depicted in this image?", "How PLEASANT is this image?", "How SOCIALLY ACCEPTABLE are the events in this image?", "How physically THREATENED do you feel by this image?", "How much do you RELATE to any FEELINGS depicted in this image?", "How AFFECTIONATE do you feel toward the subject of this image?", "How much do you DESIRE the subject of this image?", "How ASTONISHED does this image make you feel?", "How much do you want to INTERACT with the subject of this image?"

These emotion categories aligned to the basic emotions (Eckman, 1992; 1994; Cowen & Keltner, 2017) and the appraisal dimensions aligned to appraisal models of emotion (Fontaine, Scherer, Roesch, & Ellsworth, 2007; Scherer, 1984a; Scherer, 1984b; 2003; 2007; 2009). We binned stimuli into a valence category (positive or negative) based on a median-split of the average participant ratings from the valence appraisal dimension, resulting in 70 negative stimuli and 66 positive stimuli.

These data were conducive for investigating valence differences in the representation of appraisal, but not emotion, because of the 6 basic emotions, only 1 is clearly positive (joy). We then calculated the representational structure of appraisal space (not including valence, because that was used to create the valence categories). After removing valence, this resulted in 12 ratings per stimulus. For each stimulus, we calculated the pairwise correlation distance between participants in 12-dimensonal space, resulting in 136 representational dissimilarity matrices (Figure 2). Finally, we then converted these values from distance to similarity to obtain the inter-subject similarity of positive versus negative stimuli.

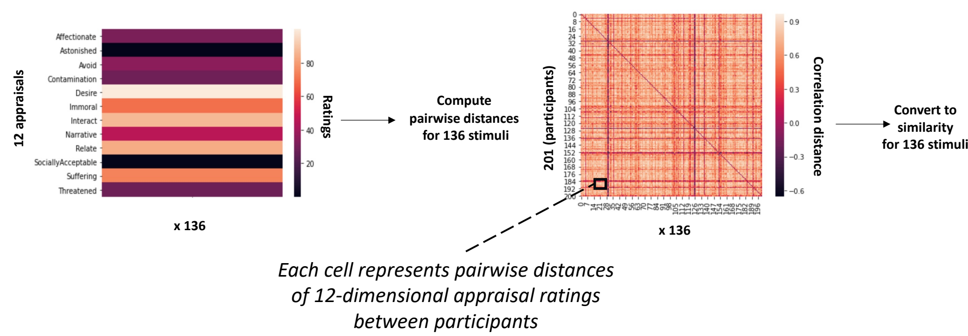

Figure 2: Representation of Appraisal.

Sample appraisal ratings for a single stimulus (left) used to compute the pairwise correlation distance between participants. Sample representational dissimilarity matrix (right) used to convert to similarity and obtain inter-subject correlation values for each stimulus.

Data for study 2 were obtained from Cowen & Keltner (2017). For a full review of methods and materials, see Cowen & Keltner, 2017. 853 participants viewed 2,185 emotional videos. A subset of (9–17) participants rated each video on 13 appraisals (approach, arousal, attention, certainty, commitment, control, dominance, fairness, identity, improvement, obstruction, safety, valence) and 27 emotions (admiration, adoration, aesthetic appreciation, amusement, anger, anxiety, awe, awkwardness, boredom, calmness, confusion, contempt, craving, disappointment, disgust, empathic pain, entrancement, envy, excitement, fear, guilt, horror, interest, joy, nostalgia, pride, relief, romance, sadness, satisfaction, sexual desire, surprise, sympathy, triumph). We binned stimuli into a valence category (positive or negative) based on a median-split of the average participant ratings from the valence appraisal dimension, resulting in 883 negative stimuli and 1,302 positive stimuli.

These data were conducive for investigating valence differences in the representation of emotion and appraisal because there was more than 1 positive emotion. We could not, however, investigate the complexity of the representational space because only 9–17 participants rated each stimulus, so there were fewer datapoints (participants) than features (appraisal dimensions and emotion categories). We calculated the representational structure of the appraisal space (not including valence, because that was used to create the valence categories). After removing valence, this resulted in 12 appraisal ratings and 27 emotion ratings per stimulus. For each stimulus, we calculated the pairwise correlation distance between participants in 12-dimensonal space, resulting in 2,185 representational dissimilarity matrices. Finally, we then converted these values from distance to similarity to obtain the inter-subject similarity of positive versus negative stimuli.

2.4 Results

In study 1, we found that positive images were appraised more similarly across individuals than negative images ($M_{ISS\ diff}$ = .21, $p < .001$; Figure 3). Similarity is computed by calculating the inter-subject correlation. To further explore this difference, we investigated if valence differences reflected differences in the complexity of the representational space. Results revealed that it took fewer components to explain 90% of variance in positive than negative appraisals ($t(134) = -7$, p .001; Figure 4).

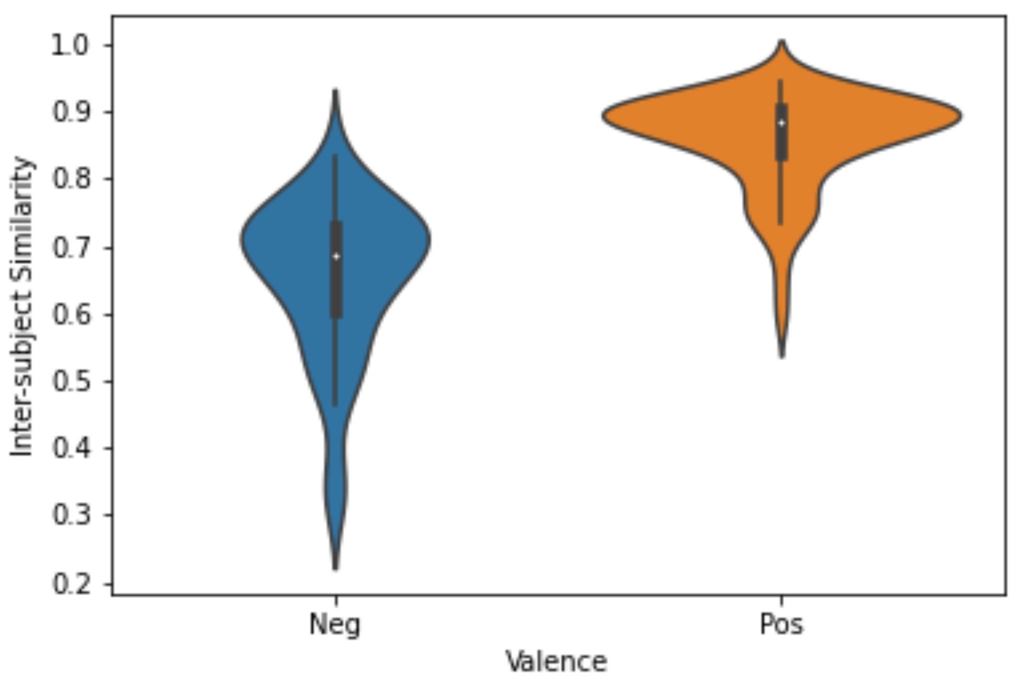

Figure 3: Inter-subject Similarity of Appraisal Space.

Inter-subject correlation of 12-dimensional appraisal space for 136 static emotional images. Y-axis represents similarity in 12-dimensional space across 201 participants. Higher values represent higher similarity/lower variability across subjects in how a given stimulus was appraised. Results of a two-sample permutation test demonstrated that positive images were appraised more similarly across individuals than negative images ($M_{ISS\ diff} = .21$, $p < .001$).

Principal Components Analysis Number was used to determine the number of components to explain 90% of the variance in 13-dimensional appraisal space. Fewer components explained 90% of variance in positive than negative appraisals ($M_{\#\ comp\ pos} = 6.97$; $M_{\#\ comp\ neg} = 7.37$; $t(134) = -7$, $p < .001$).

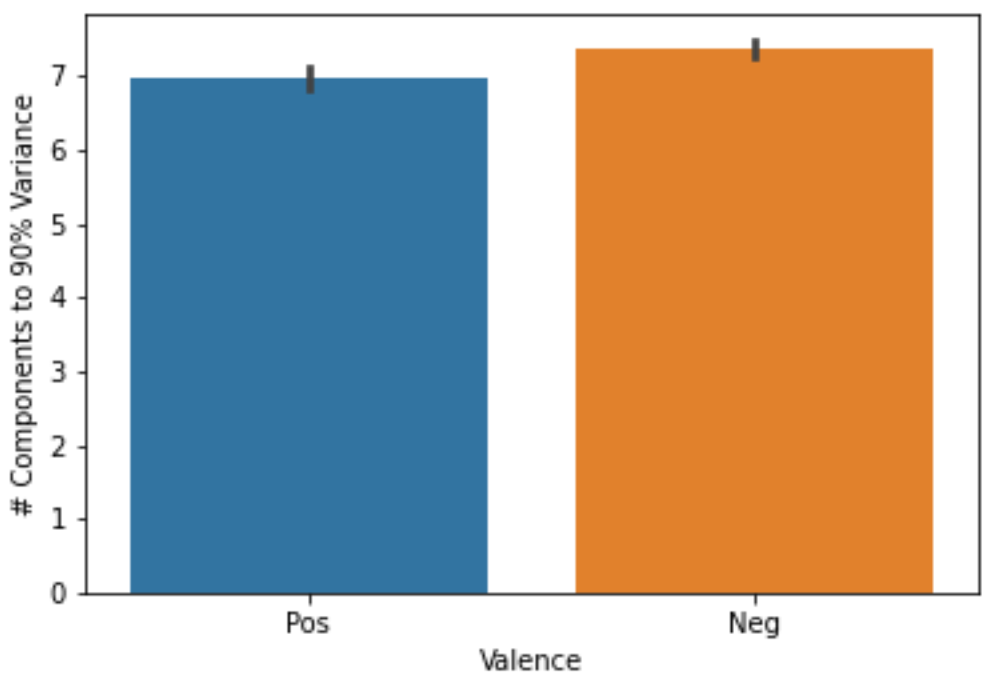

Figure 4: Complexity of Appraisal Space.

In study 2, we found that positive videos were more similarly appraised than negative videos ($M_{ISS\ diff}$ = .19, p = .002; Figure 5). In addition, positive videos were more similarly experienced than negative videos ($M_{ISS\ diff}$ = .19, p = .002, Figure 6).

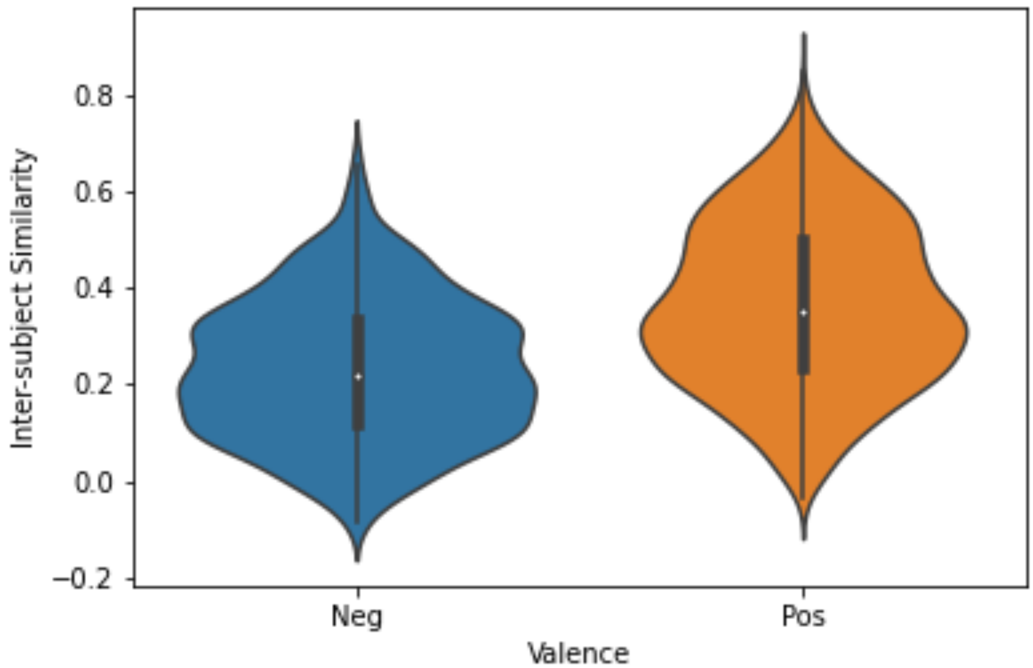

Figure 5: Inter-subject Similarity of Appraisal Space.

Inter-subject correlation of 12-dimensional appraisal space for 2,185 emotional videos. Y-axis represents similarity in 12-dimensional space across participants. Higher values represent higher similarity/lower variability across subjects in how a given stimulus was appraised. Results of a two-sample permutation test demonstrated that positive images were appraised more similarly across individuals than negative images ($M_{ISS\ diff}$ = .19, p = .002).

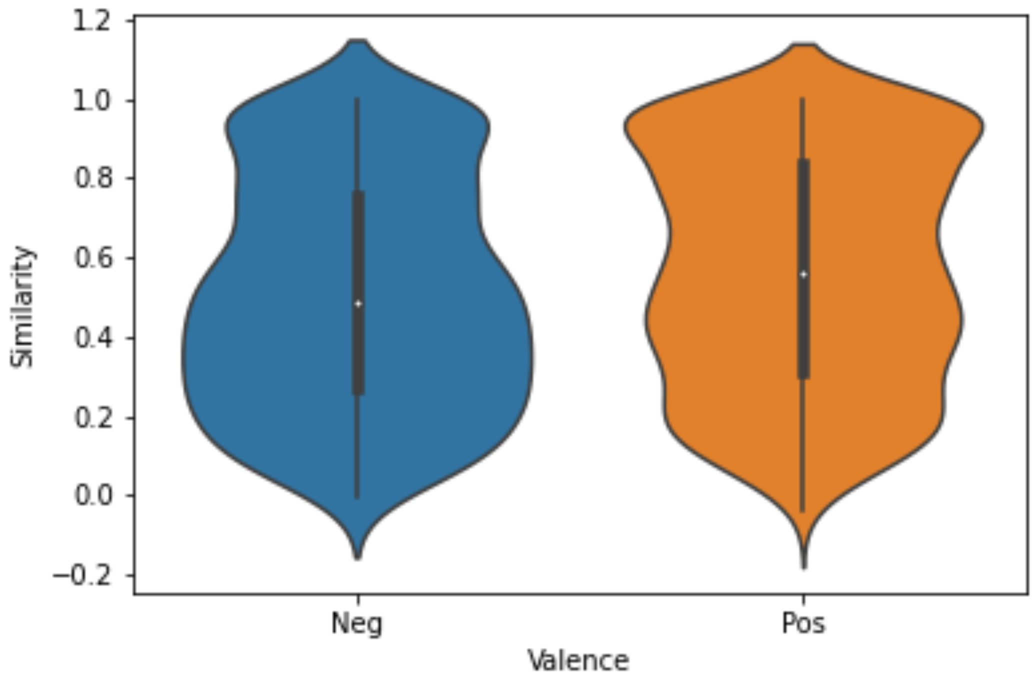

Figure 6: Inter-subject Similarity of Emotion Space.

Inter-subject correlation of 27-dimensional appraisal space for 2,185 emotional videos. Y-axis represents similarity in 27-dimensional space across participants. Higher values represent higher similarity/lower variability across subjects in how a given stimulus was appraised. Results of a two-sample permutation test demonstrated that positive videos were experienced more similarly across participants than negative images ($M_{\text{ISS diff}}$ = .19, p = .002).

2.5 Discussion

We asked how similar people are in their positive versus negative experiences and showed that positive events are appraised and experienced more similarly than negative and that appraisals of positive events are represented in a lower dimensional space, resulting in more similar emotional experiences. In other words, positive events are less complex and there are fewer ways to describe positive compared to negative events. Taken together, this work provides new insight into characterizing individual variation in emotional experiences.

It may be adaptive for individuals to have a more fine-grained representation of negative compared to positive emotional events. For example, it may be particularly important for survival to have a diversity of ways to describe negative events. However, another interpretation of these findings is that it may be more difficult to elicit positive emotions in the laboratory. Although we demonstrate that individuals appraise positive stimuli more similarly than negative across 2 distinct datasets and mediums (the stimuli used to elicit emotional responses were static images for study 1 and videos for study 2), both studies were conducted inside the laboratory, which may limit how natural and complex the experiences were. Future research could expand these findings with experience sampling to examine if individuals experience positive events more similarly than negative outside the laboratory (Burr & Samanez-Larkin, 2020).

These findings also reveal an unknown aspect of emotion. There are differences in how people conceptualize emotion based on valence—people have more granular concepts of negative emotions than positive and there are more informative dimensions for negative events than positive, suggesting that not all emotions can be simply captured by 2 dimensions. However, circumplex models of emotion argue that emotion categories can be defined based on their location in 2-dimensional space, such as valence and arousal (Barrett, 2006a; 2006b; Russell, 2003). Taken together, this exposes a limitation of circumplex models. These data, in addition, expose a limitation of basic emotion theory, which posits that different emotions are fully discrete and does not account for shared dimensionality among emotions (Eckman, 1992; 1994; Cowen & Keltner, 2017), yet we find a shared feature (i.e. complexity) across certain emotion categories, but not others. These findings suggest evidence for dimensionality of some kind—some emotions vary on more dimensions than others, suggesting higher complexity and granularity. This may suggest a hybrid model where there are different appraisal dimensions once you split on the core dimension of valence (Harmon-Jones, Harmon-Jones, & Summerell, 2017).

This chapter highlights the value of studying emotion in a multidimensional framework. Without collecting multidimensional data and preserving the dimensionality of emotion in our analyses, we would not reveal these core differences in emotion based on valence. Specifically, detecting that individuals appraise and experience positive events more similarly than negative and that appraisals of positive events are represented in a lower dimensional space than negative events would remain undetected if only measuring 2 dimensions of emotion, such as valence arousal. Although individuals vary in important ways in their experience of valence and arousal (Dejonckheere, 2018), rich measurements capture a more precise account of emotion. These results illustrate that individual differences in emotion vary more *along multiple dimensions* for negative than positive events. Importantly, univariate methods and analyses would not be equipped to detect these differences and would only capture differences between single dimensions. Taken together, this work offers a new methodological approach for and provides new insight into characterizing individual variation in emotional experiences.

3. Neural Basis of Emotion-Regulation Tendency

The content from this chapter is verbatim from the below publication and has only been reformatted for this dissertation:

Burr, D. A., d'Arbeloff, T., Elliott, M. L., Knodt, A. R., Brigidi, B. D., & Hariri, A. R. (2020). Functional connectivity predicts the dispositional use of expressive suppression but not cognitive reappraisal. *Brain and Behavior*, 10(2), e01493.

3.1 Abstract

Previous research has identified specific brain regions associated with regulating emotion using common strategies such as expressive suppression and cognitive reappraisal. However, most research focuses on a priori regions and directs participants how to regulate, which may not reflect how people naturally regulate outside the laboratory. Here, we used a data-driven approach to investigate how individual differences in distributed intrinsic functional brain connectivity predict emotion regulation tendency. Specifically, we used connectome-based predictive modeling to extract functional connections in the brain significantly related to the dispositional use of suppression and reappraisal. These edges were then used in a predictive model and cross-validated in novel participants to identify a neural signature that reflects individual differences in the tendency to suppress and reappraise emotion. We found a significant neural signature for the dispositional use of suppression, but not reappraisal. Within this whole-brain signature, the intrinsic connectivity of the default mode network was most informative of suppression tendency. In addition, the predictive performance of this model was significant in males, but not females. These findings help inform how whole-

brain networks of functional connectivity characterize how people tend to regulate emotion outside the laboratory.

3.2 Introduction

Individuals choose to regulate their emotions in response to stressors in a variety of ways. Two common emotion regulation strategies are cognitive reappraisal and expressive suppression (Gross, 2002). Expressive suppression is an avoidance-based regulation strategy characterized by masking your outward emotional responses (Gross, 2002; Gross & John, 1998). Conversely, cognitive reappraisal involves reframing the meaning of a stimulus to change the associated emotional response (Buhle et al., 2013; Gross & John, 1998).

A major goal of emotion regulation research has been to identify how individuals vary in their tendency to suppress and reappraise. For example, research has illustrated that increased use of suppression is associated with negative health outcomes, such as anxiety (Amstadter, 2008; Cisler & Olatunji, 2012; Gross, 2002; Gross & Levenson, 1997; Troy, Wilhelm, Shallcross, & Mauss, 2010), though increased use of reappraisal is associated with lower levels of anxiety (Denny, Inhoff, Zerubavel, Davachi, & Ochsner, 2015; Jamieson, Mendes, Blackstock, & Schmader, 2010). In addition, research has demonstrated sex differences in dispositional use of suppression and reappraisal. Women report using a wider range of regulation strategies than men (Aldao & Nolen-Hoeksema, 2013; Nolen-Hoeksema & Aldao, 2011) and men report using suppression more than reappraisal (Gross & John, 2003).

Emotion regulation research has aimed to characterize biomarkers associated with suppression and reappraisal (Cutuli, 2014; Dennis & Hajcak, 2009; Gross & John, 2003; Kalisch, Wiech, Herrmann, & Dolan, 2006; Kanske, Heissler, Schönfelder, & Wessa, 2012; Urry et al., 2006). For example, studies have linked reappraisal with increased activity in the dorsolateral and ventromedial prefrontal cortices (Buhle et al., 2013; Goldin, McRae, Ramel, & Gross, 2008), and both reappraisal and suppression have been associated with decreased activity in the amygdala (Buhle et al., 2013; Chen, Chen, Yang, & Yuan, 2017). Similarly, research has identified how patterns of intrinsic functional connectivity differ between suppression and reappraisal. Decreased coupling between the amygdala and medial prefrontal cortex has been associated with reappraisal, whereas increased coupling between the amygdala and dorsal anterior cingulate cortex has been associated with suppression (Pan et al., 2018; Picó-Pérez et al., 2018; Uchida et al., 2015). Globally, intrinsic activity within the default mode network, which supports self-referential processes, has been associated with suppression (Pan et al., 2018) and reappraisal (Gao et al., 2018; Gao, Chen, Biswal, Lei, & Yuan, 2018; Martins & Mather, 2016; Sripada et al., 2013; Xie et al., 2016).

Although these findings have informed the brain basis of suppression and reappraisal, they have been limited in several key areas. First, most emotion regulation research often relies on instructing individuals to regulate in specific ways (Buhle et al., 2013; McRae et al., 2010; McRae, Misra, Prasad, Pereira, & Gross, 2012). However, this may not reflect how individuals tend to regulate outside the laboratory. Second, existing studies have largely focused on *a priori* regions of interest, though evidence has rapidly accrued that complex cognitive processes are more likely supported by distributed networks of brain regions (Chang, Gianaros, Manuck, Krishnan, & Wager, 2015; Pan et al., 2018). Third, existing research that explores whole-brain maps of cognitive processes are often subject to extreme issues of multiple comparisons and based on overfit models (Shen et al. 2017). Fourth, most existing studies have smaller sample sizes and amounts of data, which limits reliability and the ability to map individual differences on to the dispositional use of suppression and reappraisal (Bennett and Miller, 2010; Elliott et al., 2019).

Here, we attempt to address these limitations by using a data-driven approach to identify patterns of distributed intrinsic functional connectivity predictive of dispositional use of suppression and reappraisal. In order to increase reliability and benefit from the most amount of data, we collapsed across task and resting-state scans into general functional connectivity (GFC; Elliott et al., 2019). We employed connectome-based predictive modeling (CPM; Shen et al., 2017) to select the most informative features (functional connections) from GFC matrices and predict individual differences in the dispositional use of suppression and reappraisal without overfitting the data. In light of the pronounced sex differences in the dispositional use of suppression and reappraisal (Aldao & Nolen-Hoeksema, 2013; Gross & John, 2003; Nolen-Hoeksema & Aldao, 2011), we examined how the predictive performance of this model varied based on sex.

3.3 Materials and Methods

Participants

Data were available from 1,316 participants (age range = 18-22 years old; 43% men) who completed the Duke Neurogenetics Study between January 2010 and July 2014

(Table 1). This study was approved by the Duke University Medical Center Institutional Review Board. The authors assert that all procedures contributing to this work also complied with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

Table 1: Duke Neurogenetics Sample.

	Total (N = 1316)	Women (n = 755)	Men (n = 561)
Age (years)	19.70 ± 1.25	19.66 ± 1.23	19.75 ± 1.27
ERQ Reappraisal (1-7)	5.18 ± 0.89	5.26 ± 0.85	5.07 ± 0.92
ERQ Suppression (1-7)	3.79 ± 1.16	3.63 ± 1.16	4.01 ± 1.13
Any Diagnoses (*n*)	268	134	134
MDD (n)	66	44	22
Bipolar (n)	35	19	16
Panic Disorder (n)	26	20	6
Social Anxiety (n)	12	5	7
GAD (n)	24	15	9
OCD (n)	15	7	8
PTSD (n)	2	1	1
Alcohol Abuse (n)	142	61	81
Substance Abuse (n)	48	21	27
Eating Disorder (n)	11	8	3
Scanner			
Scanner 1 (n)	1089	625	464
Scanner 2 (n)	227	130	97

All participants provided informed consent before participation and were excluded in the present sample if they met any of the following criteria: (a) medical diagnoses of cancer, stroke, diabetes requiring insulin treatment, chronic kidney or liver disease, or lifetime history of psychotic symptoms (b) use of psychotropic, glucocorticoid, or hypolipidemic medication (c) conditions affecting cerebral blood flow and metabolism (e.g., hypertension) or (d) failed quality control criteria for functional magnetic resonance imaging (fMRI) data. Diagnosis of any past or current DSM-IV Axis I disorder or select Axis II disorders (antisocial personality disorder and borderline personality disorder) were assessed with structured clinical interviews (Sheehan et al., 1998). Such diagnoses were, however, not exclusion criteria, as the Duke Neurogenetics Study sought to establish broad variability in multiple behavioral phenotypes related to psychopathology. Of the 1,316 participants included in our analyses, 66 met criteria for major depressive disorder, 35 for bipolar disorder, 26 for panic disorder, 12 for social anxiety disorder, 24 for generalized anxiety disorder, 15 for obsessive compulsive disorder, 2 for post-traumatic stress disorder, 142 for alcohol abuse, 48 for substance abuse, 11 for eating disorder (bulimia or anorexia) and 3 experienced psychotic symptoms.

Self-report Questionnaires

Individual differences in dispositional emotion regulation practices and negative affect were assessed with the following self-report questionnaires. The Emotion Regulation Questionnaire (ERQ), a 10-item self-report questionnaire, was used to measure individual differences in suppression and reappraisal (Gross & John, 2003). The ERQ has two subscales—ERQ-Suppression, including items such as "I control my emotions by not expressing them." and ERQ-Reappraisal, including items such as "I control my emotions by changing the way I think about the situation I'm in." All items are rated on a 7-point scale from 1 (strongly disagree) to 7 (strongly agree) and summed within each subscale to generate overall scores for suppression and reappraisal. The ERQ has been consistently shown to be a valid and reliable index of regulation tendency (Gross & John, 2003).

MRI data acquisition

Each participant was scanned using one of two identical research-dedicated GE MR750 3T scanners equipped with high-power high-duty-cycle 50-mT/m gradients at 200 T/m/s slew rate, and an eight-channel head coil for parallel imaging at high bandwidth up to 1MHz at the Duke-UNC Brain Imaging and Analysis Center. A semi-automated high-order shimming program was used to ensure global field homogeneity. A series of 34 interleaved axial functional slices aligned with the anterior commissure-posterior commissure plane were acquired for full-brain coverage using an inverse-spiral pulse sequence to reduce susceptibility artifacts (TR/TE/flip angle=2000 ms/30 ms/60; FOV=240mm; 3.75×3.75×4 mm voxels; interslice skip=0). Four initial radiofrequency excitations were performed (and discarded) to achieve steady-state equilibrium. For each participant, functional MRI was collected during various combinations of a single resting-state and four task scans. Due to the multi-phasic nature of the study, while all participants completed some fMRI scanning, not all participants had the same fMRI scans. See Figure 7 for a breakdown of the specific scans available for each participant.

Amygdala Reactivity Paradigm	Ventral Striatum Paradigm	Hippocampa l Paradigm	Working memory Paradigm	Resting State Scan	# Subject s
					960
					306
					29
					8
					3
					3
					2
					2
					1
					1
					1
				Total	**1316**

Figure 7: Scan Availability.

MRI Preprocessing

Anatomical images for each participant were skull-stripped, intensity-normalized, and nonlinearly warped to a study-specific average template in the standard stereotactic space of the Montreal Neurological Institute template using the ANTs SyN registration algorithm (Avants, Epstein, Grossman, & Gee, 2008; Klein et al., 2009). Time-series images for each participant were despiked, slice-time-corrected, realigned to the first volume in the time series to correct for head motion using AFNI tools (Cox, 1996), co-registered to the anatomical image using FSL's Boundary Based Registration (Cox, 1996; Greve & Fischl, 2009), spatially normalized into MNI space using the non-linear ANTs SyN warp from the anatomical image, resampled to 2mm isotropic voxels, and smoothed to minimize noise and residual difference in gyral anatomy with a Gaussian filter set at 6-mm full-width at half-maximum. All transformations were concatenated so that a single interpolation was performed.

Time-series images for each participant were furthered processed to limit the influence of motion and other artifacts. Voxel-wise signal intensities were scaled to yield a time series mean of 100 for each voxel. Motion regressors were created using each participant's 6 motion correction parameters (3 rotation and 3 translation) and their first derivatives (Jo et al., 2013; Satterthwaite et al., 2013) yielding 12 motion regressors. White matter and cerebrospinal fluid nuisance regressors were created using CompCorr (Behzadi, Restom, Liau, & Liu, 2007). Images were bandpass filtered to retain frequencies between .008 and .1 Hz, and volumes exceeding 0.25mm frame-wise displacement or 1.55 standardized DVARS (Nichols, 2017; Power et al., 2014) were censored. Nuisance regression, bandpass filtering and censoring for each time series was performed in a single processing step using AFNI's 3dTproject.

General Functional Connectivity

We combined all available BOLD data (task and resting-state) for each participant into a single time-series. Using our recently developed methods (Elliott et al., 2019), we extracted measures of GFC for each participant using a 264-region parcellation scheme derived in a large independent dataset (Power et al., 2011). BOLD time-series were averaged within 5 mm spheres surrounding each of the 264 coordinates in the parcellation and extracted time-series were concatenated. Importantly, we regressed out the task structure from each time-series to reduce the effect of task-related activation on estimates of functional connectivity (Elliott et al., 2019). Correlation matrices were derived from these time-series using Pearson correlation, resulting in 34,716 edges in the Power et al. parcellation. Sensitivity Analyses excluding participants with fewer than 400 TRs (Elliott et al., 2019) did not change our findings reported below.

Connectome-Based Predictive Modeling

Dispositional use of suppression and reappraisal were independently predicted from patterns of GFC using CPM, (Shen et al., 2017). This framework provides a general method to predict any measure from intrinsic connectivity matrices. Functional connections in the brain that had a $p < .01$ correlation with self-reported suppression and reappraise tendency were selected and used as features in a predictive model. Three linear regression predictive models are then built—one from the positive features (edges positively correlated with the measure of interest), one from the negative features (edges negatively correlated with the measure of interest) and one from the combination of positive and negative features (Shen et al., 2017). Here, we discuss the combined model that predicts dispositional regulation styles from positive and negative features in the brain (Shen et al., 2017).

Models were trained using a leave-one-out cross-validation scheme wherein data from all participants except one were used to predict the measure in the left-out participant. This was repeated until all participants had been left out. The Spearman correlation between predicted and true scores was adopted as an unbiased effect size measure of predictive utility. Model predictions of suppression and reappraisal tendency were assessed for significance using a parametric test for significance of correlations. All p values from correlations with suppression and reappraisal tendency were corrected for multiple comparisons using the false discovery rate (Benjamini & Hochberg, 1995). All confidence intervals for CPM prediction estimates were generated with bootstrap resampling, using AFNI's 1dCorrelate tool.

To first establish and then separate between- and within-network GFC, significant positive and negative edges for each of the 264 nodes were independently sorted into seven established neural networks (Yeo et al., 2011) based on pre-defined network assignations of each node. Any node that did not fall into one of these established networks was assigned to an "other" category. The number of edges within and between networks were then assessed for significance using random-sorted permutation testing to establish null distributions for comparison and determine how many connections would be expected by chance ($p < .001$; after correcting for multiple comparisons (.05/38 total within and between comparisons = .001)). In order to examine sex differences in the predictive performance of the models, we correlated the true and predicted dispositional regulation measures (i.e. the output of the CPM model) separately for males and females. Based on previous behavioral and neuroimaging literature noting that men use ES more than females (Aldao & Nolen-Hoeksema, 2013; Cai, Lou, Long, & Yuan, 2016; Gross & John, 2003; McRae, Ochsner, Mauss, Gabireli, & Gross, 2008) Nolen-Hoeksema & Aldao, 2011), we predicted that this correlation would be stronger in males.

3.4 Results

Self-report measures

Means and standard deviations for the self-report questionnaires were as follows: ERQ-Suppression (3.79 ± 1.16, range = 7) and ERQ-Reappraisal (5.18 ± .89, range = 7).

There were significant sex differences ($t(1223.7) = 6.05$, $p < 0.001$) in ERQ-Suppression subscores, with men (4.01 ± 1.13) scoring higher than women (3.63 ± 1.16). There were significant sex differences ($t(1159.2) = -3.78$, $p < 0.001$) in ERQ-Reappraisal subscale scores as well, with women (5.26 ± 0.86) scoring higher than men (5.07 ± 0.92). ERQ-Reappraisal and ERQ-Suppression subscales were not significantly correlated (r = -.04, p = .97).

Connectome-based predictive modeling

We investigated if there was a whole-brain signature for the dispositional use of suppression and reappraisal using a predictive and cross-validated model. There was no pattern of distributed functional connectivity in the brain that predicted individual differences in the dispositional use of reappraisal (r = .02, p = .37). We compared the correlations between actual and predicted ERQ–Reappraisal scores (i.e., the output and predictive utility of the CPM models) in men and women and found no sex difference ($r_{male} = -.009$, p = .8; $r_{female} = .039$, p = .36; Figure 8).

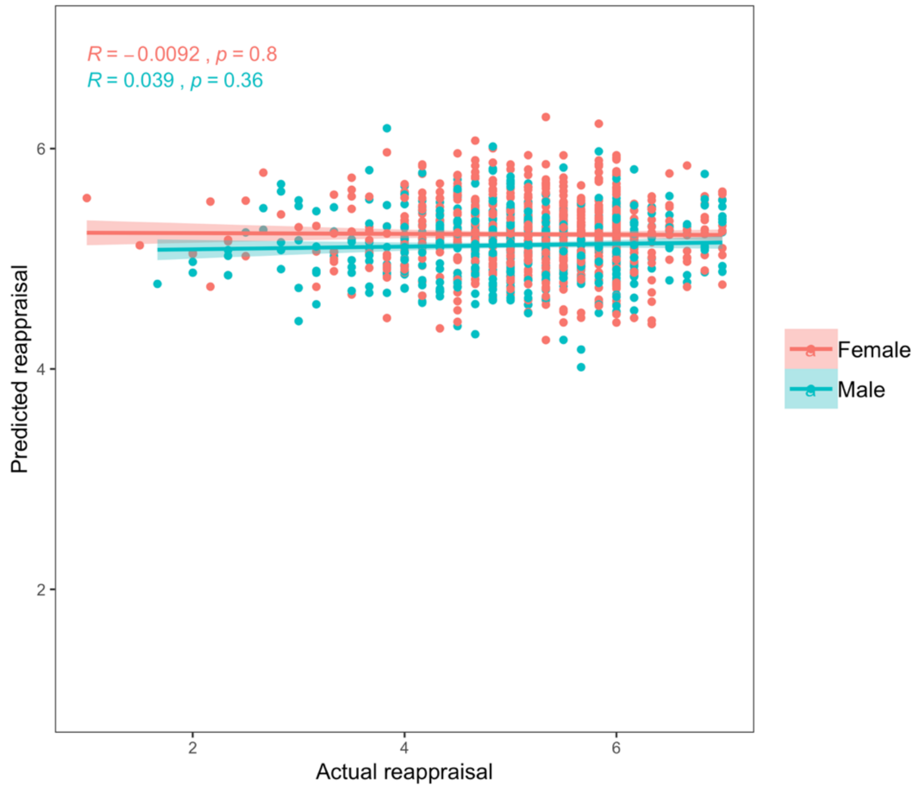

Figure 8: Actual versus Predicted ERQ–Reappraisal Scores.

In contrast, there was a whole-brain signature for the dispositional use of suppression (r = .135, p <.001). 176 functional connections were positively correlated and 123 functional connections were negatively correlated with ERQ-Suppression (Table 2). Within-network analyses revealed that the visual network had the most (41) positive predictive edges (Figure 9A) and the somatomotor network had the most (25) negative predictive edges (Figure 9B). The most (35) between-network positive connections were across frontoparietal and default mode networks and the most (32) between-network negative connections were across somatomotor and default mode networks (Figure 9A and B). Random sampling permutation tests of within-network patterns confirmed significant positive associations for visual, default mode, and frontoparietal networks, and significant negative associations for the somatomotor network. The only between-network connections expected above chance were across default mode and frontoparietal networks (positive) and default mode and somatomotor networks (negative).

	Direction	
Network	*Positive*	*Negative*
Within		
Visual (VisN)	41 *	0
Default Mode (DMN)	27 *	1
Frontoparietal (FPN)	7 *	0
Dorsal Attention (DAN)	2	0
Somatomotor (SMN)	0	25 *
Ventral Attention (VAN)	0	1
Limbic (LimN)	0	0
Other (Othr)	0	0
Between		
FPN - DMN	35 *	2
VisN - DAN	12	0
VAN - DMN	9	10
Othr - SMN	8	4
LimN - FPN	5	1
VAN - FPN	5	0
VisN - DMN	3	12
VisN - LimN	3	4
SMN - FPN	3	3
DAN - FPN	3	0
Othr - VAN	3	0
VisN - FPN	3	0
Othr - DMN	2	2
Othr - VisN	1	3
SMN - VAN	1	3
VisN - SMN	1	3
LimN - DMN	1	0
Othr - LimN	1	0
SMN - DMN	0	32 *
VisN - VAN	0	8
SMN - DAN	0	5
SMN - LimN	0	2
DAN - DMN	0	1
VAN - LimN	0	1
DAN - LimN	0	0
DAN - VAN	0	0
Othr - DAN	0	0
Othr - FPN	0	0
Total	176	123

Table 2: Functional Connections Correlated with ERQ–Suppression.

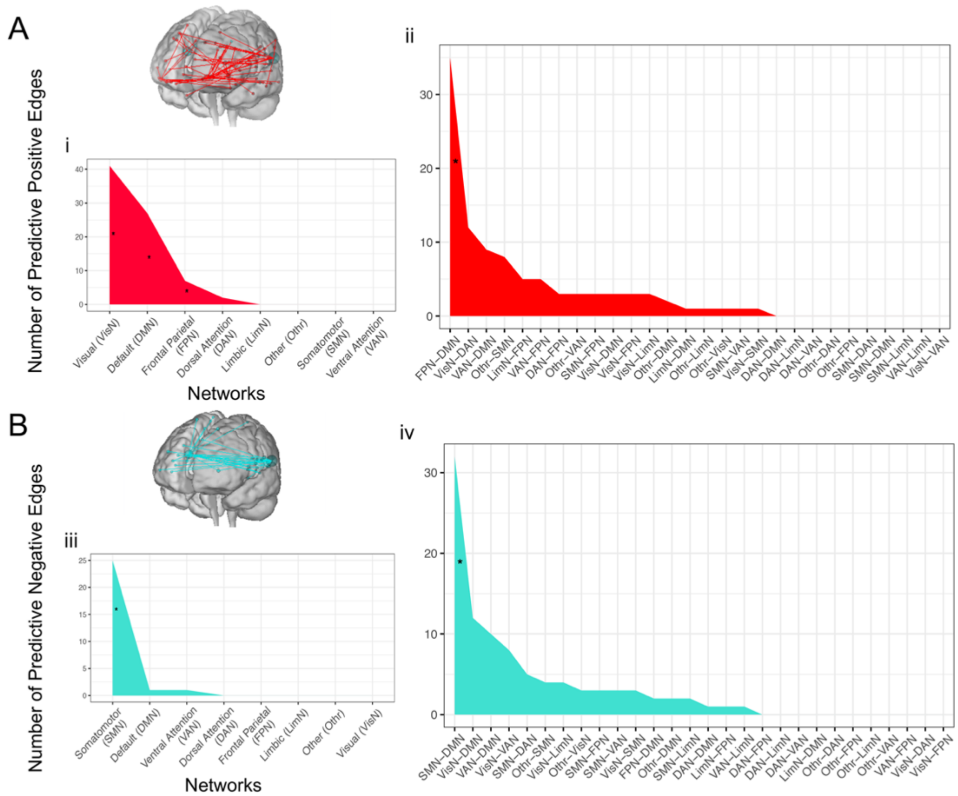

Figure 9: Functional Connections Correlated with ERQ–Suppression.

When examining sex differences in the neural signature of dispositional suppression, we found that the predictive performance of the model (the correlation between actual and predicted ERQ–Suppression scores) was only significant in men (r_{male}= .17, $p < .001$; r_{female} = .05 , p = .09; Figure 10). Moreover, the correlation coefficients between men and women were significantly different (z = 1.96, p = .049). In addition, we re-ran our CPM model with past or present psychiatric diagnosis as a covariate, which confirmed the neural signature associated with suppression was not driven by diagnosis (r = 13, $p < .001$). Because not all data were collected on the same scanner (Table 1), we conducted a final sensitivity analysis using scanner as a covariate, which confirmed the significant whole-brain signature of the dispositional suppression (r = .11, p < .001).

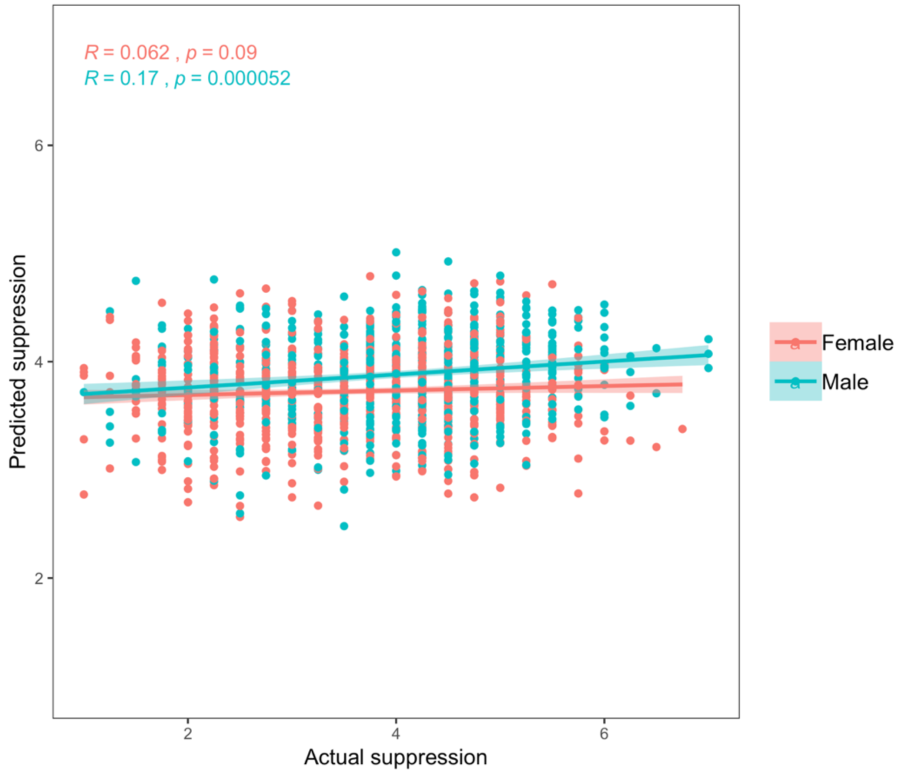

Figure 10: Actual versus Predicted ERQ–Suppression Scores.

3.5 Discussion

In a large sample of 1,316 participants, we used a data-driven and theory-free approach to examine if there is a neural signature for how people tend to regulate their emotions. Instead of limiting patterns of functional connectivity to the typical 5 to 10 minutes of resting-state scans (Elliott et al., 2019), we used GFC to leverage shared features of task and resting-state fMRI and generate more reliable estimates of intrinsic functional connectivity. Most available research investigating individual differences in intrinsic connectivity is based on resting-state scans. However, most resting-state scans are typically not sufficiently long enough to generate reliable estimates of intrinsic functional connectivity. GFC has been shown to be a reliable measure of stable, trait-like individual differences in behavior, such as dispositional regulation tendency (Elliott et al., 2019). By adopting GFC, we increased our ability to investigate neural signatures of individual differences in emotion regulation strategies.

In addition to benefiting from using all available functional data, our findings begin to address other limitations often present in emotion regulation research. For example, existing research often finds overlapping patterns of neural activity for suppression and reappraisal, confounding the ability to distinguish between them. As our approach is wholly data-driven, we are able to analyze distributed patterns for each strategy separately. In addition, existing neuroimaging research that explores brain-behavior relationships is often biased toward specific regions of interest or explores whole-brain maps that may be overfit and vulnerable to false positives (Shen et al. 2017). Using CPM, we circumvent these limitations and generate a predictive model that is cross-validated in novel samples.

As with prior research on whole-brain networks associated with suppression, our results indicate that functional connectivity between the frontoparietal and default mode networks is positively correlated with the tendency to suppress negative emotion (Pan et al., 2018). The default mode network, initially named so because it is active in the absence of an explicit goal or task, is commonly implicated in self-reflection, mind wandering, and self-generated thought (Andrews-Hanna, 2012; Andrews-Hanna, Smallwood, & Spreng, 2014). The default mode network has been implicated in suppression in prior studies employing a univariate analysis approach as well (Goldin, McRae, Ramel, & Gross, 2008). This dual recruitment of default mode and frontoparietal networks is consistent with prior research indicating that the default mode network may support emotional processing and reflection, and the frontoparietal network may support emotional control—abilities that align to primary descriptions of suppression as the conscious inhibition of emotional expression (Gross & Levenson, 1993).

Consistent with demonstrated sex differences in emotion regulation, the neural signature of dispositional use of suppression identified in our current study was specific to men who tend to habitually use and are more successful at implementing suppression (Cai et al., 2016; Gross & John, 2003). Similarly, electromyography findings have shown that men show reduced emotional expressions when viewing negative emotional stimuli (Grossman & Wood, 1993). Prior research has shown that men are socialized to refrain from expressing emotion and therefore have more developmental experience with suppressing negative emotion (Brody & Hall, 2010; Katkin & Hoffman, 1976; Williams & Best, 1990). Such differences may contribute to our sex-specific effects. Future work is necessary to replicate this sex difference.

Importantly, the neural signature of dispositional suppression remained significant after excluding participants with psychiatric diagnoses, suggesting that clinical manifestations associated with suppressing emotion are not driving the predictive relationship between patterns of functional connectivity and suppression tendency. Although the tendency to suppress negative emotion is one characteristic of depression and anxiety (Amstadter, 2008; Cisler & Olatunji, 2012; Gross, 2002; Gross & Levenson, 1997; Troy, Wilhelm, Shallcross, & Mauss, 2010), healthy adults may also use suppression in certain situations (Doré, Silvers, & Ochsner, 2016; Suri, Sheppes, Young, Abraham, McRae, & Gross, 2018). Thus, the use of suppression is likely not categorically maladaptive and, indeed, may be adaptive in particularly stressful situations (Doré, Silvers, & Ochsner, 2016).

We found a pronounced whole-brain signature of the tendency to suppress negative emotion, but found no comparable signature for reappraisal. Specifically, despite prior research implicating the default mode network in the reappraisal of negative emotion, we found no such signature. However, these findings typically come from studies with small sample sizes, which increase the likelihood of false positives (Chen, Biswal, Lei, & Yuan, 2018; Gao et al., 2018). Moreover, emotion regulation research typically involves instructing participants to employ an explicit strategy (Cutuli, 2014; Dennis & Hajcak, 2009; Gross & John, 2003; Kalisch, Wiech, Herrmann, & Dolan, 2006; Kanske, Heissler, Schönfelder, & Wessa, 2012; Urry et al., 2006). But, emotion regulation during laboratory protocol may not accurately reflect how people tend to choose to regulate their emotions in the real world (Aldao, Nolen-Hoeksema, & Schweizer, 2010; Gross & John, 2003; Moore, Zoellner, & Mollenholt, 2008). Thus, the differences between our current null findings and the positive findings of prior studies may reflect our focus on typical, daily strategies for regulation versus directed use of an experimental strategy for regulation.

One possibility for not identifying a neural signature for reappraisal specifically could be that reappraisal is a more heterogeneous construct with numerous subtypes than suppression (Doré, Silvers, & Ochsner, 2016). For example, although reappraisal is predominantly thought to be implemented in the service of reframing a stimulus to be less negative, individuals may use reappraisal to reframe a stimulus to be more positive (Doré, Silvers, & Ochsner, 2016). In addition, people can reappraise stimuli to feel less personal and more detached (Ossenfort, Harris, Platzek, & Isaacowitz, 2018). In contrast, suppression is a more homogenous strategy with less variability in its implementation. As opposed to having numerous possible goals and subtypes, expressive suppression is a less complicated technique that invariably involves trying to mask your feelings from the outside world (Gross, 2002; Gross & John, 1998). Therefore, it may be more difficult to capture a stable neural signature of something as variable and multifaceted as reappraisal in comparison with suppression. The behavioral phenotypes predicted by our models are based on a the ERQ-Suppression and Reappraisal subscales. The heterogeneity of reappraisal may be adding too much noise for the scale to be significantly predicted from patterns of functional connectivity. Relatedly, it may be difficult to self-report on a cognitively demanding and multifaceted technique such as reappraisal, making it difficult for a brain-behavior relationship to be identified.

Our study is not without limitations. Although GFC explicitly removes task-related activation from estimates of functional connectivity, such connectivity may nevertheless be affected by the inherent task performed during data acquisition (Elliott et al., 2019). Future research could investigate how functional connectivity estimated only from resting-state data maps onto the dispositional use of reappraisal and suppression. Future studies may also aim to include a more diverse sample, as our sample was comprised of relatively high-functioning university students. Similarly, our data was cross-sectional, which limits our ability to determine if GFC patterns drive the use of suppression or if the use of suppression drives changes in GFC. In addition, our measure of regulation tendency was based on self-report. Thus, examining the neural signature of suppression we have identified during experimentally-controlled emotion regulation will be important. Lastly, the ERQ measures the tendency to use either suppression or reappraisal, but does not capture alternative strategies that people may adopt.

4. Psychophysiological Basis of Emotion-Regulation Tendency

The content from this chapter is verbatim from the below publication and has only been reformatted for this dissertation:

Burr, D. A., Pizzie, R. G., & Kraemer, D. J. (2021). Anxiety, not regulation tendency, predicts how individuals regulate in the laboratory: An exploratory comparison of self-report and psychophysiology. *Plos One*.

4.1 Abstract

Anxiety influences how individuals experience and regulate emotions in a variety of ways. For example, individuals with lower anxiety tend to cognitively reframe (reappraise) negative emotion and those with higher anxiety tend to suppress negative emotion. Research has also investigated these individual differences with psychophysiology. These lines of research assume coherence between how individuals regulate outside the laboratory, typically measured with self-report, and how they regulate during an experiment. Indeed, performance during experiments is interpreted as an indication of future behavior outside the laboratory, yet this relationship is seldom directly explored. To address this gap, we computed psychophysiological profiles of uninstructed (natural) regulation in the laboratory and explored the coherence between these profiles and a) self-reported anxiety and b) self-reported regulation tendency. Participants viewed negative images and were instructed to reappraise, suppress or naturally engage. Electrodermal and facial electromyography signals were recorded to compute a multivariate psychophysiological profile of regulation. Participants with lower anxiety exhibited similar profiles when naturally regulating and following instructions to

reappraise, suggesting they naturally reappraised more. Participants with higher anxiety exhibited similar profiles when naturally regulating and following instructions to suppress, suggesting they naturally suppressed more. However, there was no association between self-reported reappraisal or suppression tendency and psychophysiology. These exploratory results indicate that anxiety, but not regulation tendency, predicts how individuals regulate emotion in the laboratory. These findings suggest that how individuals report regulating in the real world does not map on to how they regulate in the laboratory. Taken together, this underscores the importance of developing emotion-regulation interventions and paradigms that more closely align to and predict real-world outcomes.

4.2 Introduction

Stressful experiences are an inevitable aspect of life. Although most individuals can commiserate about shared distressing events, such as a traffic jam or a breakup, there is significant variability in how individuals respond to stressors (John & Gross, 2007). Consider two individuals, Kathleen and Tom, who may both encounter the same negative experience, such as failing an exam, but Kathleen may reframe the failing grade as a consequence of not studying enough after starting to feel upset and embarrassed, motivating her to hit the books. In contrast, Tom may be very anxious and mask his emotions instead of actively processing the experience. Kathleen and Tom naturally chose to respond to the stressor using different strategies and consequently experienced it in different ways.

Various strategies exist for trying to change the intensity, duration, and quality of emotional experiences, collectively referred to as emotion regulation. Two common strategies for trying to modulate the emotional impact of a stimulus are cognitive reappraisal (henceforth reappraisal) and expressive suppression (henceforth suppression; Gross, 2008). Reappraisal, as exemplified by Kathleen, is characterized by actively reframing a stimulus in order to change its meaning or value (Buhle et al., 2013; Castella et al., 2017; Gross, 1998). Multiple studies have illustrated that reappraisal helps reduce negative affect and combat the potentially harmful effects of chronic stress (Buhle et al., 2013; Denny et al. 2015; Dore et al. 2016; Goldin, McRae, Ramel, & Gross, 2008; Jamieson et al., 2010). Suppression, as exemplified by Tom, is considered an avoidance-based emotion regulation strategy that aims to modulate the response to an emotional stimulus by reducing the outward expression of negative emotion (Gross, 1998; Gross, 2002). However, suppression often fails to durably alter the associated internal experience (Dan-Glauser & Gross, 2013). Reappraisal and suppression also differ in *when* they occur in the lifecycle of an emotion; reappraisal typically occurs earlier in the emotional experience and is considered an antecedent-focused strategy, whereas suppression typically occurs later in the emotional experience and is considered a response-focused strategy (Gross, 1998; Gross, 2008; Gross, 2015; Sheppes, Suri, & Gross, 2015).

Research has explored how the tendency to reappraise and suppress relates to larger health outcomes. Specifically, previous research has demonstrated the myriad ways that anxiety influences how individuals process and regulate emotions. For example, individuals who tend to suppress experience heightened anxiety, whereas those who tend to reappraise report decreased anxiety (Amstadter, 2008; Cisler & Olatunji, 2012; Denny, Inhoff, Zerubavel, Davachi, & Ochsner, 2015; Gross, 2002; Gross & Levenson, 1997; Jamieson, Mendes, Blackstock, & Schmader, 2010; Troy, Wilhelm, Shallcross, & Mauss, 2010). In addition to anxiety influencing how individuals tend to regulate their emotions, it also impacts how they respond to regulation instructions/interventions (De Witte, Sütterlin, Craet, & Mueller, 2017) and process negative stimuli in general (Lang, Bradley, & Cuthbert, 1998).

Psychophysiology offers an additional lens through which to measure anxiety and emotion regulation. This line of research has shown that suppression leads to reduced activity in the corrugator muscle—a muscle important for frowning and implicated in feeling anger and sadness (Cacioppo et al., 2000; Cacioppo, Tassinary, & Bernston, 2007; Künecke et al., 2014)—and the levator muscle—a muscle associated with the expression of disgust (Larsen, Norris, & Cacioppo, 2003; Tassinary & Cacioppo, 1992; Vrana, 1993; Wolf, 2015). Despite suppression resulting in a decrease in the outward expression of negative emotion, individuals typically exhibit increased sympathetic arousal and skin conductance, usually measured with electrodermal activity (EDA; Gross, 2002; Gross & Levenson, 1993; Levenson, 2000; Lindquist et al., 2012; Mauss et al., 2005; Peters, Overall & Jamieson, 2014;) These findings suggest that suppression may have a counterintuitive effect that modulates the outward expression of emotion, but fails to durably address the underlying emotional experience (Dan-Glauser & Gross, 2013). On the contrary, reappraisal has been shown to decrease both the outward expression of negative emotion *and* the internal subjective experience (Ray, McRae, Ochsner & Gross, 2010). Taken together, this suggests that suppression leads to a lack of coherence between subjective and psychophysiological components of emotion (Brown, Van Doren, Ford, Mauss, Sze, & Levenson, 2020; Dan-Glauser & Gross, 2013). Individuals suffering from excessive anxiety tend to automatically exhibit these same response patterns. For example, individuals who suffer from excessive anxiety experience increased arousal and activity of frowning muscles in response to negative stimuli (Rosebrock, Hoxha, Norris, Cacioppo, & Gollan, 2017). In fact, *Botulinum toxin* (colloquially referred to as Botox) therapy has been shown to relieve anxiety by reducing automatic excitation of frowning muscles (Dong, Fan, Luo, & Peng, 2018).

Current Study

The vast majority of research on emotion regulation has focused on reappraisal and suppression. Moreover, the wealth of research on anxiety and emotion regulation emphasizes reappraisal and suppression (Amstadter, 2008; Cisler & Olatunji, 2012; Gross, 2002; Gross & Levenson, 1997). Relatedly, the ERQ—the gold-standard scale of natural regulation tendency— measures reappraisal and suppression (Gross & John, 2003). Therefore, the current study focused on these strategies and informed predictions based on existing research.

Research describing the psychophysiological correlates of anxiety and emotion regulation is typically conducted in the laboratory. Participants will follow instructions to regulate while viewing emotionally-evocative stimuli, as well as complete a series of self-report measures so researchers can gain insight into their subjective experience. However, it is unclear if participants behave similarly inside and outside the laboratory—how individuals regulate in an experiment may not align to how they regulate in the real world. To bridge this gap, affective self-report measures often attempt to capture how individuals tend to experience and regulate emotions in the real world. However, this assumes individuals are aware of and can accurately characterize their experience to answer questions such as “what did I do to feel less negative?” (McCambridge, de Bruin & Witton, 2012). Importantly, this reflective and metacognitive skill may be particularly difficult for individuals with anxiety (Philippi & Koenigs, 2014). Individuals with anxiety often ruminate about the self and suffer from heightened self-consciousness, which is associated with deficits in perception (Philippi & Koenigs, 2014). Self-report is also limited by demand characteristics (Rosenman, Tennekoon & Hilll, 2011; Tellegen, 1985). Moreover, self-report measures are not always investigated for coherence with other affective measures, such as psychophysiology, which may be less affected by demand characteristics (Dunstan, Scott & Todd, 2017; Shoemaker & McCombs, 1989). To address these gaps, we computed multivariate psychophysiological profiles of uninstructed (natural) regulation in the laboratory and investigated the coherence between these profiles and a) self-reported anxiety and b) self-reported regulation tendency.

Instead of only measuring changes in facial musculature, typically measured with electromyography (EMG), or EDA in isolation, we combined these channels to more comprehensively index how individuals regulate in a variety of contexts. We first validated psychophysiological profiles of reappraisal and suppression and tested how these profiles vary based on trait anxiety. Based on this proof-of-concept model testing the psychophysiological signature of emotion regulation, we conducted an exploratory analysis to examine the coherence between self-reported and psychophysiological indices of emotion and emotion regulation.

Prior research has emphasized that emotions involve the coordination of subjective, behavioral and psychophysiological response systems (Brown, Van Doren, Ford, Mauss, Sze, & Levenson, 2020). Moreover, coherence among these response systems indicates higher levels of well-being (Brown, Van Doren, Ford, Mauss, Sze, & Levenson, 2020). However, research has yet to explore how indices of emotion regulation converge. We aimed to investigate how subjective self-reporting of anxiety and natural regulation tendency influenced how individuals spontaneously regulate emotion in the laboratory. To accomplish this goal, we computed a multivariate psychophysiological dissimilarity metric that captures how much participants naturally reappraised and suppressed, in the absence of regulation instructions. We then compared this metric with two common self-report measures of the subjective experience of emotion and emotion regulation—natural regulation tendency and trait anxiety.

Foundational research on the psychophysiological correlates of emotion regulation and anxiety guided predictions in the current study. Anxiety fundamentally influences, and even predicts, how individuals experience and regulate emotion (Cisler & Olatunji, 2012). Individuals with heightened anxiety tend to naturally suppress and exhibit increased psychophysiological arousal in response to negative emotion (Amstadter, 2008; Gross, 2002; Gross & Levenson, 1997). Therefore, we predicted that participants who tend to suppress negative emotion would exhibit higher skin conductance. Similarly, we predicted that these patterns would be particularly true for individuals with heightened anxiety, as they are more likely to naturally suppress negative emotion (Amstadter, 2008; Cisler & Olatunji, 2012; Gross, 2002; Gross & Levenson, 1997). Based on the mechanisms of suppression (Goldin, McRae, Ramel, &

Gross, 2008; Gross, 1998; Gross & Levenson, 1997; McRae et al., 2010; Ochsner & Gross, 2008; Silvers et al., 2012), we similarly predicted that increased suppression would be negatively correlated with EMG activity. To the extent that reappraisal effectively reduces negative affect and facial expressions change accordingly, we similarly predicted that increased reappraisal would be negatively correlated with EMG activity (Ray, McRae, Ochsner & Gross, 2010).

Based on the extent to which anxiety shapes perceptions and experiences of emotion (Amstadter, 2008; Cisler & Olatunji, 2012); we collectively predicted that participants would regulate differently depending on how anxious they were. Specifically, based on prior research (Amstadter, 2008; Cisler & Olatunji, 2012; Gross, 2002; Gross & Levenson, 1997; Troy, Wilhelm, Shallcross, & Mauss, 2010), we predicted that participants with higher anxiety would exhibit uninstructed (natural) psychophysiological profiles that resembled suppression and participants with lower anxiety would exhibit uninstructed (natural) psychophysiological profiles that resembled reappraisal. Similarly, we predicted that participants who reported frequently reappraising would exhibit uninstructed (natural) psychophysiological profiles that resembled reappraisal and participants who reported frequently suppressing would exhibit uninstructed (natural) psychophysiological profiles that resembled suppression.

4.3 Materials and Methods

Participants

Fifty-eight undergraduate students were recruited to participate in this study from a pool of 488 students enrolled in introductory psychology and neuroscience courses in a small college in New England. Data collection was part of a different study and recruitment was therefore based on scores from the Math Anxiety Rating Scale (Suinn & Winston, 2003), a self-report questionnaire that assesses anxiety and negative affect directed toward mathematics. All eligible participants from this different study were included in the present study. Six students were excluded from further analyses: one participant was excluded for extremely low accuracy (not significantly different from chance-level responding, ~50%) on the math and/or analogy trials (see Pizzie & Kraemer, 2018), two participants were excluded for having a large number of missing responses (> 3 standard deviations above the mean number of non-response trials), and three students were not included in data analysis because they did not complete the task due to fatigue or power failure. Fifty-two participants were included in the dataset for analysis (M_{Age}= 19.56, SD_{Age} = 1.14, 63.5% female). All participants provided written informed consent to participate in a psychophysiological experiment and all procedures were approved by the Dartmouth Committee for the Protection of Human Subjects. Participants were compensated with course extra credit or cash.

This sample size was idealized for a different empirical question (see Pizzie & Kraemer, 2018) and results should be interpreted cautiously. However, our sample size in line with or larger than numerous studies that use the same emotional stimuli and similarly investigate the effects of regulation strategies (Buhle et al., 2014; Moodie et al. 2020).

Training

Participants were told that they would see a cue at the beginning of each block of trials instructing them how to engage with the stimuli over the course of the following twenty trials. This cue would either explicitly instruct them how to regulate their emotions (“REAPPRAISE” or “SUPPRESS”) or direct them to engage with the stimuli as they naturally would (“LOOK”), constituting an uninstructed condition (Silvers, Wager, Weber, & Ochsner, 2014). In the uninstructed condition, participants were not directed to refrain from regulating their emotions, but rather were directed to spontaneously engage, allowing them to regulate as they see fit. Participants were trained on the two instructed emotion regulation strategies (“REAPPRAISE” and “SUPPRESS”). This twenty-minute training mirrored training used in published research on emotion regulation and has been established to teach participants how to reappraise and suppress (Goldin, McRae, Ramel, & Gross, 2008; Gross, 1998; Gross & Levenson, 1997; McRae et al., 2010; Ochsner & Gross, 2008; Pizzie, McDermott, Salem, & Kraemer, 2020; Silvers et al., 2012). Participants practiced using each instructed emotion regulation strategy and described the strategy in their own words. During the blocks of suppression trials (“SUPPRESS”), participants were instructed to monitor and control their facial expressions to maintain a neutral expression, such that if they experienced any emotion, no one would know what they were feeling. During the blocks of reappraisal trials (“REAPPRAISE”), participants were instructed to use a method of reinterpreting the meaning of the stimuli to feel less negative about it (Denny & Ochsner, 2014; Ochsner & Gross, 2008). Specifically, participants were instructed to use an emotional distancing reappraisal strategy and were told to imagine looking at the stimuli from an objective perspective. For example, participants could imagine that the image had a broader context that made it less negative by creating a personal narrative (e.g., “Although at first I thought he looked lonely and sad, I imagined the man pictured waiting at the window was waiting for his grandchildren who were playing outside”).

Participants could also adopt a perspective that allowed them to focus on the technical details of the photograph in order to feel less negative, such as imagining that they were a photographer examining the picture or a medical professional evaluating pictures of individuals who had been injured. After being trained on reappraisal and suppression, participants described these strategies to the experimenter, and the experimenter provided feedback when necessary. Participants practiced problems in twelve categories of stimuli (three (emotion regulation strategy: look, reappraise, suppress) x four (stimuli: negative, neutral, analogy, math), and reported how they used the appropriate regulation strategy. The experimenter provided verbal feedback and redirected responses to align with the emotion regulation strategy instructions when necessary. The present study only discusses uninstructed, reappraise and suppress blocks while engaging with negative stimuli (twenty trials per condition = sixty trials per participants). To review the other stimuli conditions, see Pizzie & Kraemer, 2018.

Task

Participants were directed to apply the instructed emotion regulation strategies ("REAPPRAISE" or "SUPPRESS") or engage naturally ("LOOK") to four different types of stimuli: negative images, neutral images, math problems and analogies. Images were obtained from the International Affective Picture System (Lang, Bradley, & Cuthbert, 1997) based on their high negative valence and arousal ratings ($M_{\text{valence}} = 1.74$, $SD_{\text{valence}} = 0.17$, $M_{\text{arousal}} = 6.37$, $SD_{\text{arousal}} = 0.58$). However, the present study only discusses uninstructed, reappraise and suppress blocks while engaging with negative stimuli (twenty trials per condition = sixty trials per participants). To review the other stimuli conditions, see Pizzie & Kraemer, 2018.

At the beginning of each block of trials (sixty trials), participants were presented with a cue directing them to use an emotion regulation strategy (Figure 11). Although participants can rapidly switch between regulation strategies from one trial to the next, this blocked strategy allowed us to make within-subject comparisons across regulation strategies, but reduced the amount of confusion or distraction that might be created by rapidly switching emotion regulation strategy on each trial (McRae, et al., 2012). The order of all blocks and trials were randomized. For each negative image trial, participants viewed an image for 5000 ms and were instructed to maintain attention on the image, then were presented with an answer screen with either an identical image or an image that had been slightly altered (i.e., subtle alterations made using photo editing software) for 5000 ms. Participants indicated with a button press whether they thought the answer image was identical to the first image or not. Accuracy was determined by whether the participant correctly indicated if the image that they observed had been altered or was exactly identical to the original image. Trials were separated by a jittered inter-trial-interval. Participants completed sixty negative image trials, with twenty trials in each emotion regulation condition. Blocks were presented in a randomized order and all participants completed twelve blocks of trials (three emotion regulation strategies x four stimulus categories). The present study only discusses psychophysiological data from the 5000 ms stimulus window during uninstructed, reappraise and suppress blocks while engaging with negative stimuli (twenty trials per condition = sixty trials per participants). To review the other stimuli conditions, see Pizzie & Kraemer, 2018. To review all data, see Pizzie & Kraemer, 2018.

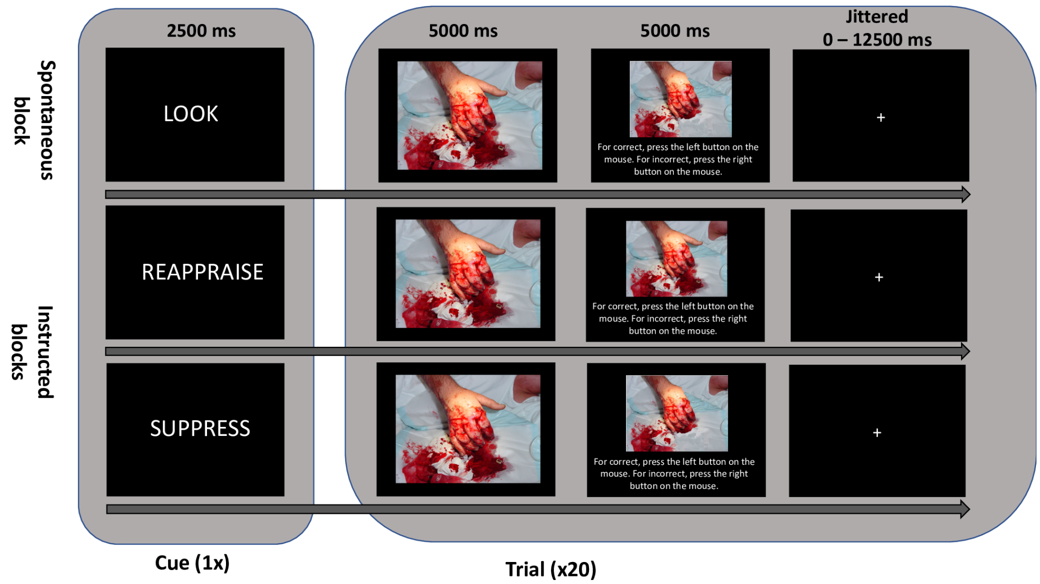

Figure 11: Trial Cadence.

Trial cadence for emotion regulation task depicting the instructed conditions ("REAPPRAISE" and "SUPPRESS" cues) and uninstructed condition ("LOOK" cue). Participants were given a cue at the beginning of a block of twenty trials. Participants first saw an original stimulus for 5000 ms. On the subsequent answer screen, participants either saw the identical image again, as depicted in the middle (REAPPRAISE) row, or a slightly altered image, as depicted in the top (LOOK) and bottom (SUPPRESS) rows. With a button press, participants indicated whether the image was identical ("correct") or had been altered ("incorrect"). Stimuli were not repeated between conditions and were randomly presented within blocks. The order of emotion regulation conditions was randomized. Images from the International Affective Picture System were used in the experiment. However, the above image is not from this database. The photo used is credited to https://litfl.com/clinical-cases/ and was edited and reused here with permission under the Creative Commons Attribution-ShareAlike 3.0 Unported license (https://creativecommons.org/licenses/by/3.0/legalcode).

At the end of the experiment, participants completed a series of self-report questionnaires and provided demographic information. In these analyses, we focus on how trait anxious participants are, which was measured by self-reported trait anxiety (Spielberger State-Trait Anxiety Inventory—trait subscale, STAI; Spielberger, 2010). In addition to measuring uninstructed modulation of negative emotion in the "LOOK" condition, we measure natural regulation tendency with the Emotion Regulation Questionnaire (ERQ; Gross & John, 2003). The ERQ includes two subscales—reappraisal (e.g. "I control my emotions by changing the way I think about the situation I'm in") and suppression (e.g., "I control my emotions by not expressing them"). Each facet is scored separately, resulting in independent reappraisal and suppression tendency scores.

Psychophysiological Data Collection

We collected EDA and facial EMG data throughout the task. For each trial, we used responses from the 5000 ms stimulus window and the 5000 ms response window. In order to account for the shape of the biological functions that represent psychophysiological data (i.e., skin conductance response), we calculated the area under the curve (AUC) to separately model the responses during the 5000 ms stimulus window (Bach, Friston, & Dolan, 2010). AUC is an established method for measuring mean and overall level of skin conductance over a period of time, more similar to measuring skin conductance level during the stimulus window. This method does not require that activity during intervals be categorized as specific skin-conductance responses or not (Bach, Friston, & Dolan, 2010). To account for individual differences in baseline levels of psychophysiological reactivity, the AUC measurements were z-scored within each subject in order to mean-center the comparisons across conditions. Processing of psychophysiological data was done using standard procedures in BioPac's AcqKnowledge software (Braithwaite, & Watson, 2015).

Electrodermal Activity

We measured sympathetic nervous system activity with EDA from the hand of each participant by attaching a pre-gelled Ag/Ag-Cl electrode to the second phalanx of the index and middle finger on the non-dominant hand (Tassinary & Berntson, 2007). The data were sampled at rate of 1,000 Hz and preprocessed by passing the signal through a band pass filter, isolating the signal between .5 Hz and 60 Hz (Figner & Murphy, 2011). The data were first processed with a BioPac amplifier, with a gain of 5 mΩ/V., and the signal was DC restored. The data were processed using BioPac's AcqKnowledge software and mean value smoothed using a 500 ms window to amplify the signal-to-noise ratio.

Electromyography

We measured changes in electrical activity in facial musculature using EMG from the corrugator supercilii—a muscle group adjacent to the eyebrows frequently associated with increased negative affect (Larsen, Norris, & Cacioppo, 2003; Tassinary & Cacioppo, 1992)—and levator labii superioris—a muscle group implicated in disgust reactions (Vrana, 1993). We recorded from the left side of the face using 4mm Ag/Ag-Cl electrodes that were filled with isotonic gel (Fridlund & Cacioppo, 1986; Cacioppo, Berntson, & Larson, 2000). We exfoliated the skin at each site with a gel to lightly abrade the skin and cleaned with an alcohol wipe before attaching the electrodes and checked that impedance at each site was at acceptable levels (< 10 Ω). We sampled EMG signals at 1,000 Hz and initially processed with a BioPac amplifier with a gain of 2000. We then processed EMG signals with a 100 Hz high pass filter and a 500 Hz low pass filter (effectively a band pass filter). Although EMG signals may begin at frequencies below 100 Hz (EMG frequency signal typically ranges between several Hz to 500 Hz; Tassinary, Cacioppo, & Vanman, 2007), we used a high pass filter in order to more conservatively filter the signal and eliminate 60 Hz electrical noise that may interfere with the signal. We demeaned and rectified the data to produce a positive signal and calculated AUC to model responses during the 5000 ms stimulus window (Bach, Friston, & Dolan, 2010). AUC is an established method for measuring mean and overall level of changes in electrical activity in facial musculature over a period of time and does not categorize specific responses as a change in facial musculature or not (Bach, Friston, & Dolan, 2010).

Data Analysis

The present study only discusses uninstructed, reappraise and suppress blocks while engaging with negative stimuli. Stimuli not discussed were collected as part of a different study investigating a different empirical question (see Pizzie & Kraemer, 2018). Similarly, data were collected on fifty-eight participants who were recruited for this study investigating a different empirical question and analyses were conducted on fifty-two of those participants who passed standards of data quality (see Participants). Participants were recruited to obtain a sample and effect size for this different study (see Pizzie & Kraemer, 2018). Therefore, the current study is exploratory in nature and effects should be interpreted cautiously.

To quantify uninstructed regulation, we computed a continuous measure of multivariate psychophysiological dissimilarity among emotion regulation conditions. We computed a multivariate physiological profile of each participant's emotion regulation conditions to measure dissimilarity across types of emotion regulation. To do this, we first computed each participant's multivariate psychophysiology profile of regulation (Figure 12). Each participant has their own unique pattern of skin conductance, corrugator and levator activity when they are reappraising, suppressing and naturally engaging (uninstructed). The value corresponding to the psychophysiological signal for each regulation condition is the average activity for that psychophysiological signal across all twenty trials in that regulation condition. It was crucial to compare how participants naturally responded to negative stimuli versus how they responded when being instructed to suppress or reappraise. This approach allowed us to compute a multivariate psychophysiological profile of participants' natural regulation style, and compare that to their suppression and reappraisal profiles to quantify the extent to which participants naturally suppressed and reappraised.

Based on these unique profiles, we computed the distance between each condition as a measure of how dissimilar their instructed and uninstructed profiles were (Figure 12). Each participant's unique psychophysiology profile of each regulation condition was then compared using correlation distance as a measure of dissimilarity among conditions in order to quantify how much that participant was naturally reappraising (dissimilarity between uninstructed and instructed reappraisal) and suppressing (dissimilarity between uninstructed and instructed suppression). We used correlation distance to capture the relationship among regulation conditions in order to value the inherent relativity of participants' psychophysiological signals when engaging with stimuli (ranging from 0 to 2, with 0 representing perfect correlation, 1 representing no correlation and 2 representing perfect anti-correlation; https://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.spatial.distance.correlation.html). Comparing multivariate psychophysiological distance is a well-validated technique when working with high-dimensional data (Connor & Moss, 2012; Zapala & Schork, 2006). Here, we explore if this approach can be used to understand the relationship between how people naturally engage with versus follow instructions to regulate negative stimuli.

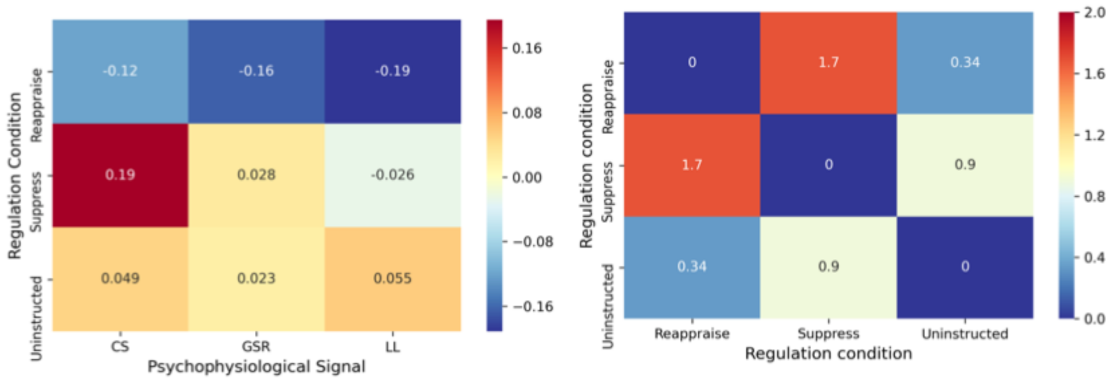

Figure 12: Sample Patterns of Psychophysiological Activity and Multivariate Distance.

Pattern of psychophysiological activity for each regulation condition for a single sample participant (left) and correlation distance among regulation conditions based on sample participant's unique profile (right). CS = corrugator supercilii, GSR = galvanic skin response (skin conductance) and LL = levator labii. The value corresponding to the psychophysiological signal for each regulation condition (left) is the average activity for that signal across all twenty trials in that regulation condition and participant. Psychophysiological data are within-subject z-scored. Dissimilarity (right) is measured with correlation distance (ranging from 0 to 2, with 0 representing perfect correlation, 1 representing no correlation and 2 representing perfect anti-correlation). Smaller y-axis values represent greater similarity.

4.4 Results

Descriptives

Before analyzing the psychophysiological correlates of emotion regulation, we explored how mean levels of skin conductance, corrugator and levator activity varied based on emotion regulation condition and level of trait anxiety (Figure 13). Although trait anxiety was a continuous measure, for illustrative purposes, it is divided into three groups corresponding to one SD below the mean (Low, $M_{\text{z-scored trait anxiety}} = 1.63$, $n = 24$), within one SD of the mean (Middle, $M_{\text{z-scored trait anxiety}} = 2.22$, $n = 19$) and one SD above the mean (High, $M_{\text{z-scored trait anxiety}} = 2.86$, $n = 9$).

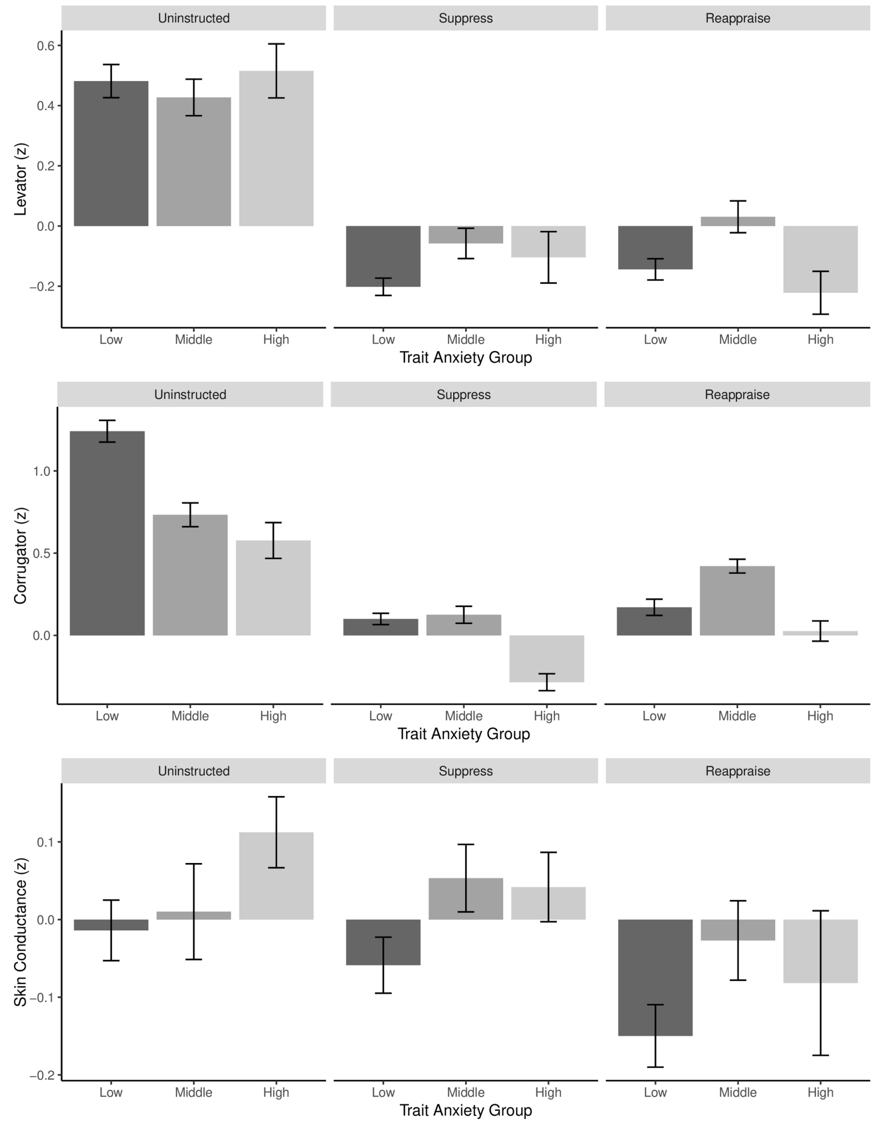

Figure 13: Psychophysiological Activity by Regulation Condition and Trait Anxiety.

Mean physiological activity for each measure in each emotion regulation condition, grouped by trait anxiety. Although trait anxiety (State-Trait Anxiety Inventory; STAI) is a continuous measure, for visualization purposes it is divided here into three groups corresponding to below one SD below the mean (Low), within one SD of the mean (Middle) and above one SD above the mean (High). All psychophysiological data are within-subject *z*-scored across all conditions in the study.

Can Psychophysiological Activity Differentiate Reappraisal and Suppression?

Before comparing psychophysiological and self-reported indices of emotion and emotion regulation, we first tested if there was a pattern of psychophysiological activity that reflected reappraisal and suppression. Based on prior research demonstrating that trait anxiety impacts psychophysiological reactivity to negative stimuli, we also tested how this pattern differed based on level of STAI-trait subscale. In order to test this, we determined the psychophysiological correlates of reappraisal and suppression in our sample with a mixed-effects logistic regression that allowed for random participant intercepts. This model tested if anxiety and activity from all three psychophysiological signals—skin conductance, corrugator EMG, and levator EMG—differentiated the reappraise versus suppress conditions. In other words, we modeled which patterns of anxiety, skin conductance and EMG activity reflected reappraisal versus suppression.

Figure 14 illustrates the results of this logistic regression, which predicted how likely participants were in the reappraise as opposed to suppress condition. In line with prior research (Gross, 2002; Gross & Levenson, 1993) and the descriptive differences between reappraise and suppress conditions observed in Figure 12, participants with increased skin conductance were less likely to be reappraising and more likely to be suppressing (β = -.12, 95% CI [.-.22 -.02], p =- .02). Similarly, participants exhibiting decreased corrugator activity were less likely to be reappraising (β = .24, 95% CI [.15, .34], $p < .001$) and this relationship was strongest for those with higher anxiety (β = .36, 95% CI [.15, .58], $p < .001$). In addition, participants exhibiting decreased levator activity and who had higher anxiety were less likely to be reappraising and more likely to be suppressing (β = -.23, 95% CI [-.43, -.04], p = .02). Levator activity (β = .06, 95% CI [-.05, .16], p = .29) and the interaction between skin conductance activity and trait anxiety (β = -.01, 95% CI [-.22, .2], p = .89) were non-significant predictors of instructed regulation condition.

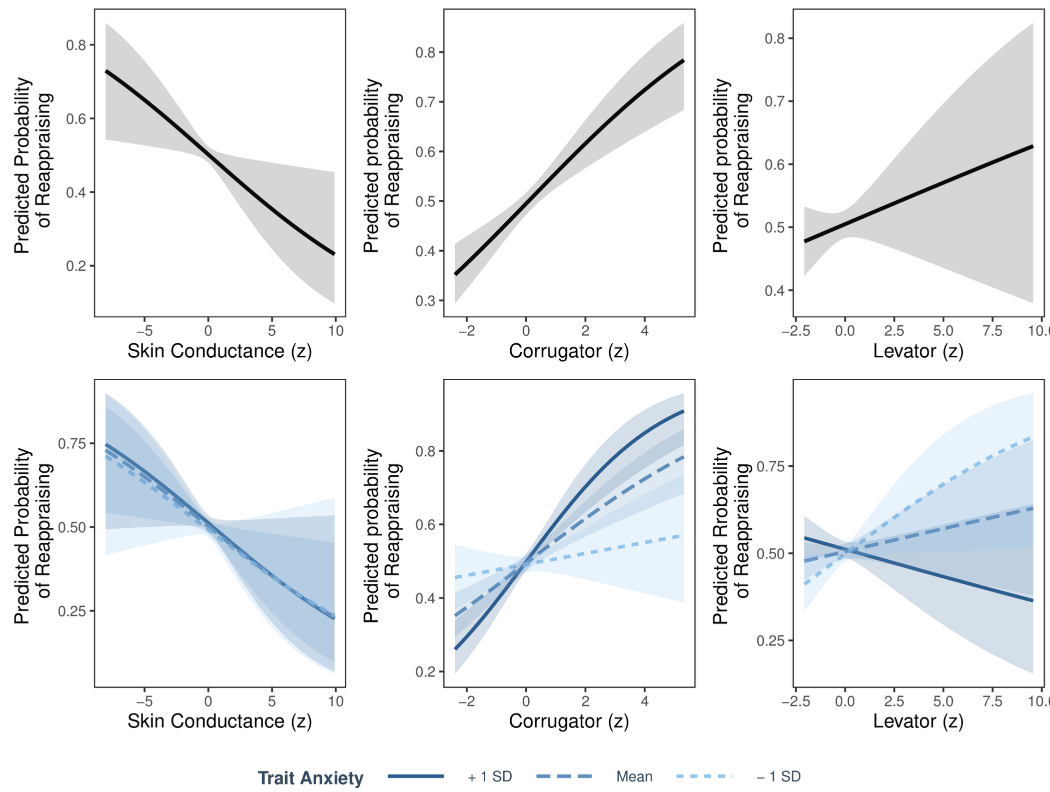

Figure 14: Psychophysiological Patterns Associated with Reappraisal versus Suppression.

Logit function from a mixed-effects logistic regression predicting if participants were in the reappraise or suppress condition. Top: significant effect of skin conductance (left), significant effect of corrugator (middle) and non-significant effect of levator activity (right) on the predicted probability of being in the reappraisal condition as opposed to the suppress condition. Bottom: non-significant interaction between skin conductance and trait anxiety (left), significant interaction between corrugator and trait anxiety (middle) and significant interaction between levator and trait anxiety (right) on the predicted probability of being in the reappraisal condition as opposed to the suppress condition. All psychophysiological data are within-subject *z*-scored.

Do Subjective and Psychophysiological Measures of Emotion and Emotion Regulation Align?

We then used this signature of emotion regulation as a comparison against uninstructed ("LOOK") condition to understand how much participants were naturally suppressing and reappraising. By computing the multivariate psychophysiological dissimilarity among regulation conditions, we quantified how close participants' uninstructed and instructed (reappraise and suppress) conditions were (i.e. how similar or dissimilar their multivariate psychophysiological profiles were). In other words, the multivariate psychophysiological dissimilarity between each participant's unique uninstructed and reappraise conditions represents how much they naturally reappraise in the uninstructed ("LOOK") condition. Similarly, the multivariate psychophysiological dissimilarity between each participant's unique uninstructed and suppress conditions represents how much they naturally suppress in the uninstructed ("LOOK") condition.

We tested if participants' self-reported regulation tendency and trait anxiety distinguished their psychophysiological profiles during instructed and uninstructed regulation. Specifically, we examined if participants' self-reported regulation tendency and trait anxiety predicted if their psychophysiological profiles resembled a reappraisal profile or a suppression profile. To do this, we ran three linear mixed-effects regressions that allowed for random subject intercepts predicting psychophysiological dissimilarity between uninstructed and instructed regulation. Model 1 included instructed condition and STAI as regressors; Model 2 included instructed condition ERQ-Reappraisal as regressors; Model 3 included instructed condition and ERQ-Suppression as regressors. All 3 models predicted the same dependent variable—distance between uninstructed and instructed regulation conditions. To be clear, the effect of instructed condition (a categorical variable determining if the uninstructed psychophysiological profile was compared to either instructed reappraise or instructed suppress) was identical across all three models. All 3 models noted a significant effect of instructed condition ($\beta = -.04$, 95% CI [-.06, -.02], $p < .001$), simply demonstrating that there is a difference between the dissimilarity between uninstructed and reappraise versus uninstructed and suppress. Specifically, psychophysiological profiles are more similar, on average, between uninstructed and suppress than uninstructed and reappraise. Figure 15 illustrates effects from Models 1, 2 and 3.

Model 1 revealed that participants' trait anxiety significantly distinguished if their uninstructed psychophysiological profiles resembled reappraisal versus suppression ($\beta = -.45$, 95% CI [-.05, -.04], $p < .001$). Specifically, trait anxiety interacted with instructed condition such that participants with higher anxiety showed uninstructed psychophysiological profiles resembling suppression, whereas participants with lower anxiety showed uninstructed psychophysiological profiles resembling reappraisal. There was no main effect of trait anxiety ($\beta = .22$, 95% CI [-.08, .52], $p = .15$).

Model 2 revealed that self-reported reappraisal tendency did not distinguish participants' psychophysiological profiles. In addition to the aforementioned significant effect of instructed condition, the main effects of ERQ-Reappraisal ($\beta = .04$, 95% CI [-

.12, .21], p = .61) and interaction between ERQ-Reappraisal and instructed regulation condition (β = -.02, 95% CI [-.04, .01], p = .23) were non-significant predictors of psychophysiological dissimilarity between uninstructed and instructed regulation. In other words, participants who reported frequently reappraising did not show a psychophysiological profile that resembled reappraisal.

Model 3 revealed that self-reported suppression tendency did not distinguish participants' psychophysiological profiles. In addition to the aforementioned significant effect of instructed condition, the main effects of ERQ-Suppression (β = .12, 95% CI [-.02, .26], p = .11) and interaction between ERQ-Suppression and instructed regulation condition (β = -0, 95% CI [-.03, .02], p = .86) were non-significant predictors of psychophysiological dissimilarity between uninstructed and instructed regulation. In other words, participants who reported frequently suppressing did not show a psychophysiological profile that resembled suppression.

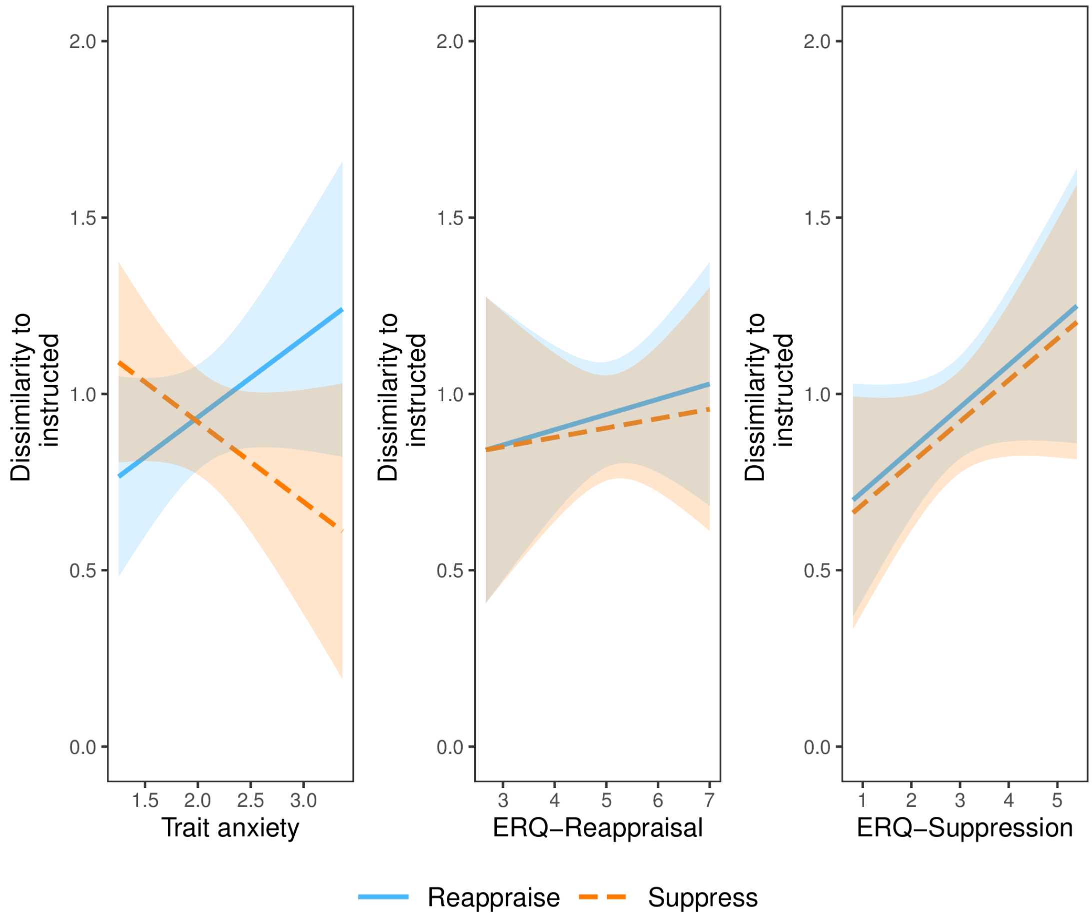

Figure 15: Individual Differences in Multivariate Psychophysiological Dissimilarity.

Participants' self-reported regulation tendency did not differentiate how they naturally regulated, but their trait anxiety did. Effects from Models 1, 2 and 3 on multivariate psychophysiological dissimilarity between instructed and uninstructed conditions. Left (Model 1): significant interaction between trait anxiety (STAI) and instructed condition. Middle (Model 2): non-significant interaction between ERQ-Reappraisal and instructed condition. Right (Model 3): non-significant interaction between ERQ-Suppression and instructed condition. Dissimilarity is measured with correlation distance (ranging from 0 to 2, with 0 representing perfect correlation, 1 representing no correlation, and 2 representing perfect anti-correlation). Smaller y-axis values represent greater similarity. ERQ scores are from the Emotion Regulation Questionnaire (Gross & John, 2003) and trait anxiety scores are from the State Trait Anxiety Inventory-trait Subscale (Spielberger, 2010).

4.5 Discussion

Emotion research has examined individual differences in affective experiences with self-report and psychophysiology. Most research relies on instructing individuals when and how to regulate their emotions, and self-report measures often intend to capture how individuals typically regulate outside the laboratory. But self-report measures of emotion and emotion regulation may not always cohere with psychophysiology. Research strives for ecological validity and hopes for alignment between how individuals report tending to regulate in the real world and how they regulate during an experiment. Moreover, how an individual performs during an emotion-regulation training is often assumed to indicate future performance inside and outside the laboratory. However, individuals may not always regulate similarly inside and outside the laboratory, but these relationships are seldom directly explored. To bridge this gap, we compared self-reported and psychophysiological measures of emotion and emotion regulation. To do this, we computed a multivariate psychophysiological measure of how much participants naturally reappraised and suppressed—free of instruction—then examined how closely this measure converged with self-report. Our results indicate that anxiety, but not regulation tendency, predicts how individuals regulate emotion in the laboratory. These findings suggest that how individuals report regulating in the real world does not map on to how they regulate in the laboratory.

Based on the logistic regression demonstrating the patterns of psychophysiological activity that differentiate reappraisal from suppression, individuals flattened their affect (according to EMG activity) and had higher skin conductance when suppressing compared to reappraising, which aligns to prior research (Cacioppo et al., 2000; Cacioppo, Tassinary, & Bernston, 2007; Künecke et al., 2014; Larsen, Norris, & Cacioppo, 2003; Tassinary & Cacioppo, 1992; Peters, Overall & Jamieson, 2014; Vrana, 1993; Wolf, 2015; Gross & Levenson, 1993). Moreover, participants who were the most anxious flattened their affect more and exhibited the highest levels of skin conductance activity. In line with a suppression profile, participants with lower anxiety did not exhibit increased skin conductance activity when naturally engaging with negative stimuli, yet were more emotionally expressive (Gross, 2002; Gross & Levenson, 1993). Consistent with prior research, this suggests that trait anxiety influences not only how individuals freely engage with negative stimuli, but also how they respond to regulation instructions (Amstadter, 2008; Cisler & Olatunji, 2012; Gross, 2002; Gross & Levenson, 1997; Troy, Wilhelm, Shallcross, & Mauss, 2010). Surprisingly, reappraisal was associated with increased corrugator activity, which was inconsistent with our predictions. Similarly, reappraisal was associated with increased levator activity—but only for highly anxious individuals. This may suggest that although reappraisal may decrease the subjective experience of negative emotion, it may not always impact other channels of emotion, such as facial expression.

These findings are also consistent with previous research demonstrating a psychophysiological marker of emotion regulation. We collected EMG and EDA activity to measure psychophysiological profiles of emotion regulation. Although EMG is traditionally used to study emotional experiences and communication (Cacioppo, et al., 2000; Chanes et al., 2018; Rosebrock, Hoxha, Norris, Cacioppo, & Gollan, 2017; Williams, Leong, Collier & Zaki, 2019), it can be used as a biomarker for emotion regulation as well (Izard, 1990; Ray, McRae, Ochsner & Gross, 2010), as underlying emotional experiences and expressions change in response to the successful regulation of emotion. Based on these psychophysiological underpinnings of regulation, we examined the relationship between self-reported and psychophysiological measures of emotion and emotion regulation.

Participants' self-reported regulation tendency did not significantly differentiate how they naturally regulated, *but their trait anxiety did*. As predicted, participants with *lower levels of anxiety* exhibited similar psychophysiological profiles when naturally regulating and following instructions to reappraise, suggesting they naturally reappraise more. Conversely, participants with *higher levels of anxiety* exhibited similar psychophysiological profiles when naturally regulating and following instructions to suppress, suggesting they naturally suppress more. However, the current study did not identify a relationship between psychophysiological profiles of regulation and self-reported regulation tendency.

Taken together, these results suggest that anxiety may be a better indicator than self-reported regulation tendency of how individuals regulate in the laboratory. Compared to subjective measures of emotion-regulation tendency, there is stronger coherence between subjective measures of anxiety and psychophysiological measures of emotion regulation. In line with prior research (Amstadter, 2008; Cisler & Olatunji, 2012), anxiety fundamentally shapes how individuals experience emotion. However, self-reported regulation style may not always capture how individuals regulate in the laboratory. This is critical because a) self-reported regulation tendency is often treated as the ground truth, b) coherence among various response systems is indicative of well-being and mental stability (Brown, Van Doren, Ford, Mauss, Sze, & Levenson, 2020) and c) performance in an experiment is often interpreted as indicative of future behavior outside the laboratory. Measuring trait anxiety in conjunction with psychophysiology offers a new method for studying coherence between subjective and psychophysiological measures of emotion and emotion regulation.

This study is not without limitations. First, our psychophysiological measures investigated how facial expressions and arousal change as a function of regulating emotion. However, suppression may also involve verbal and behavioral changes (Goldin, McRae, Ramel, & Gross, 2008), which we did not investigate. Similarly, suppression, by definition, involves altering motor movements, which influence skin conductance differently than reappraisal (Gross & Levenson, 1993). Therefore, it is difficult to explicate changes in skin conductance from suppressing versus simply the physical effort and attentional focus required to implement suppression. However, though arousal on its own is a non-specific measure not necessarily indicative of a specific type or valence of emotion, we consider changes in arousal in the context of changes in emotional expression and in response to engaging with stimuli shown to elicit negative emotion (Borrell-Carrió, Suchman, & Epstein, 2004; Cacioppo, et al., 2000). Second, we measured how participants naturally engaged with negative emotion in an uninstructed ("LOOK") condition. However, these trials were conducted after being trained on reappraisal and suppression and that prior training may have influenced responses to the uninstructed modulation of negative emotion condition. Though this is a common paradigm (Doré et al., 2016; Doré, Weber & Ochsner, 2017) and blocks of trials were presented in a randomized order to reduce carryover effects, it may be unclear how much variability in psychophysiological profiles in the uninstructed condition was due to dispositional differences in regulation tendency versus priming from the training session. Future work should aim to collect uninstructed data prior to training in order to truly gauge how individuals naturally choose to regulate of their own volition.

Importantly, participants viewed negative stimuli and either naturally engaged, reappraised or suppressed. Pairwise-distances in three-dimensional space (corrugator, levator and skin conductance activity) were used to determine how similar participants' natural (uninstructed) profiles were to their reappraisal and suppression profiles. Based on the focus of reappraisal and suppression in the current study, the analyses are limited to quantifying how much participants' natural regulation profiles resembled reappraisal and suppression profiles. To align to the strategies measured with the ERQ and heavily associated with the STAI, the current study limited its focus to reappraisal and suppression. However, individuals may regulate in numerous ways (Opitz, Cavanagh, & Urry, 2015). The current study's analyses therefore do not speak to how much participants' natural regulation profiles do or do not resemble other regulation strategies. Moreover, some participants' natural regulation profiles were not similar to either a reappraisal or suppression profile, as indicated by a correlation dissimilarity of 1, suggesting they may be regulating in different ways. Future work should include additional strategies to more comprehensively study variability in the uninstructed modulation of negative emotion.

Another question that warrants further research is how coherence between subjective and psychophysiological indices of regulation varies based on state versus trait experiences. The state-trait taxonomy has allowed research to emphasize differences between processes pertaining to transient versus stable responses. However, research has also demonstrated that this distinction is often arbitrary and lacking a clear boundary. For example, the classification of state versus trait is often attributable to no more than how experimental instructions are phrased (Allen & Potkay,1981; Chaplin, John, & Goldberg, 1988). Specifically, though state measures of emotion and emotion regulation are tied to the specific environmental demands, trait measures, such as the ERQ and STAI-trait subscale used in the present study, are inextricably linked to states and amount to the summation of a series of states (Allen & Potkay, 1981). This study collected data about natural regulation tendency and anxiety with trait-based measures—and did not collect state or trial-by-trial data. Therefore, the current study explored how stable affective traits influence how individuals *tend to* experience and engage with negative emotion. Future research should explicate how stable affective tendencies differ from state measures in terms of subjective and psychophysiological coherence.

Importantly, this was an exploratory analysis aimed at quantifying spontaneous regulation of emotion. These data were collected as part of a different study (see Pizzie & Kraemer, 2018) and the sample size was idealized for a different empirical question. We hope these exploratory findings inspire future research to validate and extend what we know about dispositional emotion regulation in a larger sample collected for this empirical question.

Future Directions

These findings illuminate key differences in how anxiety influences how individuals respond naturally to negative stimuli and *respond to instructions to regulate*. Most therapeutic protocols and interventions for depression and anxiety are based on regulation training that is commonly applied to a wide audience (Beck, 2011). This work indicates that instructed regulation may not be well captured by a one-size-fits-all model. These findings highlight the need for personalized treatment paradigms and introduce a potential platform for detecting individuals that may respond to different styles of emotion-regulation interventions. In addition, these findings suggest that how individuals report regulating in the real world does not map on to how they regulate in the laboratory (Opitz, Cavanagh, & Urry, 2015). Taken together, this underscores the importance of developing emotion-regulation interventions and paradigms that more closely align to and predict real-world outcomes.

These findings reveal a puzzle in emotion regulation—either a) individuals are not reporting their true regulation style or b) how individuals regulate in the real world is not captured by laboratory experiments. Individuals may find it challenging to reflect on and characterize how they regulate when they are not actively regulating in that moment. Moreover, individuals may not be able to sum up their regulation style in a single measure—how they choose to regulate may greatly vary based on the situation and their personal goals. Regulation may be too contextual and idiosyncratic to varying goals and circumstances to distill into a single dispositional tendency (Blanke et al., 2020; Troy, Shallcross, & Mauss, 2013), highlighting the importance of conducting research outside the laboratory (Burr & Samanez-Larkin, 2020). However, anxiety may be a more stable trait that better predicts how individuals regulate. Anxiety may be the more fundamental disposition, which can be accurately captured by self-report, and informs how individuals regulate (Dan-Glauser, Aue, & Scherer, 2006). Future research should explore this puzzle further to understand the disconnect between self-report and laboratory measures of emotion.

5. Leaving the Laboratory

5.1 Advancements in Emotion-Regulation Choice from Experience Sampling

The content from this chapter is verbatim from the below publication and has only been reformatted for this dissertation:

Burr, D. A. & Samanez-Larkin, G. R. (2020). Advancements in emotion-regulation choice from experience sampling. *Trends in Cognitive Sciences*, 24(5), 344-346.

5.1.1 Abstract

Recent experience-sampling studies by Blanke *et al*. and Grommisch *et al*. provide insights into how individuals regulate their emotions in daily life. The rich datasets accessible from experience sampling allow researchers to detect nuances in the relationship between emotion-regulation choice and psychological health that may not be observed in traditional laboratory studies.

5.1.2 Introduction

Stressors are common in life, from traffic jams on the way to work to chronic illnesses. How individuals respond to stressors is an important indicator of psychological health and well-being (Gross & John, 2003). Research conducted in the laboratory has led to foundational discoveries of how individuals regulate their emotions in response to stressors and how their regulation choices are associated with different health outcomes (Buhle et al., 2013; Burr, Castrellon, Zald, & Samanez-Larkin, 2021; Goldin, McRae, Ramel, & Gross, 2008; Gross & John, 2003; Shiota & Levenson, 2009; Winecoff, Labar, Madden, Cabeza, & Huettel, 2011). However, how individuals regulate in the laboratory may not reflect how they regulate in their daily lives. To study how emotion regulation is associated with psychological health and well-being, it is important to study how individuals choose to regulate outside the laboratory.

New research by Blanke and colleagues (Blanke et al., 2019) and Grommisch and colleagues (Grommisch et al., 2019) has ventured into the wild using experience sampling to investigate how individuals choose to regulate in varying contexts—outside the confines of the laboratory. They gathered data about how individuals were feeling and choosing to regulate by sending brief surveys to their phones. These studies helped to identify new patterns of how individuals choose to regulate in complex, evolving environments. By collecting rich and versatile datasets, they detected valuable information about the consequences and dynamics of how individuals regulate outside the laboratory. These methodological and analytical advances have brought us closer to a more comprehensive understanding of how individuals choose to regulate based on their personal goals and the larger context.

Blanke and colleagues (Blanke et al., 2019) investigated how variable individuals were in their regulation choices by analyzing data from four experience-sampling studies. They investigated whether individuals who were more variable in their use of regulation strategies experienced less negative affect than individuals who were more rigid (less variable) in their regulation choices. To do this, they analyzed how variable individuals were in their use of a specific regulation strategy over time (within-strategy variability) *and* in how they regulated at specific sampling occasions (between-strategy variability). Within- and between-strategy variability capture distinct constructs. An individual with low within-strategy variability may always, for example, strongly suppress negative emotion, regardless of the circumstances. Separately, an individual with high between-strategy variability may use a range of strategies but prioritize, for example, cognitively reframing, at a given moment. However, an individual with low between-strategy variability may be more lackadaisical in how they chose to regulate and endorse numerous regulation strategies to the same extent, without prioritizing one. For the first time, Blanke et al. show that individuals who prioritized certain regulation strategies (i.e. high between-strategy) over others experienced less negativity. However, the relationship between within-strategy variability and negativity varied based on how depressed individuals were (i.e. level of depressive symptoms). Specifically, individuals who did not rigidly regulate in the same way across varying contexts (i.e. had high within-strategy variability) experienced less negativity, but only when controlling for depressive symptoms. Furthermore, individuals with higher levels of depressive symptoms were more likely to have higher within-strategy variability, indicating that within-strategy variability may be maladaptive (Blanke et al., 2019).

Grommisch and colleagues (Grommisch et al., 2019) similarly investigated how individuals' regulation choices influenced their well-being. They analyzed how individuals' repertoire of strategies—the range of strategies they used across situations—influenced how happy and satisfied they were with their lives. They computed profiles of regulation for each occasion and classes of individuals to understand differences in regulation choices over time. They identified five classes of individuals—those who used a diversity of strategies but tended to actively regulate, such as by removing themselves from or accepting the situation; those who used a diversity of strategies but tended to suppress negative emotion; those who moderately used most strategies; those who did not regulate; and those who intensely used all strategies. Based on these phenotypes capturing how individuals tended to regulate across varying situations, Grommisch and colleagues determined that those who used a diversity of profiles but tended toward active regulation strategies experienced lower anxiety and higher positivity than those who tended to suppress. These results illustrate that using more strategies is not necessarily adaptive. Rather, the type of strategies individuals employ is important. Individuals who use a range of strategies may be healthier, but that varies based on which strategies they employ [8].

These findings are important because how individuals regulate in the laboratory may not be an accurate indicator of how they regulate in everyday life. Experience sampling allows researchers to study how individuals choose to regulate in a variety of ways and synchronize their regulation choices to the environment, outside the laboratory. Healthy regulation emerges from a complex interaction between the individual, the situation and the technique (Doré, Silvers, & Ochsner, 2016). Taken together, these findings help to bring the field closer to a personalized account of emotion regulation.

5.1.3 Conclusion

Experience sampling offers a tool for gathering data in everyday life, so researchers do not have to limit or dictate how individuals regulate across a range of contexts. Researchers in the laboratory typically instruct individuals to use specific strategies or allow them to choose between a limited range of strategies. In addition, researchers in the laboratory may expose individuals to a select range of stimuli and not adequately vary the situational demands and context (Buhle et al., 2013; Burr, Castrellon, Zald, & Samanez-Larkin, 2021; Goldin, McRae, Ramel, & Gross, 2008; Gross & John, 2003; Shiota & Levenson, 2009; Winecoff, Labar, Madden, Cabeza, & Huettel, 2011). In addition, by collecting data at numerous momentary occasions, individuals do not have to bear the difficult tasks of recalling responses from past events or summarizing how they tend to regulate.

Future research may benefit from further investigating how individuals regulate in various ways. For example, it is important to characterize the relationship between regulation choices and well-being in various contexts. What are the occasions that are best suited for a certain regulatory profile? In addition, future research should aim to disentangle the temporal dynamics of concurrently using various regulation strategies. Is there a specific order of implementing those strategies that is most effective for certain individuals, regulatory goals and contexts?

Insights from recent experience sampling should not simply motivate additional experience-sampling studies but should inform laboratory studies. Laboratory studies of emotion regulation are crucial cornerstones of research that continuously move the field forward. Researchers conducting studies in the laboratory could aim to collect temporally-rich data to better understand the dynamics of regulation. Similarly, researchers could expand how many choices individuals can make about how to regulate. By combining versatile laboratory studies and experience sampling studies that allow individuals to freely engage in daily life, we can move closer to a personalized account of emotion regulation.

5.2 Age Differences in Emotion and Emotion Regulation

The content from this chapter is verbatim from the below publication and has only been reformatted for this dissertation:

Burr, D. A., Castrellon, J. J., Zald, D. H., & Samanez-Larkin, G. R. (2021). Emotion dynamics across adulthood in everyday life: Older adults are more emotionally stable and better at regulating desires. *Emotion, 21*(3), 453–464.

5.2.1 Abstract

Older adults report experiencing improved emotional health, such as more intense positive affect and less intense negative affect. However, there are mixed findings on whether older adults are better at regulating emotion—a hallmark feature of emotional health—and most research is based on laboratory studies that may not capture how people regulate their emotions in everyday life. We used experience sampling to examine how multiple measures of emotional health, including mean affect, dynamic fluctuations between affective states and the ability to resist desires—a common form of emotion regulation—differ in daily life across adulthood. Participants (*N* = 122, ages 20-80) reported how they were feeling and responding to desire temptations for 10 days. Older adults experienced more intense positive affect, less intense negative affect and were more emotionally stable, even after controlling for individual differences in global life satisfaction. Older adults were more successful at regulating desires, even though they experienced more intense desires than younger adults. In addition, adults in general experiencing more intense affect were less successful at resisting desires. These results demonstrate how emotional experience is related to more successful desire regulation in everyday life and provide unique evidence that emotional health and regulation improve with age.

5.2.2 Introduction

Emotional experiences are inherently dynamic processes that unfold over time and in response to the current environment. How individuals regulate their emotions is a key component of this evolving process. Importantly, individuals may choose to regulate their emotions in different ways across adulthood (Carstensen, Pasupathi, Mayr, & Nesselroade, 2000; Sims, Hogan, & Carstensen, 2015). One major form of regulation that may differ across adulthood is how individuals resist tempting desires. Consider Alex, a young adult in their twenties who is feeling distressed and unstable all morning, then receives an invite to a bar opening that evening. If Alex has been trying to avoid alcohol and has an important work presentation the following morning, they may attempt to resist this temptation and stay home. But Alex may also have trouble finding the courage to stay home when they are already feeling so bad. However, consider Lee, an older adult in their sixties who may be particularly motivated to not feel guilty and decide to resist the temptation to join friends for dinner out that evening in order to succeed at their work presentation the following morning. In order to adequately characterize individuals' emotional experiences, researchers could consider how desire regulation, emotional intensity and emotional stability co-occur and differ across adulthood.

Emotional health and stability are invariably related to the larger context, such as the presence of tempting stimuli in the environment. Throughout the day, people of all ages try to self-regulate and resist many appetitive desires—in essence, regulate their emotions to avoid certain feelings and behaviors that conflict with long-term goals. Individuals experience appetitive desires (henceforth referred to as desires) when they are driven to approach or behave in a certain way in order to feel pleasure (Koole, van Dillen, & Sheppes, 2011; Koole, van Dillen, & Sheppes, 2011). The urge to indulge in a desire, such as skipping school to go to the movies or watching television instead of helping out a friend, is natural and commonplace. Temptation is a ubiquitous feature of human life across the life span.

How individuals respond to temptation is important for emotional health and well-being (Boals, vanDellen & Banks, 2011; Hofmann, Baumeister, Förster, & Vohs, 2012; Hofmann, Luhmann, Fisher, Vohs, & Baumeister, 2014; Koole, van Dillen, & Sheppes, 2011). For example, someone might resist the desire to check Twitter notifications during the workday in order to be more productive or go for a run instead of eating fast food to be healthier. The world is saturated with tempting stimuli, and being able to resist these omnipresent desires is a hallmark of psychological stability and well-being (Baumeister & Vohs, 2004; Gross & Munoz, 1995; Hofmann, Baumeister, Förster, & Vohs, 2012).

Tempting desires often result in conflict between short-term and long-term goals. Although the original desire may generate an approach-related emotion, the conflict between short-term and long-term goals can be unpleasant. In order to reduce this conflict, individuals may, in turn, regulate their emotions by resisting the desire and any actions associated with the desire. In other words, the feeling of desire is the target of emotion regulation. Though individuals sometimes regulate their emotions automatically and with little effort, resisting desires is generally thought to reflect an effortful form of self-regulation that entails the cognitive control of emotion (Hofmann, Luhmann, Fisher, Vohs, & Baumeister, 2014; Koole, van Dillen, & Sheppes, 2011).

Extensive research has demonstrated how emotional experiences vary across the adult life span in numerous domains (Carstensen & Charles, 1999; Feng, Courtney, Mather, Dawson, & Davison, 2011; Röcke, Li., & Smith, 2009; Scott, Sliwinski, Mogle, & Almeida, 2014). Specifically, older adults have been shown to experience higher levels of positive relative to negative affect (Carstensen et al., 2011; Carstensen, Pasupathi, Mayr, & Nesselroade, 2000) and respond to, attend more deeply to, and better remember positive compared to negative stimuli (Feng, Courtney, Mather, Dawson, & Davison, 2011; Mather & Carstensen, 2003). However, other research has noted that older adults may be particularly vulnerable in certain emotional contexts and experience heightened negative affect when exposed to stressors (Mroczek, Daniel & Almeida, David, 2004; Stawski et al., 2019). Beyond the intensity of affective experiences, research has outlined how dynamic aspects of emotional experience differ across adulthood. For example, older adults are known to be more emotionally stable (Carstensen et al., 2011; Carstensen, Pasupathi, Mayr, & Nesselroade, 2000; Röcke, Li., & Smith, 2009). In addition to being more stable, research shows that older adults more often experience the co-occurrence of positive and negative emotional states, an adaptive trait thought to offer resilience against stressors (Hershfield, Scheibe, Sims, & Carstensen, 2013; Larsen & McGraw, 2011; Scott, Sliwinski, Mogle, & Almeida, 2014).

Despite convergent research illustrating how emotional experience differs across adulthood, research on how older adults differentially regulate emotion—a key component of emotional health—is more limited and mixed. For example, numerous behavioral and neuroimaging studies have emphasized how adolescents regulate in distinct ways (Guassi Moreira, McLaughlin, & Silvers, 2019; Silvers et al., 2017; Nook, Bustamante, & Somerville, 2019). But it is both theoretically and empirically unclear if older adults are better at resisting desires than younger adults. Some research has shown that older adults are better at cognitively reframing the meaning of stimuli (Shiota & Levenson, 2009), while others have found a decline in this ability (Winecoff, Labar, Madden, Cabeza, & Huettel, 2011), or no age-related differences (Martins, Sheppes, Gross, & Mather, 2018; Martins & Mather, 2016). Similarly, research conducted in the laboratory has demonstrated that older adults are more successful at suppressing their emotions (Magai, Consedine, Krivoshekova, Kudadjie-Gyamfi, & McPherson, 2006; Phillips, Henry, Hosie, & Milne, 2008), though others have found no age-related differences (Kunzmann, Kupperbusch, & Levenson, 2005). In addition, theoretical accounts of emotional processing across adulthood (e.g. Socioemotional Selectivity Theory; Carstensen, 2006; Carstensen, Isaacowitz, & Charles, 1999; Charles & Carstensen, 2010) do not provide clear directional predictions about desire regulation in older adults. For example, socioemotional selectivity theory posits that older adults prioritize short-term and emotionally meaningful goals due to a perceived time constraint in their life, resulting in better regulation of emotion (Carstensen, 2006; Carstensen, Fung, & Charles, 2003; Carstensen, Isaacowitz, & Charles, 1999; Charles & Carstensen, 2010). However, this perceived time constraint could lead to older adults relinquishing long-term goals that conflict with desires. For example, why not experience the joy of a piece of cake now instead of the longer-term advantages of weight loss in the future? Existing empirical and theoretical literature suggest competing hypotheses about whether older adults are better or worse at resisting desires. Research is needed to reconcile this ambiguity in how older adults regulate emotion.

Importantly, how individuals experience desires and attempt to resist them is also tied to larger contextual variables independent of age, such as if the desire conflicts with personal goals and if other individuals are present enacting the desire that the person is trying to resist (Hofmann, Baumeister, Förster, & Vohs, 2012; Mischel et al., 1996). What makes a desire more or less tempting is inherently individualized to the person, situation and stimuli. A desire only warrants regulation insofar as it conflicts with personal goals. The desire to eat cake when attempting to lose weight would naturally lead to a conflict and some attempt to resist said desire in order to meet their goal. By contrast, someone whose job is to manage social media profiles would typically not aim to resist browsing Twitter. Similarly, a tempting desire may be more difficult to resist when others are around enacting that desire. It may be easy to avoid eating cake if you are just walking past a cake shop, but increasingly difficult at a birthday party when others are present enacting the desire (Hofmann, Baumeister, Förster, & Vohs, 2012; Hofmann, Luhmann, Fisher, Vohs, & Baumeister, 2014). It is important to capture this natural variability and study desire regulation outside the laboratory.

The majority of research investigating individual differences in emotion regulation across adulthood are restricted to the laboratory and rely on instructing participants how and when to regulate. However, this may not reflect true differences in how older adults experience and regulate desires (Sims & Carstensen, 2014; Sims, Hogan, & Carstensen, 2015). Indeed, findings from experience sampling studies provide more consistent evidence that older adults are more effective at regulating their emotions in the real world (Sims, Hogan, & Carstensen, 2015). Data collected in everyday life suggests that older adults are more successful at regulating their emotions, often by carefully choosing situations that align to their personal goals—a strategy typically not possible in laboratory-based experiments (Carstensen, Pasupathi, Mayr, & Nesselroade, 2000; Sims, Hogan, & Carstensen, 2015).

Prior research has suggested that both regulation ability and affective instability are important components of emotional health (Baumeister & Vohs, 2004; Gross & Munoz, 1995; Hofmann, Baumeister, Förster, & Vohs, 2012; Houben, Van Den Noortgate, & Kuppens, 2015), yet no research of which we are aware has directly explored the connection *between* these core components. Switching between affective states may disrupt peoples' self-regulatory goals (Mueller, 2011). The present study expands upon prior research largely informed by average snapshots of affect intensity to measure regulation and stability in everyday life in order to offer a more nuanced index of how peoples' feelings change. In the present study, we replicated and clarified prior research on adult age differences in emotional experience. Importantly, we built on previous research and offer a novel contribution that examines how one form of emotion regulation, the regulation of desires, differs across adulthood.

In line with prior research, we examined how affective intensity and instability differ across adulthood. By allowing adults to naturally engage in their daily lives and obtaining time-structured data, we were able to characterize how affective dynamics and regulation success differ across adulthood. We also controlled for global life satisfaction (well-being) in our models. Though many studies have investigated how happiness is associated with higher life satisfaction (Koval, Sütterlin, & Kuppens, 2016), the current study examines how emotional experiences differ across adulthood while controlling for varying levels of life satisfaction. For example, it is unclear if improvements with age in emotional experience or desire regulation are only observed in individuals who are more satisfied with their lives in general. In addition, it is unclear how life satisfaction interacts with affect intensity and instability to influence desire regulation. In order to bridge this gap in the existing literature, the current study aimed to disentangle the effect of life satisfaction, affect intensity and affect instability on desire regulation. Taken together, we offer a novel contribution that illustrates how individuals across adulthood regulate desires in everyday life.

Based on prior research demonstrating that emotional health improves over the adult life span (Carstensen & DeLiema, 2018; Charles, Reynolds, & Gatz, 2001), we predicted that older adults would experience more intense and frequent positive affect and less intense and frequent negative affect in their daily lives. Similarly, and in line with prior research, we expected that older adults would be more stable in their affective experiences (Carstensen et al., 2011; Lang & Carstensen, 2002; Röcke, Li., & Smith, 2009). Importantly, we had no strong directional hypotheses about age differences in emotion regulation based on the mixed empirical evidence. Finally, we expected that individuals would be better at resisting desires if the temptation conflicted with personal goals and worse at resisting desires when others were around enacting the desire (Hofmann, Baumeister, Förster, & Vohs, 2012; Mischel et al., 1996).

5.2.3 Materials and Methods

Participants

We collected experience sampling measures of emotional experience and regulation as supplementary data within larger neuroimaging studies of aging and decision making. We determined sample size for these larger studies based on the expected effects for associations between aging, brain function and decision making. However, past research on emotion and aging suggests that there should be enough data within these samples to detect effects. For example, a similar cross-sectional study using experience sampling of emotion across adulthood reported a negative correlation between age and negative affect of ($r = -.29$) in a between-subject analysis (Carstensen, Pasupathi, Mayr, & Nesselroade, 2000). In order to obtain an effect this large, we would need a sample of 91 for at least 80% power. Our initial sample consisted of 122 healthy, adult participants ranging in age from 20 to 80 ($M_{age} = 41$, $SD_{age} = 15$; 55% female; 4% Asian, 1% Hispanic, 9% Black, 86% White). Given some minimal missing observations, analyses are based on specific sample sizes (e.g, n = 113 or n = 117), which are provided in each result section and in figure captions.

All participants provided written informed consent to participate and all procedures were approved by the Institutional Review Board at Vanderbilt University. Participants were all psychiatrically and neurologically healthy as determined by initial medical screening including a Structured Clinical Interview for the DSM-IV (First, Spitzer, Gibbon & Williams, 1996) and a brief physical exam.

Data collection

In order to study emotional dynamics in everyday life, we relied on ecological momentary assessment (EMA) as an experience sampling technique. We messaged participants on their mobile device three times a day, for 10 days in order to assess current emotional states; we provided mobile devices to participants who did not have their own. Typical awake hours were split into three equal time periods and one survey link was randomly messages to the participant during each period. Participants rated the degree to which they felt eight emotional states on a 5-point scale ranging from "Slightly or not at all" to "Extremely." These emotional states align to the Affect Valuation Index (Tsai, Knutson, & Fung, 2006). The eight emotional states were: positive-pleasant ("How happy, satisfied, or content do you feel right now?"), which reflects moderate arousal pleasant states; low-arousal positive ("How calm, at rest, relaxed, peaceful, or serene do you feel right now?); high-arousal positive ("How enthusiastic, excited, elated, or strong do you feel right now?"); negative-unpleasant ("How sad, lonely, or unhappy do you feel right now?), which reflects moderate arousal unpleasant states; low-arousal negative ("How dull, sleepy, or sluggish do you feel right now?"; and high-arousal negative ("How fearful, hostile, or nervous do you feel right now?"; low arousal ("How quiet, still, or passive do you feel right now?"); high arousal ("How aroused, surprised, or astonished do you feel right now?").

Researchers continue to investigate the underlying structure of affective space (Cacioppo & Berntson, 1994; Mattek, Wolford, & Whalen, 2017; Russell, 1980; Watson & Tellegen, 1985). Consequently, there is inconsistency in how affective dimensions such as valence and arousal are treated in experimental design and analysis. In factor analyses, low-arousal states—such as feeling calm—load on both positive and negative valence factors (Watson & Clark 1994), or load on a distinct factor unrelated to positivity or negativity. Based on this, many studies only utilize high arousal affective markers. However, studies often pool across low-arousal and high-arousal terms to reduce the dimensionality of the data (e.g., Carstensen et al., 2011; Carstensen, Pasupathi, Mayr, & Nesselroade, 2000). In order to be consistent with prior research, the current study used a similar pooling and operationalization of positive affect as the average of low-arousal positive, high-arousal positive, and positive-pleasant ratings ($\propto$ = .63) and negative affect as the average of low-arousal negative, high-arousal negative, and negative-unpleasant ratings ($\propto$ = .38). Although there is lower internal consistency among the negative affect scales, suggesting that the scales are not all indexing the same factor, the current study uses the pooled scales in order to align to the research being replicated (e.g., Carstensen et al., 2011; Carstensen, Pasupathi, Mayr, & Nesselroade, 2000). Hereafter, the current manuscript refers to the pooled positive ratings as positive and the pooled negative ratings as negative. However, given the low internal reliability of the composite measures, we also provide analyses of the un-pooled data, using just the moderate arousal level positive-pleasant and negative-unpleasant terms and excluding high- and low-arousal terms, in the supplemental material. Using the un-pooled data, the overall pattern of results does not differ substantially.

In addition to providing emotion ratings, participants then answered questions regarding which desires, if any, were tempting them and if they were able to resist the desires or not in the past 3 hours. Participants indicated the nature of the desire ("Eating, snacking, nonalcoholic drinks; Alcohol, cigarettes, tobacco, other drugs; Entertainment media (TV, movies, web browsing, video games); Social media (Facebook, Twitter, Instagram, etc.); Spending; Sex; Sleep; Social contact (in person or phone conversation, texting, Facetime, etc.); Leisure and relaxation; Exercise; Work; Other; None"). If participants noted that they experienced any type of desire within the past three hours, they were prompted with further questions. Specifically, they indicated: the strength of the desire on an 8-point scale ranging from "No desire at all" to "Irresistible;" the extent to which the desire conflicted with personal goals on a 5-point scale ranging from "No conflict at all" to "Very high conflict;" if they attempted to resist the desire or not; if they enacted the desire; and if others were present (physically or via media) enacting the desire. Participants could indicate up to 3 desires per measurement occasion. The current manuscript only presents analyses from the first-mentioned desire.

In addition to the time-structured EMA data, participants also responded once to the Satisfaction with Life Scale (SWLS) (Diener, Emmons, Larsen, & Griffin, 1985). The SWLS measures life satisfaction in five questions each on a 7-point scale, but explicitly avoids questions about current affect. To assess global life satisfaction, we calculated within-subject average scores, with higher average scores representing higher life satisfaction. In addition, participants completed a brief neurocognitive assessment and responded to a series of decision-making tasks while undergoing functional magnetic resonance imaging. The current manuscript only presents the experience sampling and SWLS data (Koval, Sütterlin, & Kuppens, 2016; Kuppens, Realo, & Diener, 2008).

Data preprocessing

The affective EMA afforded the possibility of measuring both mean affect and affective instability. We computed root mean successive square difference (rMSSD) as a measure of affective instability. rMSSD captures trial-by-trial variability in affective experiences and short-term fluctuations over time (Koval et al., 2013; Koval, P., Sütterlin, S., & Kuppens, 2016; Shaffer & Ginsberg, 2017). rMSSD is employed as a time-series statistic that accounts for changes over time and therefore reflects instability (Carstensen et al., 2011; Jahng, Wood, & Trull, 2008; Leiderman & Shapire, 1962; von Neumann, Kent, Bellinson, & Hart, 1941). For each participant, we obtained the rMSSD of positive and negative affect by computing the average of the squared differences in affect ratings between successive sampling occasions:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{N-1}^{i=1}(RR_{i+1} - RR_i)^2}$$

Modeling emotion dynamics

With this sample, we were able to model state-based intraindividual affect dynamics and between-subject trait level differences. The structure of the data is inherently nested, so, where appropriate, we used multilevel modeling to accurately model intraindividual variability and between-subject differences. Specifically, all multilevel linear mixed models accounted for time (measurement occasion) nested within each participant and allowed for random subject intercepts (Koval et al., 2013; Koval, Sütterlin, & Kuppens, 2016). Models were implemented using lme4 and lmerTest in R (Bates, Mächler Bolker, & Walker, 2015; Kuznetsova, Brockhoff, & Christensen, 2017).

5.2.4 Results

Affect intensity across adulthood: Do older adults experience more positive affect than younger adults?

We ran a linear mixed model allowing for random subject intercepts including age as a fixed effect to test how average level of positive affect differed across the adult life span (positive affect = $\beta_{0j} + \beta_{1j\mathrm{Age}} + e_{ij}$; $R^2 = .36$, n = 117). Older adults experienced significantly higher levels of positive affect ($\beta = .13$, 95% CI [.03, .22], $p = .01$). Importantly, we followed up this model with a model including global life satisfaction as a covariate in order to examine whether age effects varied based on level of global life satisfaction (positive affect = $\beta_{0j} + \beta_{1j(}\mathrm{age}_{\mathrm{ij})} + \beta_{2j(}$global life satisfaction$_{\mathrm{ij})}$ + $\beta_{3j(}$age x global life satisfaction$_{ij)}$ + $e_{ij;}$ R^2 = .36). Older adults still experienced significantly higher levels of positive affect, even after accounting for global life satisfaction, (β = .14, 95% CI [.06, .23], p = <.001; Figure 16). As expected, higher levels of global life satisfaction were significantly associated with higher positive affect (β = .18, 95% CI [.10, .25], p < .001; Figure 16. The interaction between age and global life satisfaction did not significantly predict mean level of positive affect (β = .02, 95% CI [-.05, .1], p =.57).

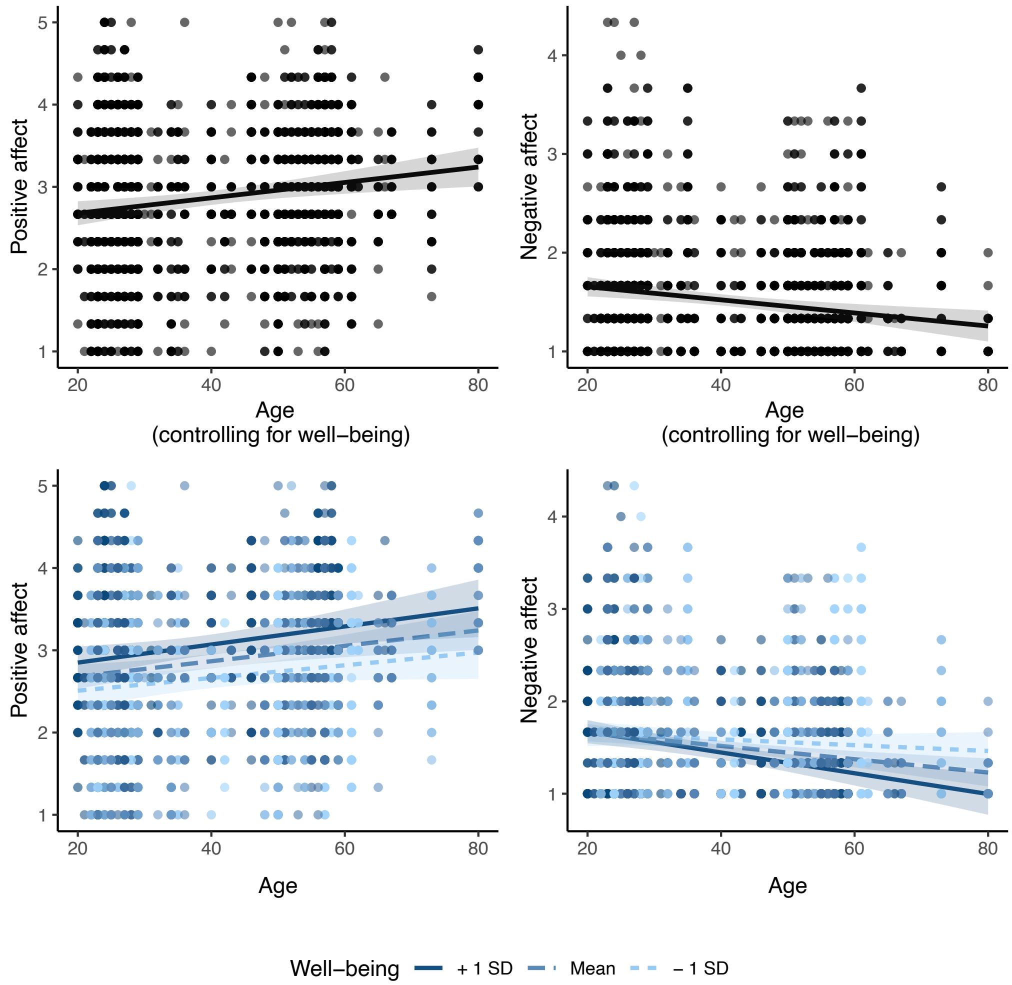

Figure 16: Affect Intensity Across Adulthood.

Effects of age and global life satisfaction (well-being) on positive and negative affect (n = 117). Top left: significant positive effect of age on positive affect after controlling for well-being. Top right: significant negative effect of age on negative affect after controlling for well-being. Bottom left: nonsignificant interaction between age and well-being on positive affect. Bottom right: significant interaction between age and well-being on negative affect. All predictor variables are mean centered for analysis. Well-being is based on mean Satisfaction With Life Scale. Regression lines are the model fit and shading represents the 95% confidence intervals. See the online article for the color version of this figure.

Affect intensity across adulthood: Do older adults experience less negative affect than younger adults?

We ran a linear mixed model allowing for random subject intercepts including age as a fixed effect to test how average level of negative affect differed across the adult life span (negative affect = $\beta_{0j} + \beta_{1j(}age_{ij)} + e_{ij};$ $R^2 = .30$, n = 117). Older adults experienced significantly lower levels of negative affect ($\beta = -.10$, 95% CI [-.16, .04], $p < .001$). We further investigated whether this effect varied based on global life satisfaction by including global life satisfaction as a covariate (negative affect = $\beta_{0j} + \beta_{1j(}age_{ij)} + \beta_{2j(}$global life satisfaction$_{ij)}$ + $\beta_{3j(}$age x global life satisfaction$_{ij)}$ + $e_{ij;}$ $R^2 = .30$. When including global life satisfaction as a covariate, older adults still experienced lower levels of negative affect ($\beta = -.11$, 95% CI [-.17, -.06], $p < .001$). Age also interacted with global life satisfaction such that older adults who were most satisfied with their lives experienced the lowest levels of negative affect ($\beta = -.08$, 95% CI [-.13, -.02], $p = .01$; Figure 16). In addition, participants with higher levels of global life satisfaction experienced lower levels of mean negative affect, irrespective of age ($\beta = -.08$, 95% CI [-.13, -.02], $p = .01$). Based on these results and the results above on positive affect, we included global life satisfaction in all future models.

Affect instability across adulthood

In order to more sensitively investigate the dynamics of affective experiences across the adult life span, we next modeled fluctuations in affect throughout the day (Eid & Diener, 1999). Because affect instability is captured with a non-repeated measure, we ran two linear regression models (ordinary least squares) to test the effects of age and global life satisfaction on positive affective instability ($R^2 = .09$, $n = 113$) and negative affective instability ($R^2 = .12$, $n = 113$). See Figure 17 for all instability effects.

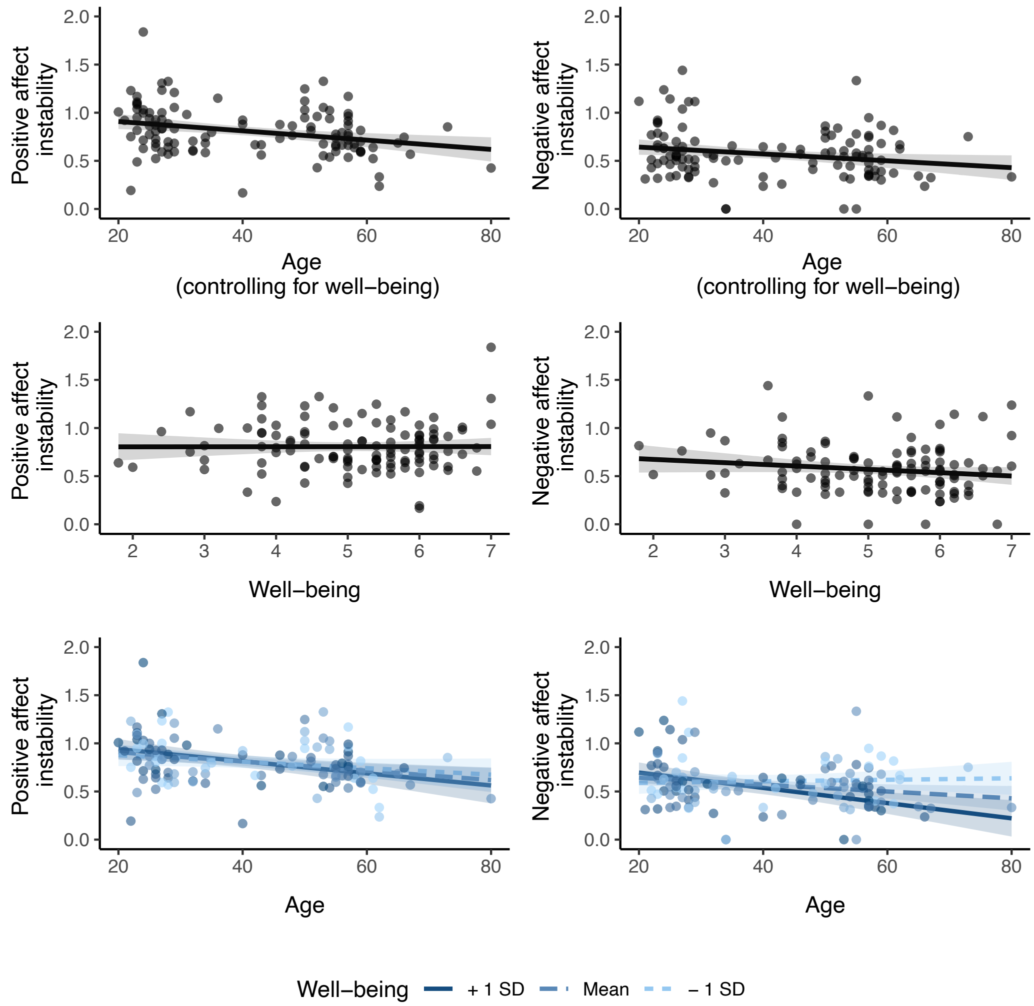

Figure 17: Affect Instability Across Adulthood.

Effects of age and global life satisfaction (well-being) on positive and negative affective instability (n = 113). Top left: significant positive effect of age on positive affective instability after controlling for well-being. Top right: significant negative effect of age on negative affective instability after controlling for well-being. Middle left: nonsignificant effect of well-being on positive affective instability. Middle right: nonsignificant effect of well-being on negative affective instability. Bottom left: nonsignificant interaction between age and well-being on positive affective instability.

Bottom right: significant interaction between age and well-being on negative affective instability. All predictor variables are mean centered for analysis. Positive and negative affect instability are based on the root mean squared successive differences of affect ratings across all measurement occasions. Well-being is based on mean Satisfaction With Life Scale. Regression lines are the model fit and shading represents the 95% confidence intervals.

Older adults were less unstable (i.e., more stable) in their positive affective experiences ($\beta = -.07$, 95% CI [-.12, -.03], $p < .001$), and this did not vary based on how satisfied they were with their lives ($\beta = -.02$, 95% CI [-.07, .02], $p = .33$). Interestingly, there was no main effect of global life satisfaction ($\beta = 0.00$, 95% CI [-.05, .05], $p = .98$). Older adults were also more stable in their negative affective experiences ($\beta = -.05$, 95% CI [-.10, -.01], $p = .02$). In addition, age interacted with global life satisfaction such that older adults who were most satisfied with their lives were the most stable in their negative affective experiences ($\beta = -.07$, 95% CI [-.11, -.02], $p = .01$). However, global life satisfaction did not significantly predict negative affect instability ($\beta = -.04$, 95% CI [-.09, .01], $p = .10$). See Figure 17 for all instability effects.

Desire regulation across adulthood: Are older adults better at resisting desires than younger adults?

To investigate how age and global life satisfaction influenced participants' ability to successfully resist desires, we computed a measure of successful emotion regulation. Importantly, we also included extent to which desires conflicted with personal goals and if others were present enacting the desires as covariates in order to more comprehensively measure the experience of desires. If a participant was experiencing a desire that they were attempting to resist and then consequently enacted the desire, that event was classified as an episode of unsuccessful regulation. Conversely, if they were experiencing a desire they were attempting to resist and did not enact it, that event was classified as an episode of successful regulation.

Using this binary variable as our outcome measure, we ran a multilevel logistic regression model allowing for random subject intercepts to test if age, positive affect, negative affect, global life satisfaction, strength of desire, extent that desire conflicts with personal goals, if others were present enacting the desire, positive and negative affect, and positive and negative affective instability influenced how likely participants were to successfully regulate desires (successful regulation = $\beta_{0j} + \beta_{1j(}\text{age}_{ij)} + \beta_{2j(}\text{positive affect}_{ij))} +$ $\beta_{3j(}\text{negative affect}_{ij)} + \beta_{4j(}\text{global life satisfaction}_{ij)} + \beta_{5j(}\text{desire strength}_{)} + \beta_{6j(}\text{extent desire conflicts}_{)} + \beta_{7j(}\text{others present}_{)} + \beta_{8j(}\text{negative affective instability}_{)} + \beta_{9j(}\text{positive affective instability}_{)} + \beta_{10j(}\text{age x positive affect}_{)} + \beta_{11j(}\text{age x negative affect}_{)} + \beta_{12j(}\text{age x global life satisfaction}_{ij)} + \beta_{13j(}\text{age x desire strength}_{ij)} + \beta_{14j(}\text{age x extent desire conflicts}_{ij)} + \beta_{15j(}\text{age x others present}_{)} + \beta_{16j(}\text{age x positive affective instability}_{ij)} + \beta_{17j(}\text{age x negative affective instability}_{ij)} + e_{ij}$; $R^2 = .37$, n = 113). See Figure 18 for all effects. In general participants were able to successfully resist their tempting desires when collapsing across age—91% of desire episodes were successfully regulated. Relatedly, participants experienced desires 99% of the time and attempted to regulate them 30% of the time. There was a main effect of age such that older adults were significantly more likely to successfully resist desires ($\beta = .54$, 95% CI [.22, .85], $p < .001$). In addition, age interacted with global life satisfaction ($\beta = -.48$, 95% CI [-.77, -.18], $p < .001$) such that younger adults with higher levels of global life satisfaction were more successful at resisting their desires than those with low global life satisfaction (Figure 19), but this pattern was not seen in older subjects. More specifically, individual differences in global life satisfaction did not account for older adults being able to resist desires—older adults were better at resisting their desires independent of global life satisfaction.

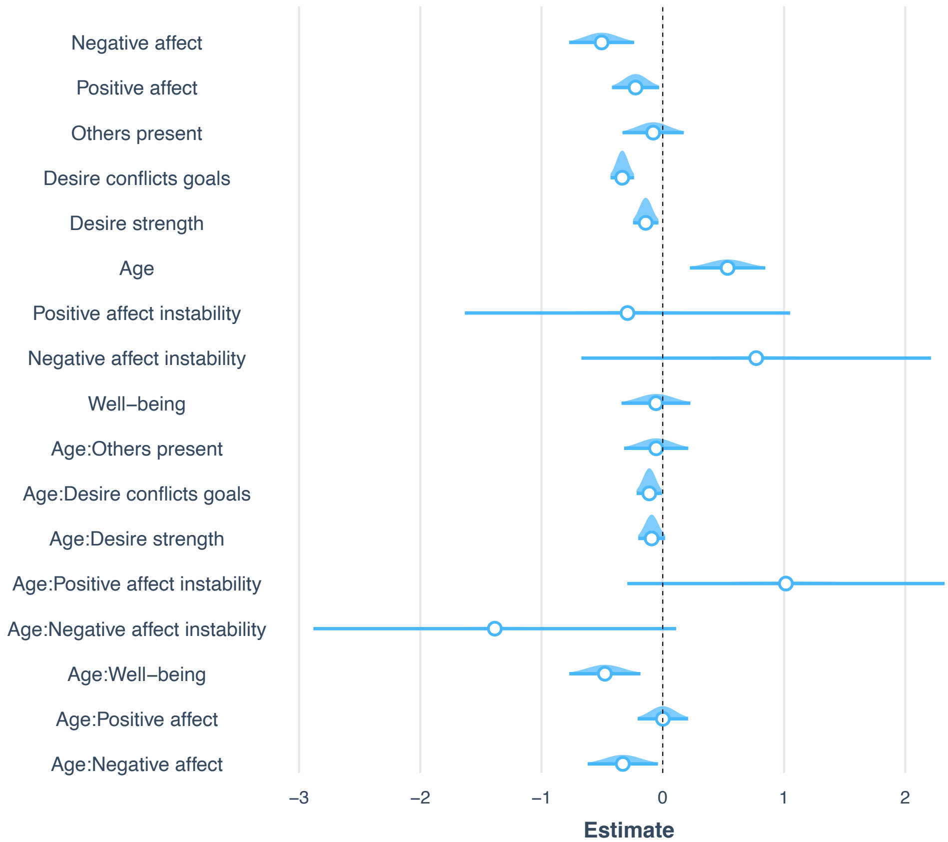

Figure 18: Predictors of Successfully Resisting Desires.

Standardized (mean-centered) regression coefficients from multilevel logistic regression predicting successful regulation of desires (n = 113). Well-being is based on mean Satisfaction With Life Scale. Positive and negative affect instability are based on the root mean squared successive differences of affect ratings across all measurement occasions.

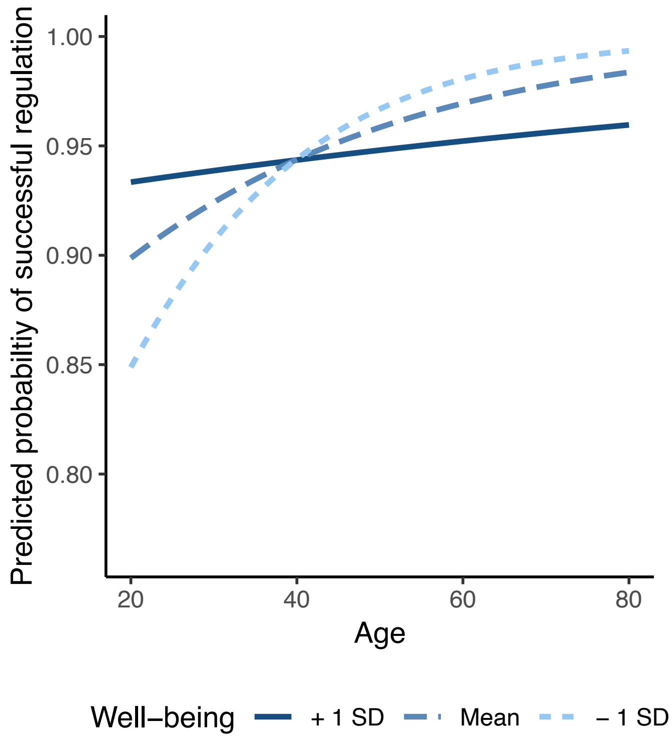

Figure 19: Desire Regulation Across Adulthood.

Effect of interaction between age and global life satisfaction (well-being) on probability of successful regulation from multilevel logistic regression predicting successful regulation of desires (n = 113). Well-being is based on mean Satisfaction With Life Scale.

Participants experiencing greater desire strength ($\beta = -.14$, 95% CI [-.25, -.04], $p = .04$) and desire with greater personal conflict ($\beta = -.33$, 95% CI [-.43, -.24], $p < .001$) were significantly less likely to successfully resist desires. Surprisingly, older adults experiencing desires that greatly conflicted with personal goals were the least successful at regulating desires ($\beta = -.11$, 95% CI [-.22, -.01], $p = .04$). Thus, despite overall greater ability to resist desires, older adults had a more selective challenge when resisting desires that were in conflict with their personal goals. In addition, participants experiencing higher levels of negative affect ($\beta = -.5$, 95% CI [.77, -.24], $p < .001$) were less likely to successfully resist desires. Age also interacted with negative affect such that older adults experiencing the highest levels of negative affect were worse at resisting desires ($\beta = -.33$ 95% CI [-.62, -.18], $p < .001$). Adults experiencing more intense positive affect were also more successful at resisting desires ($\beta = -.22$, 95% CI [-.42, -.03], $p = .02$), but this did not vary based on age ($\beta = 0$, 95% CI [-.21, .21], $p = .99$). Thus, despite older adults being generally superior at resisting desires, they were particularly affected by deleterious effects of negative affect, but not positive affect, when resisting desires. See Figure 18 for all effects.

In contrast to the above significant effects, others being present enacting the desire ($\beta = -.08$, 95% CI [-.33, 17], $p = .54$), positive affective instability ($\beta = -.29$, 95% CI [-1.63, 1.05], $p = .67$), negative affective instability ($\beta = .77$, 95% CI [-.67, 2.21], $p = .29$) and global life satisfaction ($\beta = -.06$, 95% CI [-.34, .23], $p = .7$) were non-significant predictors of successful regulation of desires. Two-way interactions between others being present and age ($\beta = -.05$, 95% CI [-.32, .21], $p = .69$), desire strength and age ($\beta = -.07$, 95% CI [-.22, .07], $p = .32$), age and positive affective instability ($\beta = .1.02$, 95% CI [-.29, 2.32], $p = .13$), and age and negative affective instability ($\beta = -.1.39$, 95% CI [-2.88, .11], $p = .07$) were non-significant predictors of successfully resisting desires.

Desire regulation across adulthood: Do older adults experience and attempt to regulate desires more than younger adults?

The above logistic regression model demonstrated that older adults were more successful at resisting desires. This finding raises a question of whether older adults may experience desires more frequency or intensely. A multilevel logistic regression model allowing for random subject intercepts tested whether age and global life satisfaction influenced whether desires were present or not (desire presence = $\beta_{0j} + \beta_{1j(}$age$_{ij)} + \beta_{2j(}$global life satisfaction$_{)} + \beta_{3j(}$age x global life satisfaction$_{)} + e_{ij}$; R^2 = .94, n = 117). There were no significant age-related differences in desire presence (β = 26.50, 95% CI [-46.03, 99.03], p = .47). In addition, global life satisfaction (β = 17.38, 95% CI [-.82.98, 48.22], p = .60) and the interaction between age and global life satisfaction (β = -14.09, 95% CI [-68.17, 39.99], p = .61) were non-significant predictors of whether participants were experiencing desires or not.

Similarly, we explored if older adults experienced more intense desires than younger adults. A multilevel regression model allowing for random subject intercepts tested whether age and global life satisfaction influenced desire strength (desire strength = $\beta_{0j} + \beta_{1j(}$age$_{ij)} + \beta_{2j(}$global life satisfaction$_{)} + \beta_{3j(}$age x global life satisfaction$_{)} + e_{ij}$; R^2 = 0.30). Older adults reported experiencing significantly stronger desires (β = .21, 95% CI [.06, .36], p = .01). Global life satisfaction (β = .09, 95% CI [-.05, .24], p = .22) and the interaction between age and global life satisfaction (β = -.11, 95% CI [-.26, .04], p = .14) were non-significant predictors of desire strength.

Finally, we tested if older adults were simply attempting to resist desires more than younger adults. A multilevel logistic regression model allowing for random subject intercepts tested whether age and global life satisfaction influenced how frequently participants attempted to resist desires (attempt to resist = $\beta_{0j} + \beta_{1j(}$age$_{ij)} + \beta_{2j(}$global life satisfaction$_{)} + \beta_{3j(}$age x global life satisfaction$_{)} + e_{ij}$; R^2 = 0.29, n = 117). Older adults attempted to resist desires less than younger adults (β = -.41, 95% CI [-.62, -.19], p <

001). In addition, participants who were less satisfied with their lives attempted to resist desires more (β = -.36, 95% CI [-.58, -.15], $p < .001$). The interaction between age and global life satisfaction (β = -.01, 95% CI [-.22, .2], $p = .93$) did not predict whether participants attempted to resist desires or not.

5.2.5 Discussion

In the current study, we examined how emotional experiences and regulation differ across adulthood in everyday life using experience sampling methods. Consistent with prior research, we show that older adults experience increased positive affect, decreased negative affect and are more stable in their affective experiences. In addition, we offer a novel finding demonstrating individual differences across adulthood in a key aspect of emotional regulation in everyday life. Specifically, we demonstrate that older adults and adults in general experiencing less intense affect are better at resisting temptation.

Affective intensity and stability

The overall results are consistent with other evidence that emotional health improves across adulthood (Carstensen et al., 2011; Carstensen, Pasupathi, Mayr, & Nesselroade, 2000). Older adults experienced higher levels of positive affect and lower levels of negative affect—even after accounting for individual differences in global life satisfaction. Moreover, as expected, older adults with the highest levels of global life satisfaction experienced the lowest levels of negative affect. Individual differences in global life satisfaction did not influence the relationship between age and positive affect. Beyond age-related differences in mean levels of affect, older adults were additionally more stable in their affective experiences and fluctuated less between affective states. Collectively, these findings echo prior experience sampling research and document important ways in which older adults experience improved emotional health (Carstensen et al., 2011; Carstensen, Pasupathi, Mayr, & Nesselroade, 2000).

Importantly, prior research has more consistently demonstrated age-related differences in emotional experience through a decrease in negative affect across adulthood, as opposed to an increase in positive affect (e.g., Carstensen, Pasupathi, Mayr, & Nesselroade, 2000). However, here we found that older adults experienced *both* higher levels of positive affect and lower levels of negative affect. There may be some methodological differences that contribute to differences in the detection of increases in positive affect across studies. For example, some prior research has found that older adults experience an increase of low-arousal positive affect, but not high-arousal affect (Kessler & Staudinger, 2009). Nevertheless, the present findings strongly converge with prior literature demonstrating age-related improvements in emotional experience, generally characterized as an increasing ratio of positive to negative affect (Carstensen & Mikels, 2005; Charles, Mather, & Carstensen, 2003; Diehl, Hay, & Berg, 2011; Reed, Chan, & Mikels, 2014; Mather & Carstensen, 2005).

Global life satisfaction

We sought to examine how emotional experiences differ across adulthood when controlling for global life satisfaction. Though it is typical for empirical research to model global life satisfaction as an outcome (Hofmann, Luhmann, Fisher, Vohs, & Baumeister, 2014; Koval, Sütterlin, & Kuppens, 2016), here we used global life satisfaction as a covariate in models of daily affect in order to evaluate whether global life satisfaction eliminated or modified how emotional experiences differ across adulthood. We showed that older adults experience higher levels of positive affect, independent of how satisfied they are with their lives. Individual differences in global life satisfaction did, however, modify the effect of age on negative affect such that older adults with the highest levels of global life satisfaction experienced the lowest levels of negative affect.

Desire regulation

Our analyses revealed that older adults are more successful at regulating their desires in everyday life than younger adults, despite there being no age differences in how frequently they experienced desires. Moreover, we show that older adults experienced stronger desires than younger adults, yet were still better at resisting those desires. Strikingly, even older adults who were not satisfied with their lives were highly successful at resisting tempting desires. However, younger adults who were the least satisfied with their lives struggled to resist desires. Individuals experiencing desires that conflicted with their personal goals were worse at resisting desires, and this was particularly true for older adults. These findings are in line with theoretical accounts of age differences in emotional experiences, suggesting that older adults are more focused on achieving goals that optimize well-being in the present (Carstensen, Isaacowitz, & Charles, 1999).

In general, adults experiencing more intense affect were less likely to successfully regulate their desires. While our methodology lacked the temporal precision to address the causal relationships here, the data are consistent with a greater difficulty resisting desires when experiencing intense emotions. This observation may also reflect cooccurring personality traits, rather than a specific impact of affect (Whiteside & Lynam, 2001). For example, research indicates that relationships between trait-positive and -negative affect and impulse buying are primarily explained by extraversion and neuroticism, rather than being narrowly driven by trait affect (Thompson & Predergast, 2015). Future research should investigate this possibility with a more temporally precise experimental design.

Taken together, these findings present novel evidence for how emotional experience is related to regulation across adulthood. By allowing people to naturally engage with a complex environment, we found that older adults were more successful at resisting tempting desires—a concrete measure of successful emotion regulation. Existing laboratory research has produced mixed findings, with some studies finding that older adults more successfully regulate their emotions (Magai, Consedine, Krivoshekova, Kudadjie-Gyamfi, & McPherson, 2006; Phillips, Henry, Hosie, & Milne, 2008), and others finding no age-related effects (Kunzmann, Kupperbusch, & Levenson, 2005). Here, we showed that older adults more successfully resisted desires when allowed to engage naturally. Interestingly, older adults were also more successful at regulating desires, despite experiencing somewhat more intense desires than younger adults. Importantly, older adults did not experience or attempt to regulate desires more frequently—rather they were overall more successfully regulating them when they occurred. These findings echo existing research that has attributed increased global life satisfaction and positive affect in old age to more successful emotion regulation (Sims, Hogan, & Carstensen, 2015; Urry & Gross, 2010).

These results are consistent with a wealth of research on emotional experience and aging. Older adults appeared to struggle to resist desires when feeling intensely negative or when experiencing a particularly conflicting desire. In addition, older adults attempted to resist desires less often than younger adults, but were better at resisting desires when they tried. It is possible that older adults experience less negative affect in general, but when they do experience intense negative affect, they are more vulnerable and struggle to regulate their emotions. Taken together, these findings appear in line with theoretical explanations of emotion regulation across adulthood that suggest that older adults struggle to effectively regulate when in intensely arousing states (Charles, 2010).

Future research should attempt to identify the more general conditions under which older adults are able to successfully resist or more likely to fail to resist desires. For the first time, we investigate individual differences in how older adults resist tempting desires in everyday life. How individuals resist desires is not only a naturalistic form of emotion regulation that is free of the confines of the laboratory, but a unique form of individuals down-regulating appetitive stimuli. When individuals experience desires, they are, by definition, motivated to approach stimuli in order to experience pleasure (Hofmann, Kotabe, Vohs, & Baumeister, 2015). However, the vast majority of regulation studies, both within and outside the laboratory, focus on how individuals reduce negative affect or increase positive affect, not how they resist tempting desires. Future work should continue to explore how this special form of regulation is different than others and varies across individuals and situations.

The current study centered on how tempting desires are regulated and did not attempt to capture differences in how and what desires are experienced across adulthood.

Potential research should investigate the various types of desires experienced and how that may influence regulation. It is possible that age differences in the types of desires influence the ability to resist them. However, such an exploration requires a greater density of samples to ensure enough examples of each desire type. The design of the present study was not optimized to evaluate potential interactions with desire types. Importantly, we also did not address the techniques used to resist desires. The current study did not ascertain, for example, if individuals reframed the meaning of a desire, suppressed the emotional response without any type of reframe or simply distracted themselves. Future research should investigate how older adults choose to regulate in different ways. Similarly, future research should explore other forms of emotion regulation in the real world to understand differences in how older adults choose to regulate. For example, recent work has suggested that older adults more frequently use strategies that intervene earlier in emotional experiences, such as simply changing or avoiding the stressful situation (Livingstone & Isaacowitz, 2019).

Future research would benefit from examining whether age-related differences in emotional experience are related to cognitive biases. For example, related studies have illustrated older adults preferentially process positive over negative information in cognitive tasks, known as the age-related positivity effect (Mathers & Carstensen, 2005). However, it is unclear how differences in such cognitive biases necessarily cause the improvements in emotional experience across adulthood or vice-versa (Isaacowtiz & Blanchard-Fields, 2012).

There are several important limitations in the current study that should be addressed in future research. For example, one weakness of the current data was the limited range used in the Likert scales (Bishop & Herron, 2015; Lishner, Cooter, & Zald, 2008). Although Likert scales are ordered and often treated as interval, humans may not perceive levels of the scale as being equal distance from each other. It is recommended that future experience sampling studies use more continuous interval scales that better measure variance in emotional experience. Finally, a limitation of our research was that the sample was majority White participants. Future research should consider evaluating whether these effects replicate in more demographically representative samples and include people who may have common health problems.

5.2.6 Supplemental Material

The primary analyses pooled low-arousal positive, high-arousal positive, and positive-pleasant affect ratings as "positive affect" and low-arousal negative, high-arousal negative, and negative-unpleasant affect ratings as "negative affect". In the below supplemental analyses we examine just positive-pleasant and negative-unpleasant affect without pooling across arousal levels (i.e., excluding high and low arousal categories). The supplemental results are organized to align to the primary pooled analyses.

Affect intensity across adulthood: Do older adults experience more positive affect than younger adults?

We ran a linear mixed model allowing for random subject intercepts including age as a fixed effect to test how average level of positive-pleasant affect differed across the adult life span. Older adults experienced significantly higher levels of positive-pleasant affect ($\beta = .16$, 95% CI [.04, .28], $p = .01$). Importantly, we followed up this model with a model including global life satisfaction (well-being) as a covariate in order to examine how age effects varied based on level of well-being. When accounting for well-being, older adults still experienced significantly higher levels of positive-pleasant affect (β = .19, 95% CI [-.08, .29], $p < .001$). As expected, higher levels of well-being were significantly associated with higher positive-pleasant affect (β = .27, 95% CI [.17, .38], $p < .001$). The interaction between age and well-being did not significantly predict mean level of positive-pleasant affect (β = .05, 95% CI [-.06, .15], $p = .41$).

Affect intensity across adulthood: Do older adults experience less negative affect than younger adults?

We ran a linear mixed model allowing for random subject intercepts including age as a fixed effect to test how average level of negative-unpleasant affect differed across the adult life span. Older adults experienced less negative-unpleasant affect than younger adults (β = -.10, 95% CI [-.16, -.04], $p < .001$). When including global life satisfaction as a covariate in the model, age still significantly predicted negative-unpleasant affect (β = -.11, 95% CI [-.17, -.06], $p < .001$). As expected, lower levels of well-being were significantly associated with negative-unpleasant affect (β = -.08, 95% CI [-.13, -.02], $p = .01$). Age interacted with well-being such that older adults with higher levels of well-being experienced the lowest levels of negative-unpleasant affect (β = -.06, 95% CI [-.12, -.01], $p = .03$).

Affective instability across adulthood

We ran two linear regression models (ordinary least squares) to test the effects of age and global life satisfaction on positive-pleasant affective instability ($R^2 = .08$, n = 113) and negative-unpleasant affective instability ($R^2 = .06$, n = 113).

Older adults were less unstable (i.e., more stable) in their positive-pleasant affective experiences (β = -.09, 95% CI [-.16, -.02], $p = .01$), and this did not vary based on how satisfied they were with their lives ($\beta = -.03$, 95% CI [-.09, .04], $p = .41$). Interestingly, there was no main effect of global life satisfaction ($\beta = .04$, 95% CI [-.03, .11], $p = .27$). Although in the primary analyses age and the interaction of age and global-life satisfaction were significant predictors of negative affect instability ($p = .02$ and $p = .01$ respectively), when limited to moderate arousal negative-unpleasant affect terms, age ($\beta = -.07$, 95% CI [-.16, .02], $p = .14$), and the interaction between age and global life satisfaction ($\beta = -.07$, 95% CI [-.15, .02], $p = .14$) were non-significant predictors of un-pooled negative-unpleasant affect instability, and the main effect of global life satisfaction ($\beta = -.08$, 95% CI [-.17, .01], $p = .07$), similarly did not reach statistical significance.

Desire regulation across adulthood: Are older adults better at resisting desires than younger adults?

We next examined how age and well-being influenced participants' ability to successfully resist desires, but this time using the un-pooled positive-pleasant and negative-unpleasant affect variables (excluding high and low arousal affect) as covariates. We ran a multilevel logistic regression model allowing for random subject intercepts to test if age, well-being, strength of desire, extent that desire conflicts with personal goals, if others were present enacting the desire, positive-pleasant and negative-unpleasant affect, and positive-pleasant and negative-unpleasant affective instability influenced how likely participants were to successfully regulate desires. Interestingly, there was a main effect of age such that older adults were significantly more likely to successfully resist desires ($\beta = .52$, 95% CI [.22, .82], $p < .001$). In addition, age interacted with well-being ($\beta = -.48$, 95% CI [-.77, -.2], $p < .001$) such that younger adults with higher levels of well-being were more successful at regulating their desires. In other words, individual differences in well-being did not account for older adults being able to resist desires—older adults were better at resisting their desires independent of well-being. Participants experiencing greater desire strength were significantly less likely to successfully resist desires (β = -.17, 95% CI [-.27, -.06], $p < .001$). Similarly, participants experiencing a desire with greater personal conflict were significantly less likely to successfully resist desires (β = -.35, 95% CI [-.44, -.25], $p < .001$). In addition, older adults experiencing the most conflicting desires were the least successful at resisting desires (β = -.13, 95% CI [-.23, -..03], $p = .01$).

Effects of others being present enacting the tempting desire (β = -.06, 95% CI [-.31, .19], $p = .66$), positive-pleasant affective instability (β = - .19, 95% CI [-1..08, .69], $p = .67$), negative-unpleasant affective instability (β = .28, 95% CI [-.31, .88], $p = .35$), positive-pleasant affect (β = -.02, 95% CI [-.16, .12], $p = .78$), negative-unpleasant affect (β = 0, 95% CI [-.01, .02], $p = .77$) and well-being (β = .04, 95% CI [-.24, .31], $p = .8$) were non-significant predictors of successfully resisting desires. Similarly, interactions between others being present enacting the desire and age (β = -.03, 95% CI [-.29, .23], $p = .82$), desire strength and age (β = -.08, 95% CI [-.22, .06], $p = .26$), age and positive-pleasant affect (β = .06, 95% CI [-.09, .21], $p = .42$), age and negative-unpleasant affect (β = 0, 95% CI [-.01, .02], $p = .77$), age and positive-pleasant affective instability (β = .79, 95% CI [-.13, 1.71], $p = .09$) and age and negative-unpleasant affective instability (β = -.48, 95% CI [-1..09, .14], $p = .13$) were non-significant predictors of successfully resisting desires.

6. Conclusion

No two individuals are alike in how they experience and regulate their emotions. This becomes increasingly clear when you consider multiple levels of analysis, such as subjective, neural and psychophysiological. Moreover, multivariate analyses that study distributed patterns of activity and preserve the high-dimensional structure of data reveal tremendous variability in how individuals experience and regulate emotions that would remain otherwise uncovered.

Taken together, this body of work shows that individuals experience emotion differently. No two individuals are alike in how they experience and regulate their emotions. We have numerous tools as scientists to see these unique experiences reflected in individuals' faces, brains and bodies. Similarly, the differences between individuals becomes more pronounced when analyzing distributed patterns of activity and preserving the high-dimensional structure of emotion.

This dissertation revealed the immense variability in emotional experience and regulation using a diversity of psychological and neuroscientific methods. The previous chapters collectively demonstrated that individuals have more similar positive experiences than negative experiences, brain and psychophysiological signatures predict how individuals regulate emotion, there is a disconnect between how individuals regulate emotion in the lab versus in daily life, and individuals experience improved emotional health in daily life across adulthood.

More specifically, chapter 2 demonstrated, across 2 different studies, that individuals appraise and experience positive stimuli more similarly than negative. Relatedly, positive stimuli are less complex than negative stimuli, suggesting that not all emotions can be captured by 2 dimensions, as purported by numerous emotion theories. These results highlight the extensive variability in how individuals appraise and consequently experience emotional stimuli.

Chapter 3 demonstrated that there is a whole-brain signature of the tendency to suppress negative emotion, but no comparable signature for reappraisal. One reason for this difference may be that reappraisal is a more heterogeneous technique that may vary greatly within and between individuals. This neural signature may be used as a potential biomarker for identifying individuals at risk for negative health outcomes and psychopathologies characterized by increased use of suppression.

Chapter 4 identified a psychophysiological marker of emotion regulation. Based on these psychophysiological underpinnings of regulation, Chapter 4 showed that participants' self-reported regulation tendency did not differentiate how they naturally regulated, but their trait anxiety did. Specifically, participants with lower levels of anxiety exhibited similar psychophysiological profiles when naturally regulating and following instructions to reappraise, suggesting they naturally reappraise more. Conversely, participants with higher levels of anxiety exhibited similar psychophysiological profiles when naturally regulating and following instructions to suppress, suggesting they naturally suppress more. Taken together, these results suggest that anxiety may be a better indicator than self-reported regulation tendency of how individuals regulate in the laboratory. Measuring trait anxiety in conjunction with psychophysiology offers a new method for studying coherence between subjective and psychophysiological measures of emotion and emotion regulation.

Chapter 5 discussed the importance and benefits of experience sampling to study individual differences in emotion regulation. Chapter 5 then presented empirical evidence, based on experience sampling, that one individual difference factor—age—accounted for differences in emotional experience and regulation. The study found that older adults are happier, more stable and better at regulating emotion than younger adults. These results demonstrate how emotional experience is related to more successful regulation in everyday life and provide unique evidence that emotional health improves with age.

Chapters 4 and 5 underscored the importance of considering how individuals behave inside and outside the laboratory. Scientists conduct well-controlled laboratory research to better dissect the nature of emotion in the hopes that they are delineating the core nature of emotion that underpins what individuals experience in everyday life. One obvious difference between the laboratory and the real world is the extent of variability in stimuli. When studying emotion, it is critically important to have substantial variability on numerous dimensions in both stimuli and questions asked about the stimuli; otherwise, the nature and scope of the results will be inherently limited (Smith & Ellsworth, 1985). Indeed, "…if a meaningful dimension is not represented...it will not be found in the data" (Smith & Ellsworth, 1985, p. 815). The data obtained and consequential results of any given experiment are constrained by the stimuli used (Mattek, Burr, Shin, Whicker, & Kim, 2020). Experience sampling removes this challenge and ensures ecological variability (Burr & Samanez-Larkin, 2020).

The relationships among subjective, behavioral, neural and psychophysiological channels of emotion are often studied to help disambiguate competing theories of emotion. This dissertation does not directly tackle the question of *what emotions are*; rather, it argues for the need to research how individuals vary in their emotional experiences in numerous ways to adequately study emotion in the first place. However, the conclusion of this dissertation will consider how the results presented in the preceded chapters, which collectively emphasize tremendous variability in affective experiences, are consistent with appraisal models of emotions.

The extensive variability in every aspect of an emotion—from the biological and subjective responses to the appraisals that inform what something means—largely defies a basic account of emotion. Kathleen's experience of anger is not the same as Sade's. Moreover, Sade's anger today is not the same as their anger tomorrow. What Sade experiences in response to a stimulus today may not be the same as their response tomorrow. Studying emotion from multiple levels of analysis allows researchers to fully appreciate the depth and extent of this individual variability, which generally challenges claims of universality and contradicts the dominant theory of emotion for over a century.

Together, the findings presented in this dissertation are more consistent with appraisal, compared to basic or 2-dimensional theories of emotion. Specifically, Chapter 2 illustrated that positive events are appraised and experienced more similarly than negative events and appraisals of positive events are represented in a lower dimensional space, resulting in more similar emotional experiences. In other words, positive events are less complex and there are fewer ways to describe positive compared to negative events. This exposes a limitation of 2-dimensional models of emotions, which argue that emotion categories can be defined based on valence and arousal. However, chapter 2 reveals that positive emotions are organized differently than negative ones. However, these data also expose a limitation of basic emotion theory, which posits that different emotions are fully discrete, yet we find a shared feature (i.e., complexity) across certain emotion categories, but not others.

Chapters 3, 4 and 5 support that individuals tend to regulate their emotions in distinct ways and naturally regulate in their daily lives, which is related to larger health outcomes. Though not directly tested in this dissertation, models of emotion regulation that align to these findings are theoretically and empirically embedded in appraisal theories of emotion insofar as individuals can change their emotional experiences by appraising the event in a different way than before. Reappraisal is the natural consequence of appraisal and allows for more variability in and changes to emotional experiences. Indeed, appraisal theory allows for an infinite number of emotional states. In addition, Chapter 5 presents evidence from experience sampling that emotional improvements across adulthood go beyond simply how positive or negative individuals feel, but how volatile they are in their affective states and successful at resisting desires.

However, these findings do not equate emotions to being *solely* attributable to a constellation of appraisal dimensions. If appraisals were cut off from the rest of the world and the individual, it would be easier to argue that emotional experiences are reducible to a pattern of appraisals. But appraisals don't exist in a vacuum and other variables—such as past experiences, personal and regulatory goals, the social surroundings and larger circumstances—collectively contribute to the appraisal process and inform an emotion

(Frija, Kuipers, & ter Schure, 1989; Kuppens, Van Mechelen, & Rijmen, 2008; Kuppens, Van Mechelen, Smits, & De Boeck, 2003).

These individual differences in appraisals are further complicated by the dynamic and intertwined relationship between emotion and emotion regulation. The various components of an emotion are continuously updated and regulated (Cunningham, Zelazo, Packer, & Van Bavel, 2007). Although it is useful in empirical research to disentangle emotion from emotion regulation, this distinction blurs into the background and is purely academic outside the laboratory. Some previous research has even considered emotion regulation a component of emotion (Scherer, 2007). Emotions are dynamic and unfolding responses to the environment, which are continuously changing as new information is taken in and evaluated. This process is ever changing—boundaries between when the emotion finishes and the regulation begins is somewhat irrelevant. The emotion-generation versus -regulation taxonomy becomes even blurrier when discussing the ways in which individuals spontaneously regulate their emotions, outside the confines of the laboratory.

Emotions are complex and multivariate experiences that cannot be reduced to single entities—they are naturally constructed of multiple components. Researching 1 of those channels is inherently limited to a single facet of emotion. Yet, empirical and theoretical research too often narrowly focuses on one measure over another, or even puts one measure on a pedestal above all others (Niv, 2021). Certainly many empirical endeavors are rightfully focused on a single channel, such as subjective self-report, but it is important to be clear about that limitation. A wide range of individual differences is overlooked and devalued by looking at one measure.

It is increasingly important to consider multiple channels of emotion when characterizing spectrums of psychopathology. Currently, the healthcare system rests on pigeonholing individuals into heterogeneous categories (Allsopp, Read, Corcoran, & Kinderman, 2019; Scherer, 2007). One measurement failure that may be fueling this approach is focusing on single biomarkers of mental illnesses (Scherer, 2007). Relying on multiple measures of emotion allows researchers to separate heterogeneous categories into more refined and homogenous categories (Scherer, 2007). This is particularly important for emotion, as emotion dysregulation is at the heart of many mental illnesses (Gross, Uusberg, & Uusberg, 2019).

It is problematic to pit one channel against another as more valuable or enticing, as each component holds value and is part of a multicomponent system (Niv, 2021). Multiple levels of analysis are not in opposition or contention with another. Indeed, if, for example, behavioral and psychophysiological measures suggest two different outcomes, that introduces the importance of considering coherence among measures—not that one measure is inherently wrong or inferior to the other. Each level of analysis has its own benefits and pitfalls. By studying emotion from multiple levels of analysis, there may be additional avenues for identifying issues with and treatment opportunities for emotional processing. In addition to deepening our understanding and treatment possibilities, investigating multiple channels of emotion allows for a more multivariate and multidimensional account of emotion, which may reveal even more signatures of emotional processing. Chapters 2, 3 and 4, for example, demonstrate the benefit to measuring emotion in high-dimensional space. Armed with this comprehensive and multivariate account of emotion, research can ultimately lead to improved quality of life and personalized treatment options.

This research emphasizes the vast variability in how individuals experience emotions depending on their goals and the larger context. Collectively, this should help reduce the insidious stigma that still exists around mental illness, despite longitudinal evidence that 40% or more of the population experience mental illness at some point in their life (Caspi et al., 2020; Moffitt et al., 2010; Schaefer et al., 2017). Each approach highlights a different aspect of emotional functioning. Collectively, this holistic framework enhances our understanding of the full spectrum of emotional functioning. Taken together, identifying the various markers and channels of emotional functioning opens the door for researchers and clinicians to explore additional treatment avenues that may bring the field closer to a personalized account of emotion.

The body of work in this dissertation presents subjective, neural, and psychophysiological channels of emotion to demonstrate this extensive variability. The thread that connects these methods and levels of analysis is individual differences. There is no one-size-fits-all account or model of emotion. The larger contribution of this body of work is on individuating emotion across channels.

6.1 Future Directions

Future research should aim to characterize multiple channels of emotion and emotion regulation within the individual. Overly simplified accounts, which only consider a single or few aspects of emotional functioning in isolation, inevitably pigeonhole individuals into categories and treatment trajectories. Researchers can build a sensitive and specific model of emotional functioning by considering multiple levels of analysis. For example, specific channels may be useful for identifying symptoms that can be targeted with a particular treatment option, but not others. A multichannel approach may be valuable for identifying more nuanced manifestations of emotional functioning. This framework and approach helps move the field away from a simplified, categorical account of mental health and toward a specific and personalized account. Collectively, this can help reduce the trial-and-error milieu that dominates the healthcare system today.

Future research should also investigate how individuals understand their own attempts at regulating emotion. This awareness—*regulatory interoception*—may shape how emotions unfold over time, and influence how individuals experience and respond to those emotions. Peoples' knowledge of how they can regulate under which circumstances (i.e. their repertoire of regulatory strategies and how to best match them to the situation) is a crucial skill set for psychological health and well-being. Indeed, appraisal theories of emotion argue that knowing how to cope with a situation may fundamentally alter the emotion people experience. However, more research is needed to fully elucidate the impacts of regulatory interoception on emotion.

Every emotional experience—both within and between individuals—is unique. Individuals vary extensively in how they experience and manage emotion depending on their goals and the larger context. Delineating and appreciating this complex variability enhances our understanding of the full spectrum of emotional functioning and brings the field closer to a personalized account of emotion.

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