

**Structure and Dynamics of Emotional Experience
in Depression**

by

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Dedicated to my family
and countless
generous
individuals
who made this
dissertation
possible.

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ABSTRACT

Structure and Dynamics of Emotional Experience In Major Depressive Disorder

by

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Human emotional experience is extremely complex and dynamic. Multiple factors contribute to the ever changing subjective experience of emotion. Exteroceptive information from our senses, interoceptive information from muscles, internal organs and conceptual information about the past, the present and future get combined allowing a person to experience discrete states of happiness, sadness, anger, elation or a variety of other emotional states. While our verbal descriptions of our emotional experiences are invaluable, they rarely capture the elusive richness and role of emotion in daily life. First of all, no two moments of happiness, sadness or anger are the same. Second, emotional experience is not static. It fluctuates within the ebb and flow of daily life. In this dissertation, I introduce two new methods to characterize the rich structural complexity of emotion as well as its elusive temporal dynamics. I use these methods to identify seemingly contradictory results regarding the impact of Major Depressive Disorder on structural and dynamic properties of human emotional experience. Furthermore, in order

to ensure ecological validity, I use mobile computerized experience sampling which allows people to provide information about multiple facets of their emotional experiences during daily life longitudinally across time with minimal interference. I conclude with a discussion of the implications of the findings for basic and clinical science as well as future directions.

Chapter I

Introduction

Human emotional experience is rich and complex. Even though, we might use single emotion adjectives such as happy, sad and angry to describe and communicate our emotional experiences, it is well known that no two moments of happiness, sadness and anger are the same. In fact, when individuals are asked to report their emotional experiences, they often report multiple emotion adjectives as being relevant. Furthermore, electrophysiological, psychophysiological and brain imaging studies fail to find reliable and replicable patterns that underpin emotional states that subtend experiences described by the same emotional adjective. Overall, basic and clinical science of emotion indicates that emotional experiences emerge at the confluence of a number of latent underlying mechanisms such as valence (pleasantness and unpleasantness), physiological activation (arousal) and conceptual information (Barrett, Mesquita, Ochsner & Gross, 2007; Ellsworth & Scherer, 2003; Frijda, 1986). Memories, goals, uncertainty and a number of other appraisals play an important role in the subjective experience of emotion.

It is important to emphasize that, as of today there is no evidence for a universal and robust mapping between various emotion adjectives and the latent variables described above (Barrett, 2006b; Mauss & Robinson, 2009). In other words, happiness, sadness, excitement and the whole range of emotion adjectives could potentially be referring to different types of experiences across different people. Hence, it is essential to not only identify latent dimensions describing emotional experiences but also develop

measures that describe properties of emotional experience independent of its content. To draw an analogy, our goal is to identify constructs such as volume, area, speed and acceleration in classical mechanics, which can be studied independent of the objects they describe. In this dissertation, I investigate the structure and dynamics of emotional experience in the context of Major Depressive Disorder. I introduce two new methods to investigate emotional granularity and emotion regulation respectively.

There are a total of five chapters in this dissertation and they are organized as follows: The first chapter is an introduction, which identifies the issues at a very broad level and describes the organization of the dissertation. The second, third and fourth chapters describe the results of empirical and methodological research investigating the structure and dynamics of emotional experience in depression. The final and fifth chapter concludes the dissertation by providing a brief overarching conclusion and outlining the future research directions.

The experimental data used in this dissertation were collected at University of Michigan and Stanford University. Data collection entailed prompting healthy controls and people with depression to respond to a series of questions in their daily lives. Participants provided moment to moment information about aspects of their subjective experience (i.e. emotion, attention and exercise). The methodological portion of this dissertation entailed the introduction of two novel methods to investigate the structure and dynamics of emotional experience. These methods are described as parts of chapter three and four and expand our understanding of the structure and dynamics of human emotional experience respectively.

The second chapter, “Feeling Blue or Turquoise? Emotional Differentiation in Major Depressive Disorder”, is a manuscript that is currently in press at Psychological Science. This chapter describes differences in emotional granularity associated with people in depression. Specifically, the results show that people with depression have less granular negative emotional experiences potentially making it difficult to act adaptively in the face of life stressors. The third chapter, provides a more comprehensive analysis of the structure of emotional experience using high dimensional modeling. The modeling is high dimensional because, for instance, happiness that is concurrently present with excitement, anger, sadness is a different state than one that is concurrently present with being tired, frustrated and anxious. The results show that people with depression have unnecessarily complicated experiences of pleasant emotions. Finally, the fourth and the last empirical chapter describes differences in emotion regulation associated with depression. The paper uses dynamical systems to characterize the causal relationships among various aspects of emotional life as well as resilience to life stressors. The results show that people with depression have difficulty increasing their pleasant emotional experiences after a negative episode. Furthermore, people with depression have difficulty being resilient in the face of life stressors.

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Chapter II

Feeling Blue or Turquoise? Emotional Differentiation in Major Depressive Disorder

This is the first of three papers which is currently in press at Psychological Science.

Feeling Blue or Turquoise? Emotional Differentiation in Major Depressive Disorder

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Abstract

Some individuals have very specific and differentiated emotional experiences such as anger, shame, excitement, and happiness, whereas others have more general affective experiences of pleasure or discomfort that are not as highly differentiated. Considering the cognitive deficits demonstrated by individuals with Major Depressive Disorder (MDD) for negative information (such as over-general memory for negative events), we predicted that participants with MDD would have less differentiated negative emotional experiences than would healthy individuals. To test this hypothesis, participants' emotional experiences were assessed using a 7-day experience-sampling protocol. Depression was assessed using structured clinical interviews and the Beck Depression Inventory-II. As predicted, individuals with MDD had less differentiated emotional experiences than did healthy controls, but only for negative emotions. These differences were above and beyond emotional intensity and variability.

Keywords: emotions, depression, happiness, emotional control, individual differences

Feeling Blue or Turquoise? Emotional Differentiation in Major Depressive Disorder

Imagine yourself at the funeral of a friend from high school. You might be filled with an intense feeling of *sorrow*. You might also feel *happy* that he lived a fulfilling life. And you might feel *awed* by the large crowd that has gathered to honor him. Perhaps you also feel *surprised* to see acquaintances and friends that you haven't seen in some time, along with *frustration* about losing someone close to you, but also *determination* to make the most of every moment of every day that follows. Accompanying daily events, people often experience a changing stream of emotions. Sometimes these emotions are discrete and highly specific, as in the example here. But another person in the same situation might feel a general gnawing unpleasantness or deep despair with no distinguishing features. In this paper, we report an investigation of whether people diagnosed with Major Depressive Disorder (MDD) experience less differentiated emotions in daily life than do healthy persons. We use our results to ground a discussion of how the ability to differentiate a variety of emotional experiences plays an adaptive role in dealing with life stressors.

At every waking moment, we have access to exteroceptive information from our senses, interoceptive information from our muscles and internal organs, and conceptual information about the past, the present, and the future. Emotional processes combine these pieces of information, allowing a person to experience discrete states of happiness, sadness, anger, elation, or a variety of other emotional states (Barrett, Mesquita, Ochsner & Gross, 2007; Ellsworth & Scherer, 2003; Frijda, 1986). The situations encountered during daily life are often multidimensional, with elements that can lead a person to feel

happiness and sadness both at the same moment. At such times, a person might have an experience such as “Part of me is sad about the death of my friend, but part of me is happy that he lived such a fulfilling life.” The more differentiated a person’s emotional reaction, the better able she is to calibrate her behavioral response to the demands of the specific situation (Barrett, Gross, Christensen & Benvenuto, 2001). For instance, distinguishing anger from anger laced with shame and guilt determines the course of action one will take in response to a specific situation (Ellsworth & Tong, 2006). Previous research has conceptualized and quantified the differentiation among emotions (Barrett, 2004; Barrett & Bliss-Moreau, 2009). Furthermore, investigators have shown that people differ in their degree of emotional differentiation (e.g., Barrett, 2004; Kashdan, Ferrisizidis, Collins & Muraven, 2010). In this paper, we examine whether people with MDD are less differentiated in their day-to-day experiences of emotion than are healthy controls.

MDD is a common and debilitating psychiatric condition. Approximately one in six people in the United States experience MDD during their lifetime. The cost of medical treatment and lost productivity is approximately \$85 billion each year (Greenberg et al., 2003). Depressed people are 30 times more likely to commit suicide than are healthy individuals (Joiner, 2010) and 5 times more likely to abuse drugs. They are twice as likely to take sick days and seven times more likely to be unemployed (Lerner et al., 2004). Depression also aggravates the course of cardiovascular conditions; it is linked to obesity, osteoporosis, arthritis, type 2 diabetes, certain cancers, periodontal disease, and frailty, down-regulates immune responses, and makes it more difficult to quit smoking.

A primary reason for the widespread and cascading adverse effects of depression is that this mood disorder fundamentally alters the way in which the self is situated in the physical and social world. People with depression have over-general autobiographical memory (Williams & Scott, 1988). Compared with healthy individuals, they have greater difficulty removing irrelevant information from short-term memory (Joormann, Nee, Berman, Jonides & Gotlib, 2010); are less able to perceive contrasts in the visual world (Bubl, Kern, Ebert, Bach & Ludger, 2010); are less sensitive to context in emotional processing (Rottenberg, Gross, & Gotlib, 2005); and are impaired in executive functioning (Joormann, 2005). The common theme among these findings is that depression is associated with a diminished ability to differentiate elements of information from one another at the level of perception, memorial processing, and executive functioning. Each of these elements is thought to be associated with our momentary emotional experience (Barrett, 2006a). Accordingly, we hypothesized that people with depression have less differentiated emotional experiences in their daily lives than do healthy people.

When people experience a discrete emotional state, such as anger or sadness or fear, they attend to certain features of the stimulus field and ignore others. People's states of pleasure and arousal become meaningfully conceptualized, so that it is possible to make reasonable inferences about that experience, to predict what to do to resolve or enhance it, and to communicate the experience to others (e.g., Barrett, 2006a). For instance, consider a situation in which healthy people would typically feel angry with themselves (e.g., missing an appointment due to not waking up in time; Ellsworth & Tong, 2006). These individuals would take an action that is appropriate to this specific

emotional experience to ameliorate the situation. In this case, the anger would be directed at the self rather than the outside world. Now, consider a situation in which a driver disregards a stop sign and crashes into another person's car. The victim's experience can also be categorized as anger; however, it does not have elements of shame and guilt, and the referent of the experience of anger is the driver who disregarded the stop sign. People who lack the ability to differentiate these particular emotional states from each other or from a general feeling of unpleasantness might choose an action that is not appropriate to the current situational context and might exacerbate the problem.

Studying the experience of emotion presents a challenge to researchers because it is difficult to study subjective experience in an objective way. Reviews of the literature indicate that there is no essential signature within the brain or body that is specific to a particular emotion as humans experience it (Barrett, 2006b; Mauss & Robinson, 2009). This is similar to the experience of light, for instance, in which there is variability in the assignment by humans of a particular wavelength to a color category (Barrett, 2006a; Berlin & Kay, 1969). Furthermore, extensive research suggests that people make biased responses when asked to evaluate their emotional lives (Dunning, Heath, & Suls, 2004); therefore, it is not possible to obtain an accurate measure of differentiation simply by asking individuals how differentiated they feel their emotions are (although this might be useful information to understand meta-emotional processes). One of the best ways to study subjective experiences in a more objective way is to assess the richness of momentary emotional experience as it is lived using experience sampling (Barrett & Barrett, 2001; Larsen & Csikszentmihalyi, 1983). According to this procedure, individuals are probed at various times throughout the day and are asked to characterize

their momentary experience using a set of emotion adjectives. We used this method to measure participants' emotional experiences over the course of a week. The ratings were later analyzed to reveal the extent to which people report differentiated versus global emotional feelings (Barrett & Bliss-Moreau, 2009). The correlation patterns in the reports provide an objective estimate of emotional differentiation. For example, if temporal fluctuations in anger are highly correlated with temporal fluctuations in sadness across situations, then from a statistical standpoint, these adjectives are describing the same state (i.e., negative emotion) and so emotions would not be well-differentiated (e.g., Barrett, 2004). The less related the change in one emotion over time is on change in other emotions, the higher an individual's emotional differentiation.

We predicted that people with MDD would experience less differentiated emotions than would demographically matched healthy individuals. Given that the cognitive biases exhibited by individuals diagnosed with MDD appear to be stronger for the processing of negative than of positive information, we hypothesized that the decrease in emotional differentiation would be limited to negative emotional experiences. We predicted further that emotional differentiation is unique from other emotional constructs implicated in MDD, such as emotional intensity or variability, the importance of which in this same sample have been described elsewhere (Thompson, Mata, Jaeggi, Buschkuhl, Jonides & Gotlib, in press). We did not have specific predictions about whether emotional differentiation would be related to average emotional intensity; however, given that previous work has shown that lower clarity of emotion is related to higher emotional variability (Thompson, Dizen & Berenbaum, 2009), we did expect to

find an inverse relation of differentiation and emotional variance throughout the experience sampling period.

Method

Participants

One hundred and six participants between the ages of 18 and 40 ($M = 27.8$ years; $SD = 6.5$ years) were recruited for the current study, which was part of a larger project (see Mata, Thompson, Jaeggi, Buschkuhl, Jonides, & Gotlib, 2011; Thompson et al., in press; Thompson, Mata, Jaeggi, Buschkuhl, Jonides, & Gotlib, 2011). All of the participants were native English speakers. Individuals were eligible to participate if they either (1) experienced no current/past history of any mental health disorders and scored below 9 on the Beck Depression Inventory-II (BDI: Beck, Steer & Brown, 1996; control group: $n = 53$; 71.7% women); or (2) were currently diagnosed with MDD (depressed group: $n = 53$; 67.9% women) as assessed by the Structured Clinical Interview for DSM-IV Axis I Disorders (SCID-I: First, Spitzer, Gibbon & Williams, 1997) and had a BDI-II score above 13. Additional requirements for the depressed group included absence of: (a) alcohol/drug dependence in the past six months, (b) Bipolar I or II diagnoses, and (c) psychotic disorders. The MDD and control groups did not differ in years of education, gender, race and ethnicity composition; however, depressed participants ($M = 28.2$, $SD = 6.4$) were on average three years older than healthy participants ($M = 25.4$, $SD = 6.4$), $t(104) = -2.19$, $p = 0.03$. Including age as a covariate in the analyses did not influence any of the reported results.

Participants were recruited from the communities surrounding the University of Michigan in Ann Arbor, Michigan, and Stanford University in Stanford, California.

Advertisements were posted online (e.g., Craigslist) and at local agencies and businesses (e.g., bulletin boards). An approximately equivalent number of participants were recruited in each location. Participants recruited at the two sites differed in gender composition, $\chi^2(1) = 11.77, p < .01$, with the Michigan sample having more men than the Stanford sample (Michigan sample: 44.6% men; Stanford sample: 14.0 % men). There was also a significant difference in years of education between the two sites, $\chi^2(3) = 9.67, p < .05$: whereas the majority of the Michigan sample (55.4%) reported having “some college,” the majority of the Stanford sample (66%) reported having earned a bachelor’s degree or a professional degree. This difference in education status is also reflected in age: the Michigan sample was younger than the Stanford sample $t(104) = 4.69, p < .01$; (Michigan sample: $M = 24.2$ years, $SD = 5.5$ years; Stanford sample: $M = 29.7$ years, $SD = 6.5$ years). The two sites did not differ in ethnic or racial distribution, $\chi^2(5) = 4.78$, or depression status, $\chi^2(1) = 1.00$, both $p > 0.1$. Because the samples did not differ on central variables of interest (i.e., emotion ratings), we combined the two samples for the remaining analyses (see Table S1 in the Supplemental Material for detailed demographics).

Materials and Procedure

Participants were administered the SCID and BDI prior to the experience-sampling period. If more than two weeks had passed since the administration of the SCID, participants’ diagnostic status was re-assessed with another SCID to ensure eligibility. Participants were provided with hand-held electronic devices (Palm Pilot Z22) and were individually instructed on the experience-sampling protocol, including completing a full practice trial. The handheld devices were programmed using the Experience Sampling

Program 4.0 (Barrett & Barrett, 2001). Participants were prompted (via a tone signal) eight times per day between 10 am and 10 pm. The majority of the participants carried the device for seven to eight days in order to be prompted 56 times. Prompts occurred at random times within eight 90 minute-windows per day; thus, prompts could occur from as little as two minutes apart to almost 180 minutes apart. After participants were prompted, they had three minutes to respond to the initial question on the Palm Pilot; otherwise, the device switched to hibernation until the next prompt, and the data for that trial were recorded as missing. Up to 56 trials of data were recorded for each participant. The depressed and control participants did not differ in the number of completed trials (considering each prompt to be a trial). Participants provided informed consent and were compensated for their participation in the study, with an extra incentive for responding to more than 90 percent of the prompts.

At each measurement, using a 4-point scale (not at all = 1, little = 2, much = 3, a great deal = 4), participants indicated the degree to which each of eleven emotion adjectives described their current emotional state. There were seven negative-emotion adjectives (sad, anxious, angry, frustrated, ashamed, disgusted, and guilty) and four positive-emotion adjectives (happy, excited, alert, and active). The adjectives were drawn from various sources, such as the Positive Affect Negative Affect Scale (Watson, Clark, & Tellegen, 1988) and other commonly studied emotions (Ekman, Friesen & Ellsworth, 1972). Emotion differentiation was computed as the average inter-emotion correlation between all pairs of positive and negative emotions (Tugade, Fredrickson & Barrett, 2004).

Calculation of Emotion Differentiation, Intensity, and Variability

To quantify emotional differentiation, for each participant the Pearson's correlation was calculated between all possible pairs of negative emotions ($\rho_{\text{sad, anxious}}$, $\rho_{\text{sad, angry}}$, $\rho_{\text{sad, frustrated}}$, ...) and of positive emotions ($\rho_{\text{happy, excited}}$, $\rho_{\text{happy, alert}}$, $\rho_{\text{happy, active}}$, ...). The average of the Fisher's z-transformed correlations was used to quantify positive and negative emotional differentiation for each participant. The larger the correlation, the less the person distinguishes between various categories of emotional experience when describing his or her feelings. In addition, we transformed the scores by subtracting from 1, such that larger values indicate higher differentiation.

Emotional intensity was measured by averaging the emotion ratings at each prompt, separately for the seven negative and four positive emotions. Then a mean was taken across the entire sampling period, resulting in one negative and one positive intensity score. Higher scores indicated that the individual experienced emotions with higher intensity. Temporal variability was measured by calculating the variance of the intensity of each emotion over the sampling period, again separately for the negative and positive emotions. Higher scores indicated that the individual experienced emotions with higher variability. Emotions with zero temporal variance were pruned from the correlation-based differentiation analyses. Considering that four positive and seven negative emotions were used in this study, participants with three or more positive emotions with zero temporal variance (1 MDD) and six or more negative emotions with zero temporal variance (5 Controls) were excluded from the analyses because correlations could not be calculated with such data (see bootstrap analyses in Supplemental Online Material for a description of the robustness of our analyses to

excluding these participants). In order to investigate the effect of differentiation above and beyond emotional intensity and variability, we included intensity and variability as covariates in our analyses.

Results

Emotional Differentiation

As predicted, people with MDD had less differentiated negative emotions (Table 1) than did healthy controls ($F(1,98) = 7.18, p < 0.01, d = -0.54$). Also as predicted, there was no difference between the MDD and control participants in differentiation of positive emotions. A two-way analysis of variance (ANOVA) yielded no significant main effects of participant group or valence but did yield a significant interaction of participant group and valence ($F(1,196) = 6.60, p = 0.01$), suggesting that the differences in differentiation between people with MDD and controls was limited to negative emotions. Negative and positive emotional differentiation were not correlated for people with MDD or controls, suggesting that differentiation of positive and negative emotions depends on different psychological mechanisms (see Table S3 in the Supplemental Online Material for differentiation scores for individual emotion pairs). An examination of the mean levels of negative differentiation for men and women led us to investigate the role of gender. Although we had no *a priori* hypotheses concerning gender differences in emotion differentiation in MDD, we conducted an exploratory three-way ANOVA on emotion differentiation including gender as the third factor (with valence and group). The three-way interaction of participant group, gender, and valence was not significant ($F(1,192) = 2.32, p \leq 0.13$) indicating that gender was not a significant moderator of the relation between depression and emotional differentiation (see Table S4 in the Supplemental

Online Material for results provided separately for male and female participants, and for a description of additional bootstrapping analyses that explain and confirm this finding).

Emotional Differentiation Beyond Emotional Intensity and Variability

It is possible that the observed differences in differentiation were due to group differences in emotional intensity or variability. In fact, in previous research based on these data, we reported differences between people with MDD and controls in emotional intensity (Mata et. al., 2011) and variability (Thompson et. al., in press). To test whether group differences in intensity and variability were linked to group differences in negative emotional differentiation, we used two multiple regression models, one predicting changes in positive emotional differentiation and one predicting changes in negative emotional differentiation. Predictors were depression as a nominal variable, as well as intensity and variability as continuous predictors. After controlling for intensity and variability, depression remained a significant predictor of low differentiation only for negative emotions ($F(1,96) = 7.51, p < 0.01$), indicating that between-group differences in negative differentiation is not due to differences in intensity and variability. Emotional variability remained a significant predictor of both negative ($F(1,96) = 6.53, p < 0.02$) and positive ($F(1,96) = 5.21, p < 0.03$) emotional differentiation, whereas emotional intensity was a significant predictor of only positive emotional differentiation, $F(1,96) = 4.25, p < 0.05$.

Positive emotional intensity was modestly negatively correlated with emotional differentiation for both people with MDD, $r(50) = -0.19, p < 0.09$, and controls, $r(46) = -0.21, p < 0.08$, suggesting that individuals who experienced positive emotions with high intensity tended to have less differentiated positive emotional experiences. There was no

significant relation between negative emotional intensity and differentiation for either group (see Table 2).

For people with MDD, emotional variability was negatively correlated with both positive, $r(50) = -0.35$, $p < 0.005$, and negative, $r(50) = -0.27$, $p < 0.03$, emotional differentiation. Similarly, controls exhibited a tendency for emotional variability to be negatively correlated with both positive, $r(46) = -0.22$, $p < 0.07$, and negative, $r(46) = -0.21$, $p < 0.08$, emotional differentiation. These results suggest that individuals whose emotional experiences were more variable across time had less differentiated experiences of positive and negative emotions (see Table 2; also see Table S2 in Supplemental Online Material for adjusted means and Table S4 and S5 for results separately provided for male and female participants).

Discussion

The present study is the first to show that people diagnosed with MDD experience negative emotions with less differentiation in their daily lives than do healthy controls. We found that the relation between emotional differentiation and depression could not be accounted for by emotional intensity or variability. This finding suggests a fundamental way in which the emotional lives of individuals diagnosed with MDD are altered independent of increased negative emotional intensity and emotional variability.

Earlier research supporting the “affect-as-information” perspective shows that specific emotional states (e.g., anger, sadness, fear, etc.) have more adaptive value than do global affective (e.g., pleasant and unpleasant) states. This is because specific and differentiated negative emotional experiences are less subject to misattribution errors (Schwarz & Clore, 1996). One of the important distinguishing features of discrete

emotional states is that, compared to an undifferentiated and global state, specific emotions are generally associated with a causal object, whereas global affective states are not (Russell & Barrett, 1999). It is important to identify the source and cause of an emotional state in order to generate an adaptive response. In fact, earlier research has shown that negative emotional differentiation is correlated with emotion regulation (Barrett et. al., 2001). Accordingly, decreased differentiation might lead people with MDD to regulate their emotions less frequently than healthy controls. Future research should specifically test this hypothesis.

It is important to note that people with MDD did not differ from controls in positive emotional differentiation. First, this finding suggests that the psychological mechanisms that underlie emotional differentiation can be selectively altered for negative emotions, as one might expect for MDD. Second, this finding further supports the claim that emotional differentiation, intensity, and variability are independent constructs. That is, people with MDD can have positive emotional experiences with decreased intensity but unaltered differentiation. It could be that people with MDD use differentiated positive emotional experiences as a buffer against life stressors (Tugade et. al., 2004), and this is one of the reasons that they retain differentiation among positive emotions. It could also be that the high-arousal positive emotions that we sampled are not representative of the domains in which people with MDD might experience alterations in emotional differentiation. In future studies, we plan to use a larger number of positive emotions, including such emotions as compassion and calmness.

Previous research has shown that depression is associated with alexithymia (Honkalampi, Hintikka, Tanskannen, Lehtonn & Vilnamaki, 2000), defined as the

inability to recognize and verbalize emotions. Alexithymia is often associated with emptiness of feelings, poverty of imagination, difficulty in communicating with other people, lack of positive emotions, and high prevalence of negative emotion. The major difficulty in interpreting this body of research is its reliance on asking people to report their ability to differentiate emotions (Dunning, et. al., 2004). Earlier research suggests that people make flawed, biased responses when asked to evaluate their abilities globally, and that these abilities are best captured using skill-based measurements. Therefore, it is important to measure individuals' subjective emotional experiences and quantify the degree of emotional differentiation. This is especially important if we want to understand the mechanisms of emotional experience in healthy and depressed populations.

Despite some success in developing empirically validated diagnoses and interventions for depression and other mental health disorders, the mechanisms of even the most successful treatments are still unclear. For example, in a recent summary of the literature on mechanisms of change in psychotherapy research, Kazdin (2007) concludes, "... after decades of psychotherapy research, we cannot provide an evidence based explanation for how or why even our most well studied interventions produce change, that is, the mechanism(s) through which they operate" (p.1). This noted lack of progress may be due, in part, to how we measure emotional states in various psychopathologies. The present results indicate that the use of momentary experience sampling, coupled with techniques that extract relations among emotions, may be helpful in increasing our understanding the structure and dynamics of emotional experience in depression (Palmier-Claus et al., 2011; Peeters, Nicolson, Berkhof, Delespaul, & deVries, 2003; Wichers et al., 2011) because it goes beyond retrospective self-report, which is

influenced by beliefs and attitudes. This approach should broaden the perspective taken to examine any mental illness by allowing us to study not only what individuals report feeling in the past, but assessing what they feel on a moment-to-moment basis in the present (which may not be the same; Robinson & Clore, 2002). This breadth of perspective and assessment of momentary experience may inform the development of improved diagnostic criteria, which should play a crucial role in the development and validation of more effective treatments.

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Table 1
Emotion differentiation, intensity and variability scores

	Positive Emotions		Negative Emotions	
	Participants with MDD	Control Participants	Participants with MDD	Control Participants
Differentiation	0.57 (0.21)	0.54 (0.18)	0.51 (0.22)	0.64 (0.27)
Intensity	1.68 (0.39)	2.17 (0.45)	1.88 (0.53)	1.15 (0.17)
Variability	0.51 (0.24)	0.50 (0.27)	0.59 (0.29)	0.14 (0.13)

Note. Standard deviations are in parentheses.

Table 2
 Correlations between emotional intensity, variability and differentiation

	Positive Emotions		Negative Emotions	
	Participants with MDD	Control Participants	Participants with MDD	Control Participants
Intensity	-0.19 <i>p</i> <0.09	-0.21 <i>p</i> <0.08	0.12 <i>p</i> >0.19	-0.13 <i>p</i> >0.17
Variability	-0.35 <i>p</i> <0.005	-0.22 <i>p</i> <0.07	-0.27 <i>p</i> <0.03	-0.21 <i>p</i> <0.08

Table S1. Demographic Characteristics of Participants with MDD and Control Participants

	<i>Participants with MDD (n=53)</i>	<i>Control Participants (n=53)</i>	Statistics
BDI score, M(SD)	32.2 (8.6)	1.7 (2.3)	t(104) = -24.86, p<.001
Age, M(SD)	28.2 (6.4)	25.4 (6.4)	t(104) = -2.19, p=0.03
Ethnicity (<i>n</i>)			$\chi^2(5) = 7.79, p=0.17$
African American	3	5	
Asian	2	9	
Caucasian	39	33	
Hispanic	2	1	
Multiracial	5	5	
Other	2	0	
Education (<i>n</i>)			$\chi^2(3) = 6.67, p=0.08$
High school	6	0	
Some college	20	25	
Bachelor's	23	23	
Master's	4	5	
Gender (<i>n</i>)			$\chi^2(1) = 0.18, p=0.83$
Female	38	36	
Male	15	17	
# of completed prompts, M(SD)	44.0 (7.6)	42.4(7.8)	t(104) = 1.08, p=0.29
Mean PA over the week, M(SD)	1.7(0.4)	2.2(0.5)	t(104) = 5.54, p<0.001
Mean NA over the week, M(SD)	1.9 (0.5)	1.1(0.2)	t(104) = 9.98, p<0.001

Note:

MDD = Major Depressive Disorder

BDI = Beck Depression Inventory – II;

PA = Positive Affect (Average of the pleasant emotion adjectives);

NA = Negative Affect (Average of the unpleasant emotion adjective)

Table S2. Original and adjusted emotion differentiation scores.

	Positive Emotions		Negative Emotions	
	<i>Participants with MDD</i>	<i>Control Participants</i>	<i>Participants with MDD</i>	<i>Control Participants</i>
Differentiation	0.57 (0.21)	0.54 (0.18)	0.51 (0.22)	0.64 (0.27)
Differentiation (adjusted)	0.65 (0.15)	0.68 (0.14)	0.39 (0.21)	0.55 (0.16)

Note: Adjusted scores indicate levels of emotion differentiation after controlling for intensity and temporal variability.

MDD = Major Depressive Disorder

Table S3. Differentiation (1- ρ) scores for all pairs of emotion adjectives

	<i>Participants with MDD</i>		<i>Control Participants</i>	
	<u>Mean</u>	<u>SD</u>	<u>Mean</u>	<u>SD</u>
Pleasant				
ρ (Happy, Excited)	0.49	0.22	0.46	0.16
ρ (Happy, Alert)	0.70	0.23	0.65	0.25
ρ (Happy, Active)	0.71	0.24	0.67	0.23
ρ (Excited, Alert)	0.60	0.20	0.60	0.18
ρ (Excited, Active)	0.61	0.23	0.59	0.18
ρ (Alert, Active)	0.52	0.22	0.53	0.23
Unpleasant				
ρ (Sad, Anxious)	0.56	0.27	0.69	0.27
ρ (Sad, Angrv)	0.55	0.26	0.62	0.32
ρ (Sad, Frustrated)	0.57	0.23	0.61	0.31
ρ (Sad, Ashamed)	0.53	0.25	0.73	0.35
ρ (Sad, Disgusted)	0.51	0.25	0.53	0.36
ρ (Sad, Guilty)	0.55	0.24	0.66	0.32
ρ (Anxious, Angrv)	0.67	0.27	0.64	0.27
ρ (Anxious, Frustrated)	0.58	0.24	0.73	0.25
ρ (Anxious, Ashamed)	0.66	0.26	0.78	0.29
ρ (Anxious, Disgusted)	0.63	0.25	0.70	0.28
ρ (Anxious, Guilty)	0.61	0.26	0.75	0.28
ρ (Angrv, Frustrated)	0.48	0.22	0.51	0.24
ρ (Angrv, Ashamed)	0.59	0.26	0.73	0.30
ρ (Angrv, Disgusted)	0.58	0.26	0.60	0.34
ρ (Angrv, Guilty)	0.60	0.25	0.71	0.30
ρ (Frustrated, Ashamed)	0.62	0.22	0.83	0.27
ρ (Frustrated, Disgusted)	0.63	0.26	0.72	0.29
ρ (Frustrated, Guilty)	0.62	0.22	0.82	0.27
ρ (Ashamed, Disgusted)	0.45	0.18	0.51	0.39
ρ (Ashamed, Guilty)	0.35	0.22	0.43	0.33
ρ (Disgusted, Guilty)	0.44	0.22	0.47	0.35

Note: MDD = Major Depressive Disorder

Table S4. Emotion differentiation, intensity and variability for male and female participants.

	Positive Emotions				Negative Emotions			
	<i>Participants with MDD</i>		<i>Control Participants</i>		<i>Participants with MDD</i>		<i>Control Participants</i>	
	Male	Female	Male	Female	Male	Female	Male	Female
Differentiation	0.52 (0.19)	0.59 (0.22)	0.54 (0.20)	0.55 (0.18)	0.55 (0.16)	0.50 (0.24)	0.54 (0.33)	0.69 (0.23)
Intensity	1.75 (0.54)	1.67 (0.32)	2.08 (0.43)	2.21 (0.46)	1.62 (0.33)	1.98 (0.55)	1.21 (0.27)	1.13 (0.10)
Variability	0.55 (0.34)	0.48 (0.24)	0.53 (0.20)	0.51 (0.26)	0.48 (0.34)	0.63 (0.26)	0.19 (0.22)	0.12 (0.08)

Note: MDD = Major Depressive Disorder

To investigate the role of gender in the relation between MDD and emotional differentiation, we conducted a three-way analysis of variance (ANOVA) with the independent variables of gender, participant group, and valence, and the dependent variable of emotional differentiation. The three-way interaction of gender, participant group, and valence was not significant, $F(1,192) = 2.32, p < 0.13$. The two-way interaction of participant group and valence, however, was still significant, $F(1,192) = 6.70, p < 0.01$.

Because this study was designed to investigate MDD, and because females constitute nearly 2/3 of the population of people with MDD, we matched the number of male and female participants in this study to reflect this proportion. Accordingly, we have nearly 2.5 times as many females as males in our sample (32 vs 74) (see Table S1 for demographics). Therefore, the male group had less power than did the female group. Furthermore, in two additional bootstrapping analyses, we determined that the three-way interaction remained nonsignificant. First, we randomly selected (without replacement) 32 participants from the 74 female participants, ensuring an equal number of people with

MDD and healthy controls. There are roughly 10^{20} such random samples. From this, we took 10000 random samples and evaluated the results of the three-way ANOVA described above for each of them. In 9632 of these analyses, the interaction remained non-significant, giving us confidence about the robustness of our finding regarding the absence of a moderating effect of gender. In the second analysis, we randomly selected (with replacement) 74 male participants from our sample, again ensuring an equal number of people with MDD and healthy controls. There are roughly 10^{90} such random samples. Therefore, we took 100000 random samples and evaluated the results of the three-way ANOVA described above for each one of them. In 96735 of these analyses the interaction remained nonsignificant, again giving us confidence about the robustness of our finding regarding the absence of a moderating effect of gender. In addition to the fact that there was no strong theoretical reason for hypothesizing a gender difference in emotional differentiation, these findings indicate that the absence of gender differences should be treated with caution until it is replicated by future work.

Table S5. Correlations among emotional intensity, variability and differentiation.

	Positive Emotions				Negative Emotions			
	<i>Participants with MDD</i>		<i>Control Participants</i>		<i>Participants with MDD</i>		<i>Control Participants</i>	
	Male	Female	Male	Female	Male	Female	Male	Female
Intensity	-0.33 p=0.12	-0.12 p=0.23	0.04 p=0.44	-0.34 p<0.03	0.08 p=0.39	0.14 p=0.20	-0.19 p=0.24	0.10 p=0.30
Variability	-0.51 p<0.03	-0.28 p<0.05	0.16 p=0.28	-0.37 p<0.02	-0.23 p=0.21	-0.28 p<0.05	-0.26 p=0.18	0.01 p=0.48

Note: MDD = Major Depressive Disorder

Bootstrap Analyses

In the main manuscript, we reported results indicating that people with MDD have less differentiated unpleasant emotional experiences than do their healthy peers. We reached this conclusion by calculating the correlations among a set of 4 pleasant and 7 unpleasant emotion adjectives that participants used to rate their momentary emotional experience.

In order to show that our results are not due simply to the difference in the number of pleasant and unpleasant emotion adjectives, we conducted a bootstrap analysis. In this analysis, we conducted t-tests comparing people with depression and healthy controls for all possible 4-adjective subsets of the 7 emotion adjectives. 97.1% of the t-tests yielded p-values <0.05, indicating that the difference in emotional differentiation between people with depression and healthy controls is robust across various emotion adjectives, and that it is not an epiphenomenon of the larger number of unpleasant emotion adjectives. We also provide Table S3, which shows the degree to which individual emotion adjectives are differentiated from one another. This table also shows that the difference in differentiation between people with depression and healthy controls is pervasive across all emotion adjectives.

Furthermore, in our study, there was one person with depression who had 3 pleasant emotion adjectives with zero temporal variance and 5 healthy controls with 6 unpleasant emotion adjectives with zero temporal variance. We excluded these participants from analyses in the manuscript because emotion differentiation scores could not be calculated for them. In order to ensure that pruning these individuals from our participant pool did not lead to differences between groups in emotion differentiation, we conducted a separate bootstrap analysis. In this analysis, 1 healthy control and 5 people with depression were randomly selected to be pruned from the participant pool. Then the emotion differentiation calculations were computed for the remainder of the participants. This random selection procedure was carried out 1000 times. Of these 1000 instances, 973 yielded a significant difference in emotion differentiation between people with depression and healthy controls. This shows that our findings are robust (97.3%) and not epiphenomenally linked to the between-group differences in the likelihood to report nonzero values for the emotion ratings.

In order to ensure the robustness of our findings, we took the bootstrap analyses a step further. In this set of bootstrap analyses we carried out a more refined matching process. For every i number of healthy controls who had zero temporal variance for j emotion ratings, we randomly selected i people with depression and randomly excluded j of their emotion ratings. This procedure was carried out to ensure that the healthy controls and people with depression were matched in psychometric properties that could confound the results. The random selection process was executed 1000 times, and for 964 of the instances, people with MDD had less differentiated unpleasant emotional experiences

than did their healthy peers. This further shows that our findings are robust (>96%) and that they are not epiphenomenally linked to between group-differences in emotion reporting behavior.

Chapter III

Depression Complicates Happiness

This is the second of three papers and it will be submitted after my defense

Depression Complicates Happiness

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Abstract

Happiness comes in many forms. The warmth of the sun, a walk in nature, love, supportive relationships, and engaging activities can each make us happy in very unique ways. In this paper, we introduce a new approach, which enables participants to describe their unique experience of happiness using multiple emotion adjectives in daily life throughout a week. We use this method to investigate the complexity of happiness in Major Depressive Disorder (MDD). We predict that people with MDD would have more complex experiences of happiness since even during the most pleasant moments, they likely have small traces of unpleasant feelings and this complexity might make it more difficult for people with MDD to pursue happiness. To test this hypothesis, participants' emotional experiences were assessed using a 7-day experience sampling protocol. Depression was assessed using structured clinical interviews and the Beck Depression Inventory-II. As predicted, individuals with MDD had more complex pleasant emotional experiences than health controls. This effect was above and beyond differences in emotional intensity, variability, and differentiation.

Keywords: emotions, depression, happiness, emotional control, individual differences

Depression Complicates Happiness

There are countless things that can make us happy in life. Being surrounded by friends and family, falling in love, losing yourself in the flow of an engaging daily activity, eating your favorite meal, traveling the world, helping others, or participating in your favorite hobby are all associated with happiness for a large number of people (Gilbert, 2006; Waterman, 1993) Even though all of these emotional experiences are described as *happiness*, they certainly are not identical. Time with family and friends might provide contentment and a sense of belonging, whereas losing oneself in a state of flow might have elements of alertness. Falling in love, on the other hand, might be exciting and arousing whereas helping others might have elements of compassion. More importantly, there are large individual differences in the kinds of emotions people experience in response to life events. Therefore, it is best to consider happiness and other emotion adjectives (i.e. *sadness*, *excitement*, *anger*,...) as an attribute of a psychological state. In this paper, we introduce a new approach that characterizes the complexity of emotional experience using multiple emotion adjectives. For instance, the emotional experience while spending time with family might best be characterized by simultaneously using the emotion adjectives *happiness*, *contentment* and *belonging*. Using this new approach, which uses multiple emotion adjectives, we report an investigation of whether people with Major Depressive Disorder (MDD) experience more complex states of happiness than do healthy controls. We hypothesize that people with MDD are more likely to have traces of negative thought even in their happiest moments, making their pleasant experiences more complex. We use our

results to ground a discussion of how an unnecessarily complex positive emotional life might make it more difficult to pursue happiness especially in the context of depression.

Human emotional life is rich and complex. Even the process of observing emotion in another person's face, which was assumed to be basic for many years (Smith, Cottrell, Garrison, Gosselin, Schyns, 2005), is influenced by descriptions of the social situation (Barrett, 2006), body postures (Van den stock, Righart, de Gelder, 2007), voices, scenes, or other emotional faces (Russell & Fehr, 1987). This suggests that processing of emotional information takes place in a highly contextual fashion incorporating conceptual knowledge about the various properties of the current situation. In fact, evidence suggests that it is not only the external surroundings that constitute the context in which human emotional life manifests itself. Rather, every moment, as emotions are perceived, expressed and experienced, there is a set of parallel brain processes that dynamically constrain or shape how various pieces of information are integrated (Barrett, Lindquist, Gendron, 2007; Lindquist, Wager, Kober, Bliss-Moreau & Barrett, 2012). Accordingly, to best characterize and communicate this rich experience, humans, when given the chance, use multiple emotion adjectives to describe their emotional experiences.

Cross cultural research in psychology also suggests that a single emotion adjective might not be sufficient to uniquely describe an emotional experience. For example, in English, there is no corresponding adjective for the German word *Schadenfraude*, yet English speaking individuals experience this emotional state and describe it as "being happy about someone else's misfortune". *Küskünlük*, in Turkish,

is a specific mixture of anger and sadness not quite captured by the words resentment or sulking in English. There are countless such examples of emotion concepts from languages across the world which refer to specific types of emotional experience but cannot be described using a single phrase in English. In fact, even within English, we know that the word *happiness* can refer to many different forms of subjective emotional experience (Gilbert 2006). One can be happy in the context of professional achievement, at the sight of their newborn, or due to winning the lottery. Therefore, happiness is really an attribute of a complex emotional experience just like stocks, an expensive car or house are attributes of wealth. This means that, it is more accurate to treat emotion adjectives (i.e. *happiness, sadness, anger, excitement, ...*) as attributes of a rich emotional experience.

The captivating richness and subjective nature of emotional life makes it a challenge to study human emotional experience. This is especially the case because there is no essential signature within the brain or body that is specific to a particular emotion as humans experience it (Barrett, 2006b; Mauss & Robinson, 2009). This is similar to the experience of light, for instance, in which there is variability in the assignment by humans of a particular wavelength to a color category (Barrett, 2006a; Berlin & Kay, 1969). Furthermore, extensive research shows that people make biased responses when asked to evaluate properties of their emotional lives by asking general questions (i.e. How emotional are you ?) (Dunning, Heath, & Suls, 2004; Robinson & Clore, 2004).

One of the best ways to study subjective experiences in a more objective way is to assess the richness of momentary emotional experience as it is lived using

experience sampling (Barrett & Barrett, 2001; Larsen & Csikszentmihalyi, 1983). In this procedure, individuals are prompted at various times throughout the day and are asked to characterize their momentary experience using a set of emotion adjectives. We used this method to measure participants' emotional experiences over the course of a week. Individuals were asked to characterize their momentary experience using a set of emotion adjectives (*sad, anxious, angry, frustrated, ashamed, disgusted, guilty, happy, excited, alert, active*) drawn from well established sources in the literature. The ratings were later analyzed to reveal the complexity of people's positive and negative emotional experiences. The complete pattern of ratings at each emotional moment was used as a high dimensional descriptor of an emotional experience. We used the recurrence of these patterns to investigate the complexity of happiness in depression and health. We hypothesized that people with depression would have more complicated pleasant emotional experiences due to the pervasive presence of negative affect. In other words, if you are depressed, even if the sky is blue, the birds are chirping, the sun is shining, and it is your favorite day, you are likely to have something about which you are simultaneously sad, anxious, ashamed, guilty or frustrated. This makes happiness more complicated and difficult to stumble upon.

Method

Participants

One hundred and six participants between the ages of 18 and 40 (M= 27.8 years; SD = 6.5 years) were recruited for the current study, which was part of a

larger project (see Demiralp, Thompson, Mata, Jaeggi, Buschkuhl, Barrett... & Jonides), in press; Mata, Thompson, Jaeggi, Buschkuhl, Jonides, & Gotlib, 2011; Thompson et al., in press; Thompson, Mata, Jaeggi, Buschkuhl, Jonides, & Gotlib, 2011). All of the participants were native English speakers. Individuals were eligible to participate if they either (1) experienced no current/past history of any mental health disorders and scored below 9 on the Beck Depression Inventory-II (BDI: Beck, Steer & Brown, 1996; control group: n=53; 71.7% women); or (2) were currently diagnosed with MDD (depressed group: n=53; 67.9% women) as assessed by the Structured Clinical Interview for DSM-IV Axis I Disorders (SCID-I: First, Spitzer, Gibbon & Williams, 1997) and had a BDI-II score above 13. Additional requirements for the depressed group included absence of: (a) alcohol/drug dependence in the past six months, (b) Bipolar I or II diagnoses, and (c) psychotic disorders. The MDD and control groups did not differ in years of education, gender, race and ethnicity composition; however, depressed participants ($M=28.2$, $SD = 6.4$) were on average three years older than healthy participants ($M=25.4$, $SD = 6.4$), $t(104) = -2.19$, $p=0.03$. Including age as a covariate in the analyses did not influence any of the reported results.

Participants were recruited from the communities surrounding the University of Michigan in Ann Arbor, Michigan, and Stanford University in Stanford, California. Advertisements were posted online (e.g., Craigslist) and at local agencies and businesses (e.g., bulletin boards). An approximately equivalent number of participants were recruited in each location. Participants recruited at the two sites differed in gender composition, $\chi^2(1) = 11.77$, $p < .01$, with the Michigan sample

having more men than the Stanford sample (Michigan sample: 44.6% men; Stanford sample: 14.0 % men). There was also a significant difference in years of education between the two sites, $\chi^2(3) = 9.67, p < .05$: whereas the majority of the Michigan sample (55.4%) reported having “some college,” the majority of the Stanford sample (66%) reported having earned a bachelor’s degree or a professional degree. This difference in education status is also reflected in age: the Michigan sample was younger than the Stanford sample $t(104) = 4.69, p < .01$; (Michigan sample: $M = 24.2$ years, $SD = 5.5$ years; Stanford sample: $M = 29.7$ years, $SD = 6.5$ years). The two sites did not differ in ethnic or racial distribution, $\chi^2(5) = 4.78$, or depression status, $\chi^2(1) = 1.00$, both $p > 0.1$. Because the samples did not differ on central variables of interest (i.e., emotion ratings), we combined the two samples for the remaining analyses (see Table S1 in the Supplemental Material for detailed demographics).

Materials and Procedure

Participants were administered the SCID and BDI prior to the experience-sampling period. If more than two weeks had passed since the administration of the SCID, participants’ diagnostic status was re-assessed with another SCID to ensure eligibility. Participants were provided with hand-held electronic devices (Palm Pilot Z22) and were individually instructed on the experience-sampling protocol, including completing a full practice trial. The handheld devices were programmed using the Experience Sampling Program 4.0 (Barrett & Barrett, 2001). Participants were prompted (via a tone signal) eight times per day between 10 am and 10 pm. The majority of the participants carried the device for seven to eight days in order to be prompted 56 times. Prompts occurred at random times within eight 90 minute-

windows per day; thus, prompts could occur from as little as two minutes apart to almost 180 minutes apart. After participants were prompted, they had three minutes to respond to the initial question on the Palm Pilot; otherwise, the device switched to hibernation until the next prompt, and the data for that trial were recorded as missing. Up to 56 trials of data were recorded for each participant. The depressed and control participants did not differ in the number of completed trials (considering each prompt to be a trial). Participants provided informed consent and were compensated for their participation in the study, with an extra incentive for responding to more than 90 percent of the prompts.

At each measurement, using a 4-point scale (not at all = 1, little = 2, much = 3, a great deal = 4), participants indicated the degree to which each of eleven emotion adjectives described their current emotional state. There were seven negative-emotion adjectives (sad, anxious, angry, frustrated, ashamed, disgusted, and guilty) and four positive-emotion adjectives (happy, excited, alert, and active). The adjectives were drawn from various sources, such as the Positive Affect Negative Affect Scale (Watson, Clark, & Tellegen, 1988) and other commonly studied emotions (Ekman, Friesen & Ellsworth, 1972). The pattern of participants' ratings for the eleven emotion adjectives was used to characterize an emotional moment. The complexity of individuals' emotional life was measured by calculating the degree to which they re-experience an emotional moment described by the same exact set of eleven ratings as that of a previous moment throughout the sampling period. We hypothesized that people with MDD would have more diversified pleasant emotional experiences making it less likely for them to re-experience an

emotional moment, hence making their positive emotional life complex and potentially difficult to traverse.

Calculation of Emotion Complexity, Intensity, and Variability

To quantify emotional complexity, for each participant, each measurement moment was characterized as a vector with eleven elements containing the rating for each emotion adjective (e.g., happy=4 , excited=2, alert=3, active=3, sad=1, anxious=2, angry=2, frustrated=1, ashamed=1, disgusted=1, guilty=2). The number of times the identical eleven element vector appeared within the weeklong sampling period was used as a measure of emotional complexity. If an individual used the identical ratings for all eleven emotion adjectives throughout the week, that individual was characterized as having low emotional emotional complexity. This calculation was carried out separately for overall pleasant and unpleasant emotional moments. Pleasant emotional moments were characterized as those for which the average of the positive emotion adjectives was larger than the average of the negative emotion adjectives. Negative emotional moments were characterized in a complementary fashion.

Emotional intensity was measured by averaging the emotion ratings at each prompt, separately for the seven negative and four positive emotions. Then a mean was taken across the entire sampling period, resulting in one negative and one positive intensity score. Higher scores indicated that the individual experienced emotions with higher intensity. Temporal variability was measured by calculating the variance of the intensity of each emotion over the sampling period, again separately for the negative and positive emotions. Higher scores indicated that the

individual experienced emotions with higher variability. Additionally a simpler, correlation-based emotional differentiation score was calculated for positive and negative emotions adjectives for each individual. In order to investigate the effect of complexity above and beyond emotional intensity, variability and low order measures of differentiation, we included these variables as covariates in our analyses.

Results

Emotional Complexity

As predicted, people with MDD had more complex positive emotions than did healthy controls ($F(1,83) = 44.4$ $p < 0.001$, $d = -1.49$). Consistently with previous research on decreased negative emotion differentiation (ref Demiralp Psych Science in press), people with MDD reported experiencing less complex negative emotions ($F(1,83) = 7.3$, $p < 0.01$, $d = 0.61$).

Table 1
Emotion complexity, differentiation, intensity and variability scores

	Positive Emotions		Negative Emotions	
	Participants with MDD	Control Participants	Participants with MDD	Control Participants
Complexity	0.93 (0.11)	0.72 (0.18)	0.93 (0.12)	0.99 (0.07)
Differentiation	0.61 (0.17)	0.58 (0.12)	0.56 (0.17)	0.65 (0.23)
Intensity	1.68 (0.39)	2.09 (0.45)	1.89 (0.53)	1.19 (0.19)
Variability	0.40 (0.20)	0.43 (0.20)	0.47 (0.29)	0.16 (0.11)

Note. Standard deviations are in parentheses.

A two-way analysis of variance (ANOVA) yielded significant main effects of participant group ($F(1,166) = 15.4, p < 0.001$) and valence ($F(1,166) = 26.1, p < 0.001$), as well as a significant interaction of participant group and valence ($F(1,166) = 49.18, p < 0.001$) suggesting that the differences in emotional complexity between positive and negative emotional experiences were limited to healthy controls and that this difference was sufficiently substantive to manifest itself as a main effect of valence and group. Negative and positive emotional complexity was not correlated for people with MDD or controls, suggesting that positive and negative emotional complexity is underlain by different psychological mechanisms. Although we had no a priori hypotheses concerning gender differences in emotion complexity in MDD, we conducted an exploratory three-way ANOVA on emotion differentiation including gender as a third factor (with valence and group). The three-way interaction of participant group, gender, and valence was not significant ($F(1,162) = 1.39, p = 0.24$) indicating that gender was not a significant moderator of the relation between depression and emotional complexity.

Emotional Complexity Beyond Differentiation, Intensity and Variability

It is possible that the observed differences in emotional complexity were due to group differences in emotional differentiation, intensity or variability. In fact, in previous research based on these data, we reported differences between people with MDD and controls in emotional intensity (Mata et al, 2011) and variability (Thompson, et. al., in press). To test whether group differences in differentiation, intensity and variability were linked to group differences in positive and negative

emotional complexity, we used two multiple regression models, one predicting changes in positive emotional complexity and one predicting changes in negative emotional complexity. Predictors were depression as a nominal variable, as well as intensity, variability, and differentiation as continuous predictors. After controlling for intensity, variability and differentiation, depression remained a significant predictor of high emotional complexity for positive emotions and low emotional complexity for negative emotions, indicating that between-group differences in positive and negative emotional complexity are not due to differences in differentiation, intensity, or variability. Emotional variability was the only other significant predictor of negative emotional complexity ($F(1,80) = 16.89, p < 0.001$).

Table 2
Correlations between intensity, variability, differentiation and complexity

	Positive Emotions		Negative Emotions	
	Participants with MDD	Control Participants	Participants with MDD	Control Participants
Intensity	-0.05 <i>p</i> =0.37	0.23 <i>p</i> <0.10	-0.05 <i>p</i> =0.34	0.01 <i>p</i> =0.47
Variability	-0.05 <i>p</i> =0.37	0.10 <i>p</i> =0.27	0.27 <i>p</i> <0.03	-0.10 <i>p</i> =0.24
Differentiation	-0.08 <i>p</i> =0.28	-0.10 <i>p</i> =0.29	0.01 <i>p</i> =0.46	0.00 <i>p</i> =0.49

Only positive emotional intensity was modestly correlated with emotional complexity for only the control participants ($r(32) = 0.23, p < 0.1$), suggesting that healthy controls who experienced positive emotions more intensely had a tendency to have more complex experiences of positive emotion. Similarly, only controls exhibited a tendency for emotional variability to be positively correlated with

positive ($r(32) = 0.27, p < 0.07$) emotional experiences. Interestingly, only people with MDD exhibited a strong relationship between negative emotional variability and complexity ($r(49) = 0.43, p < 0.01$). These results suggest that healthy controls whose positive emotional experience were more variable across time had more complex experiences of positive emotions whereas people with MDD whose negative emotional experiences were more variable across time had more complex experiences of negative emotions.

Emotional differentiation and emotional complexity were not correlated for positive or negative emotional experiences for people with depression or healthy controls, suggesting that these are two different properties of the structure of emotional life, further signifying the need to explore the structure of emotional life using novel methods.

Discussion

The present paper is the first to introduce a new comprehensive approach to measuring emotional complexity. The results are the first to show that people diagnosed with MDD experience more complex positive emotions and less complex negative emotions in their daily lives than do healthy controls. We found that the relation between emotional complexity and depression could not be accounted for by emotional differentiation, intensity or variability. These findings suggest a fundamental way in which the emotional lives of individuals diagnosed with MDD are altered independent of increased negative emotional differentiation, intensity and variability.

Earlier research on emotional complexity and mental disorders showed a relationship between the structure of emotional life and mental health (Demiralp et al., in press; Gara, Vega, William, Lesser, Escamila & Lawson, 2011; Carstensen, Pasupathi, Mayr & Nesselroade, 2000). The relationship is believed to exist because a granular emotional life allows for more adaptive behavior (Barrett, Gross, Christensen, & Benvenuto), and specific negative emotional experiences are less subject to misattribution errors (Schwarz & Clore, 1996). While previous research has done a nice job of capturing structural properties of emotional life, existing methods fail to capture the full richness of emotional life. In this paper, we introduced a new high dimensional modeling approach that captures higher order relationships between the mechanisms underlying emotional experiences. We accomplished this by characterizing an emotional moment using all of the emotion adjectives that subjects use to describe it. Our analyses reveal that this rich characterization of human emotional experience points to a fundamental way in which the positive emotional experiences of people with depression are altered from healthy controls. Specifically, the pleasant emotional moments lived by people with depression are much more complex and less likely to recur, potentially making them less likely to achieve well-being.

It is important to note that our measures of emotional complexity revealed different patterns for positive and negative emotions. First, this finding suggests that the mechanisms that underlie emotional complexity can be independently and selective altered for positive and negative emotions. Second, this finding supports the claim that emotional complexity, differentiation, intensity, and variability are

independent constructs. In other words, people with MDD can have positive or negative emotional experiences with altered intensity, variability, and differentiation but unaltered complexity. It could be that people with MDD are unnecessarily specific about their positive emotional experiences as they try to tether to them and use as a buffer against life stressors (Tugade et al. 2004), and this is one of the reasons that they have more complex emotional lives. Considering that we were able to discover novel properties of the emotional lives of people with depression by using only 11 emotion adjectives, in future studies we intend to use a larger number of emotion adjectives to further investigate emotional lives of people with depression.

It is important to note that the notion of emotional complexity in itself is complex. In other words, an individual can be emotionally complex in a number of ways. One can think of at least four ways of being emotionally complex: one could have the ability to see the positive and negative in life; one could have the ability to describe feelings with detail and precision; one could have the capability to predict feelings in the future or a given situation and finally one could have a tendency to remember experiencing many emotions simultaneously (Lindquist & Barrett, 2008). Furthermore, an individual might simply believe that they are emotionally complex regardless of how they perceive, experience or remember emotions. It is important to study each one of these different types of emotional complexity. Our analyses in this study reflect emotional complexity in the context of moment to moment emotional experience. Different types of emotional complexity might be and often have different relationships to various individual differences and mental faculties.

Hence it is essential to have a deep understanding of the realm of emotional complexity while being granular about the particular type of emotional complexity that is under consideration.

It is possible that emotional complexity might be related to alexithymia which has been shown to be associated with depression (Honkalampi, Hintikka, Tanskanen, Lehtonen, & Vilnamäki, 2000). Alexithymia is defined as the inability to recognize and verbalize emotions and is often associated with an emptiness of feelings, poverty of imagination as well as difficulty in communicating with other people. It is quite possible that people with depression might have difficulty identifying similarly pleasant moments as they are caught up in recurrent negative thoughts and rumination (Papageorgiou & Wells, 2001). Of course, the very result that complexity differs by valence suggests that alexithymia can't explain our results, however it is possible that alexithymia might be limited to positive emotions, but there is no evidence for this. In future studies, it would be worthwhile to investigate the relationship between alexithymia and emotional complexity as we measure it.

Overall, this paper and the results presented in it contribute both to the basic science of emotion as well as to applied clinical understanding of mental health disorders. First, this paper empirically displays the utility of considering multiple aspects of emotional life when modeling psychological function in mental health. In other words, we offer a way to operationalize the subtle differences between various forms of happiness, sadness and anger using the ensemble of emotion adjectives used to describe an emotional moment. Second, this paper shows that one way in which people with MDD might be maladaptive in traversing emotional life

might be that they complicate happiness. Future research in this direction can investigate the implications of these findings in the context of diagnostics and therapy in depression and mental health disorders.

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Appendix

To see how high dimensional modeling works, let's consider a hypothetical study in which individuals' experiences of three emotions, namely happiness, sadness and fear, are sampled across time. In this study, participants indicate the degree to which they experience each of the emotions using a scale ranging from 1 (neutral) to 4 (very intense). Therefore, [1,1,2] means that the individual was not feeling any happiness or sadness but was slightly afraid. Now suppose that we have two participants Tom and Jane each of whom is sampled 5 times. Their data look like the following:

Tom_{t=1} = [1,1,3] Tom_{t=2} = [1,1,3] Tom_{t=3} = [4,2,1] Tom_{t=4} = [3,2,1] Tom_{t=5} = [4,2,1]
Jane_{t=1} = [1,3,3] Jane_{t=2} = [1,4,3] Jane_{t=3} = [4,2,1] Jane_{t=4} = [3,3,1] Jane_{t=5} = [4,1,1]

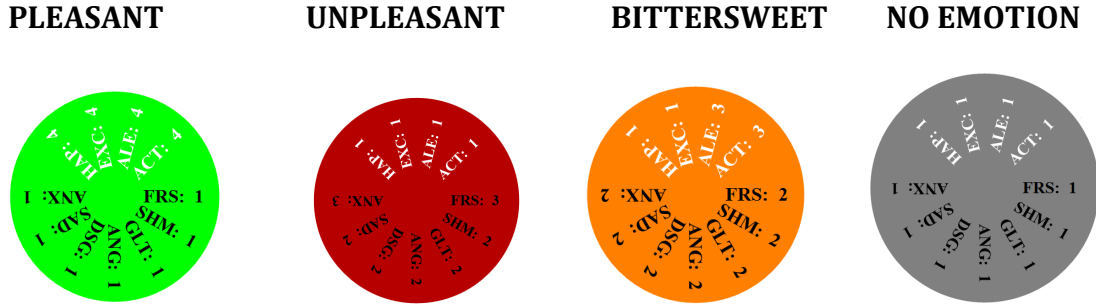
Normally, with a standard aggregation analysis, we would conclude that Tom and Jane experience identical levels of happiness and fear. This approach inherently treats each measurement moment as if it can be captured by a series of univariate variables. But what if each measurement moment was treated as a multivariate combination? From this perspective Tom is experiencing the exact same mental moment at times 1 and 2, and at times 3 and 5. Throughout the experience-sampling period, Tom traverses an emotional landscape that is characterized by 3 unique emotional states. Tom also has two stereotyped experiences that he visits twice. The first one, represented by the vector [1,1,3] is a state of moderately high fear. The second, represented by [4,2,1] is a state of high happiness with a touch of

sadness. This is perhaps a bittersweet state. Jane on the other hand, experiences 5 unique emotional states, each with its own combination of happiness, sadness and fear. Therefore she traverses an emotional landscape with a larger proportion of unique mental states. We can easily quantify the uniqueness of each mental state as a single measurement moment in this way. Notice that emotion adjectives are now being treated as the features of a rich, complex experience rather than as elemental units that are strung together like the beads on a string to make a mental moment, by counting the number of unique states and dividing it by the number of total emotional states. In the case of Tom, there are three unique emotional states, [1,1,3], [4,2,1] and [3,2,1]. Therefore his uniqueness ratio would be $3/5 = 60\%$. Jane on the other hand has 5 unique emotional states making her uniqueness ratio $5/5 = 100\%$. This ratio is a high dimensional version of emotional granularity which is traditionally calculated using bivariate statistics such as p-correlations and factor analysis. The uniqueness ratio is much more sensitive to subtle differences in the patterns of emotional experience. From a univariate perspective, Jane's emotional experiences of fear at time 1 and 2 are identical, even though she actually experiences a mental moment with a slightly higher level of sadness at time 2. This difference is captured in the high dimensional version of emotional granularity. In our previous research, we found that the additional information about the high dimensional nature of individuals' emotional experiences can be informative in the context of mental health.

In our research on depression, we sampled participants' experiences of 11 emotions at each measurement moment (happy, excited, alert, active, anxious, sad,

disgusted, angry, guilty, ashamed and frustrated). Individuals reported the degree to which they experienced each emotion on a scale of 1 (none) to 4 (great deal). Therefore each mental state for each individual was characterized by an 11 dimensional vector such as [4,1,4,1,2,1,1,1,2,2,1], which would represent in our data set an experience of heightened happiness and alertness. Individuals were sampled 8 times a day between the hours of 10 am and 10pm for 7 consecutive days, providing 56 samples of their emotional experiences. We partitioned the data into 4 segments. The first segment, visualized in green below, was all the sampling moments for which the average of the pleasant emotions (happy, excited, alert, active) were higher than the unpleasant emotions (anxious, sad, angry, guilty, ashamed, frustrated). This segment represents an overall sense of positive or pleasant emotionality. The second segment, visualized in red below, represents unpleasant emotional states and contained all the sampling moments where unpleasant emotions on average had higher ratings than pleasant emotions. The third segment, visualized in orange, contains sampling moments with bittersweet emotionality, meaning that the positive and negative emotions on average had equivalent intensity. The fourth segment, visualized in gray, contains sampling moments in which the participant reported experiencing none of the emotions.

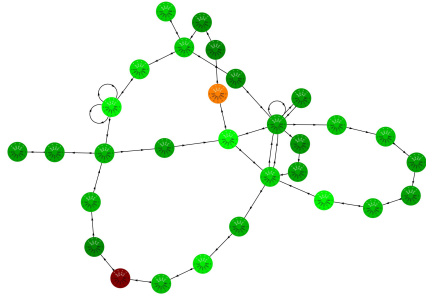
Figure S1
 Visualization of the high dimensional states that subtend pleasant, unpleasant, bittersweet emotional experiences as well as no of emotion.



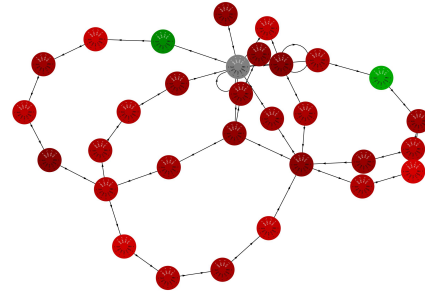
First, it is possible to actually quantify the number of times a person experiences a unique state (i.e., a unique combination of the 11 variables) within each of these categories. And, if the categories were anger, or sadness, or fear (i.e., we defined the segments by moments having the highest score for a given emotion category), then we would be able to test the extent to which there are individual differences in the variability and complexity of emotional experiences within a single category.

Furthermore, it is possible to examine how a person (either healthy control or depressed) traverses through life (during the sampling period). The geometric locations of the vertices in the graphs (below) are arbitrary, however their connectedness to other vertices is representative of the specifics of the individual's sampling of emotional experience. Notice that it is easy to see that the individual with depression has more loops than the healthy control. Accordingly, the depressed individual has fewer number of unique experiences compared to the healthy control.

Figure S1
 High dimensional graph representations of the emotional experience of a healthy control and a person with depression sampled throughout a week.



HEALTHY CONTROL



PERSON WITH DEPRESSION

The mathematics behind the different findings can best be explained using previous theoretical research on High Dimensional Model Representation (Demiralp, 2003; Rabitz & Alis, 1999; Sobol, 1993;2003). Consider a function

$$f(x) \equiv f(x_1, x_2, \dots, x_n)$$

which represents the mapping between input variables x_1, x_2, \dots, x_n defined on the domain $\Omega \subseteq R^n$ and the output f :

$$f(x) \equiv f_0 + \sum_i f_i(x_i) + \sum_{i < j} f_{ij}(x_i, x_j) + \dots + f_{12\dots n}(x_1, x_2, \dots, x_n)$$

Here f_0 denotes the zeroth order effect, which is a constant everywhere in the domain Ω . The function $f_i(x_i)$ gives the effect associated with the variable x_i acting independently, upon the output f . The function $f_{mn}(x_m, x_n)$ describes the cooperative effects of variables x_m and x_n , and higher-order terms reflect the cooperative effects of increasing number of variables acting together to impact upon f . In the case of experience sampling of emotional experience, the zero order effect

can be thought of as the role of emotional intensity, the first order effects will incorporate the role of emotional variance, the second order effects can be thought of as representing correlations or two-way interactions amongst various emotion ratings. The remaining higher order terms can best be thought of as collections of high order interactions. In our traditional analyses of emotional granularity, only the zero, first and second order terms of this representation are incorporated into the calculation. The remaining items are treated as random variance. The high dimensional modeling approach, in contrast, incorporates information from all of the low and high order effects within the data. Since we define differentiation in high dimensional space, we also don't have to estimate the role of each one of the 2^n effects present in the decomposition described above. In our previous research, we have displayed the utility of using high dimensional representations in computer vision (Demiralp, 2009a; 2009b) and it makes intuitive sense that the richness of individual's emotional experiences will benefit from algorithms that better characterize the richness of our visual percepts.

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Chapter IV

When you work hard but can't play hard:

Maladaptive Emotion Regulation in Major Depressive Disorder

This is the third of three papers and it will be submitted after my defense

When you work hard but can't play hard:
Maladaptive Emotion Regulation in Major Depressive Disorder

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Abstract

It is evident that social, cognitive, and affective processes change over time in a meaningful and important way. Emotion is no exception. The way you felt yesterday can have an immense influence on the things you choose to do today. Even if your behaviors are not influenced, a happy day preceded by an unpleasant day might feel more potently pleasant. In order to operationalize this relationship and track it quantitatively, we sampled the degree to which people felt pleasant and unpleasant over a week-long period in their daily life. We also recorded the presence of significant life events (and the degree to which these events were pleasant) to investigate the role of life stressors in emotion regulation. We used these three variables to investigate the dynamics of emotional experience as it unfolds over a period of one week. We used dynamical systems modeling to segregate the causal relationships within the individual's emotional life from those that are tethered to external events such as significant life events. Our findings suggest that people with depression have a difficult time boosting their pleasant emotional experiences after a negative emotional episode. People with depression are also far more influenced by negative significant life events compared to controls. We discuss the implications of these findings in the context of the basic science of emotion as well as clinical diagnoses and treatment.

Keywords: emotions, depression, emotion regulation, happiness, emotional control, individual differences, dynamical systems modeling, causal modeling

When you work hard but can't play hard: Maladaptive Emotion Regulation in Major Depressive Disorder

Human emotional life is dynamic and constantly changing (e.g., Freeman & Ambady, 2011; Read, et. al., 1997; Read & Miller, 1998). Ample research suggests the existence of various physiological and affective cycles in everyday life (e.g. Brown, 2000; Stone, 1985). Even popular beliefs such as the “blue Monday” phenomenon (Larsen & Kasimatis, 1990; Huttenlocher, 1992; Reid, 2000) allude to the existence of weekly cycles in mood. Broad research studies investigate changes in mood and circadian activity (e.g., Larsen, 1985a; Murray, Allen, Trinder, & Burgess, 2002; Rusting & Larsen, 1998) and associations between various forms of cycles and other key aspects of life (e.g. Brown, 2000; Pettengill, 1993). In this paper, we take a closer look at the nature and determinants of change in positive and negative emotion in people with depression. We also investigate the role of significant life events on moment-to-moment emotional fluctuations.

Even though there is ample evidence for the dynamic and fluctuating nature of emotional experience in everyday life, methodologies necessary to explore the richness of these changes are still lacking. A large number of comprehensive studies (e.g. Diener, Fujita, & Smith, 1995; Eid & Diener, 1999) utilize multichannel longitudinal designs but rely on a linear notion of change. Some studies investigate the spectral properties (Larsen & Kasimatis, 1990) while others focus on other types of frequency-domain and time-series analyses (e.g., growth curves and hierarchical linear models; Bryk & Raudenbush, 1987; McArdle & Epstein, 1987; Meredith & Tisak, 1990). Ultimately, mood regulation is by nature a dynamic

process (Larsen 2000; Carver & Scheier, 1982, 1990). Considering this theoretical intuition, we introduce the use of dynamical systems modeling which relies on differential equation based modeling of the dynamics of human emotions. Previous work by Friston (2003) and Demiralp et. al. (in press) provides a direct mathematical basis for exploring properties of emotional regulation using dynamical systems modeling. In our results, we discuss basic properties of emotion regulation such as up-regulation and down-regulation of positive and negative emotions. We also emphasize the direct as well as moderating role of significant life events on emotional intensity and regulation.

Dynamical systems modeling focuses on how the present state of a system leads to the future state of that system. Therefore, dynamical systems analysis is focused on how change in a system occurs and evolves, and this is why differential equations are frequently used to specify dynamical models (Boker, et.al., 2001; Boker & Laurenceau, 2006). In addition, differential equations capture nonlinear relationships in data that other methods might miss. In neuroimaging, for example, dynamical systems modeling is used to investigate temporal causal relationships that exist between functional brain areas in the context of tasks (Friston et. al. 2003; Stephan et. al. 2008). For instance, this method allows researchers to investigate how the connectivity between frontal and occipital cortices is altered when participants perform a particular task, such as judging emotions of faces. In psychology, dynamical systems theory offers a way to formalize concepts of emotion-regulation as well as the influences of the context in which this emotion-regulation takes place. Using dynamical systems modeling, we

investigate how certain situations influence the intrinsic dynamics of emotion regulation.

It is also important that emotional life is multifaceted and an individual's emotional profile can be characterized using a number of features. For instance, the intensity of emotional experience is the extent to which an individual's level of emotional experience deviates from the baseline. In this paper, intensity is conceptualized and used to refer to states rather than stable personality traits. In order to characterize the dynamics of any system, it is essential to relate the changes in various parts of the system to states of its components. In this sense, the rate of change (x') represents the magnitude of change in intensity over one unit of time. In other words, the rate of change characterizes the change in emotion intensity in relation to time (i.e. mathematically, the first derivative of emotion intensity with respect to time). Previous research on changes in emotional intensity over time links such fluctuations to emotional clarity (Salovey, Mayer, Goldman, Turvey, Palfai, 1995) as well as hostility (Fredrickson et al. 2000). Our previous research (Demiralp et. al., (in press)) indicates that people with depression have less differentiated negative emotional experiences which might make it difficult for them to regulate their emotion. Considering that, emotion regulation, by definition unfolds over time, we found it imperative to investigate change in emotion over time using dynamic causal modeling.

Considering earlier research on learned helplessness and depression (Seligman, 1975) we hypothesized that after intensely negative emotional experiences, people with depression would have maladaptive emotional regulation

that would be suboptimal in bringing them to an overall pleasant state of mind. Furthermore, considering earlier research on the stress sensitivity of individuals with depression, we hypothesized that people with depression would be more influenced by significant negative life events. We also explored whether such significant life events altered the emotion regulation mechanisms in daily life. In order to ensure that our results are not spurious outcomes of well-known alterations in emotional intensity and variability in depression, we conducted additional analyses to display that the emotion regulation and resilience to life stressors as extracted using dynamical systems was above and beyond differences in these psychological variables.

Method

Participants

One hundred and six participants between the ages of 18 and 40 ($M = 27.8$ years; $SD = 6.5$ years) were recruited for the current study, which was part of a larger project (see Demiralp et al., in press; Mata, Thompson, Jaeggi, Buschkuhl, Jonides, & Gotlib, 2011; Thompson et al., in press; Thompson, Mata, Jaeggi, Buschkuhl, Jonides, & Gotlib, 2011). All of the participants were native English speakers. Individuals were eligible to participate if they either (1) experienced no current/past history of any mental health disorders and scored below 9 on the Beck Depression Inventory-II (BDI; Beck, Steer & Brown, 1996; control group: $n = 53$; 71.7% women); or (2) were currently diagnosed with MDD (depressed group: $n = 53$; 67.9% women) as assessed by the Structured Clinical Interview for DSM-IV Axis I

Disorders (SCID-I: First, Spitzer, Gibbon & Williams, 1997) and had a BDI-II score above 13. Additional requirements for the depressed group included absence of: (a) alcohol/drug dependence in the past six months, (b) Bipolar I or II diagnoses, and (c) psychotic disorders. The MDD and control groups did not differ in years of education, gender, race and ethnicity composition; however, depressed participants ($M=28.2$, $SD = 6.4$) were on average three years older than healthy participants ($M=25.4$, $SD = 6.4$), $t(104) = -2.19$, $p=0.03$. Including age as a covariate in the analyses did not influence any of the reported results.

Participants were recruited from the communities surrounding the University of Michigan in Ann Arbor, Michigan, and Stanford University in Stanford, California. Advertisements were posted online (e.g., Craigslist) and at local agencies and businesses (e.g., bulletin boards). An approximately equivalent number of participants were recruited in each location. Participants recruited at the two sites differed in gender composition, $\chi^2(1) = 11.77$, $p < .01$, with the Michigan sample having more men than the Stanford sample (Michigan sample: 44.6% men; Stanford sample: 14.0 % men). There was also a significant difference in years of education between the two sites, $\chi^2(3) = 9.67$, $p < .05$: whereas the majority of the Michigan sample (55.4%) reported having “some college,” the majority of the Stanford sample (66%) reported having earned a bachelor’s degree or a professional degree. This difference in education status is also reflected in age: the Michigan sample was younger than the Stanford sample $t(104) = 4.69$, $p < .01$; (Michigan sample: $M= 24.2$ years, $SD = 5.5$ years; Stanford sample: $M=29.7$ years, $SD = 6.5$ years). The two sites did not differ in ethnic or racial distribution, $\chi^2(5) = 4.78$, or depression status, $\chi^2(1)$

= 1.00, both $p > 0.1$. Because the samples did not differ on central variables of interest (i.e., emotion ratings), we combined the two samples for the remaining analyses (see Table S1 in the Supplemental Material for detailed demographics).

Materials and Procedure

Participants were administered the SCID and BDI prior to the experience-sampling period. If more than two weeks had passed since the administration of the SCID, participants' diagnostic status was re-assessed with another SCID to ensure eligibility. Participants were provided with hand-held electronic devices (Palm Pilot Z22) and were individually instructed on the experience-sampling protocol, including completing a full practice trial. The handheld devices were programmed using the Experience Sampling Program 4.0 (Barrett & Barrett, 2001). Participants were prompted (via a tone signal) eight times per day between 10 am and 10 pm. The majority of the participants carried the device for seven to eight days in order to be prompted 56 times. Prompts occurred at random times within eight 90 minute-windows per day; thus, prompts could occur from as little as two minutes apart to almost 180 minutes apart. After participants were prompted, they had three minutes to respond to the initial question on the Palm Pilot; otherwise, the device switched to hibernation until the next prompt, and the data for that trial were recorded as missing. Up to 56 trials of data were recorded for each participant. The depressed and control participants did not differ in the number of completed trials (considering each prompt to be a trial). Participants provided informed consent and were compensated for their participation in the study, with an extra incentive for responding to more than 90 percent of the prompts.

At each measurement, using a 4-point scale (not at all = 1, little = 2, much = 3, a great deal = 4), participants indicated the degree to which each of eleven emotion adjectives described their current emotional state. There were seven negative-emotion adjectives (sad, anxious, angry, frustrated, ashamed, disgusted, and guilty) and four positive-emotion adjectives (happy, excited, alert, and active). The adjectives were drawn from various sources, such as the Positive Affect Negative Affect Scale (Watson, Clark, & Tellegen, 1988) and other commonly studied emotions (Ekman, Friesen & Ellsworth, 1972). Participants also indicated whether they experienced a significant life event since the last prompt. If participants answered yes to this question, they were subsequently asked to indicate whether this life event was pleasant or unpleasant using a continuous scale from -50 to 50.

Calculation of Emotion Regulation and Resilience

To quantify emotion regulation, for each participant, two time courses were constructed by averaging positive (happy, excited, alert, active) and negative (sad, anxious, angry, frustrated, ashamed, disgusted, guilty) emotion ratings over a week-long period. The degree to which change in positive emotion was predicted by prior negative and positive emotional moments was quantified to represent emotion regulation. The identical approach was used for negative emotions leading to a total of 4 parameters. If an individual had an intense negative emotional experience, in order to return to a pleasant emotional state, the adaptive regulation strategy would be to increase positive emotions (i.e. engaging in activities that are pleasant or reappraisal) or decrease negative emotions (i.e. engaging in soothing and calming activities that decrease emotional intensity). Similarly, if an individual had an

intense positive emotional experience, in order to retain that pleasant emotional state, the adaptive strategy would be to either keep increasing or retain positive emotions and retaining or further decreasing negative emotions. Hence, it is generally safe to assume that an emotion dynamic, which results in increased intensity of positive emotions and decreased intensity of negative emotions is adaptive.

Emotional resilience was conceptualized as the sensitivity of the individuals' emotional state to significant life events. Specifically, if an individual experienced a surge in negative emotion after an unpleasant life event and if this individual's ability to regulate this emotional surge was degraded to the presence of the life stressor, that individual was characterized as not being resilient.

We predicted that people with depression would have maladaptive emotion regulation dynamics and might be more sensitive and less resilient to negative life stressors.

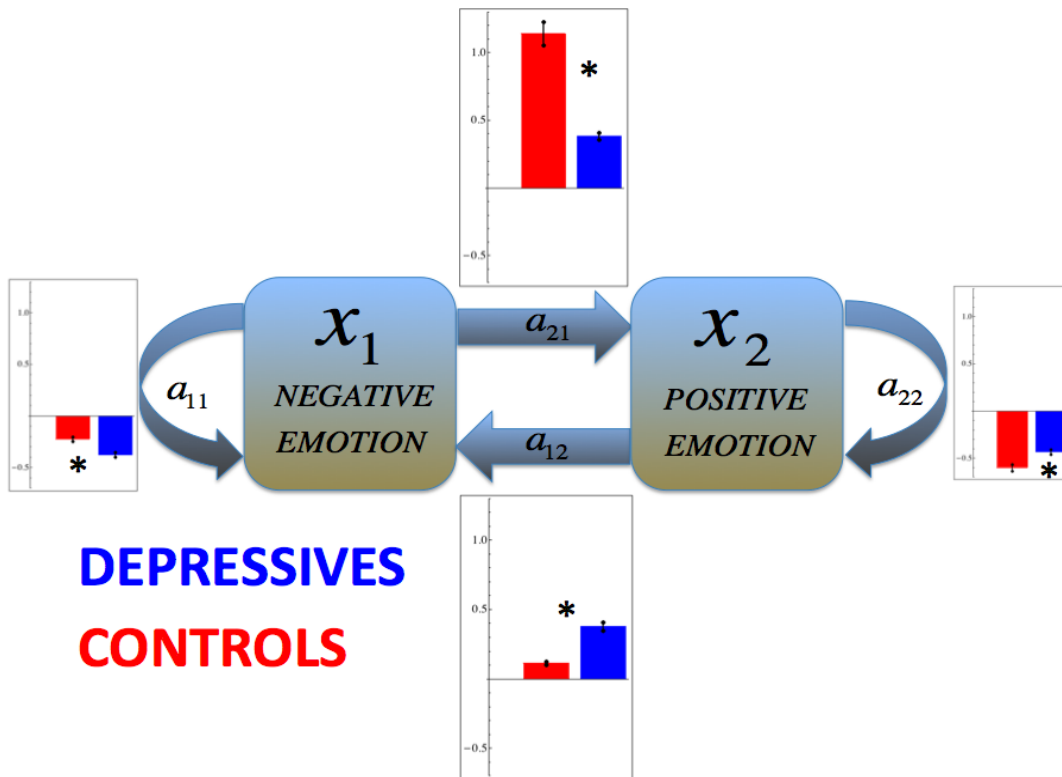
Results

Emotion Regulation

As predicted, subsequent to intensely negative emotional experiences, people with depression increased their positive emotions to a significantly lesser degree than healthy controls ($F(1,104)=75.25, p<0.001$). This suggests that healthy controls had strategies or mechanisms in place, which brought them to an overall pleasant emotional state by increasing the intensity of positive aspects of the subsequent emotional experiences. As expected, after intensely positive emotional experiences, healthy controls did not experience an increase in negative aspects of their

emotional experiences. This adaptive strategy allows healthy controls to retain a purely positive emotional experience once such an emotional state is attained.

Figure 1
Dynamics of emotional experience in people with depression (depressives) and healthy controls sampled throughout a week.



On the other hand, after intensely pleasant emotional experiences, people with depression increased their negative emotional experiences to a significantly larger degree than healthy controls ($F(1,104) = 64.89, p < 0.001$). In fact, there was no difference between the degree to which people with depression increased their positive and negative emotional experiences after an intensely unpleasant and pleasant emotional experience respectively. These results suggest that people with depression have difficulty engaging in emotion regulation strategies which allow

them to deal with life stressors by increasing and retaining positive aspects of emotional experiences.

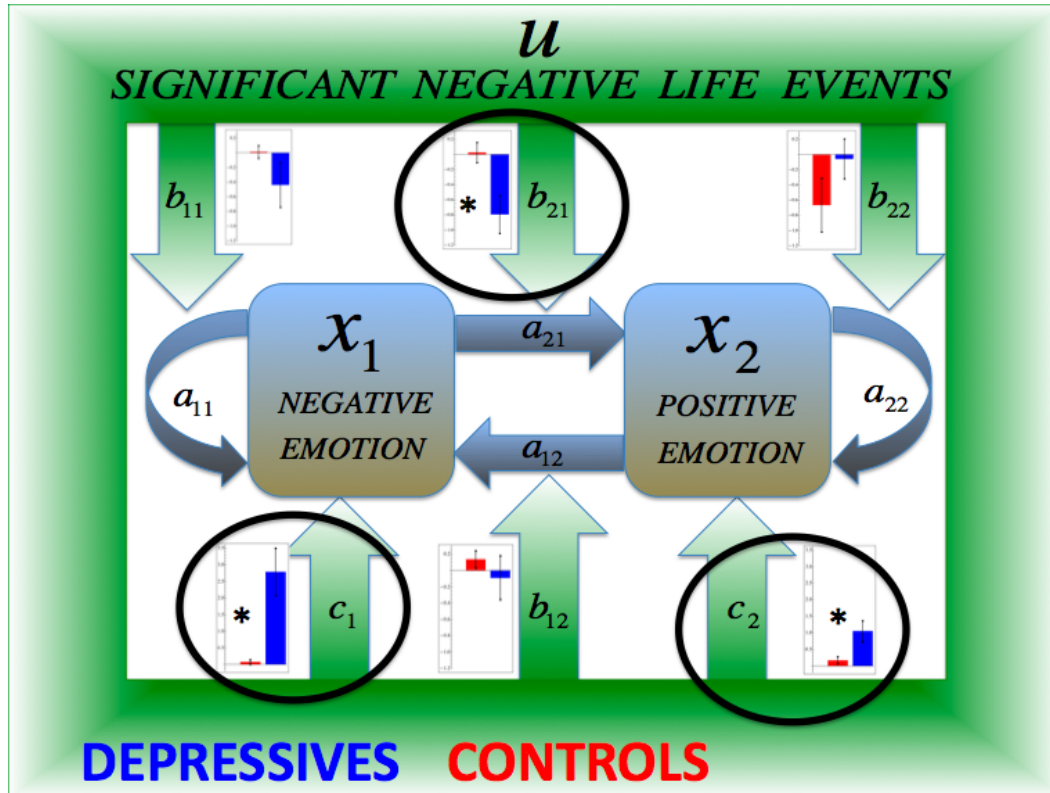
Of course, up-regulating positive emotion in the face of intense negative emotional experience is not the only way in which individuals regulate their emotions. One other approach is to simply focus on decreasing the intensity of the negative emotional experience as a form of psychological feedback. For instance, an individual might choose to work on simply calming down in the face of a life stressor such as someone running a red light and almost causing a deadly traffic accident. We investigated this form of feedback in people with depression and controls as well. Our results showed that people with depression had larger negative feedback in negative emotions compared to healthy controls ($F(1,104) = 13.97, p < 0.001$). The converse was true for healthy controls, in that they had larger negative feedback in positive emotions compared to people with depression ($F(1,104) = 20.46, p < 0.001$). These results suggest that people with depression do indeed dedicate more adaptive feedback to down-regulate the intensity of their emotions after intense negative emotional experiences. Healthy controls also down-regulate their emotions after intense positive emotional experiences. These results support the view that emotion is to some degree a source of information, and in order to label things as being pleasant and unpleasant, one must allow the intensity of emotional experiences to regress to a norm such that in subsequent experiences the intensity of emotional experience might be increased again. In this sense, this is an adaptive strategy and shows that the maladaptive aspect of emotion regulation in

people with depression is the inability to up-regulate positive emotional experiences after intense negative emotional experiences.

Emotional Resilience

As predicted people with depression were more influenced by life events that they identified as being significant and negative. In order to investigate this, we investigated a number of properties of their emotional dynamics. First, an examination of the degree to which negative significant life events lead to increased negative emotional experiences revealed that people with depression were more influenced by such life stressors ($F(1,104) = 13.42, p < 0.001$). Interestingly people with depression also had a significant increase in their positive emotional experiences after negative life stressors ($F(1,104) = 6.24, p < 0.015$). This is most likely due to the fact that some of the positive emotion adjectives used in this study could be used to also reflect (i.e. alert, active) mental states that are not related to levels of pleasantness. Overall, our results suggest that people with depression are influenced to a larger degree by negative significant life events. On the other hand, positive life events lead to an increase in positive emotional experiences for people with depression ($F(1,104) = 5.98, p < 0.02$) and healthy controls ($F(1,104) = 5.76, p < 0.02$). There was no significant difference between the two groups.

Figure 2
 Dynamics of emotional experience in people with depression (depressives) and healthy controls sampled throughout a week in the presence of significant negative life events.



We also investigated, whether negative significant life events had a moderating effect on the emotion regulation dynamics of people. Our analyses revealed the emotion regulation dynamics of people with depression, when faced with a life stressor gets significantly altered. Specifically, people with depression have a more difficult time up-regulating their positive emotional experiences after significantly negative emotional moments when they are also dealing with a life stressor ($F(1,104) = 7.99, p < 0.006$). In fact, when faced with a life stressor and intense negative emotional experience, people with depression have decreased pleasant emotional experiences in the subsequent moment, potentially making them

spiral into a state of helplessness. By contrast, healthy controls when faced with a negative significant life event did not experience a direct increase in positive or negative emotional experience. Positive life events did not have such a moderating effect for neither the people with depression nor healthy controls. The emotion regulation dynamics of healthy controls were also not influenced by the presence or absence of a significant life stressor.

Emotion Regulation & Resilience Beyond Emotional Intensity & Variability

It is possible that the observed differences in emotion regulation and resilience were due to group differences in emotional intensity or variability. In fact, in previous research based on these data, we reported differences between people with MDD and controls in emotional intensity (Mata et. al., 2011) and variability (Thompson et. al., in press). To test whether group differences in intensity and variability were linked to group differences in emotional regulation and resilience, we used a multiple regression model, predicting depression. Predictors were the ten continuous parameters that represent emotion regulation and resilience, as well as four continuous parameters representing positive and negative emotional intensity and variability respectively. Controlling for intensity and variability of positive emotional experiences did not change between group differences in our results, indicating that between-group differences in emotion regulation and resilience are not due to differences in emotional intensity or variability.

Discussion

The present paper is the first to use dynamical systems modeling to characterize four important components of emotion regulation, which are up- and

down-regulation of positive and negative emotion. Our results indicate that people with depression have difficulty experiencing increased pleasant emotional experiences after intensely negative emotional experiences. It is important to note that the relationship between emotional regulation and depression could not be accounted for by differences in emotional intensity or variability. Additionally, this is the first paper to investigate the moderating role of significant life events and model its influence simultaneously with emotion regulation. Our results indicate that people with depression have a more difficult time being resilient against stress associated with negative significant life events. Furthermore, significant life events fundamentally alter emotion regulation in people with depression making it even more difficult for them to up-regulate positive emotional experiences after intense negative emotional experiences. It is important to note that these differences were also not accounted for by differences in emotional intensity or variability associated with depression.

Earlier research on emotion regulation and mental health (Gross & Munoz, 1995) displays that emotion regulation is an essential feature of mental health and has an important role in various facets of normal functioning. More specifically, it is believed that emotion regulation has an important role in three overlapping domains of mental health. First, emotion regulation makes it possible for individuals to work productively. This is especially true since being productive requires sustained attention and the appropriate use of emotions for a given context. For instance, smiling pleasantly when feeling down might be necessary in the context of a corporate meeting with clients. Accordingly, the capacity to develop, sustain, and

express appropriate emotions and regulate negative emotions is important for many occupations and is necessary for an effective work life (Hoschild, 1983). Second, emotion regulation is essential in the context of relationships in our social life. Our relationships with our significant others or friends have strong emotional components. There might be times where assertiveness is necessary and deficits in skills necessary for context sensitive emotion regulation may hamper social functioning (Riggio, 1986). Finally and perhaps most importantly, emotion regulation has a key role in one's comfort with oneself. A sense of meaning, integration and self-cohesion (Erikson, 1959; Frankl, 1963) are essential for being comfortable with one's own identity. Therefore, it is essential to be able to modulate emotional states even in the absence of external events. Considering the pervasive role of emotion regulation in one's inner life as well as interaction with the outside world, we chose to use a modeling framework which had the capacity to comprehensively characterize both of these properties of emotional life in depression.

Considering the negative influences of depression in well being and its prevalence, it is essential that we have comprehensive and rich methodology for accurately characterizing emotional life in clinical mood disorders as well as subclinical depressive states. Specifically, a clinician can use a sophisticated characterization of each patient's emotional life to better diagnose and guide the health care provided for that patient. Also, in that the model describes multiple facets of emotion regulation and resilience, it allows for multiple modes of therapeutic intervention making it possible for treatments to be more effective.

Finally, dynamic systems based models of emotion regulation and resilience can allow for preventive interventions by identifying the kind of environments or thought patterns that are most likely to lead to maladaptive emotional experiences.

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Table 1
 Emotion upregulation, feedback and intensity with and without of stress. Emotional variability is also included.

	Positive Emotion		Negative Emotion	
	Participants with MDD	Control Participants	Participants with MDD	Control Participants
Emotion Upregulation	0.38 (0.19)	1.14 (0.42)	0.37 (0.22)	0.11 (0.09)
Emotion Feedback	-0.43 (0.18)	-0.59 (0.26)	-0.39 (0.21)	-0.22 (0.16)
Emotion Upregulation Under stress	-1.11 (4.65)	-0.67 (5.94)	-0.87 (5.73)	0.16 (1.25)
Emotion Feedback Under stress	0.35 (3.46)	-1.31 (5.33)	-1.63 (5.49)	-0.31 (1.78)
Emotional Intensity	1.68 (0.39)	2.17 (0.45)	1.88 (0.53)	1.15 (0.17)
Emotional Intensity Under Stress	1.45 (5.21)	2.78 (15.69)	5.73 (17.53)	0.46 (3.38)
Variability	0.51 (0.24)	0.50 (0.27)	0.59 (0.29)	0.14 (0.13)

Note. Standard deviations are in parentheses.

Appendix

Let's consider a hypothetical experience sampling study to understand the additional scientific utility of using dynamical systems modeling to understand the nature of emotion regulation and resilience. Studying our example, individuals report on the degree to which they are feeling pleasant or unpleasant, as well as their degree of subjective arousal or quiescence. There is a large body of work discussing the relationship between valence and arousal and the degree to which they are independent from each other (Barrett & Russell, 1998;1999; Larsen, et. al. 2001) . For simplicity and visualization purposes in this simulation, let's treat pleasantness and arousal as orthogonal axes. Figure A provides an example of hypothetical experience sampling data with its principal components. This representation of the data has lost all information about the time at which individuals' experiences were sampled. Figures B, C, D on the other hand describe three different temporal dynamics that might be present in the same system. For instance, the individual in B is experiencing a shift from unpleasant to pleasant emotions with random fluctuations in physiological activations throughout the week. Therefore the change in pleasantness is independent of the change in arousal. The individual displayed in C is experiencing a decrease in physiological activation(arousal) throughout the sampling period independently of his or her degree of pleasantness. In D, there is a dynamic interaction between pleasantness and arousal, in the sense that the change in levels of pleasantness across time depends on the pleasantness and the arousal levels in the previous sampling moment. (In another study example, these data could plot changes in pleasantness

and unpleasantness against objective changes in a physiological index, such as heart or respiration rate.)

Figure S1

Example of 4 different temporal dynamics (A-D) that subtend a hypothetical longitudinal data set. Plot E is a case where correlational analyses might fail to capture important dynamics.

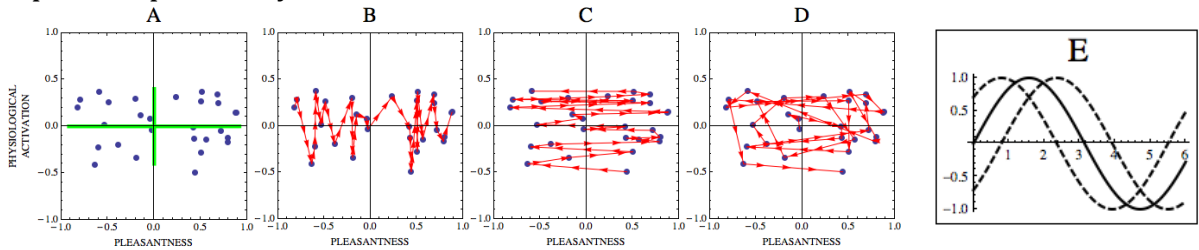


Figure E is another example where correlational analyses might fail to capture similarity inherent in the dynamics of the system. The signals represented by the dashed lines are not correlated with each other. However each of these signals are correlated with the signal represented by the full line. It could be the case that the first signal (dashed) temporally causes the second signal (filled), which then temporally causes the third signal (dashed), but none of this could be modeled using correlational approaches.

The mathematical framework that is used to extract the temporal causal relationships in any sequential data set is broadly called dynamical systems modeling. This framework is a means of describing how one state develops into another state over the course of time (Aoki & Hiraide 1994; Golubitsky 1997; Guckenheimer & Holmes, 1997; Jordan & Smith 1999; Ott, 1993). If f is any continuous function, then the evolution of the variable x can be given by the formula

$x_{n+1} = f(x)$ which can also be viewed as a difference equation $x_{n+1} - x_n = f(x) - x_n$ and if we define g such that $g(x) \equiv f(x) - x$, we have $x_{n+1} - x_n = g(x_n)$ which can be interpreted “as n changes by 1 unit, x changes by $g(x)$ ”. This is the discrete analog of the differential equation $x'(n) = g(x(n))$. Let’s consider a bilinear dynamical system with two internal state variables x_1, x_2 and external variable u which will represent the context in which the system is operating. The dynamics of the system is described by the following equation:

$$x' = A + \left(\sum_{j=1}^m u_j B^{(j)} \right) x + Cu$$

where x_i' is the derivative of x_i . In the case of experience sampling data, x_1 and x_2 represents two psychological states that change over time, such as average pleasant and unpleasant experiences. u represents a psychological context that could modulate and moderate system dynamics such as significant life events or social interaction. For a dynamical system with two internal states and one external context, the formula above can be expanded as follows:

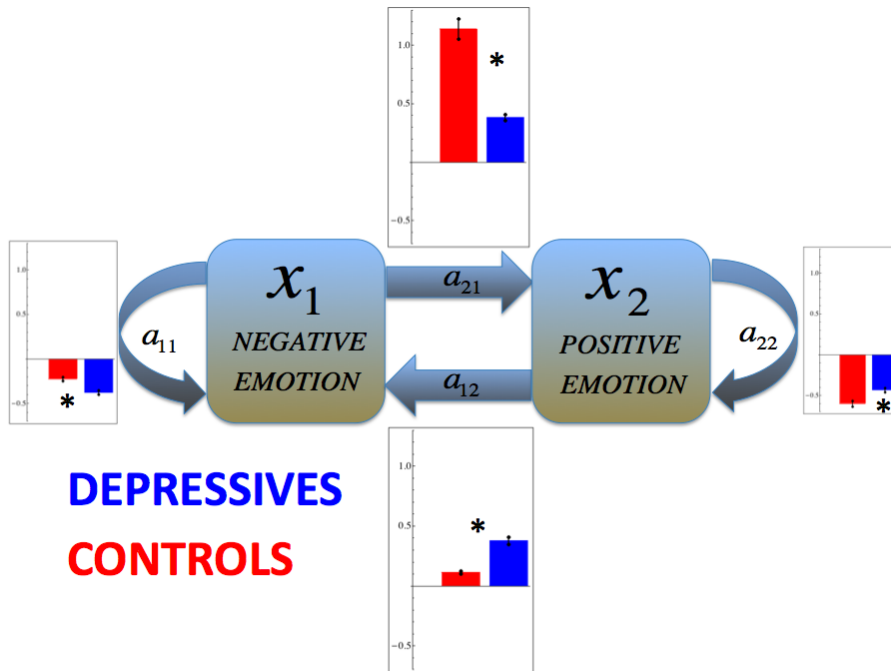
$$\begin{bmatrix} x_1' \\ x_2' \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + u \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + u \begin{bmatrix} c_1 \\ c_2 \end{bmatrix}$$

a_{ij} specifies the degree to which change in x_i is influenced by the current value x_j . Therefore a_{11} and a_{22} are the autoregressive components of the system. These determine the degree to which change in x_1 and x_2 will be predicted by their current values. a_{12} and a_{21} represent the internal dynamics of the system. For

instance, a_{12} represents the degree to which the current value of x_2 influences x_1 , which is the change in x_1 . b_{ij} specify the part of the system dynamics that is moderated by the context, u . For instance, b_{12} represents the degree to which the current value of x_2 influences change in x_1 but only when the context u is active. c_i specify the main effects of the context on x_1 and x_2 respectively. Typically, experience sampling data provide the values for x_1 , x_2 and u . The parameters a_{ij} , b_{ij} and c_i can be estimated using regular or weighted least squares (Demiralp & Demiralp, 2010) or Bayesian estimation (Friston et. al. 2003; Stephan et. al. 2008). Below, we describe the application of dynamical systems modeling to the experience sampling study of depression we mentioned earlier. The goal of this analysis is to investigate the dynamics of emotion regulation and sensitivity to negative life events in people with depression.

For this analysis, we averaged the 4 pleasant and 7 unpleasant emotions into positive and negative emotion, respectively. At each measurement moment, in addition to the emotion ratings, participants provided information about whether a significant life event took place since the last time they were prompted. Individuals indicated whether the event was positive or negative and the intensity of this experience.

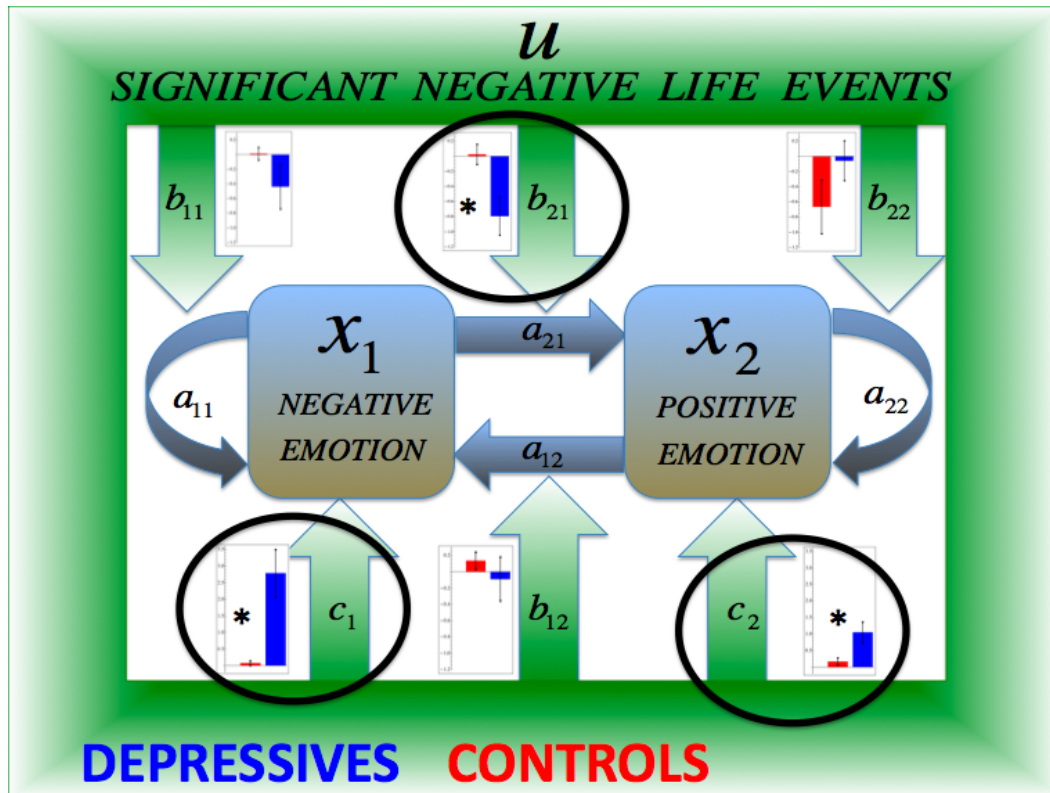
Figure S2
 Dynamics of emotional experience in people with depression (depressives) and healthy controls sampled throughout a week.



In the dynamical system depicted above, the degrees of positive and negative emotional experience are characterized by x_1 and x_2 respectively. a_{11} and a_{22} represent non-dynamic aspects of negative and positive emotion regulation respectively. These values are negative (as indicated by the bar graphs) since a negative feedback is necessary to prevent negative and positive emotions from reaching infinite intensity. In other words, if the participant is experiencing negative or positive emotion with high intensity, in subsequent measurement moments, the intensity should decrease. Intuitively, you can think of this as the system's movements towards an equilibrium after an intense feeling of happiness or fear. The bar graphs display that depressives and controls differ in this regard. Depressives have a stronger negative feedback in negative emotion and controls have a stronger

negative feedback in positive emotions. This is because depressives and controls tend to experience negative and positive emotions with more intensity, respectively. Therefore they have to work extra on moving towards equilibrium in each of these domains. It is extremely important to model the autoregressive effects in dynamical system modeling. This is because, in order to make a claim about the influence of x_1 on x_2 , it is essential to first extract the influence of the previous values of x_1 and x_2 on the change that takes place in them. Otherwise, the dynamics discovered might be spurious. a_{12} and a_{21} represent the dynamic aspects of emotion regulation. a_{21} represents the degree to which positive emotions increase after a high intensity negative emotional experience. Note that controls are substantially stronger in this type of dynamic regulation compared to depressives. This suggests that after negative emotional experiences, controls engage in activities or mental strategies that boost their positive emotions whereas depressives don't. In fact, the degree to which depressives boost positive emotions after negative experiences is not different from the degree to which they boost negative emotions after positive experiences (blue bars in a_{12} and a_{21} are not significantly different from each other). This is not an effective emotion regulation strategy if one is intending to experience positive emotions. Controls, on the other hand, do not increase their negative emotions after intense experience of positivity, making them resilient to life stressors and allowing them to maintain a dynamic equilibrium that pulls them to heightened positive emotional experience. This is a much more effective strategy for being emotionally resilient in the face of negativity that might arise in life.

Figure S3
 Dynamics of emotional experience in people with depression (depressives) and healthy controls sampled throughout a week in the presence of significant negative life events.



So far we have not talked about the psychological context in which these dynamics take place. Above, we display the dynamical systems model described above with the context also modeled. u represents the presence and degree of significant negative life events. This is a psychological context in which the dynamics of emotional experience and regulation take place. Here, b_{ij} represent the moderating role of the context. b_{11} and b_{22} represent feedback loops that are turned on when the psychological context is active. For instance, it could be the case that there is additional internal emotional regulation that is used in the presence of significant

negative life events. The two groups don't differ in this regard. b_{21} represents the degree to which positive emotion changes after an intense negative emotional experience when the psychological context is active. For instance, it seems that depressives experience a large decrease in their positive emotions if they experienced a significant negative life event and if they are currently experiencing intense negative emotions. This suggests that the maladaptive deficits in emotion regulation are exacerbated when negative significant life events take place. b_{12} represents the degree to which negative emotion changes after an intense positive emotional experience, when negative life events take place. This variable is not significantly different across the two groups. Finally c_1 and c_2 represent the direct influence of negative life events on individuals' negative and positive emotions respectively. Note that, controls are not directly influenced by significant negative life events. Depressives experience increases in both positive and negative emotional experiences after significant negative life events. This result shows that depressives experience an increase in overall emotional intensity, however they experience this increase to a larger degree for negative emotions (indicated by higher c_1 vs c_2). These findings allow us to decompose emotion regulation into its dynamic and non-interactive components. Additionally, by modeling the context as a functional scaffold, we are able to investigate the degree to which dynamics of emotional experience is situated in the environmental context.

Sampling Frequency

It is important to note that the psychological processes about which we make inferences are limited by properties of our measurement. More specifically, the sampling rate of our experience sampling method constrains the class of psychological processes about which we can expect to make inference. In its simplest form, the Nyquist-Shannon sampling theorem in information theory states that any band-limited analog signal that contains frequencies no higher than B hertz, can be discretely represented using ordinates spaced $1/(2B)$ apart in time (Shannon, 1949). Of course, in the study of human psychology, it is undesirable to uniformly sample individuals' experiences. If sampling is done uniformly, the participants might begin to predict the onset of the sampling period which can bias their responses. In fact, this can be said about any system which has the capacity to learn and predict. Hence, human participants are often sampled nonuniformly and unpredictably to minimize predictability of the protocol. In the case of our experience sampling procedure, individuals were sampled anywhere from 2 to 180 minutes apart with an average of 90 minutes. According to the Shannon sampling theory, if a band-limited signal, which in this case is the experience of emotion, is sampled non-uniformly, the signal can be represented if the average sampling rate satisfies the Nyquist condition described above (Marvasti, 2001). Hence we can treat our period as 90 minutes which is $(1/5400)$ Hz. This means that our sampling procedure will provide data to reconstruct the original signal representing emotional experience as long as that signal is not fluctuating with frequencies above $(1/10800)$ Hz. More intuitively, the dynamics represented in our analyses are best

thought to be representative of fluctuations in the actual emotional experience of the human beings taking place at 180 minute or 3 hour intervals or longer.

Unfortunately, it is not common practice to constrain the inferences made in the basic science of emotion to the limitations of the sampling rate of the experience sampling or experimental protocol. In other words, emotional properties measured across days and weeks are often discussed under the same umbrella terms such as emotional variability, intensity, regulation and complexity. This is expected as we are merely beginning to understand the psychological processes that subtend human emotional experience. In an ideal world, the basic science of emotion would be unified around an explicit theory which makes explicit and quantitative predictions about the nature of moment-to-moment human emotional experience at various periodicities. Hopefully our incisive investigation of the dynamics of human emotional experience would aid in this endeavor.

Numerical Differentiation and High Frequency Noise

It is well known that the numerical derivation of experimental data often accentuates the high frequency noise and error in the data. In fact, this is a problem that is not only limited to experimental data. Even when the canonical form of a function is known, its numerical derivatives will suffer from truncation errors in the underlying computing algebra system. This is one reason why, in mission-critical systems, tremendous effort is put into calculating the derivatives symbolically. For the specific case of our data, we wanted to make sure that the differences we were observing between people with depression and healthy controls were not due to

high frequency noise. Having pointed this out, it is important to note that our statistical analyses are multilevel and the noise described here and its effects would primarily be reflected in the first level or within-subject level of analysis. Regardless of how robust multilevel analyses are to issues such as these, we wanted to recruit some of the well known methods in numerical analysis to ensure that our numerical derivatives were not inundated with noise. The analyses described below show that our inferences are robust against high frequency noise.

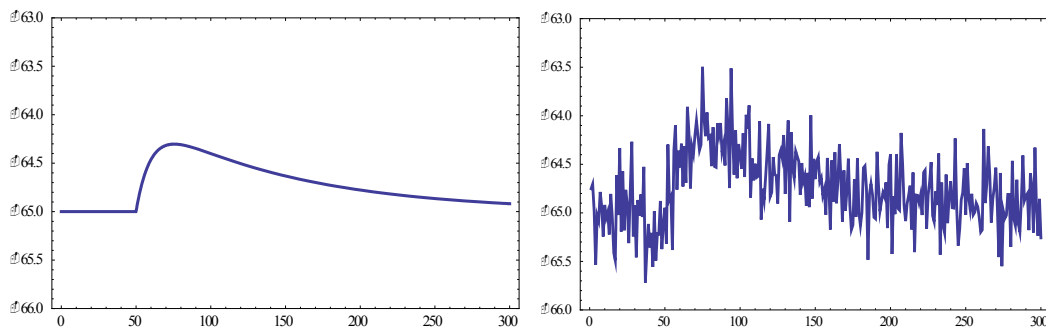
First, we decided to use the Savitzky-Golay smoothing filter which performs a local polynomial regression on the time course. The resulting smoothed values preserve the various important properties of the distribution such as relative maxima, minima while filtering high frequency noise. Second, we used the discrete Fourier transform based representation of derivatives which is a much more global representation, does not rely on local approximations, and is less susceptible to error. Finally, we used wavelet based numerical differentiation which is also less susceptible to high frequency noise. Overall all of these approaches implicitly conduct some form of low-pass filtering to ensure that high frequency does not bias the difference equations.

Savitzky-Golay Differentiation

In their seminal paper, Savitzky and Golay propose a method of smoothing data based on local least squares approximation. They show that polynomial fitting and approximation is equivalent to discrete convolution with a fixed impulse response. More generally, the Savitzky-Golay FIR lowpass filter can be thought of as a

generalized moving average. The coefficients are chosen so that the higher moments in the data are preserved, thus the distortion of essential features such as peak heights and line widths in the spectrum are preserved. The key contribution of their approach is that this is done without decrements in the suppression of random noise in the data. Below, we show two graphs. On the left is a simulated signal and on the right is the same signal with autoregressive noise added. Autoregressive noise was generated by taking the inner product of an autocorrelation matrix ($\rho=0.7$) with Gaussian Noise $N(0,0.3)$.

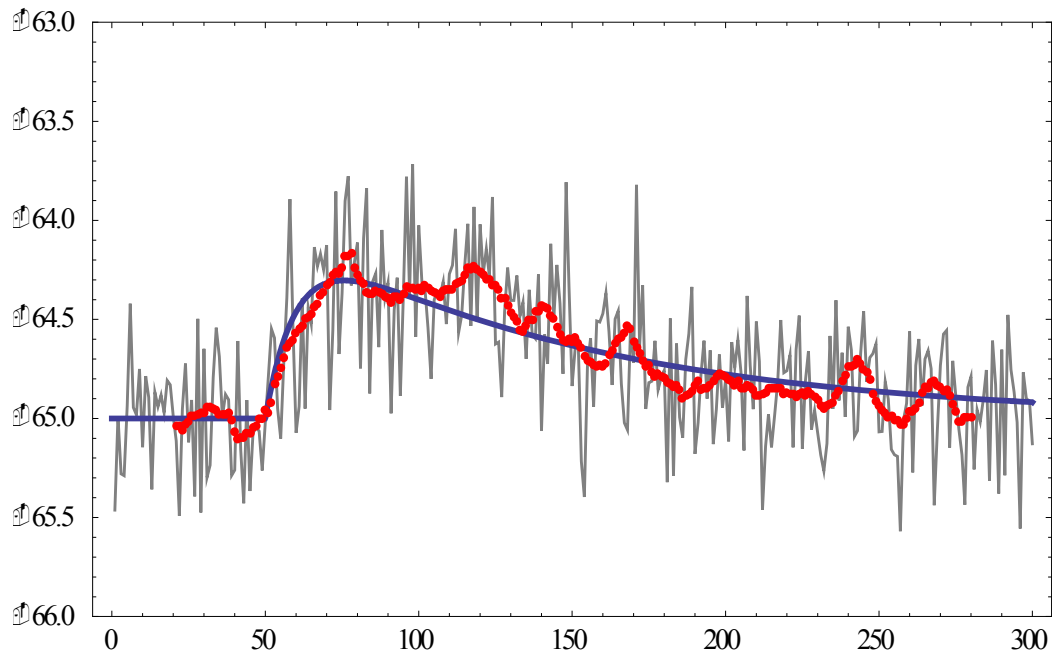
Figure S4
Simulated original signal (left) and the signal with noise added (right)



In the figure below, I include the original signal in blue, the noise added signal in gray and the output of the Savitzky & Golay filter below. The filtered time course is padded with zeros in the beginning and the end due to filtering. You will notice that the filter is quite robust against fluctuations due to noise in the data.

Figure S5

Simulated original signal (blue), the signal with noise added (grey) and the output of the Savitzky & Golay filter (red).



It is important to note that all of the low pass filters described here were applied to each participant's data within each day. This is crucial because overnight changes in mood are considerably different than within-day fluctuations in mood. In terms of data analysis, this poses challenges to us since we have only 8 data points per day for 7 days. With the loss of data points in the beginning and end due to estimation of the difference equation, we experience a significant drop in degrees of freedom and power. Nonetheless, our second level analyses were still robustly estimated. We present the dynamical systems parameters for each of the filtered data sets in addition to the original data set after we describe how the next two filters work.

DFT based differentiation

The principal idea behind the other two low-pass filters is similar to Savitzky and Golay's approach, however we wanted to include them in our analyses to ensure that high-frequency noise was not leading to spurious inferences in our analyses. The Discrete Fourier Transform (DFT) based low-pass filtering uses the algorithm proposed by earlier researchers (De Levie, Sarangapani & Czekaj, 1978; Wang (2002)). The DFT approach provides a global representation of the derivative operator and is proven to be accurate for functions with periodic boundary conditions. While our knowledge of test and measurement in psychology does not allowed for a rigorous discussion of periodic boundary conditions, they impose one criterion that is specifically relevant for our experience-sampling data set. The last probe in the experience-sampling series must be smoothly connected to the first sampling moment. In other words, the last measurement and the first measurement within the day must be united by an abstract bridging sampling moment. In order to ensure we were satisfying the periodic boundary conditions, we created an artificial sampling moment which is an average of the first and last sampling moments in each day and prepended to our time series data describing fluctuations within the day. Once this is done, the DFT approach applies a kernel to the fourier transformed data and then applies an inverse Fourier transform to obtain the derivative of the time series. After obtaining the derivative using this approach we applied dynamical systems modeling to identify causal relationships.

Wavelet based differentiation

The wavelet based differentiation approach relies on earlier research as well (Jameson, 1993). In this approach a wavelet-based filter acts as a smoothed difference quotient whose step size is of the same order as that of the usual difference quotient used in numerical differentiation. Systematic analyses of the wavelet approach show that the wavelet approach removes noise and computes the derivative with high accuracy comparable to the corresponding difference quotient calculated in the absence of noise.

Table S1

Emotion upregulation, with and without negative, neutral and positive life events. The influence of the three filters (Savitzky & Golay, DFT, Wavelet) on the results are included.

	Positive Emotion		Negative Emotion	
	Participants with MDD	Control Participants	Participants with MDD	Control Participants
Emotion Upregulation	0.38 (0.19)	1.14 (0.42)	0.37 (0.22)	0.11 (0.09)
Savitzky & Golay	0.27 (0.22)	1.03 (0.31)	0.64 (0.25)	0.05 (0.07)
DFT	0.42 (0.25)	0.99 (0.27)	0.52 (0.34)	0.15 (0.21)
Wavelet	0.35 (0.21)	1.17 (0.45)	0.35 (0.21)	0.09 (0.05)
Emotion Upregulation After Negative Events	-1.11 (4.65)	-0.67 (5.94)	-0.87 (5.73)	0.16 (1.25)
Savitzky & Golay	-1.05 (3.87)	-0.54 (4.95)	-0.86 (4.92)	0.05 (1.12)
DFT	-0.99 (3.65)	-0.65 (4.43)	-0.85 (4.45)	0.09 (1.18)
Wavelet	-1.09 (3.35)	-0.63 (3.97)	-0.79 (3.86)	0.07 (1.07)
Emotion Upregulation After Neutral Events	0.06 (0.56)	0.12 (1.09)	0.09 (1.34)	0.09 (1.22)
Savitzky & Golay	0.10 (0.65)	0.11 (0.99)	0.10 (1.24)	0.08 (0.95)
DFT	0.09 (0.78)	0.09 (1.05)	0.09 (1.13)	0.07 (0.84)
Wavelet	0.05 (0.37)	0.08 (0.89)	0.07 (0.95)	0.06 (0.65)
Emotion Upregulation After Positive Events	-0.05 (0.35)	0.53 (1.95)	-0.12 (0.56)	-0.19 (0.34)
Savitzky & Golay	-0.04 (0.25)	0.54 (2.15)	-0.11 (0.45)	-0.17 (0.28)
DFT	-0.07 (0.17)	0.47 (1.95)	-0.09 (0.54)	-0.19 (0.31)
Wavelet	-0.06 (0.28)	0.49 (1.97)	-0.08 (0.47)	-0.21 (0.29)

Note. Standard deviations are in parentheses.

Table S2

Emotion feedback, with and without negative, neutral and positive life events. The influence of the three filters (Savitzky & Golay, DFT, Wavelet) on the results are included.

	Positive Emotion		Negative Emotion	
	Participants with MDD	Control Participants	Participants with MDD	Control Participants
Emotion Feedback	-0.43 (0.18)	-0.59 (0.26)	-0.39 (0.21)	-0.22 (0.16)
Savitzky & Golay	-0.37 (0.16)	-0.67 (0.27)	-0.40 (0.25)	-0.20 (0.14)
DFT	-0.44 (0.22)	-0.60 (0.30)	-0.38 (0.23)	-0.24 (0.19)
Wavelet	-0.39 (0.19)	-0.58 (0.29)	-0.41 (0.27)	-0.26 (0.20)
Emotion Feedback after Negative Events	0.35 (3.46)	-1.31 (5.33)	-1.63 (5.49)	-0.31 (1.78)
Savitzky & Golay	0.34 (4.01)	-1.34 (5.23)	-1.61 (4.97)	-0.33 (1.67)
DFT	0.30 (3.78)	-1.35 (4.99)	-1.59 (5.14)	-0.29 (1.82)
Wavelet	0.33 (3.67)	-1.29 (4.87)	-1.64 (4.23)	-0.28 (1.79)
Emotion Feedback after Neutral Events	0.06 (3.67)	0.03 (4.53)	-0.05(3.13)	0.05 (4.76)
Savitzky & Golay	0.06 (3.01)	-0.03 (4.36)	-0.05 (3.03)	0.06 (4.67)
DFT	0.04 (3.09)	-0.04 (3.99)	-0.08 (3.15)	0.04 (4.56)
Wavelet	0.07 (3.10)	-0.07 (4.23)	-0.03 (2.97)	0.07 (4.70)
Emotion Feedback after Positive Events	-0.15 (2.34)	-0.40 (2.45)	-0.34(0.19)	0.27(1.03)
Savitzky & Golay	-0.14 (2.15)	-0.45 (2.37)	-0.33 (0.18)	0.29 (1.15)
DFT	-0.09 (1.78)	-0.43 (2.38)	-0.37 (0.15)	0.27 (1.17)
Wavelet	-0.10 (1.93)	-0.41 (2.40)	-0.31 (0.18)	0.24 (1.25)

Table S3

Emotion intensity, with and without negative, neutral and positive life events. The influence of the three filters (Savitzky & Golay, DFT, Wavelet) on the results are included.

	Positive Emotion		Negative Emotion	
	Participants with MDD	Control Participants	Participants with MDD	Control Participants
Emotional Intensity	1.68 (0.39)	2.17 (0.45)	1.88 (0.53)	1.15 (0.17)
Savitzky & Golay	1.56 (0.40)	2.09 (0.38)	1.85 (0.54)	1.16 (0.12)
DFT	1.70 (0.31)	2.10 (0.41)	1.76 (0.55)	1.09 (0.20)
Wavelet	1.58 (0.35)	2.07 (0.39)	1.84 (0.49)	1.19 (0.19)
Emotion Intensity after Negative Events	1.45 (5.21)	2.78 (15.69)	5.73 (17.53)	0.46 (3.38)
Savitzky & Golay	1.46 (5.34)	2.65 (15.82)	5.65 (16.53)	0.45 (3.20)
DFT	1.42 (7.01)	2.82 (13.05)	5.85 (15.45)	0.48 (3.25)
Wavelet	1.40 (6.04)	2.80 (13.78)	5.90 (14.87)	0.49 (3.45)
Emotion Intensity after Neutral Events	0.09 (0.96)	0.35 (0.15)	0.06 (0.45)	0.05 (0.47)
Savitzky & Golay	0.08 (1.01)	0.34 (0.13)	0.05 (0.39)	0.04 (0.35)
DFT	0.10 (0.89)	0.37 (0.12)	0.07 (0.42)	0.03 (0.39)
Wavelet	0.11 (1.10)	0.34 (0.14)	0.05 (0.45)	0.06 (0.32)
Emotion Intensity after Positive Events	1.43 (9.02)	4.45 (2.76)	0.56 (15.63)	0.39 (3.19)
Savitzky & Golay	1.42 (8.87)	4.35 (2.75)	0.54 (13.67)	0.38 (3.17)
DFT	1.38 (7.65)	4.52 (2.87)	0.57 (13.78)	0.42 (2.95)
Wavelet	1.40 (8.45)	4.38 (2.65)	0.60 (14.67)	0.40 (2.56)

Bootstrapping

In our experience-sampling procedure we have an even number of pleasant and unpleasant emotion adjectives. For the purposes of our dynamical system analyses, we had aggregated the ratings for these adjectives uniformly by taking the average of the four and seven pleasant and unpleasant emotion ratings, respectively. One might wonder whether it is appropriate to perform such arbitrarily uniform aggregation. Below we describe two categories of approaches that rely on

bootstrapping and matrix decomposition, respectively, which show that our analyses are not influenced by the uniform averaging of the unequal number of pleasant and unpleasant adjectives.

The first approach uses bootstrapping to ensure that our results are not an outcome of the uneven number of pleasant and unpleasant emotion adjectives. In order to do this, we re-ran the analyses for all possible subsets of the 7 emotion adjective ratings that contain 4 emotions. There are 35 unique ways of selecting 4 items out of 7 items without replacement. Hence the dynamical systems analyses were conducted 35 times and the resulting distribution of parameters were compared to the results from the original analyses. None of the parameter distributions were significantly different from the original results, ensuring that our results and inferences are not an epiphenomenon of different number of pleasant and unpleasant emotion adjectives. We extended the procedure above using random selection with replacement and the results were the same.

In addition to the method described above, we need to ensure that uniform aggregation of the ratings for various emotion adjectives is appropriate. For instance, one might argue that adjectives that are indicative of high arousal might need to be treated differently than others in the aggregation. Previous research (Barrett, 2004), has used multidimensional scaling to first identify individuals' space of emotional experience. Then the valence and arousal aspects of each emotional adjective were considered in subsequent calculations. Mathematically speaking, this amounts to identifying the representative bases that define the space of emotional space and then projecting the data onto these basis vectors to the bases

representing valence and arousal. Of course, it is not trivial to identify which one of the bases refers to valence and which one refers to arousal. In fact, earlier research has shown that people can report their emotional experience with a valence or arousal focus, and that this is a meaningful individual difference (Feldman, 1995). In our analyses, we first used principal component analysis to identify the dominant axis which characterized most of the variance in the data. Then we checked whether this principal axis was able to discriminate positive from negative emotion adjectives. This step was performed to ensure that a non-hedonic property of people's experiences was not driving the determination of the principal axes. Specifically we checked to ensure that the loadings for the majority of the pleasant and unpleasant emotion adjectives had opposite signs in the principal component which is characterized by the first eigenvector of the covariance matrix of our time series. Our first attempt did not produce reliable results. Subsequent investigations, identified that day-to-day differences was the main cause of this instability. Hence, we re-ran the analyses using within-day mean centering such that between-day baseline differences were not driving the effect. This approach produced principal components that passed the criteria described above.

It is well known that simply calculating the basis vectors of a data set and then projecting the same data onto those basis vectors is not very meaningful. Hence, we split our within-subject data into two pieces. The first piece was used to calculate the principal components and the second piece was used to calculate the dynamical systems model using data projected onto the basis vectors characterized by the principal components. Most likely due to decrease in power due to decreased

data size, principal component analyses for 9 healthy controls and 7 individuals with depression resulted in a highly spherical basis set which was not representative of individuals' hedonic experience. We excluded these participants from the subsequent analyses. The weighted dynamical systems model replicated the original findings about depression-related differences in emotion upregulation and feedback. However, there was not sufficient power to identify the moderating role of the significant life events, simply because individuals only report experiencing these significant life events 20% of the time in our data.

These results suggest that our original analyses using an unequal number of pleasant and unpleasant emotion adjectives with uniform weighting was not problematic with regards to making inferences about the dynamics of human hedonic experience.

Hedonic vs Arousal Dynamics Underlying Emotional Experience

It is possible that some researchers might be troubled by our selection of the pleasant emotion adjectives *happy*, *excited*, *alert* and *active*. Specifically, one could argue that reports of being alert and active refer much more to arousal than hedonics. In subsequent paragraphs, we describe a set of analyses that show that this is not an issue in our analyses. The primary reason for this is that, while the words alert and active might refer more to arousal in isolation, when coupled in an experience sampling protocol with other emotion adjectives, they might refer to the intensity of the emotion of interest. In order to be certain that our dynamical systems modeling was robust to potential differences between pleasant terms we

ran three analyses and compared the results to the parameters estimated using the average of the four pleasant emotion adjectives.

In the first set of analyses, we used the average of the ratings for alert and active to characterize positive emotions. In the second set, we used the average ratings for excited, alert, and active to characterize positive emotions. In the final set of analyses, we used the ratings for happy to characterize positive emotions. We estimated the 10 parameters describing the dynamical system for each of these three characterizations of positive emotions for each participant. Then we compared the distribution of the parameters to that of the original analyses in which positive emotions were characterized as the average of all four emotion ratings. None of the distributions was statistically significantly different from the original parameter estimates (with all p-values exceeding 0.45) suggesting that our inferences are not driven by arousal but truly characterize the hedonic aspect of pleasant emotional experience and its fluctuations in daily life.

Hysteresis

It is important to know the temporal extent to which the dynamics manifest themselves. In other words, it would be useful to know how far into the future the causal relationships between the internal variables and external moderators hold. In order to investigate this, we ran a dynamical systems model which predicted the causal relationship between measurement at time t and time $t+2$. To ensure that our findings were not spurious we included the measurements obtained at time $t+1$ in our model as well. Unfortunately, we did not have sufficient power to fit this model.

This was primarily due to two reasons. First, investigating relationships between time t and $t+1$ means that $1/8$ of our data is lost for the purposes of performing the numerical differentiation. Second, it is well known that experience sampling of emotion has intrinsic hysteresis because subsequent measurement moments are autocorrelated which is identical to the problem of multicollinearity in traditional regression analyses. We intend to further investigate this relationship using larger datasets with more samples per day and more participants in future work.

Future Methodological Work

One of our goals is to be able to create an impulse response function that represents the dynamics of emotional experience in depression. For instance, ideally we would be able to solve for the set of equations for a subject's model and determine the coefficients that characterize the dynamics and then use this model to predict subsequent behavior. Using this approach, the influence of a particular positive or negative event on human emotional experience can be predicted and the model can be refined to include other moderators. It is one of our goals to carry out such an investigation once we have a larger collection of data sets which will allow us to make more characteristic models describing the dynamics of human emotional experience.

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Chapter V

Conclusion

In this dissertation, the structure and dynamics of emotional experience in Major Depressive Disorder (MDD) are described. All of the results are based on a large empirical data set which entailed sampling individuals' experiences in daily life using computerized mobile experience sampling. The multichannel time series data obtained in this fashion were analyzed using existing correlational methods as well as two novel methods involving high dimensional and dynamical systems modeling introduced in this dissertation.

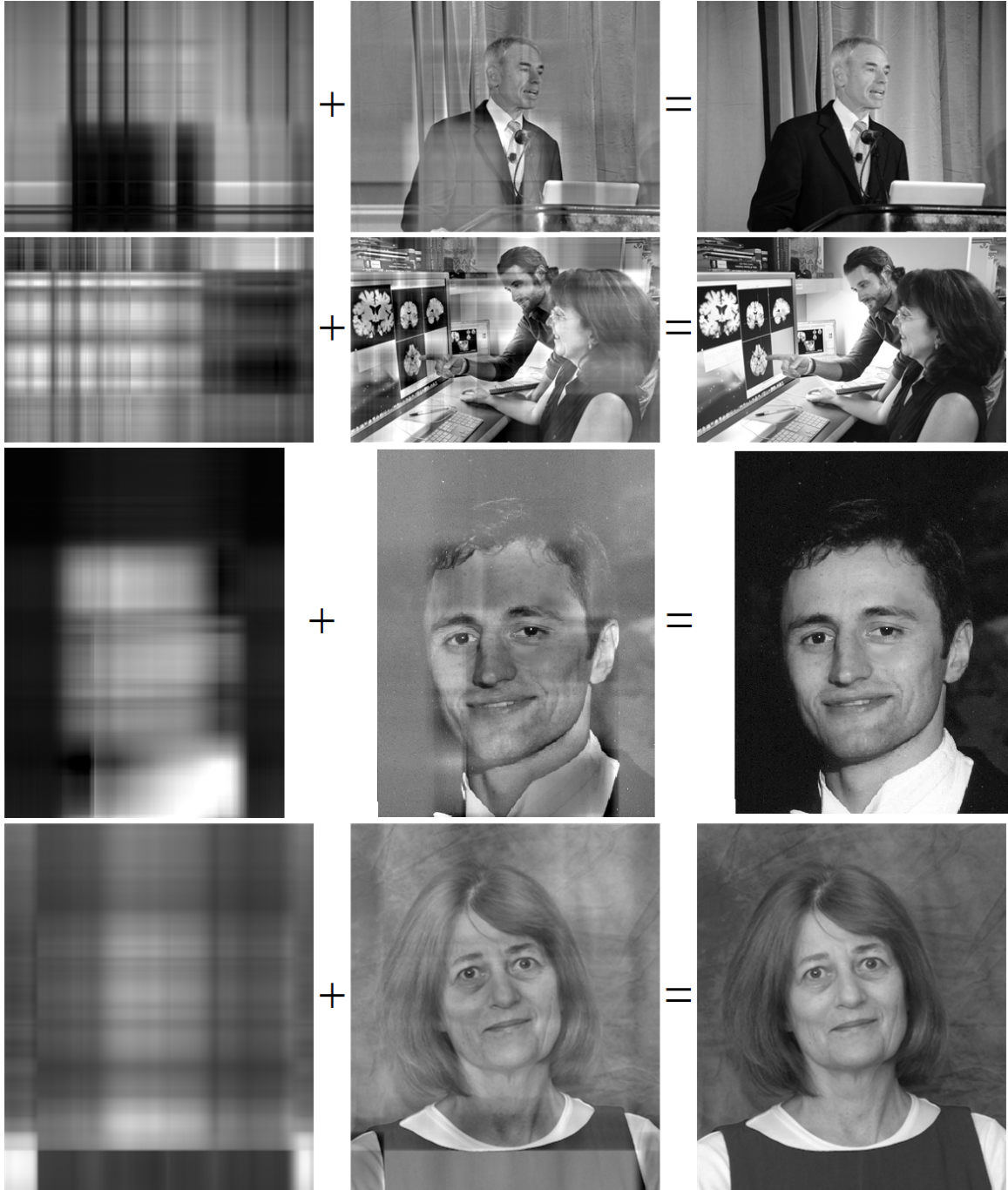
The first set of analyses indicate that people with depression have difficulty differentiating negative emotional experiences such as sadness and anger from one another, and this is not due to differences in emotional intensity and variability. The second set of analyses, which entail high-dimensional modeling of emotional life, indicate that people with depression have much more complex positive emotional lives than healthy controls, potentially overcomplicating happiness and making it difficult to maximize its benefits. The third set of analyses, which entail dynamical systems modeling of emotional life, indicate that people with depression have difficulty with emotion regulation, or more specifically increasing positive aspects of their emotional experiences, following intensity negative emotional experiences. Furthermore, people with depression also are influenced to a larger degree by negative life events compared to healthy controls.

This is the first time that differentiation of daily negative emotional experience is shown to be altered in people with clinically diagnosed MDD. This finding, as is reported in the manuscript which is currently in press at Psychological Science, is important. First, it is well known that people's global or retrospective self-reports about the structure and dynamics of emotional experience measure constructs different than the moment-to-moment emotional experience which can be captured using the ecologically valid method of experience sampling. Second, it is important that studies about MDD use individuals who are clinically diagnosed. This is especially important as inventories such as the Beck Depression Inventory (BDI) don't have the specificity of clinical diagnosis.

We also introduce two new methods which show facets of emotional life that previous methods did not. The first novel method is the high-dimensional modeling of human emotional experience, which removes the assumption that emotion adjectives refer to discrete mental states or are subtended by independent mental or neural systems. The intuition comes from the fact that individuals know that *happy* can refer to many different types of emotional states. In order to describe the different types of *happiness* experience we used the ratings of the other emotions that were concurrently reported with happiness. In this framework the emotion adjectives constitute a vector of values which collectively represent the emotional state of the individual. We then redefined emotional complexity in this high-dimensional space and showed that people with depression actually differed more from healthy controls in positive emotional experience rather than negative emotional experiences. Below I include an image that visually displays the source of this seeming discrepancy:

Figure 1

Information contained in low (up to second order) measures of emotional granularity are in the leftmost column. The middle column visualizes the information retained in the remaining higher order measures of emotional granularity. The right most column is the original image which is a simple addition of the leftmost and center column. The various rows display the application of the decomposition to four different images.



The rows from top to bottom contain images of Dr. John Jonides, Dr. Lisa Feldman Barrett, Dr. Luis Hernandez-Garcia and Dr. Phoebe Ellsworth. The left most column visualizes the amount of information that simple second-order measures of emotional differentiation leverage as we did in our first paper. The second column visualizes the amount of important information left in higher order relationships which the high dimensional modeling approach captures. Finally the last column shows the original image that was decomposed. In other words, the fact that our high-dimensional modeling based investigation of emotional complexity captures something above and beyond traditional measures of emotional differentiation should not be startling. Human emotional life is rich and can be complex in a number of different ways. In future research we will work on the degree to which various cognitive mechanisms such as working memory and attention feed into the complexity of various forms of emotional complexity. In the meantime, in applied settings, if a clinician is being successful with a therapy that focuses on increasing differentiation of negative emotions in people with depression, the clinician might be interested in systematically observing the structure and dynamics of positive emotions in people with depression in order to diagnose and intervene in the high-dimensional structure of emotional experience.

The second method that we introduce allows a systematic investigation of the change in emotional experience over time in people with depression and healthy controls. These analyses are especially informative in the context of emotion dysregulation in people with MDD. People with depression and even those at risk of depression have trouble preventing negative material from entering and remaining in their working memory, leading them to remain attached to and ruminate about negative content.

Inhibition deficits (Berman, Nee, Casement, Kim, Deldin, Kross, Gonzalez, et al. 2010) may also interfere with emotion regulation strategies such as reappraisal and the recall of mood-incongruent material, making it further difficult to recover from negative affect. Previous research has been quite successful in displaying such altered mechanisms in lab settings, however translating the notion of emotion regulation to the ecologically valid approach of experience sampling can be non-trivial. First of all, during experience sampling, in order for measurements to be ecologically valid, it is important that people do not feel like they are performing any kind of task, Hence, it is important to develop measures of emotion regulation only relying on activities people normally do. Our approach to conceptualizing emotion regulation in the ecologically valid context of experience sampling was to investigate the causal mechanisms that underlie the changes in positive and negative emotional experiences. We investigated the way in which positive and negative emotions predict change in positive and negative emotion over time. We also investigated the role of external life events in depression-related changes in emotion regulation. Our results indicated that, in daily life, people with depression had difficulty upregulating positive emotions after highly negative emotional experiences. This situation was exacerbated in the presence of negative life events for people with depression. Our analyses are the first to investigate emotion regulation during experience sampling using dynamical systems modeling. Our results reveal an aspect of human emotional experience in day to day life that might be difficult to capture in the lab or via retrospective or global interviews. In this sense, the extracted properties aid both basic and clinical science by making it possible to extract more features about human emotional experience in depression.

These results make an important contribution to basic and translation science and therefore have broad scientific and applied impact. First, in the context of the basic science of emotion, results show that structural properties of emotion such as differentiation can be altered selectively for negative emotions in the context of mental health disorders. Second, results show that some of these structure properties are substantially different for positive and negative emotional experiences and that they are independent of other properties of emotional life such as intensity and variability. Third, results from high-dimensional modeling of emotion show that there are multiple facets of emotional life such as emotional complexity which have relationships captured by higher order statistical approaches. Fourth, results from dynamical systems modeling of emotion show that the way in which emotional experiences change in time reveals meaningful causal relationship among properties of emotional life that can be altered due to mental health disorders. In the context of clinical science, it is feasible to use each one of the methods described in the three chapters as part of the diagnostic procedure to better understand the issues that are ailing people with depression. For instance, it would be feasible to sample the experiences of patients and use structural and dynamic properties of their emotional life to advise better therapeutic approaches.

Over the years, there has been substantial progress in psychotherapy research which offered new treatments and supporting evidence for their success. However, we still cannot provide a causal and mechanistic explanation of how some of the best studied interventions produce change. As research proceeds towards identifying the causal mechanisms that subtend various mental disorders and their treatments, it is essential that concepts such as emotional differentiation, emotion regulation and resilience are

operationalized accurately and comprehensively. This is essential because, ultimately, when one evaluates how change comes about, research has to look at mediators. In order to do this, researchers have to be able to operationalize and quantitatively represent multiple aspects of an emotional disorder. For instance, to draw an example from a different field, if smoking behavior is not considered, it might seem that there is a relationship between alcohol and lung cancer, where in fact the true cause of lung cancer is smoking and alcohol use is merely correlated with it. As we proceed towards understanding the mechanisms underlying mental health disorders it is essential that we consider the mediating role of all aspects of human emotional experience.

In the case of mental health, we are still scratching the surface of properly diagnosing properties of momentary emotional experience as well as its change over time. In this dissertation, we introduce two new approaches that offer more comprehensive characterizations of emotional differentiation, regulation and resilience. These new measures of emotional life will be used to populate a dashboard of diagnostics of emotional life which will help identify and characterize the best possible treatment for a particular individual.

Since existing theories of Major Depressive Disorder are not operationalized with the specificity that our methods provide, we can only speculate about which theory best explains our results. Our results on emotional differentiation expand on Beck's Cognitive Theory of Depression. The notion that there are belief themes or "schemas" that dominate depressed people's thinking is consonant with our results. Specifically, the belief themes that are related to our emotional differentiation results are depressed individuals' beliefs that they are defective or inadequate and that all of their experiences result in defeats or

failures. This kind of generalization can make it difficult to have differentiated negative emotional experiences and might complicate experiences of happiness. Our results on emotion regulation are also consonant with and expand upon Beck's Cognitive Theory of Depression. Specifically, our dynamical systems modeling approach can provide a more granular and accurate representation of one element of the Negative Cognitive Triad proposed by Beck, hopelessness.

It is well known that human emotional life is complex and difficult to operationalize. It is our long-term mission to develop and validate as many diagnostic measures of the structure and dynamics of emotional experience as is possible. A fighter jet, which is orders of magnitude less complex than the subjective experience of emotion, has a cockpit filled with hundreds of diagnostic tools and numerous controls. These tools describe properties of the device and the environment in terms of numbers. The pilot has a chance to understand the state of the fighter jet and the environment by observing all of these values and acting accordingly. Similarly, an individual or a clinician should have the means to quantify properties of their emotional experience. In this dissertation, we introduced two new such measures which reveal properties of the structure and dynamics of emotional experience respectively. We intend to pioneer a future in which people have the chance to observe themselves or their patients using a number of diagnostic criteria. To this end, we intend to validate the utility of our methods using larger datasets which represent groups with varying characteristics such as mental health status, age, culture. We also intend to identify properties of emotional life that are not altered due to such individual differences. Additionally, we intend to investigate the role of canonical and important cognitive mechanisms such as working memory and attention in human

emotional life. Currently, we have access to a large number of participants for whom experience-sampling data have been collected at the Interdisciplinary Affective Science Lab under the supervision of Dr. Lisa Feldman Barrett. We intend to begin by analyzing those datasets to further validate our methods and identify the role of individual differences on structural and dynamic properties of emotional life.

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