

Psychometric Properties of State Emotion Appraisal and Real-Time Associations with Emotion
Regulation

Madison Claire Feil

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2022

Reading Committee:

Kevin M. King, Chair

Liliana Lengua

Christine Lee

Program Authorized to Offer Degree:

Psychology

©Copyright 2022

Madison Claire Feil

University of Washington

Abstract

Psychometric Properties of State Emotion Appraisals and Real-Time Associations with Emotion
Regulation

Madison Claire Feil

Chair of the Supervisory Committee:

Kevin M. King

Department of Psychology

A primary function of emotion is to motivate behavior and dysregulated emotion-behavior associations are central to many theories of psychopathology. Despite robust between-person associations between emotional and behavioral disturbances, results from studies examining state-level associations between real-life emotion and behavioral outcomes have been more mixed. Recent conceptualizations of emotion processes suggest that an individual's *interpretation* of their emotion state influences their behavioral responses: a phenomenon that has been studied primarily within the framework of trait-like *emotion beliefs*. Emotion beliefs are thought to manifest in the moment as emotion appraisals that drive emotion regulation motivation and direct strategy selection. However, these state-level emotion appraisals are not well understood and many of these process-level hypotheses have not been tested in an ecologically valid context.

The current study sought to address these gaps by providing preliminary psychometric information on measures of emotion regulation (ER) importance and ER self-efficacy appraisals, and by testing basic hypotheses as to how these appraisals impact regulatory behaviors in day-to-day life. 123 undergraduates (age 18-20) completed eight days of ecological momentary assessment (EMA) in which they were asked about their mood, emotion appraisals, and emotion regulation behaviors 5 times per day. Between- and within-person effects of momentary ER importance and self-efficacy appraisals on different emotion regulation outcomes were tested using multi-level Poisson and logistic regression models.

Results suggested that single-item EMA measures of ER importance and self-efficacy appraisals capture important between- and within-person variance, and that they relate to other measures at both the EMA and person-level average levels largely as expected. Momentary ER importance predicted an individual's typical levels of engagement and disengagement ER strategies, as well as momentary increases in the use of both. However, average levels of ER use were better explained by covariance with negative emotionality. Lower average ER self-efficacy appraisals were associated with the use of more disengagement ER across situations, though this effect was also better explained by covariance with negative emotionality. Momentary ER self-efficacy appraisals did not predict any ER outcomes, nor was there evidence of the proposed interaction between importance and self-efficacy appraisals.

These findings give support for process-oriented theories of emotion regulation that posit that ER importance appraisals are more proximal to emotion-motivated behaviors than the emotions themselves. However, I did not find support for the theory that momentary self-efficacy appraisals play a strong role in directing ER behaviors. Perhaps more importantly, the findings from this study demonstrate a valuable proof-of-concept for the integration of

momentary appraisals into EMA research on emotion-behavior associations. Further integration of these constructs into existing process models of psychopathology has the potential to meaningfully impact future research and intervention.

Contents

Chapter 1: Introduction.....	1
1.1 Beliefs about Emotion.....	2
1.2 Emotion Appraisals and Emotion Regulation.....	4
1.3 Emotion-Behavior Associations in EMA	6
1.4 Dissertation Aims and Hypotheses	7
Chapter 2: Methods.....	13
2.1 Participants.....	13
2.2 Procedure	13
2.3 Measures	14
Chapter 3: Results.....	18
3.1 Psychometric Properties of Momentary Emotion Appraisals.....	18
3.2 Emotion Appraisals Predicting ER Behaviors: Analytic Approach	31
3.3. H1 Results: ER importance predicting total ER use, controlling for negative affect	34
3.4 H2 Results: Emotion Appraisals Predicting Disengagement and Engagement ER.....	41
3.5 Exploratory Analyses Results: Emotion appraisals predicting specific ER strategies	46
Chapter 4: Discussion	50
4.1 Psychometric Properties of Momentary Appraisal Items	51
4.2 ER Importance and Regulatory Behaviors	54

4.5 Limitations and Future Directions	61
4.6 Strengths, Clinical Implications, and Conclusions	65
5. References.....	67
Appendix 1.....	81
Appendix 2.....	82
Appendix 3.....	83

Chapter 1: Introduction

Emotion researchers generally agree that a primary function of emotion is to direct behavior (Barrett et al., 2007; Ekman, 1999; Izard, 2010; Kuppens, 2019; Sander et al., 2018; Smith & Lane, 2015). Emotions communicate information about the current situation, its relevance to the individual, and what outcomes are possible and likely. Ideally, this helps direct behavior that will be advantageous to the individual. Unfortunately, emotions can also lead to behaviors that are not advantageous, both in the short and long term. Psychological disorders are often characterized by a mixture of emotional and behavioral dysregulation, and the premise that intense and overwhelming emotional experiences precipitate problematic behaviors is pervasive within theories of psychopathology (Carver et al., 2017; Johnson-Laird et al., 2006; Werner & Gross, 2010). Importantly, many of these theories are process-oriented, meaning that emotional experiences in the moment are thought to lead *directly* to behavioral responses that are maladaptive in the long-run. Examples of these theories within specific disorders include the role of avoidance in maintaining depression and anxiety (Chawla & Ostafin, 2007; Hayes et al., 1996), tension-reduction and affect-regulation theories of alcohol abuse (Greeley & Oei, 1999; Sher & Grekin, 2007), and negative affect regulation theories of non-suicidal self-injury (Klonsky, 2007) and disordered eating (Haedt-Matt & Keel, 2011; Haynos & Fruzzetti, 2011). A key aspect of these theories is that the clinically relevant behavior is not thought to be a by-product of generalized dysregulation in response to emotion, but instead a *motivated* behavior intended to reduce the experience of an unwanted emotion or feeling. Thus, emotion regulation processes are central to many clinical theories of psychopathology. If emotional experiences can lead to either adaptive or maladaptive responses, what factors determine which response will occur?

Current theories posit that emotions prompts behavior on multiple levels, from those that are more automatic and stereotyped to those that are motivated by slower-forming appraisals of the situation at hand (Izard, 2007; Kuppens, 2019; Sander et al., 2018; Smith & Lane, 2015). There are also thought to be behaviors generated by appraisals of the emotion state *itself*. For example, constructionist approaches to emotion hypothesize that emotion states motivate behavior in part by activating *emotion concepts* that, when integrated with contextual information, provide predictions about possible behaviors and likely outcomes (Barrett et al., 2007; Edwards & Wupperman, 2019; Smith & Lane, 2015). Conceptually, behaviors motivated by emotion concepts and beliefs follow *after* the conscious, semantic representation of the emotion. (Ford & Gross, 2019; Manser et al., 2012). To date, these emotion-relevant cogitations have been primarily studied at the trait level in the form of ‘emotion beliefs.’ The measurement of their momentary form - emotion appraisals - has been largely absent from the process-level study of emotion and behavioral response, despite appraisals being a strong candidate for the component of emotion most directly related to deliberate behavioral responses. This study seeks to demonstrate the use of two emotion appraisal items within an ecological momentary assessment (EMA) study, describe the basic psychometric properties of these novel items, and test basic process-oriented hypotheses about the role of emotion appraisals in motivating regulatory behaviors.

1.1 Beliefs about Emotion

There is an expanding literature dedicated to the importance of beliefs about emotions, and how they differentially motivate behavioral responses (Edwards & Wupperman, 2019; Ford & Gross, 2019; Leahy, 2002; Manser et al., 2012; Tamir & Gutentag, 2017). Emotion beliefs include concepts about the desirability, utility, appropriateness, and malleability of different

emotions, as well as the likely outcomes and appropriate behavioral responses for different emotions in different situations. Though there are many types of beliefs any one individual might hold about emotions, there are two broad dimensions that encapsulate most of the research that has been done in this domain thus far: emotion valuation beliefs, and emotion malleability beliefs (Ford & Gross, 2019).

Emotion valuation beliefs, which have been studied under a variety of names, broadly refer to beliefs about the desirability of a certain emotion, or emotions in general (Bartsch et al., 2008; Gottman et al., 1996; Kämpfe & Mitte, 2009; Maio & Esses, 2001; Simons & Gaher, 2005; Tsai, 2017; Williams et al., 1997). Proposed dimensions of emotion valuation include hedonic value, tolerability, utility, appropriateness, and meaningfulness (Luong et al., 2016; Manser et al., 2012). Emotion valuation beliefs differ by age, gender, personality, and culture – and within person they vary by situation (see De Vaus et al., 2018 and Tamir & Gutentag, 2017 for two reviews). Beliefs that emotions are undesirable tend to be associated with poorer mental health, including less happiness and social support (Karnaze & Levine, 2018) and more depressive symptoms (Yoon et al., 2018). These beliefs can also be situation-specific in that certain emotions are believed to be valuable in achieving specific goals. For example, athletes desire to feel angry when they believe anger will improve their performance (Lane et al., 2011), and people find sadness desirable when it is shared by a group they are affiliated with (Porat et al., 2016). If believed to be useful to reach a goal or appropriate given the situation, even ‘negative’ emotions can be positively valued. Further, the perception of contextual value can have real impact on whether the emotion motivates regulation attempts, and toward which emotion goals (Tamir & Ford, 2009, 2012). Thus, emotion valuation beliefs generally convey information about whether or not an emotion should be acted on.

Emotion malleability beliefs refer broadly to beliefs about whether emotional experiences are changeable – either in general (implicit beliefs about emotion: Dweck et al., 1995; Tamir et al., 2007), or specifically by oneself (emotion-regulation self-efficacy: Bandura et al., 2003). Individuals who believe that emotions are relatively less malleable have generally poorer well-being (De Castella et al., 2018a; King & dela Rosa, 2019), have decreased emotion-regulation self-efficacy (De Castella et al., 2018a; Tamir et al., 2007) and higher levels of stress and depression (De Castella et al., 2013; Ford et al., 2018). Beliefs that emotions are relatively unchangeable prospectively predicted more negative emotions, fewer positive emotions, and a decreasing trajectory of emotional support over the first term of college (Tamir et al., 2007).

In summary, both emotion valuation and emotion malleability beliefs are associated with psychological wellbeing at the trait level: the more an individual believes emotions to be valuable, useful, and under their control, the better their psychological health.

1.2 Emotion Appraisals and Emotion Regulation

One theory of how emotion beliefs create risk for psychopathology is by biasing reactions to negative emotions towards relatively more maladaptive responses. For example, if someone holds the belief that anxiety is intolerable and relatively unchangeable, they may be motivated to respond to anxiety by withdrawing from the situation and avoiding future situation in which anxiety may occur. In contrast, someone who believes anxiety is appropriate and malleable may be more likely to respond with acceptance or reappraisal.

Beliefs about emotions are thought to influence behavior by impacting multiple stages of emotion regulation (ER: Ford & Gross, 2019). So far, the main point of interaction that has been studied is between emotion beliefs and ER strategy selection. ER strategies include both those that seek to reduce the emotion via engagement with the emotion or situation (e.g. reappraisal,

problem-solving, acceptance) and those that seek to reduce the emotion via disengagement (e.g. avoidance, distraction, suppression) (Gross, 2015). Disengagement strategy use is associated with generally worse psychosocial outcomes (Aldao et al., 2010). Therefore, many have speculated that beliefs about emotion impact the relative selection of disengagement strategies over engagement strategies, which in turn creates risk for poorer mental health (De Castella et al., 2013, 2018a; Ford et al., 2018; Ford & Gross, 2019; Kneeland et al., 2020; Ortner & Pennekamp, 2020). There has been some support for this idea at the between-person level using global self-report of both beliefs and emotion regulation: people with low malleability beliefs report less cognitive reappraisal, (De Castella et al., 2013; Ford et al., 2018; King & dela Rosa, 2019; Kneeland et al., 2020; Ortner & Pennekamp, 2020; Tamir et al., 2007), and higher levels of emotional and cognitive avoidance (De Castella et al., 2018a; Moumne et al., 2020; Ortner & Pennekamp, 2020).

But how exactly do *beliefs*, which are conceptualized as trait-like attributes, exert their influence on emotion regulation and behavioral outcomes at the *momentary* level? In theory, beliefs should manifest as specific appraisals and motivations in response to real-life emotion (Ford & Gross, 2019). For example, a negative valuation belief about anger should manifest in response to an experience of anger as an *appraisal* of undesirability. In the current study, we use the phrasing “How important is it for you to control, fix or change your mood right now?” to measure momentary valuation appraisal. Though this single item likely does not provide full coverage of all momentary appraisals related to valuation beliefs, it reflects a combination of dissatisfaction with current mood and implied desire to change current mood, without referencing motivation to engage in regulatory behaviors explicitly. For the remainder of this

paper, I'll refer to our momentary measure of emotion valuation appraisal as 'ER importance' to reflect the wording we chose to use most clearly.

Emotion malleability beliefs should similarly manifest as momentary malleability appraisals. For example, the belief that fear is not malleable should manifest in response to an experience of fear as the *prediction* that the emotion will remain unchanged. In response to an emotion state, malleability beliefs should theoretically manifest as malleability appraisals; cognitions about whether that emotion state is changeable or not in the current context. In this study, we use the phrasing "If you wanted to, how well do you think you could control, fix or change your mood right now?" to measure momentary malleability appraisal. Again, this single item may not fully capture all momentary appraisals related to malleability beliefs. However, this item does reflect the individual's perception of their current ability to change their emotions. For the rest of this paper, I'll use the term 'ER self-efficacy' to refer to our measure of momentary emotion malleability appraisal.

It is these momentary appraisals of emotions that are thought to direct subsequent emotion regulation. By translating these trait-level beliefs into momentary-level measures reflecting related cognitions, we open the door to exploring the functional role of these cognitions in directing behavior and creating risk for psychopathology. To test these process-oriented hypotheses, it is important to examine how emotion appraisals impact behavior in real life, instead of relying solely on cross-sectional studies or constrained experimental paradigms. Ecological momentary assessment (EMA) methods are particularly well suited to this task.

1.3 Emotion-Behavior Associations in EMA

The emergence of technology that allows researchers to sample from daily life frequently and with minimal intrusion has opened many doors to observing temporal relations between

dimensions of emotion and behavior (Shiffman et al., 2008; Trull & Ebner-Priemer, 2014). This family of research methods, commonly referred to as ecological momentary assessment (EMA), experience sampling methods, or ambulatory assessment, has given researchers a window into how emotion processes unfold in day-to-day life. As a result, there is a growing body of work on emotion regulation measured in EMA, including studies looking at antecedents and consequences of different regulatory behaviors (Bylsma & Rottenberg, 2011; Colombo et al., 2020). Within EMA research, self-report of either broad affective dimensions (such as positive and negative affect, arousal, or appraisal dimensions) and discrete emotion terms (such as fear, shame, anger, etc.) remain the predominant method for measuring emotion (Mauss & Robinson, 2009; Robinson & Clore, 2002). The investigation of emotion-behavior associations using EMA methods is still a relatively new line of inquiry which thus far has been promising but limited in its ability to illuminate complex interactions. One limitation of the current work on emotion-behavior associations in EMA may be that the measurement of state-level emotion constructs ends at the level of emotion identification, and thus has limited ability to describe processes that unfold between the recognition of an emotion state and the enacting of emotion-motivated behaviors. Because emotion appraisals theoretically *follow* emotion identification (Smith & Lane, 2015), it is imperative that researchers interested in how emotions impact behavior integrate appraisal processes into their models.

1.4 Dissertation Aims and Hypotheses

The current study seeks to address gaps in the literature on emotion-behavior associations by providing preliminary psychometric information on EMA measures of emotion valuation and malleability appraisals, by testing hypotheses as to how emotion appraisals impact emotion regulation and behavior in day-to-day life, and by providing exploratory tests in hopes of

generating future hypotheses in this domain. Below I describe the limited existing research on momentary emotion appraisals and the rationale for the hypotheses I put forth.

1.4.1 Aim 1: Describe the psychometric properties of novel measures of emotion valuation and malleability appraisals.

The study of state-level emotion appraisals is in its infancy. My review of the literature found only two studies which measured emotional appraisals in response to real-life experiences of emotion (Daros et al., 2020; Veilleux et al., 2018), both which measured some dimension of valuation, and none that measured malleability appraisals. There is a clear need for an understanding of how to measure these appraisals using EMA methods, and what exactly is being measured when we ask about current emotion appraisals. This is particularly important considering that global self-report measures cannot be assumed to capture momentary processes (Fisher et al., 2018; Grice et al., 2015; Kazdin, 2007; Nock, 2007).

In response to this need, the first aim of the current study is to describe the psychometric properties of two novel items designed to measure emotion appraisals in EMA. In particular, I will describe how two ER importance and ER self-efficacy appraisals relate to each other, and to other concurrent measures of emotion and behavior both within- and between-person. Though this aim will be primarily exploratory, I have some hypotheses of how these items should relate to other measures based on previous research on emotion beliefs and my theoretical understanding of the constructs.

At the momentary level, I expect ER importance to be generally related to those aspects of emotion most stereotypically thought to be ‘undesirable.’ Research suggests that in the United States, higher-energy, positive-valenced emotions are generally viewed as most desirable (Tsai, 2007). Thus, I expect that ER importance will be related to higher negative affect, lower positive

affect, and lower arousal states. Because higher-intensity and more ‘negative’ emotional experiences may be perceived as more difficult to change, I expect that higher ER self-efficacy will have the opposite pattern – being correlated with higher positive affect and lower negative affect. However, I expect that ER self-efficacy will be less strongly associated with other emotion components than ER importance is, given that ER importance is conceptually more directly related to the experience of negative affect. As an extension of this, I also expect that ER importance and ER self-efficacy will only be weakly correlated with each other.

As for correlations between emotion appraisals and behaviors occurring during the subsequent assessment period, I expect that ER importance will be correlated with total ER use and increased impulsivity across facets. I expect that ER self-efficacy will be correlated with the decreased disengagement and increased engagement ER strategies, and lower impulsivity across facets.

I generally expect that correlations between emotion appraisal tendencies (appraisals averaged over the EMA period) and other trait-level constructs will follow associations demonstrated in between-person studies of emotion beliefs. Both high average ER importance and low average ER self-efficacy should be related to negative emotionality, the use of maladaptive ER strategies, increased impulsivity, and poorer mental health outcomes.

1.4.2. Aim 2: Test the prospective impact of emotion appraisals on ER strategy selection as predicted by theories of emotion beliefs

The second aim of the current study is to test basic process-oriented hypotheses of how emotion appraisals impact regulatory behaviors. To begin, I will test the hypothesis that ER importance is a more direct predictor of emotion-motivated behaviors than affect alone. If emotion appraisals drive the individual toward specific regulatory responses, then the appraisal

of whether the current emotion state is contextually desirable is the metaphorical ‘gas pedal’ – determining first and foremost whether the emotion *needs* to be regulated (Ford & Gross, 2019). Tamir & Ford (2009, 2012) found preliminary evidence for this experimentally by showing that people who expected either anger or fear to be useful to them were motivated to increase those emotions selectively. In short, desire to experience an emotion, and conversely to *not* experience one, should promote goal-congruent regulatory responses. There is also preliminary support for this hypothesis from two studies that measured valuation appraisals using EMA. Veilleux et al., (2018) found that average distress intolerance (the appraisal that the current emotion cannot be tolerated) as measured via EMA was correlated with self-report of disengagement strategies but uncorrelated with the use of engagement strategies. Unfortunately they did not report on the association of momentary distress intolerance on concurrent emotion regulation, so it is not possible to conclude whether higher distress intolerance directly predicted the use of disengagement coping. Daros et al., (2020) assessed the momentary association between emotion valuation and regulation attempts more directly. At the momentary level, desire to change emotion was correlated with negative affect at $r = .63$ and was weakly correlated with both concurrent avoidant ($r = .26$) and engagement strategies ($r = .22$). From this small number of studies, it is unclear whether valuation appraisals are likely to promote an increase in all ER strategies, or specifically disengagement strategies. These results may also be influenced by the specific type of valuation measured – since an emotion being appraised as intolerable may promote more disengagement than the broader appraisal that the emotion should be changed. Because the item used in the current study refers to the broad importance of changing the current emotion state, my first hypothesis (*H1*) is that *ER importance will predict the total number of ER strategies used during the following assessment period, and that this effect will be significant*

over and above the effects of negative affect. The inclusion of concurrent negative affect in this analysis will serve to demonstrate whether ER importance has predictive strength in addition to what may be a considerable amount of shared variance with the experience of negative affect. If ER importance is functionally ‘the same’ as negative affect, it may not in fact be a useful construct in the context of emotion-behavior EMA research.

On the metaphorical road to regulatory behaviors, if ER importance is the gas-pedal, malleability appraisals are hypothesized to be the steering-wheel – directing the individual toward specific regulatory behaviors that they believe will be effective for reaching their emotion goals. This theory has been supported by trait-level studies that found that people with low malleability beliefs report less cognitive reappraisal, (De Castella et al., 2013; Ford et al., 2018; King & dela Rosa, 2019; Kneeland et al., 2020; Ortner & Pennekamp, 2020; Tamir et al., 2007), and higher levels of emotional and cognitive avoidance (De Castella et al., 2018a; Moumne et al., 2020; Ortner & Pennekamp, 2020). These between-person results suggest that individuals who believe emotions to be relatively unchangeable are more likely to use strategies that seek to regulate the emotion via disengagement versus those that seek to change the emotion or situation directly. This idea has found some support in experimental studies as well. For example, De Castella et al., (2018) found that people who were led to believe they were worse at ER were more likely to avoid future situations that could be potentially emotionally distressing. Similarly, Kneeland et al., (2016a, 2016b) found that individuals who were primed with low malleability beliefs engaged in less perspective-taking following a negative mood induction, and less reappraisal after an anxiety-producing speech task. However, there were no differences in rumination, reappraisal, or positive refocus in the former study, or in suppression in the latter.

Interestingly, participants who were primed with low malleability beliefs were *more* likely to use acceptance (Kneeland et al., 2016b).

Believing emotions aren't malleable may increase disengagement strategy use because the emotion has been appraised as unlikely to change through more direct methods. Notably, these studies all used laboratory-induced negative affect and measured ER strategies within a constrained setting (i.e., many naturalistic ER approaches were not available to participants). They also didn't measure concurrent desire to change their emotion state; it was assumed that individuals would be motivated to down-regulate negative emotions. This is a limitation of these studies because it is theoretically possible to appraise your current emotion state as malleable but not *want* to change it. Essentially: you can turn the steering wheel all you want, but you're only going to get somewhere if the gas pedal is down. Therefore, my second hypothesis (*H2*) is *that higher momentary ER self-efficacy will predict the use of more engagement strategies and fewer disengagement strategies. I also predict that there will be an interaction of these effects with ER importance such that they are only present when there is a desire to change the current mood.*

1.4.3 Aim 3: Exploratory tests of the effects of emotion appraisals on specific ER strategies

Emotion regulation strategies differ from one another in more ways than what is captured by the dimensions of engagement vs. disengagement. For example, some are more cognitive (reappraisal and rumination) whereas others are more explicitly behavioral (problem-solving and distraction) (Garnefski et al., 2001). Relevant to the current study, some approaches attempt to regulate the experience of emotion by changing appraisals of the situation or the emotion itself. The best examples of this are the strategies reappraisal and acceptance. In particular, acceptance may actually function to reduce ER importance via reappraisal of the emotion as 'neutral,' and the use of acceptance has been associated with lower malleability beliefs (Kneeland et al.,

2016b). Since each emotion regulation strategy has unique features, it's possible that emotion appraisals have unique effects on ER strategies within the categories of engagement and disengagement. The study of state emotion appraisals is nascent enough that hypotheses about how they are likely to impact specific ER strategies are lacking, though this type of specificity would be valuable. To contribute to the future development of such hypotheses, I will perform a set of exploratory analyses testing the main effects and the interaction effect of ER importance and self-efficacy appraisals on the likelihood of seven specific ER strategies (acceptance, problem-solving, rumination, reframing, avoidance, distraction, and suppression) being used during the following assessment period.

Chapter 2: Methods

2.1 Participants

Participants (n= 123) in this study were students enrolled in introductory psychology courses at the University of Washington. All participants in the university's Psychology Subject Pool were invited to complete a general screening survey. Those who took the survey and were between the ages of 18–20 at the time of screening, were born in the US or moved there before the age of 12, and reported at least weekly alcohol or marijuana were invited to participate in this study. The final sample was 65% female and 53% white, 25% Asian, and 22% other race/ethnicity. The mean age was 19.2. Participants were compensated in course extra credit in proportion to the number of surveys they completed.

2.2 Procedure

All study procedures were approved by the University of Washington's Institutional Review Board. Eligible participants were invited to attend an initial in-lab orientation during

which they completed computerized baseline assessments and were trained on the EMA protocol. The participant's EMA session began the Thursday after their in-lab orientation and ran for two consecutive weekends (Thursday-Sunday), for a total of eight days of data collection and 40 possible EMAs. On each of those days, participants received 5 brief surveys delivered through SMS with a link to a mobile-optimized Qualtrics survey. These surveys came randomly within 5 fixed windows between the times of 9am and 11pm, and never closer than one hour apart. Each EMA contained questions about recent emotion, affective appraisals, emotion regulation strategies, impulsive behavior, and situational factors. The morning survey included additional items about the previous day's alcohol and marijuana use. Participants were given 1 hour to complete each survey and received a reminder after 30 minutes if the survey was not complete. The average completion rate was 79% of EMAs, for a total of $n = 3903$ observations.

2.3 Measures

2.3.1 EMA measures

Emotion appraisals were measured using the items “How important is it for you to control, fix or change your mood *right now?*” reflecting ER importance and ‘If you wanted to, how well do you think you could control, fix or change your mood *right now?*’ reflecting ER self-efficacy, and Responses were recorded on a visual analogue slider scale from “not at all” to “completely,” with a central anchor of ‘somewhat.’ These scales were coded from 0 to 100 based on placement on the slider scale. See appendix 1 for how these items appear on a mobile phone.

Emotion regulation strategies were measured with seven items taken from a similar protocol designed by Tan et al. (2012) for a cell-phone EMA study of adolescents. These items were designed to assess six emotion regulation strategies commonly defined in the literature (acceptance, problem-solving, rumination, reappraisal, avoidance, and distraction) in language

that is child-friendly. For the current study, an item was added in the same style which assessed the use of suppression. Lastly, a ‘none of the above’ option was added. Participants were asked to select all strategies that they used ‘since the last assessment.’ See appendix 1 for how these items appear on a mobile phone. The variable **total ER use** will be calculated as a sum of the ER strategies reported at each EMA. The variable **disengagement ER use** will be calculated as a sum of the number of disengagement strategies (suppression, avoidance, and distraction) used. The variable **engagement ER** will be a sum of the unique engagement strategies (acceptance, problem-solving, and reappraisal) used since the last assessment. Rumination will not be included in either of these totals, as the wording of the item does not fit conceptually with either category.

Core affect dimensions were measured with two items based on the circumplex model of emotions (Russell, 1980) that ask participants to rate how pleasant they have felt in the past 10 minutes on a scale from ‘extremely pleasant’ to ‘extremely unpleasant,’ and how energetic they have felt on a scale from “extremely low-energy’ and ‘extremely high-energy,’ with central anchors of ‘neutral.’ These scales were coded from -50 to 50 based on placement on the slider scale, with 0 representing ‘neutral.’

Discrete emotions were measured by participants rating how much they felt specific negative (irritable, unhappy, anxious, angry, and bored) and positive emotions (cheerful, friendly, calm, happy, engaged) in the past 10 minutes with terminal anchors “not at all” and “very much,” and a central anchor of ‘somewhat’. We selected emotion words to reflect multiple dimensions of negative and positive affect, based on the PANAS-X and other prior work (Larson & Lampman-Petratis, 1989; Silk et al., 2003). The variables **negative affect** and **positive affect** were generated by averaging each set of items within the same assessment.

Impulsive behaviors (planning, persistence and acting on impulse) were measured with items adapted from the UPPS (Whiteside & Lynam, 2001), with item stems changed to reflect behavior “since the last assessment.” Acting on impulse items were adapted from UPPS urgency items to be free of emotional content (i.e., “I had trouble controlling my impulses”) such that they only reflect the acting on impulse aspect of urgency. Planning items were adapted from UPPS global self-report of planning, such as “I thought carefully before doing anything”. Persistence items were adapted from UPPS global self-report of persistence, such as “I saw things through to the end.” Participants rated their experiences on a visual analog scale ranging from 0 to 100 with terminal anchors “strongly disagree” and “strongly agree” and a central anchor of ‘neither agree nor disagree’. At each assessment, 3 items from each subscale were randomly administered to subjects to reduce response burden. Scale means were computed for each impulsive trait within each observation (Halvorson et al., 2019).

Person-level EMA averages were calculated for all EMA items as simple means of the values reported at all EMA assessments.

2.3.2 Global self-report measures of convergent and criterion validity

Emotional Reactivity was measured using the Emotional Reactivity Scale (ERS; Nock et al., 2008). The ERS is a 21-item self-report measure designed to assess individuals’ experience of emotion reactivity. It asks respondents to rate how much statements sound like them on a 5-point Likert scale from “not at all like me” to “completely like me.” The subscales of the ERS are emotion sensitivity (ex. “my feelings get hurt easily”, intensity (ex. “when I experience emotions, I feel them very strongly/intensely”), and persistence (ex. “when something happens that upsets me, it’s all I can think about for a long time”). The subscales show good internal consistency, with alphas ranging from .81 to .88 (Nock et al., 2008).

Cognitive Emotion Regulation was measured using the 36-items Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2001), which measures what individuals generally think when experiencing negative or unpleasant events on a five-point Likert scale from “almost never” (1) to “almost always” (5). The CERQ includes the subscales **self-blame** (ex. “I feel that I am the one to blame for it”), **other-blame** (ex. “I feel that others are to blame for it?”), **rumination** (“I often think about how I feel about what I have experienced”), **catastrophizing** (ex. “I keep thinking about how terrible it is what I have experienced”), **perspective-taking** (ex. “I think that other people go through much worse experiences”), **positive refocusing** (ex. I think of pleasant things that have nothing to do with it), **positive reappraisal** (ex. “I think that I can become a stronger person as a result of what has happened”), **acceptance** (ex. I think that I have to accept the situation”), and **refocus on planning** (ex. “I think about how I can best cope with the situation”) The subscales are calculated by taking a mean of the comprising item and have acceptable internal validity with alphas between .66 and .81 (Garnefski et al., 2001).

Trait Impulsivity will be assessed with the **urgency, planning, and persistence** subscales of the UPPS-P (Whiteside & Lynam, 2001). Analyses will use a mean value of responses to these items, which are rated on a four-point Likert scale ranging from “strongly agree” (1) to “strongly disagree” (4). Subscales have demonstrated good reliability ($\alpha = 0.83 - 0.89$).

Anxiety, Depression, and Anger were measured using Patient-Recorded Outcomes Measurement Information System (PROMIS) short form scales for fear (29 items ex. “I felt something awful would happen”), depression (28 items ex. “I felt that my life was empty”), and anger (22 items, ex. “I was irritated more than people knew”). Participants were asked to rate the

frequency of items in the past 7 days on a 5-point Likert scale from “never” to “always.” For these scales, I will compute a mean score, then convert it to t-scores based on published norms (available at <http://healthmeasures.net>).

Chapter 3: Results

All descriptive statistics and analyses were generated using R (R Core Team, 2020). All multi-level linear and logistic regression analyses were conducted using the package ‘lme4’ (Bates et al., 2015) and all count models were conducted using the package ‘glmmTMB’ (Brooks et al., 2017). For ease of reading, the rationale for each analysis, general analytic approach, and results are presented together for each set of analyses.

3.1 Psychometric Properties of Momentary Emotion Appraisals

The two appraisal items used in the current study to measure emotion appraisals were written for use in the present study based on a theoretical understanding of emotion appraisals. Because they are single items, measures of inter-scale reliability are not relevant. Instead, I aim to describe features of these items within- and between-person and to place these appraisals within the nomothetic network of other common measures of emotion and theoretically related outcomes.

3.1.1 Descriptive Statistics

Table 1 shows means and standard deviations for key study variables at both the momentary and person-level average level. For descriptive statistics of all study variables, see the complete table in appendix 2.

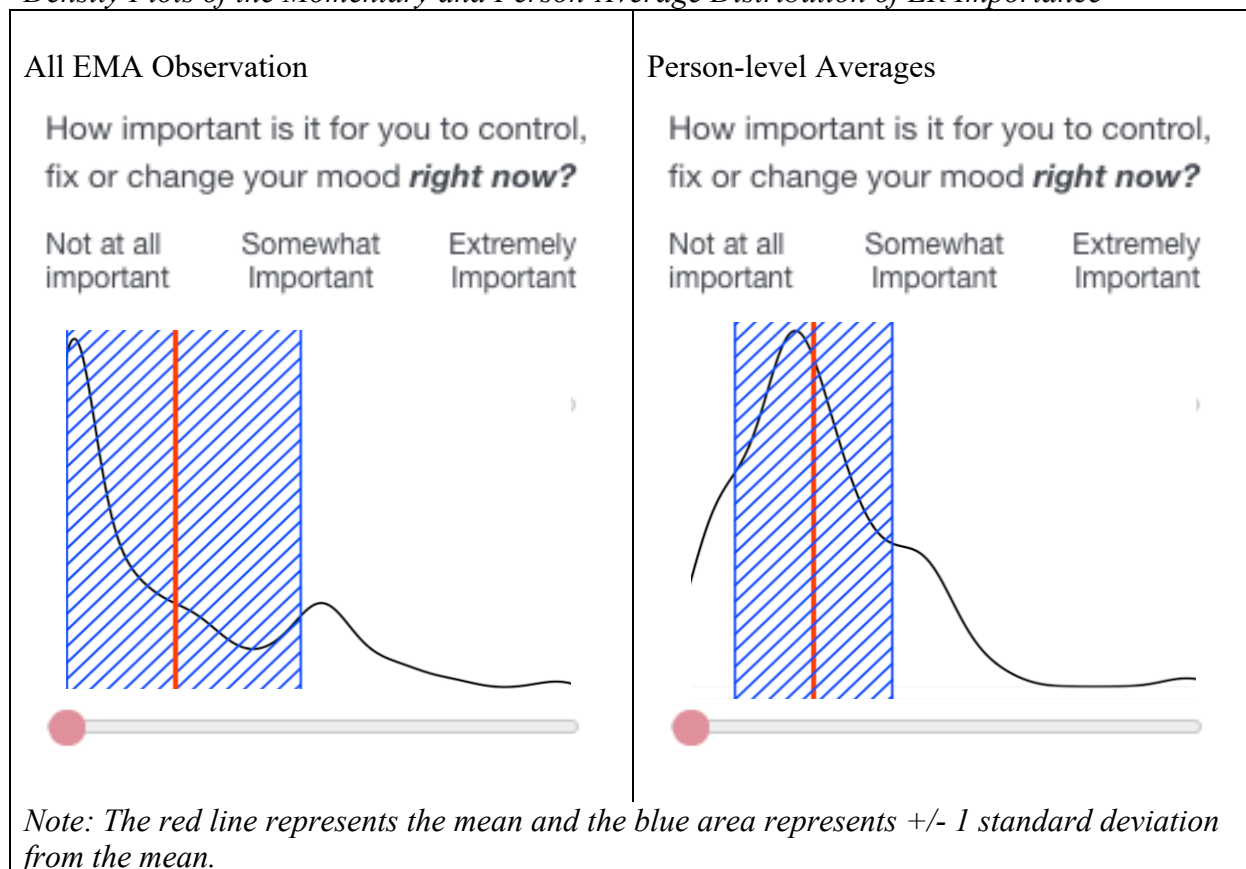
Table 1
Descriptive Statistics for Primary Study Variables

	<i>Ecological Momentary Assessment</i>		<i>Person-Level EMA Average</i>	
	Mean	SD	Mean	SD
ER Importance	21.68	25.01	22.02	14.66
ER Self-Efficacy	56.54	27.38	55.46	18.5
Negative Affect	13.2	15.28	14.14	10.43
Total ER	0.74	1.08	0.78	0.64
Engagement ER	0.37	0.64	0.39	0.35
Disengagement ER	0.26	0.59	0.27	0.27

ER Importance. The average participant in our study had a mean ER importance of 22 out of 100 – or roughly half-way between the labels ‘not at all important-’ and ‘somewhat important-’ to ‘control, fix, or change your current mood’ on our visual analogue slider scales. This person-level average had a standard deviation of +/- 15 within our sample. The average within-person standard deviation of ER importance was 19, the between-person standard deviation of which was 8. This is visualized in the context of our visual analogue scale in Figure 1.

Figure 1

Density Plots of the Momentary and Person-Average Distribution of ER Importance



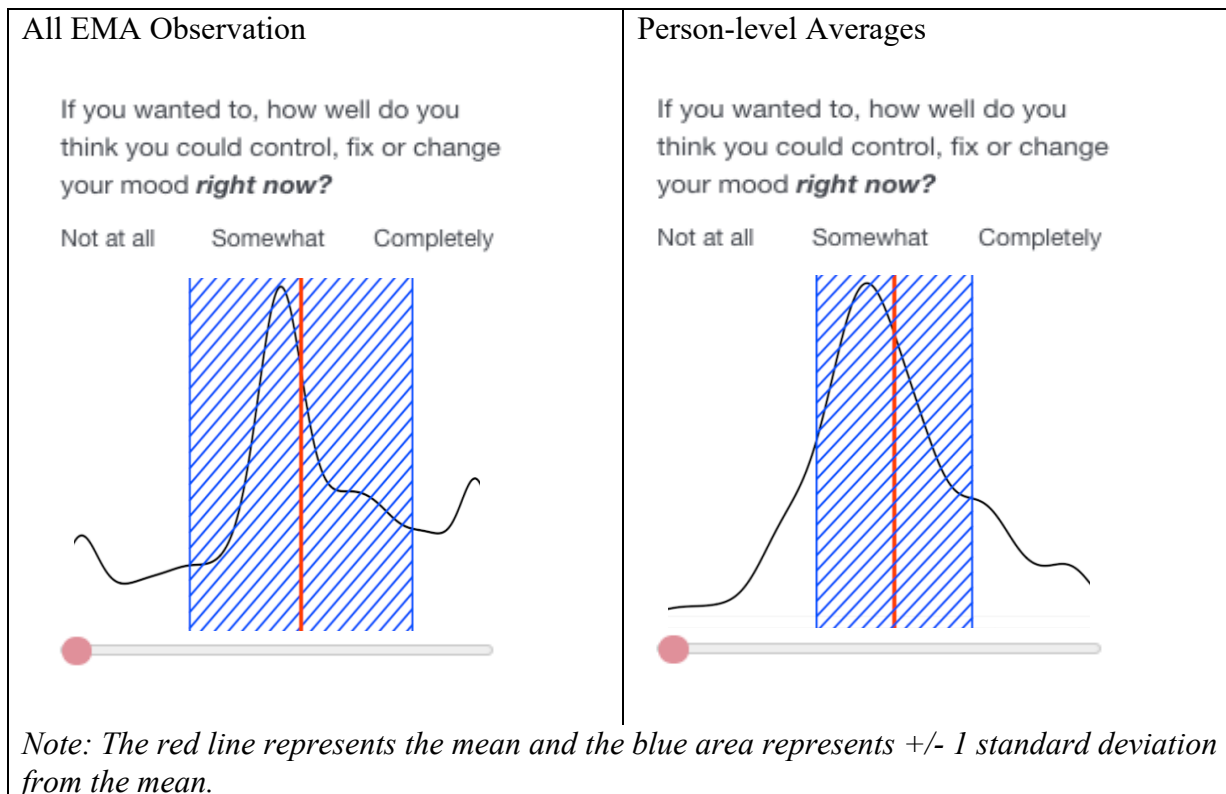
To summarize, the average participant in our study would report feeling little to no motivation to change their current emotion on a typical observation. On the majority of their assessments, their reported ER importance would range between ‘not at all important’ and ‘somewhat important.’ However, 17% of total observations were in the range between ‘somewhat’ and ‘extremely important’ and 87% of participants had at least one observation in this range. The average participant in our study felt at least moderate desire to change their emotion at approximately 15% of observations.

ER Self-Efficacy. The average participant in our study had a mean ER self-efficacy of 56 out of 100 – or slightly higher than the label ‘somewhat’ in response to ‘how well do you think

you could control, fix, or change your current mood' on our visual analogue scales. This person-level average had a standard deviation of +/- 19 within our sample. The average within-person standard deviation of ER importance was 19, the between-person standard deviation of which was 8. This is visualized in the context of our visual analogue scale in Figure 2. To summarize, the average participant in our study would report believing they could control their current mood 'somewhat' well on a typical observation. On the majority of their assessments, their reported ER self-efficacy would range between 37 and 75 out of 100. However, 34% of total observations were in the range between 'not at all well' and 'somewhat well' 92% of participants had at least one observation in this range, and 76% had at least one observation below 25 (half-way between 'somewhat' and 'not at all well'). The average participant rated their ER self-efficacy in this lower quadrant on 13% of their observations.

Figure 2

Density Plots of the Momentary and Person-Average Distribution of ER Self-Efficacy



3.1.2 Measures of Variability in Emotion Appraisals

Intraclass Correlations. First, I calculated the relative between- and within-person variance in the two appraisal items by calculating their intraclass correlations – a simple ratio of the variance between individuals and the total variance. The resulting ICCs reflect the proportion of variance in each emotion appraisals that is due to differences in person-level appraisal tendencies (e.g., some people having generally more positive appraisals than others). The remainder of the variance can be ascribed to moment-to-moment fluctuations within individuals (both those that are meaningful, and those that represent error).

Based on the ICCs from the unconditional models, 32% of the variance in ER importance and 44% of the variance in ER self-efficacy was explained by person-level differences. The

remaining variance represents a combination of within-person variance and within-person error. This suggests that the majority of variance in these measures is at the momentary level, though there is substantial between-variance as well.

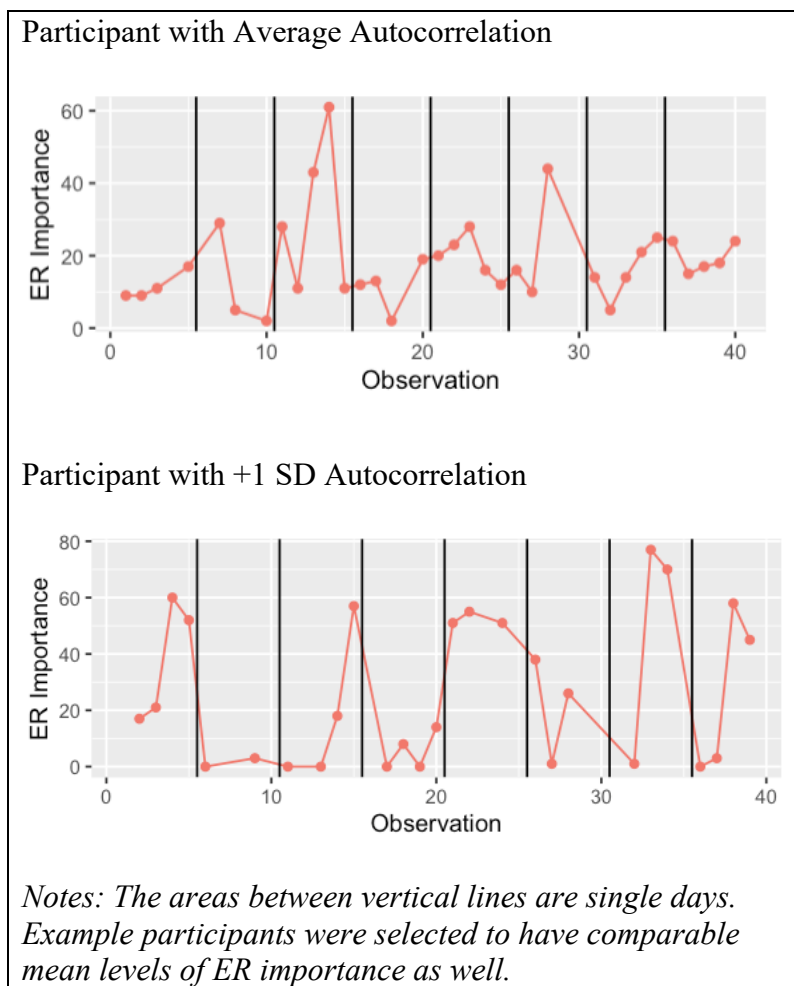
Temporal Dynamics of Appraisal Items. To describe temporal trends related to our sampling procedures, I ran multi-level linear regressions of *time of day* and *study day* predicting both emotion appraisal items. A significant effect of time of day would suggest daily trends in appraisal levels, and a significant effect of study day would suggest some level of reactivity in response to the repeated sampling procedures.

These models showed little evidence of meaningful temporal effects. There was no effect of time of day on either appraisal item. People reported slightly more ER importance as the study went on ($b = .34, p < .05$) and slightly less ER self-efficacy ($b = -.39, p < .05$). These magnitudes are extremely small in the context of our 0-100 scales, accounting for an average of approximately +/- 4 points on our 100-point scale when comparing the first day of the study to the last.

Autocorrelations – the correlation between a variable and itself at the next time point - has been proposed as a measure of ‘inertia’ or the tendency to remain in a given state over time (Hamaker & Wichers, 2017). To assess the relative stability of appraisals over time, I calculated within-person autocorrelations by lagging emotion appraisal reports onto the previous same-day report and calculating the correlation coefficient using all available observation pairs. I also calculated correlations between individual autocorrelations and individual mean levels of each appraisal dimension to see if an individual’s ‘inertia’ was related to their average level of appraisal.

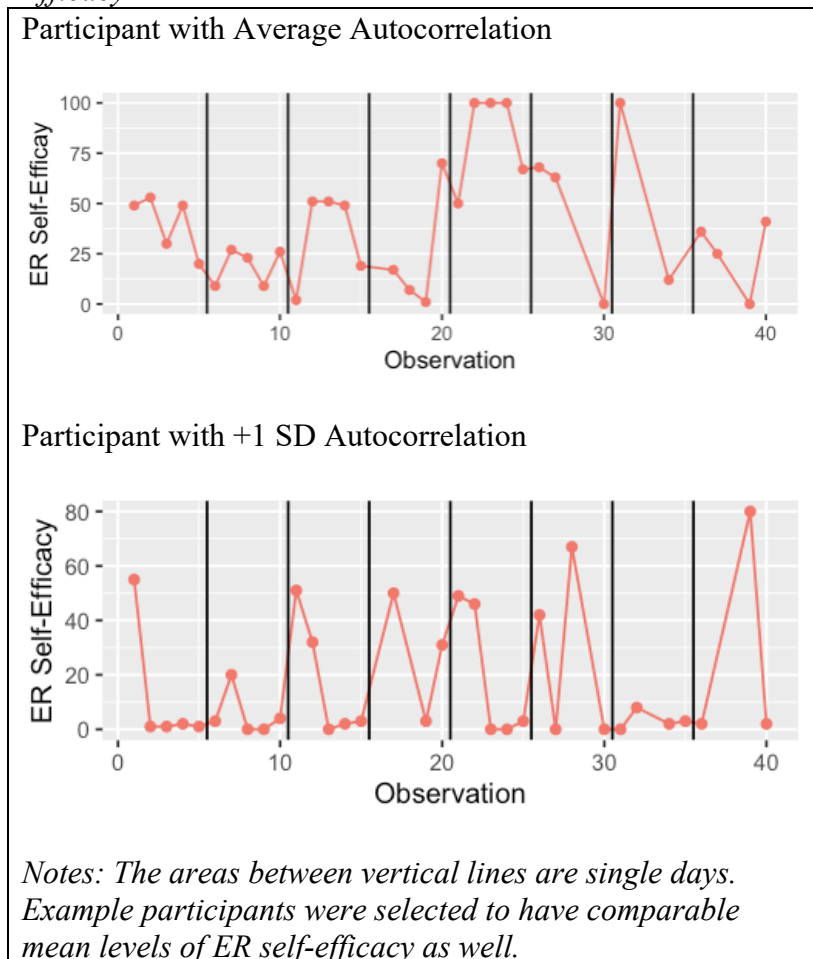
The average within-person autocorrelation of ER importance was .18 with a standard deviation of .28. Figure 3 shows the temporal data for a participant with average autocorrelation, and one with +1 SD autocorrelation for ER importance. ER importance autocorrelation was uncorrelated with average ER importance ($R = .04$).

Figure 3
Examples of Within-Person Temporal Trends in ER Importance



Average within-person autocorrelation of ER self-efficacy was .14, with a standard deviation of .28. Figure 4 shows the temporal data for a participant with average autocorrelation, and one with +1 SD autocorrelation for ER self-efficacy.

Figure 4
Examples of Within-Person Temporal Trends in ER Self-Efficacy



3.1.3 Measures of Construct Validity

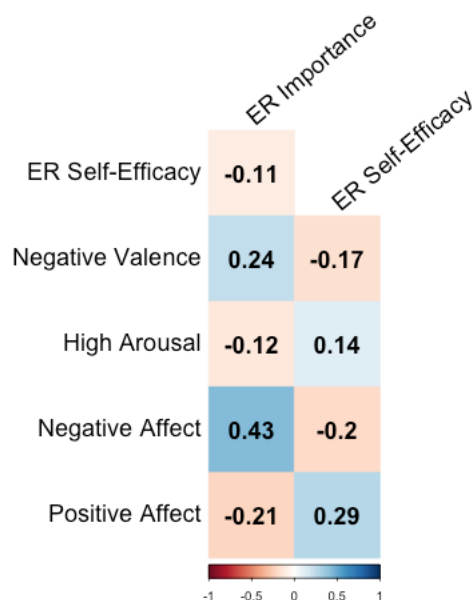
This section presents bivariate correlations between the novel emotion appraisal EMA items and items more commonly used in both EMA and trait-level studies. In all within-person tables, the emotion appraisal items are correlated with emotion items from the same observation, and with ER and impulsivity measures from the subsequent same-day timepoint (since they reflect the same assessment period). All between-person tables use the person-level average of

EMA scales when indicated. I present visualizations of the most relevant correlations here, and the full correlation matrices can be found in appendix 3.

Within-Person Convergent Validity. Figure 5 shows the correlations between emotion appraisal items and multiple measures of congruent emotions, including emotional valence, arousal, and negative and positive affect.

Momentary appraisals of ER importance and ER self-efficacy were only weakly correlated with each other ($r = -0.11$). High ER importance was moderately correlated with negative affect at the same observation ($r = .43$), and weakly associated with other emotion measures reflecting negative emotional valence, low arousal, and low positive affect (absolute values of r s = .13-.25). High ER self-efficacy was weakly associated with emotion measures reflecting positive valence and affect, higher arousal, and lower negative affect (absolute value of r s = .14-.30).

Figure 5
Bivariate correlations between emotion appraisals and congruent emotion components



Note: The color of the boxes indicates the direction and relative strength of the association as indicated by the color key.

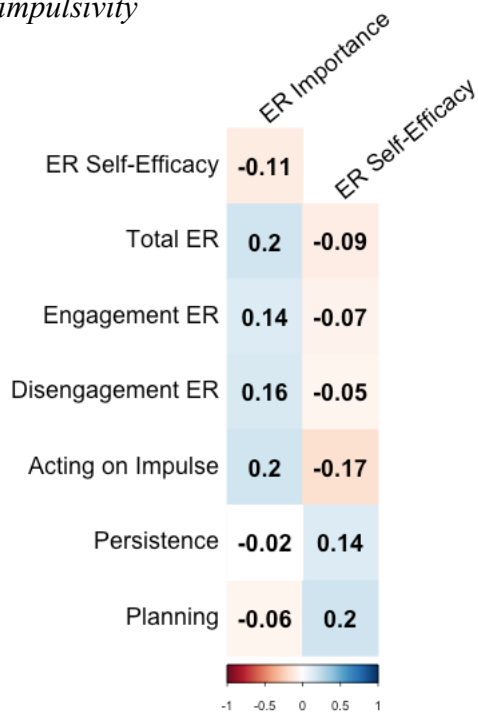
Within-Person Criterion Validity. Figure 6 shows the correlations between emotion appraisal items and multiple measures of emotion regulation and impulsivity reported at the next assessment.

Momentary appraisal of ER importance was weakly correlated with all ER measures and acting on impulse ($r_s = .14-.20$). ER importance was uncorrelated with planning or persistence.

ER self-efficacy was uncorrelated with any ER measures. It was weakly associated with less acting on impulse and more persistence and planning during the same assessment period (absolute value of $r_s = .14-.20$)

Figure 6

Bivariate correlations between emotion appraisals and congruent emotion regulation and impulsivity



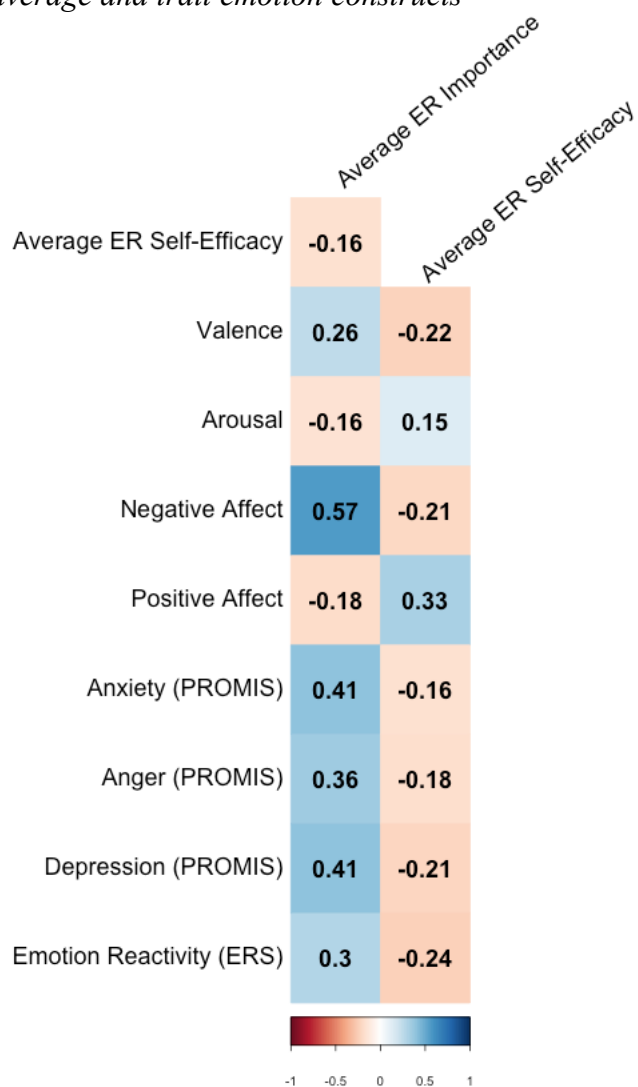
Note: The color of the boxes indicates the direction and relative strength of the association as indicated by the color key.

Between-Person Convergent Validity Figure 7 shows the correlations between the emotion appraisal items aggregated to the person-level (an individual's average tendency over the EMA period) and person-level aggregates of EMA emotion dimensions as well as trait-level measures of psychopathology and emotionality measured at baseline.

The overall pattern of correlation at the aggregate-level follows that of the momentary level discussed above, though slightly stronger in magnitude. Reporting higher average ER importance over the study period was associated with reporting more negative affect and valence, less positive affect, and lower arousal states. Reporting higher EM self-efficacy over the study period was associated with reporting less negative and more positive affect, lower valence and higher-arousal states. A tendency to report higher ER importance across the study period was moderately correlated with

Figure 7

Bivariate correlations between person-level average emotion appraisals and person-level average and trait emotion constructs



Note: The color of the boxes indicates the direction and relative strength of the association as indicated by the color key.

baseline reports of anxiety, anger, depression, and emotional reactivity. A tendency to report higher ER self-efficacy across the study period was weakly associated with lower anxiety, anger, depression, and emotional reactivity at baseline. ER importance and self-efficacy tendencies remained only weakly and inversely correlated at the person-average level.

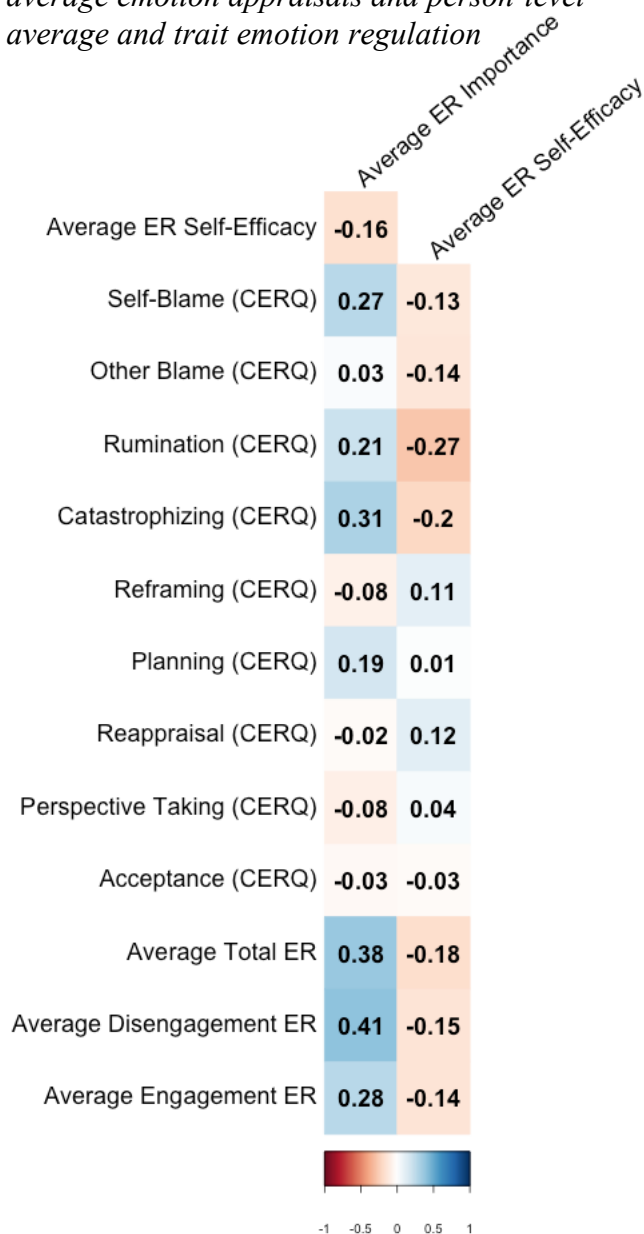
Between-Person Criterion

Validity. Figure 8 shows the correlations between emotion appraisal aggregated to the person-level (an individual's average tendency over the EMA period) and person-level aggregates of emotion regulation variables as well as trait-level measures of emotion regulation tendencies measured at baseline.

A tendency to report higher ER importance across the study period was moderately correlated with reporting more ER strategies during the same period ($r = .38$). ER importance was relatively more strongly correlated with reporting disengagement strategies ($r = .41$) compared to engagement strategies ($r = .28$). Similarly, average ER importance was weakly correlated with

Figure 8

Bivariate correlations between person-level average emotion appraisals and person-level average and trait emotion regulation



Note: The color of the boxes indicates the direction and relative strength of the association as indicated by the color key.

maladaptive cognitive coping strategies as reported at baseline (self-blame, rumination, and catastrophizing; $r_s = .21-.27$). It was uncorrelated with all adaptive cognitive coping strategies with the exception of planning ($r = .19$).

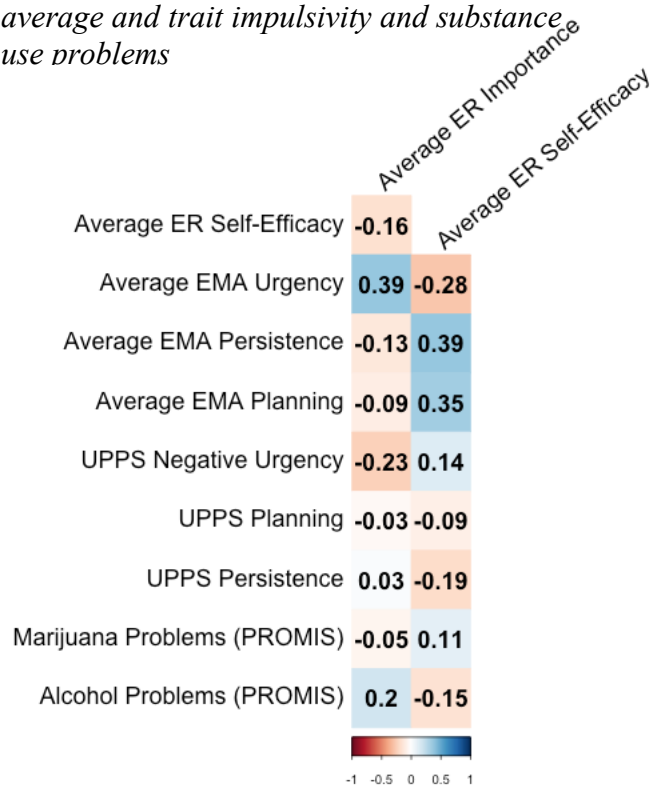
A tendency to report higher ER self-efficacy over the study period was weakly correlated with endorsing less ER on average ($r_s = -.14- .18$). Average ER self-efficacy was weakly correlated with less maladaptive coping reported at baseline ($r_s = -.13- .27$), and in particular with less rumination ($r = -.27$). Average self-efficacy was largely uncorrelated with adaptive coping reported at baseline.

Figure 9 shows the correlations between emotion appraisal aggregated to the person-level (an individual's average tendency over the EMA period) and person-level aggregates of impulsivity as well as trait-level measures of impulsivity traits measured at baseline.

Higher average ER importance over the EMA period was correlated with moderately higher average acting on impulse and trait negative urgency and was relatively uncorrelated with planning or persistence – both as an EMA aggregate and as reported at baseline.

Figure 9

Bivariate correlations between person-level average emotion appraisals and person-level average and trait impulsivity and substance use problems



Note: The color of the boxes indicates the direction and relative strength of the association as indicated by the color key.

Higher average ER self-efficacy over the EMA period was moderately correlated with higher average EMA planning and persistence and lower acting on impulse (absolute value of $r_s = .28-.39$). Average ER self-efficacy was weakly associated with lower negative urgency ($r = -.2$) and higher persistence ($r = .29$) at baseline but was uncorrelated with trait planning.

Average ER importance was weakly correlated with alcohol problems ($r = .2$) whereas average ER self-efficacy was weakly related to fewer alcohol problems ($r = -.2$). Neither were associated with marijuana problems in this sample.

3.2 Emotion Appraisals Predicting ER Behaviors: Analytic Approach

3.2.1 Centering

For all following analyses, I centered EMA variables within-person by subtracting each person's EMA average score across all observations, so that 0 represents that individual's average level over the EMA session. Unless otherwise noted, EMA variables were further scaled by dividing by 10 so that a one-unit increase can be interpreted as 1/10 of our visual analogue scale. Age was centered so that 0 is equal to age 18, the bottom end of the age range of our sample. *Time of day* is centered so that 0 is 9:00 AM and each additional unit is an hour past 9:00 AM. *Study day* is centered so that 0 is the first day and 10 is the last day of data collection. When distance between assessments was included in analyses, the unit was in hours.

3.2.2 Descriptive Statistics for ER Outcomes

The average participant in our study endorsed at least one ER strategy at 45% of their observations, and the average number of ER strategies reported at any given observation was .78. The most frequently endorsed ER strategies were acceptance (17% of observations), problem

solving (15%), distraction (12%) and rumination (11%). The least commonly endorsed were avoidance (9%), reappraisal (6%), and suppression (5%).

At least one engagement strategy was endorsed at 30% of observations, with an average of .4 engagement strategies per observations. At least one disengagement strategy was endorsed at 19% of observations, with an average of .3 engagement strategies per observations.

3.2.3. Covariates

For all regression analyses, I controlled for the effects of person-level demographic attributes that have been previously shown to be associated with emotion beliefs (De Vaus et al., 2018; Tamir & Gutentag, 2017). These include biological sex (1 = male, 0 = female), ethnicity/race (1 = non-white, 0 = white), and age. I will also control for time of day of the EMA (coded as the time elapsed since 9am, the earliest possible time of assessment), and day in the study (0-10) to control for temporal effects.

3.2.4. Model Building Approach

Specifying the Distribution. All the outcomes in these proposed models (total ER, disengagement ER and engagement ER) can be considered ‘variety’ scores - representing the total number of different discrete ER strategies within a given category used during any assessment period. Because this outcome has only discrete integer values above one, I opted to use regression approaches designed for use with count data. Count data is commonly modeled using either Poisson or negative-binomial distributions which are logarithmic in nature (Coxe et al., 2009). Negative-binomial models estimate an additional dispersion parameter and are preferable when the outcome is over-dispersed. For all Aim 2 models I compared model fit of

the Poisson and negative-binomial models as well as checking indicators of overdispersion in the Poisson model.

Modeling Extra Zeroes. I also considered the possibility that these outcomes included an inflated number of ‘zero’ reports. Theoretically, controlling for inflated zeros is called for when it is believed that either 1) some of the zero responses represent observations in which the outcome could not have been possible or 2) the prediction of going from 0 to 1 is expected to be different than the prediction of the rest of the distribution (Ridout et al., 1998). For the hypothesized effect of emotion appraisals on ER outcomes there did not seem to be a strong theoretical reason to make either of these assumptions, as the ER strategies measured are thought to be readily ‘accessible’ and I did not hypothesize that motivating one ER strategy is any different than motivating more than one. Despite the lack of a clear theoretical reason for assuming extra zeros in the data, if there is an excess of zero responses in the data that can’t be adequately accounted for by the count distribution, it is important to model these zeros in order to correctly specify the model. There are two primary approaches for modeling excess zeros – either as a zero-inflated model or as a hurdle model. Zero-inflated models model zero responses as a mixture of structural (related to the hypothesized distribution) and sampling (observations in which the outcome could not occur), whereas hurdle models model the binomial probability of a value other than zero separate from the zero-truncated conditional model (Hu et al., 2011, p.; Zorn, 1998). For all Aim 2 models I compared zero-inflated and hurdle models to those that did not account for excess zeros.

Multi-level Modeling. In all models, when emotion appraisals and negative affect were included as level 1 predictors, their person-level average was also included as a level 2 predictor of the random intercept. This allows for the disaggregation of between-person and within-person

effects. In the analyses for H1 (ER importance predicting total ER), I also tested whether a random effect of ER importance would improve model fit. Random slopes were not tested in subsequent analyses due to convergence issues in these models when these parameters were added. In models where an interaction is tested, it was added as the last step. Inclusion in the final model was determined by significance level of the interaction term and the improvement in fit as described below.

Indicators of Improved Model Fit. Final models for each hypothesis were determined by examining the log likelihood, Akaike Information Criteria (AIC), and Bayesian Information Criteria (BIC) of competing models, as well as theoretical and practical considerations favoring parsimony when models were close in both fit and predicted effects.

3.3. H1 Results: ER importance predicting total ER use, controlling for negative affect

Table 2 shows the relative fit statistics for of the 12 models tested. The Poisson hurdle model with random effect, and both Negative binomial hurdle models (fixed and random) had minor convergence warnings when using the default optimizer for the package ‘glmmTMB’ (‘nlminb’). Per the suggestion of the authors of this package, a different optimizer was used (‘BFGS’) and I compared estimates from both to determine if they varied significantly (Brooks et al., 2017). Estimates were largely the same with both optimizers. Ultimately, these models demonstrated the worst comparative fit regardless of optimizer and were not considered further.

Table 2
Model comparisons for ER importance predicting total ER

<i>Distribution Modeled</i>	<i>Extra Zeros Modeled</i>	<i>Fixed or Random effect</i>	<i>AIC</i>	<i>BIC</i>	<i>LogLik</i>	<i>Chi Squared</i>	<i>P-value</i>
Poisson	None	Fixed	5794	5859*	-2886		
		Random	5792*	5869	-2883*	6.13	0.05
	Zero-Inflated	Fixed	5796	5867	-2886		
		Random	5794	5877	-2883	6.13	0.05
	Hurdle	Fixed	6244	6316	-3110		
		Random	6248	6331	-3110	0.39	0.82
Negative binomial	None	Fixed	5795	5866	-2885		
		Random	5794	5877	-2883	5.22	0.07
	Zero-Inflated	Fixed	5797	5874	-2885		
		Random	5796	5885	-2883	5.22	0.07
	Hurdle	Fixed	6246	6324	-3110		
		Random	6250	6339	-3110	0.24	0.89

Note: The lowest values of each metric are marked with an asterisk. The selected model is indicated in bold.

Negative binomial models vary from Poisson models in that they estimate one additional parameter – a dispersion parameter that accounts for over-dispersion in the outcome. The added parameter is justified when the Poisson model suggests overdispersion. Because the Poisson and negative-binomial models I ran were comparable to each other in their fit statistics and estimates for the conditional models (inferences would not be different between the two), I chose between these models on the basis of the presence of overdispersion. A test of overdispersion on the Poisson models indicated no over-dispersion (dispersion ratio = 0.99 Pearson's Chi-Squared =

2780, p -value = 0.65). Therefore, I decided to use the Poisson distribution for the sake of simplicity and on the grounds that these models demonstrated slightly superior fit. On similar grounds I decided not to consider the Poisson models that modeled extra zeroes, as they did not demonstrate increased fit on any metric and necessitate the estimation of additional parameters. The addition of the random effect of ER importance led to a decrease in AIC but an increase in BIC. The likelihood ratio test was not significant at $\alpha = .05$. When comparing the estimates of both models – the random effect estimate was very small in magnitude and the level 1 estimates were unchanged. Given the relative equivalence of the two models, I again decided to opt for parsimony by using the fixed-slope model as my final model. Thus, the preliminary model for this hypothesis was a Poisson GLMM with a fixed effect of ER importance.

Next, I added momentary negative affect and average negative affect to the model and compared the results to determine if the effects of ER importance on ER strategies was robust over and above the effect of negative affect. The results of both models can be seen in Table 3.

Table 3
Model results for ER importance predicting total ER

Initial Model

	<i>b</i>	<i>SE</i>	<i>RR</i>	<i>95% CI</i>
Intercept	-0.96	0.24	0.38	0.24-0.61
Study Day	-0.055*	0.006	0.95*	0.94-0.96
Time of Day	-0.028*	0.007	0.97*	0.96-0.99
Average ER Importance	0.24*	0.052	1.27*	1.15-1.41
Momentary ER Importance	0.078*	0.022	1.08*	1.04-1.13

With Negative Affect Added

	<i>b</i>	<i>SE</i>	<i>RR</i>	<i>95% CI</i>
Intercept	-1.102	0.231	0.33	0.21-0.52
Study Day	-0.053*	0.006	0.95*	0.94-0.96
Time of Day	-0.028*	0.007	0.97*	0.96-0.99
Average ER Importance	0.105	0.059	1.11	0.99-1.25
Momentary ER Importance	0.070*	0.022	1.07*	1.03-1.12
Average Negative Affect	0.33*	0.081	1.39*	1.19-1.63
Momentary Negative Affect	0.03	0.017	1.03	1.00-1.07

Notes: Covariates that weren't significant in either model are not displayed. Coefficients significant at $p < .05$ are indicated with an asterisk.

3.3.1 Covariate effects.

Age, sex, and race were not significant predictors of total ER in either model. Across both models, study day and time of day were significant predictors of total ER such that for each subsequent day in the study, there was a .95 multiplicative effect on their predicted count of total ER. In general, people reported fewer ER strategies over the course of participation in the study. For example, if a participant's predicted ER count on day 1 was 1 strategy and everything else is

held constant, their predicted ER on the last day would be .57. Similarly, for each subsequent hour past 9am, there was a .97 multiplicative effect on total ER. In general, people reported fewer ER strategies later in the day. For example, if a participant's predicted count of ER at 9am was 1 strategy and everything else is held constant, their predicted ER at 9pm would be .70.

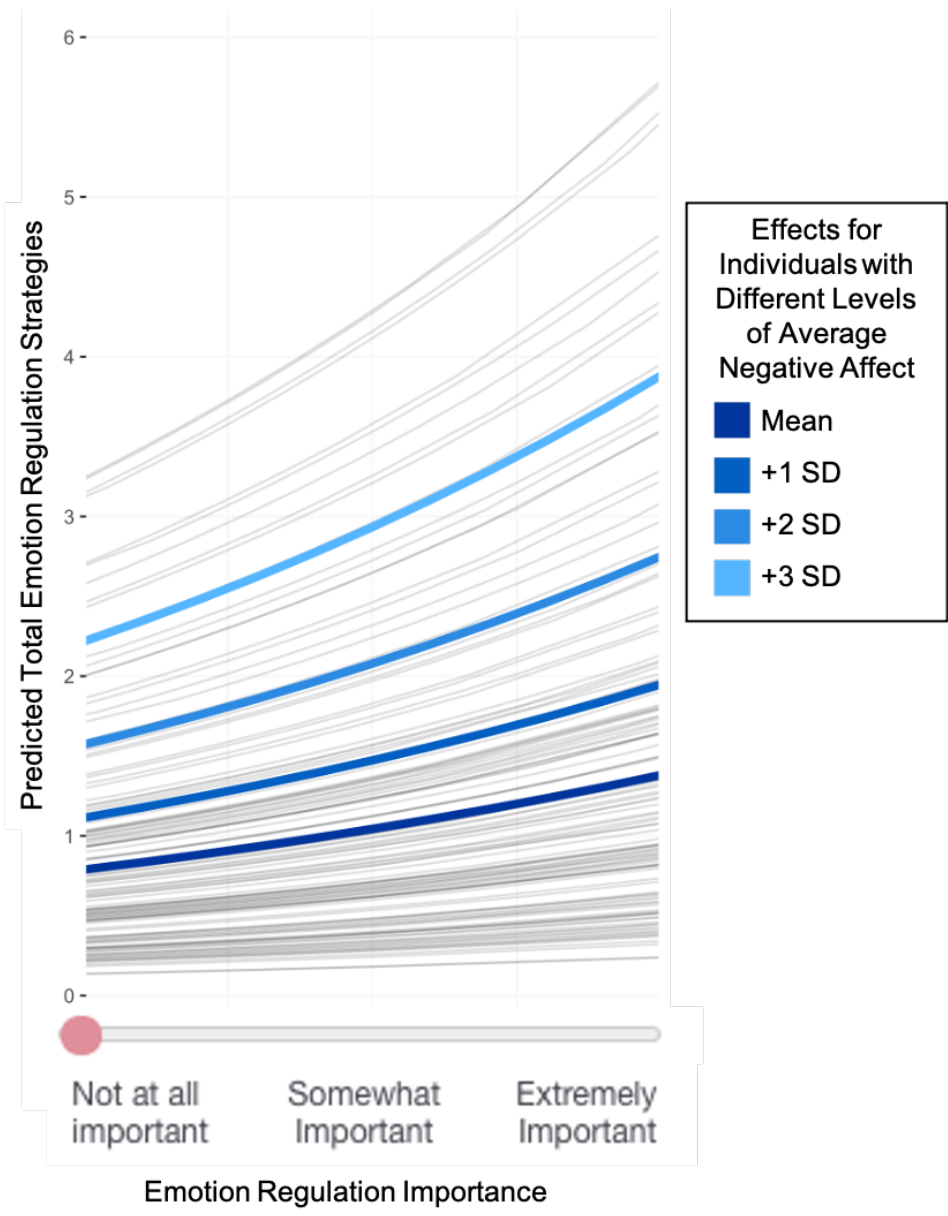
3.3.2. Average ER Importance and Negative Affect

In the preliminary model without negative affect, there was a significant effect of average ER importance on total ER such that a 10-unit increase in average ER importance predicted a 1.27 multiplicative effect on expected total ER, with everything else held constant. However, the magnitude of this effect was diminished and no longer significant when the negative affect predictors were added to the model. In the negative affect model, there was instead a significant effect of average negative affect on total ER; people who tend to report higher levels of negative affect on average also report using more ER strategies across all situations. A 10-unit increase predicted a 1.39 multiplicative effect on expected total ER, with everything else held constant. This suggests that the effect of average ER importance on total ER is due to shared variance with average negative affect (they are correlated $r = .57$ at the person-average level) and the effect on ER may be best explained by average levels of negative affect.

3.3.3. Momentary ER Importance and Negative Affect

Across both models there was a significant effect of momentary ER importance on the count of total ER use during the next assessment period such that for a 10-unit increase in ER importance there is a predicted 1.08 multiplicative effect on total ER. For example, if going from 0 ('not at all important') to 50 ('somewhat important') on our visual analogue scale, there would be a predicted 1.47 multiplicative effect on total ER, with all else held constant in the model. There was not a significant effect of momentary negative affect on total ER, and the magnitude of the effect of ER importance only decreased very slightly ($\Delta RR = .01$) when negative affect was added to the model. This suggests that above and beyond the impact of negative affect, when individuals report increased motivation to change their mood, they tend to report using more emotion regulation strategies at the next observation. Due to the logarithmic nature of the count model, the amount of predicted change in ER strategy use varies depends on the levels of other variables in the model and is difficult to summarize concisely. Figure 10 shows the predicted effect for all individuals in our study based on their own demographic and person-level average variables. This figure also demonstrated how the magnitude of the effect changes based on different person-level average levels of negative affect – the only significant predictor of the random intercept in the final model.

Figure 10
Predicted effect of ER importance on total ER at different levels of average negative affect



Note: Individual grey lines are the predicted effects for actual participants in this study. The blue lines are assuming population average levels of between-person variables and individual mean levels of within-person variables in a 20-year old non-white female at 9am on the first day of the study.

3.4 H2 Results: Emotion Appraisals Predicting Disengagement and Engagement ER

Table 4 shows the relative fit statistics for of the 6 models tested for both engagement and disengagement ER.

Table 4

Model comparisons for emotion appraisals predicting disengagement and engagement ER Use

<i>Distribution Modeled</i>	<i>Extra Zeroes Modeled</i>	<i>AIC</i>	<i>BIC</i>	<i>LogLik</i>
<i>Disengagement ER Models</i>				
Poisson	None	3254	3319	-1616
	Zero-Inflated	3241*	3312*	-1608*
	Hurdle	3524	3595	-1750
Negative binomial	None	3248	3319	-1612
	Zero-Inflated	3243	3320	-1608*
	Hurdle	3526	3603	-1750
<i>Engagement ER Models</i>				
Poisson	None	3885*	3951*	-1932*
	Zero-Inflated	3887	3958	-1932*
	Hurdle	4341	4413	-2159
Negative binomial	None	3887	3958	-1932*
	Zero-Inflated	3889	3966	-1932*
	Hurdle	4343	4420	-2159

Notes: Covariates that weren't significant in either model are not displayed. Coefficients significant at $p < .05$ are indicated with an asterisk.

For the models predicting disengagement ER, a zero-inflated Poisson model demonstrated the best fit, whereas the Poisson without excess zeros modeled fit best amongst the models predicting engagement ER.

For both models, adding the hypothesized interaction of ER importance and self-efficacy did not result in a significant coefficient or increase overall fit (disengagement: $X^2 = .26$, $p = .61$; engagement: $X^2(1) = .04$, $p = .84$). Table 5 shows the results from both models without the interaction added.

Table 5

Model results of emotion appraisals predicting disengagement and engagement ER use

	<i>b</i>	SE	RR	95% CI
<i>Disengagement ER</i>				
Intercept	-1.35	0.43	0.26	0.11-0.61
Study Day	<i>-0.07</i>	0.01	<i>0.94</i>	0.92-0.96
Time of Day	-0.03	0.01	0.98	0.95-1.00
Average ER Importance	<i>0.27</i>	0.07	<i>1.31</i>	1.15-1.49
Average ER Self-Efficacy	<i>-0.12</i>	0.05	<i>0.89</i>	0.80-0.99
Momentary ER Importance	<i>0.06</i>	0.02	<i>1.06</i>	1.03-1.10
Momentary ER Self-Efficacy	-0.01	0.02	1.00	0.96-1.03
<i>Engagement ER</i>				
Intercept	-1.19	0.41	0.30	0.14-0.68
Study Day	<i>-0.05</i>	0.01	<i>0.96</i>	0.94-0.97
Time of Day	<i>-0.03</i>	0.01	<i>0.97</i>	0.95-0.99
Average ER Importance	<i>0.18</i>	0.06	<i>1.20</i>	1.06-1.35
Average ER Self-Efficacy	-0.051	0.05	0.95	0.86-1.05
Momentary ER Importance	<i>0.057</i>	0.01	<i>1.06</i>	1.03-1.09
Momentary ER Self-Efficacy	-0.019	0.02	0.98	0.95-1.01

Note: Effects that were significant at $p < .05$ are bolded. Effects that remained significant after the addition of momentary and average negative affect are italicized.

3.4.1 Covariate Effects

Age, sex, and race were not significant predictors in either model. Study day was a significant predictor of both engagement and disengagement ER such that lower levels of both

were predicted as the study went on (disengagement RR = .94; engagement RR = .96 per subsequent study day). Time of day was a significant predictor of engagement coping (RR = .97 per subsequent hour), but not disengagement. Lower levels of engagement ER were predicted later in the day.

3.4.2 Effects of Average ER Importance and Self-Efficacy

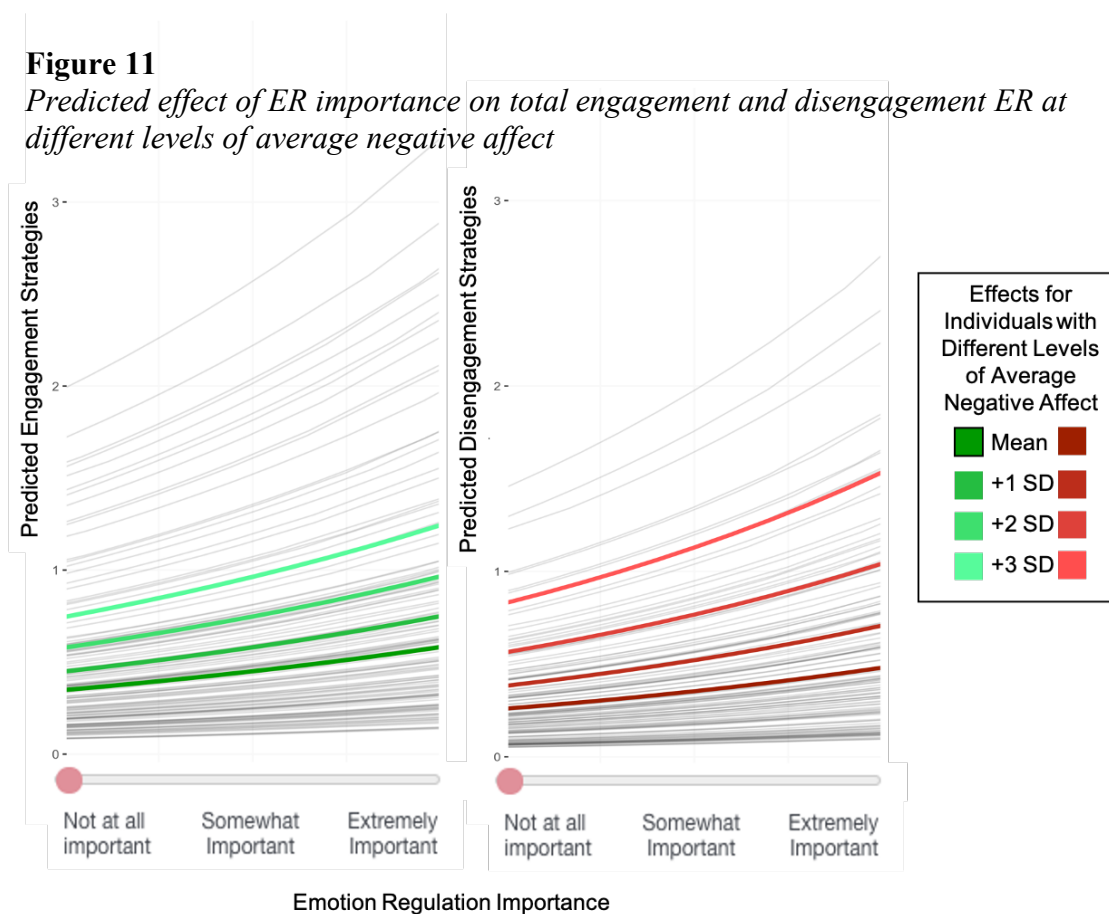
Average ER importance over the course of the study was a significant predictor of both engagement and disengagement ER. A 10-unit increase in average ER importance predicts a 1.31 multiplicative effect on disengagement ER and a 1.2 multiplicative effect on engagement ER, with all else held constant. Individuals who tend to report higher ER importance also report increased disengagement and engagement ER across situations.

Average ER self-efficacy over the course of the study was a significant predictor of disengagement ER, but not engagement ER. A 10-unit increase in average ER self-efficacy predicts a .89 multiplicative decrease in disengagement ER, with all else held constant. Individuals who tend to report higher ER self-efficacy in general also report relatively lower use of disengagement ER across situations.

3.4.3 Effects of Momentary ER Importance and Self-Efficacy

Momentary ER importance was a significant predictor of both disengagement and engagement ER reported at the subsequent assessment (RR = 1.06 for a 10-unit increase in both models). Going from 0 ('not at all important') to 50 ('somewhat important') on our scale predicted a 1.34 multiplicative effect on both engagement and disengagement ER used, with all else held constant in the model. Figure 11 shows the predicted effect of ER importance on disengagement and engagement ER for all participants in the study based on their own

demographics and person-level averages. Momentary ER self-efficacy did not predict either type of ER.



Note: Individual grey lines are the predicted effects for actual participants in this study. The blue lines are assuming population average levels of between-person variables and individual mean levels of within-person variables in a 20-year old non-white female at 9am on the first day of the study.

3.4.4 Post-Hoc Analyses: Addition of Negative Affect

Because of the level 2 effects of average negative affect on ER found in the Total ER model, I included a final step of adding both average and momentary negative affect to both of the H2 models to see if the effects were similarly impacted by the inclusion of affect. The italicized estimates in table 5 show the estimates that were robust to the addition. Similar to the H1 model, none of the person-average effects of appraisals were robust to the addition of person-

average negative affect, but the momentary effect of ER importance on subsequent ER was unchanged. In these models, average negative affect was a significant predictor of both disengagement (RR = 1.4 for a 10-unit increase) and engagement (RR = 1.3 for a 10-unit increase). Figure 11 shows the predicted effect on each ER category based on different levels of average negative affect, the only significant predictor of slope in both final models.

3.5 Exploratory Analyses Results: Emotion appraisals predicting specific ER strategies

The third aim of this study was to provide preliminary results about the associations between emotion appraisals and specific ER strategies. To do this, I ran models predicting acceptance, problem-solving, cognitive reappraisal, avoidance, distraction, suppression, and rumination. I also tested whether emotion appraisals predicted whether *any* ER strategy was used at the next time point. These models followed the same general analytic approach previously outlined, apart from using multi-level logistic regression given the binary nature of the specific ER strategies. To facilitate the models converging, EMA variables were further scaled so that the scale that was originally 0-100 was instead 0-1. I have transformed coefficients back to the 0-10 scale for reporting so that they are consistent with the previous models presented. One set of models – those with distraction as an outcome – failed to converge with all covariates in the model. I removed the three person-level covariates from the model (age, sex, and race) which allowed convergence and compared the estimates from both models. No inferences were changed between the two. The coefficients presented here for distraction are from the version without the person-level covariates. Notably, these covariates were not significant predictors of ER in any model run as part of this study.

The interaction between ER importance and ER self-efficacy was not significant and did not improve model fit for any of the eight models predicting ER strategy use and were not

included in the final models. Table 6 presents the key effects of interest. Because there are four coefficients of interest in each model and these are exploratory analyses, I opted to use a Bonferroni-corrected criterion of $p < .001$ to avoid highlighting potentially spurious association.

Table 6*Model results for emotion appraisals predicting specific emotion regulation strategies*

	<i>Acceptance</i>				<i>Problem-Solving</i>			
	<i>b</i>	<i>SE</i>	<i>OR</i>	<i>99.9% CI</i>	<i>b</i>	<i>SE</i>	<i>OR</i>	<i>99.9% CI</i>
Average ER Importance	0.25	0.01	1.28	0.96-1.71	0.24	0.10	1.27	0.94-1.70
Average ER Self-Efficacy	-0.06	0.08	0.94	0.75-1.19	0.03	0.08	0.97	0.76-1.22
Momentary ER Importance	0.09	0.03	1.09	1.01-1.19	0.06	0.03	1.06	0.98-1.15
Momentary ER Self-Efficacy	0.003	0.03	1.00	0.92-1.09	-0.06	0.03	0.94	0.86-1.02
	<i>Reappraisal</i>				<i>Avoidance</i>			
	<i>b</i>	<i>SE</i>	<i>OR</i>	<i>99.9% CI</i>	<i>b</i>	<i>SE</i>	<i>OR</i>	<i>99.9% CI</i>
Average ER Importance	0.19	0.11	1.20	0.85-1.70	0.31	0.09	1.36	1.00-1.84
Average ER Self-Efficacy	-0.12	0.09	0.88	0.67-1.17	-0.11	0.08	0.90	0.70-1.16
Momentary ER Importance	0.16	0.04	1.17	1.03-1.33	0.11	0.03	1.12	1.01-1.24
Momentary ER Self-Efficacy	-0.04	0.04	0.96	0.83-1.11	-0.07	0.04	0.93	0.83-1.05
	<i>Distraction</i>				<i>Suppression</i>			
	<i>b</i>	<i>SE</i>	<i>OR</i>	<i>99.9% CI</i>	<i>b</i>	<i>SE</i>	<i>OR</i>	<i>99.9% CI</i>
Average ER Importance	0.26	0.08	1.30	1.01-1.67	0.38	0.09	1.46	1.09-1.95
Average ER Self-Efficacy	-0.14	0.06	0.87	0.70-1.07	-0.08	0.08	0.92	0.72-1.19
Momentary ER Importance	0.03	0.03	1.03	0.94-1.13	0.15	0.04	1.16	1.02-1.31
Momentary ER Self-Efficacy	-0.01	0.03	0.99	0.90-1.10	0.08	0.05	1.09	0.94-1.26
	<i>Rumination</i>				<i>Any ER</i>			
	<i>b</i>	<i>SE</i>	<i>OR</i>	<i>99.9% CI</i>	<i>b</i>	<i>SE</i>	<i>OR</i>	<i>99.9% CI</i>
Average ER Importance	0.21	0.10	1.23	0.90-1.69	0.40	0.10	1.49	1.07-2.07
Average ER Self-Efficacy	-0.13	0.08	0.87	0.68-1.13	-0.12	0.08	0.89	0.69-1.15
Momentary ER Importance	0.09	0.03	1.09	0.99-1.21	0.10	0.02	1.10	1.02-1.19
Momentary ER Self-Efficacy	-0.08	0.03	0.92	0.83-1.03	-0.06	0.02	0.94	0.87-1.02

Note: Coefficients in bold are significant at the $p < .001$ level. Those in italics were found to be robust to the addition of momentary negative affect and average negative affect.

3.5.1 Covariate Effects

Like previous models, study day significantly predicted all individual ER strategies, except suppression, such that participants were relatively less likely to report ER strategies in later observations. Time of day was only a significant predictor of reappraisal and engaging in any ER strategy, such that they were relatively less likely to be endorsed as the day went on. The person-level covariates of age, sex, and race were not significant in any model.

3.5.2 Average Effects of ER Importance and Self-Efficacy

Average ER importance significantly predicted an individual's use of avoidance, distraction, suppression, and any ER. A participant with a 10-unit increase in average ER importance is 1.36 times more likely to endorse avoidance, 1.30 times more likely to endorse distraction, 1.46 times more likely to endorse suppression, and 1.49 times more likely to endorse *any* ER strategy across situations – with all else held equal in the model.

Average ER self-efficacy was not a significant predictor of any ER strategy.

3.5.3. Momentary Effects of ER Importance and Self-Efficacy

Momentary ER importance was a significant predictor (at $p < .001$) of all ER strategies except for problem-solving, distraction, and rumination. The odds ratios for a 10-unit increase in momentary ER importance ranged from 1.09 (for acceptance) to 1.17 (for reappraisal). A participant going from “not at all” important to “somewhat important” on our visual analogue scale of ER importance (to change current mood) is predicted to be 1.5 times more likely to report acceptance at the next timepoint, 2.2 times more likely to report reappraisal, 1.76 times more likely to report avoidance, and 2.1 times more likely to report suppression.

Momentary ER self-efficacy was not a significant predictor in any of the models based on our adjusted alpha level.

3.5.4. Post-Hoc Analyses: Inclusion of Negative Affect

Lastly, I added average and momentary negative affect to the model to explore whether these effects were robust to the inclusion. As in previous models, only momentary effects were robust to the addition, whereas the level 2 predictions of ER from average motivation were not. All the momentary effects of ER importance on specific ER strategies were robust to the inclusion of momentary NA. This suggests that at the momentary level, ER importance may be a better predictor of regulatory behaviors than affect alone. However, at the trait level, average negative affect is a better predictor of ER tendencies than average ER importance is.

Chapter 4: Discussion

Beliefs that emotions are generally undesirable and unchangeable are associated with worse mental health outcomes (De Castella et al., 2013, 2018b; Ford et al., 2018; Karnaze & Levine, 2018; King & dela Rosa, 2019; Tamir et al., 2007; Yoon et al., 2018). Researchers have posited that this association is driven by in-the-moment appraisals of emotion states that bias individuals towards emotion regulation behaviors that are less adaptive long-term, such as avoidance and suppression (De Castella et al., 2013, 2018b; Ford et al., 2018; Ford & Gross, 2019; Hu et al., 2011; Kneeland et al., 2020; Ortner & Pennekamp, 2020; Tamir & Ford, 2009, 2012). However, there is limited existing research on momentary appraisals of emotion states – let alone how they relate to subsequent regulatory behaviors. The current study aimed to present preliminary psychometric descriptions of two novel EMA emotion appraisal items and to test foundational hypotheses of how these appraisals relate to emotion regulation in day-to-day life.

4.1 Psychometric Properties of Momentary Appraisal Items

The first aim of this study was to characterize the basic psychometric properties of two emotion appraisal items. These items, which I have referred to as ER importance and ER self-efficacy, were selected because they reflect my best guess at how emotion valuation and malleability beliefs are likely manifest in the moment. In this way, I can tie our results conceptually to the body of work on trait-level emotion beliefs while also exploring process-oriented theories of emotion regulation.

Results indicated that both measures of emotion appraisals had substantial variation at both the between- and within-person level. On average, individuals endorse low level of importance for changing their current mood, and a moderate belief in their ability to change it. However, moments of increased ER importance and of both lower and higher ER self-efficacy were typical for most participants over the eight days of our data collection. For most people, momentary ER importance and ER self-efficacy ratings were not strongly impacted by their rating earlier in the day. Some individuals in our study did exhibit stronger autocorrelations, representing more ‘inertia’ in their appraisal states within the same day. This variation in autocorrelation may be a fruitful area of investigation in the future because this measure of ‘inertia’ could have meaningful interpretations within an ER process model. For example, high autocorrelation could theoretically reflect poor ER effectiveness is desire to change emotion persists longer over time. Conversely, if high ER importance at one observation predicts lower levels at the next (a negative autocorrelation), that could potentially indicate a quickly ‘resolved’ emotion state. Past studies have used autocorrelation of emotion measures as an indicator of ‘emotional inertia’ – which has been associated with maladaptive emotion regulation strategies and worse mental health outcomes (Koval et al., 2015; Kuppens et al., 2010). Exploration of

similar within-person dynamics in emotion appraisals could build on this work and further illuminate how differences in appraisals contribute to both healthy and unhealthy patterns of emotion regulation.

Placing measures of emotion appraisals within a nomothetic web of related constructs is important for understanding if they capture the constructs they were designed to, as well as understanding how they differ from measures already commonly in use. Many of my hypotheses about the correlations of these items with other measures were supported. At the momentary level, people tend to have higher ER importance when experiencing low arousal, high valence emotion states and those reflecting more negative affect and less positive affect. These correlations were weak to moderate, suggesting that though ER importance may be related to experiences of ‘negative’ emotions, it is not redundant with any of the components of emotion we measured concurrently. On the other hand, people tend to believe they can change high-arousal, positive valenced moods somewhat more than low-energy, negative moods. Notably, ER importance and ER self-efficacy were very weakly correlated with each other. This may be in part because our ER self-efficacy measure was not specific to down-regulating negative emotions. For example, high momentary self-efficacy could reflect feeling that it would be possible to temper a positive mood, whereas ER importance seems to be more tightly related to negative emotion states.

When looking at the association between momentary emotion appraisals and behaviors reported at the next observation, ER importance was only weakly correlated with ER variables. Perhaps surprisingly, ER importance was as strongly related to acting on impulse as to ER behaviors. Similarly, ER self-efficacy was weakly correlated with less acting on impulse and more planning and persistence – but unrelated to ER behaviors. This suggests that emotion

appraisals may be just as related to, or even *more* related to, general processes of behavioral control, as opposed to directing emotion-regulatory behaviors specifically. Future research could integrate measures of momentary impulsivity into process-oriented models to disentangle general behavioral dysregulation from explicitly emotion-directed behavior.

Because the momentary emotion appraisal items used in this study were selected to reflect state-level manifestations of emotion beliefs, I expected that the person-level averages of these momentary measures would behave similarly to trait-level measures of emotion valuation and malleability beliefs. Beliefs that emotions are generally less desirable and less malleable have been consistently associated with poorer mental health outcomes (De Castella et al., 2018b; Ford et al., 2018; Karnaze & Levine, 2018; Yoon et al., 2018). This was also generally borne out in my results as well; the tendency report high ER importance was related to a constellation of trait measures representing negative emotionality and more mental health symptoms whereas the tendency to report high ER self-efficacy was related to trait measures of positive affect and emotional wellbeing. Trait-level studies of emotion beliefs, particularly of malleability beliefs, have also found associated between these beliefs and emotion regulation tendencies. Low malleability beliefs have been associated with the tendency to use less cognitive reappraisal (De Castella et al., 2013; Ford et al., 2018; King & dela Rosa, 2019; Kneeland et al., 2020; Ortner & Pennekamp, 2020; Tamir et al., 2007) and higher levels of emotional and cognitive avoidance (De Castella et al., 2018; Moumne et al., 2020; Ortner & Pennekamp, 2020). Consistent with this, I found a stronger association between ER self-efficacy at the person-average level than at the momentary level. People with higher average ER self-efficacy reported that they use less maladaptive ER strategies as measured by global self-report, and less of *all* types of ER strategies when measured via EMA.

Overall, the preliminary psychometric properties of these items are largely as expected and they appear to be promising EMA measures that capture significant within-person variation without being unduly biased by temporal or sampling effects (at the current frequency and duration of sampling).

4.2 ER Importance and Regulatory Behaviors

Though negative beliefs about emotions are associated with lower wellbeing at the trait level, state-level appraisals of the usefulness of a current emotion have been found to motivate goal-congruent regulatory behaviors (Tamir & Ford, 2009, 2012), and desire to change a current emotion was associated with both engagement and disengagement ER use in one EMA study (Daros et al., 2020). These past findings suggest that the *tendency* to view emotions as unwanted may be more selectively related to negative outcomes, whereas the momentary appraisal that an emotion should change may be more broadly related to all regulatory behaviors (both those that are adaptive and maladaptive). My results partially support this idea. First, I did find that momentary ER importance predicted total ER use, disengagement and engagement ER separately, and a number of individual ER strategies. These findings lend support for the idea that momentary valuation appraisals function at the process-level as the metaphorical ‘gas-pedal’ that motivates ER behaviors. However, average ER importance was also associated with both engagement and disengagement strategies to approximately the same degree. These findings raise questions about the mechanism through which negative valuation beliefs create risk for psychopathology if they do not bias regulatory behaviors toward maladaptive ER at neither the momentary nor the trait level. Given the present findings, there are several alternative explanations. It could be that using higher levels of disengagement strategies creates risk for psychopathology even when levels of engagement ER are also high. Another possibility is that

high levels of concurrent disengagement and engagement ER as reported in EMA may capture ineffective ER use – essentially a ‘kitchen sink’ approach to regulation that creates risk because no single strategy is particularly effective. Lastly, it could be that emotion valuation beliefs are not linked to mental health outcomes via momentary processes, but through covariance with other constructs at the trait-level. I found some evidence for this possibility in my analyses that included negative affect as a covariate.

When negative affect was added to all the models in which emotion appraisals were predicting ER, only the within-person effects were robust to the addition. It’s also important to note that negative affect and ER importance were more strongly correlated at the between-person level than at the momentary level ($r = .57$ vs $r = .43$). This suggests that the general tendency to experience negative affect and the general tendency to want to change emotions share more variance than do negative affect and ER importance at the momentary level. It seems that at the between-person level, the association between average ER importance and average ER strategy use is better explained by this shared variance with the broader trait of negative emotionality – and in fact that negative emotionality may be a better predictor of typical ER use than emotion valuation tendencies. This finding is at odds with two past studies that found that negative emotion valuation beliefs were more directly related to negative health outcomes than negative affect (Karnaze & Levine, 2018; Luong et al., 2016). It’s possible this is a result of the difference between traditional measures of trait-level emotion beliefs and the person-level averages of ER importance used in the present analyses. Person-level averages of momentary appraisals and negative affect reflect an individual’s experience during the limited window of the study period. It is quite possible that because of this they tap slightly different constructs than those measured via global self-report, and that the associations between appraisals and affect may vary. Because

of this it may be important to be more specific about what was measured in the present study; my results suggest that average ER importance may be part of a larger constellation of constructs that tend to cluster together at the individual level *within the same sampling window*. To summarize, people who are experiencing more negative emotions also tend to report a desire to change their mood, and in general are doing more of all types of emotion regulation during the same two-week interval. The fact that average negative affect predicts typical ER behaviors above and beyond the effect of average ER importance suggests that average negative affect has unique variance that is associated with ER behaviors. There are many potential explanations for why we might see this at the person-average level but not the momentary level. For example, it could be that there are other factors that are exerting an impact negative affect and ER behaviors during the same sampling period that are not captured by ER importance. For example, if someone is experiencing a high level of life stressors, they may also have more negative emotions and exhibit more regulatory behaviors (such as problem-solving or distraction) that are not as directly related to the conscious desire to change the emotion perse, but to cope with or resolve the larger stressor. It could also be that the association between average negative affect and ER use is best explained by trait-level negative emotionality (i.e. people who are predisposed to experience negative emotions use a higher number of ER strategies in general, perhaps due to having a larger repertoire out of necessity) and that the person-average negative emotionality measure used in this study better taps that larger construct than person-average ER importance does. There is some evidence to support this in the correlational findings from the present study; person-average negative affect was more strongly correlated with all trait-level measures of emotionality (the ERS and PROMIS emotion scales) than person-average ER importance was.

Though the between-person association of ER importance with ER behaviors may be better explained by shared variance with negative affect, the within-person effect was robust to the addition of momentary negative affect across all models I examined. Further, negative affect was not a significant predictor of ER behaviors when included in models with ER importance. This finding lends support to process-oriented theories of ER that place emotion appraisals as more proximal to ER behaviors. Functionally, these findings support the idea that measures of momentary ER importance provide stronger prediction of emotion-motivated behaviors than emotion measures alone. This could represent a significant contribution to lines of EMA research that have attempted to connect in-the-moment emotion experiences to clinically relevant behavioral outcomes. As one example, it's been notoriously difficult to observe patterns of emotion-motivated drinking in EMA (Wray et al., 2014) and results are sometimes conflicting, such as anxiety predicting both more (Simons et al., 2010) and less alcohol use (Dvorak et al., 2014). If appraisals of ER importance are a more direct measure of the components of emotion that motivate behavior, then integrating them into these types of studies of emotion-behavior processes could help clarify these dynamics in the future.

4.3 ER Self-Efficacy and Regulatory Behaviors

Beliefs that emotions are malleable is generally associated with better wellbeing. A commonly proposed mechanism for this association is that momentary appraisals of how changeable an emotion is will bias ER strategy selection toward strategies that promote wellbeing long-term, such as reappraisal and problem-solving (Ford & Gross, 2019). The inclusion of momentary ER self-efficacy in the current study aimed to test whether higher momentary ER self-efficacy differentially predicted the use of engagement versus disengagement ER, both at the between- and within- person levels. I also aimed to test the

potential interaction between momentary ER self-efficacy and ER importance, with the hypothesis that any associations between ER self-efficacy and ER behaviors would be moderated by ER importance. Contrary to my hypotheses, momentary ER self-efficacy was not a significant predictor of ER in any model, nor was the hypothesized interaction significant in any model. Though there was variability in ER self-efficacy within person, it does not seem that moments of higher ER self-efficacy are associated with increased ER of any kind.

At the between-person level, average ER self-efficacy did significantly predict less disengagement ER, but not more engagement ER. People who in general feel more confident in their ability to change their mood tend to use disengagement strategies less. This pattern of results is consistent with past research on emotion malleability beliefs, which have found that beliefs that emotions are generally more malleable are associated with higher levels of emotional and cognitive avoidance (De Castella et al., 2018a; Moumne et al., 2020; Ortner & Pennekamp, 2020). However, other between-person studies have found that people with lower malleability beliefs report less cognitive reappraisal (De Castella et al., 2013; Ford et al., 2018; King & dela Rosa, 2019; Kneeland et al., 2020; Ortner & Pennekamp, 2020; Tamir et al., 2007), which my results did not support. Notably, the effect of average ER self-efficacy on disengagement ER was not robust to the addition of average negative affect. Like with average ER importance, it seems that at the between-person level, the impact of appraisal tendencies on ER behaviors may be redundant with the impact of negative emotionality. Past research on the association between malleability beliefs and ER behaviors has been inconsistent in including trait-level negative emotionality as a control variable, with some finding a significant effect while controlling for trait emotionality (Tamir et al., 2007; Ford et al., 2018; Kneeland et al., 2020), while others did not include this control (Ortner & Pennekamp, 2020; King & dela Rosa, 2019; De Castella et al.,

2013; Moumne et al., 2020). The current study also varies from these studies in that it is the first to my knowledge to use an EMA-derived measure of malleability beliefs. It's possible that some of the discrepancy is due to this measurement difference.

Overall, the findings on ER self-efficacy do not suggest an active role for malleability appraisals in directing ER behaviors in the moment. They also do not support the idea that average ER self-efficacy is related to general tendencies in ER use. These results cast some doubt on process-oriented theories of how emotion malleability beliefs impact mental health outcomes. However, it's also possible that the momentary effect of ER self-efficacy on ER strategy selection, if it exists, may not have been captured by the current analyses because it is *too* context specific. Because ER self-efficacy is not hypothesized to motivate behavior directly, but to direct ER once it already motivated, it's possible that including it as an interaction may not have been an adequately sensitive analytic approach for characterizing this type of contextual specificity. If this process is only evident at high levels of ER importance, it may also be that not enough moments of high ER importance were captured within our sample to be able to identify such a specific interaction. Future studies could consider modeling the effect of ER self-efficacy on strategy selection *only* in observations in which ER behaviors are endorsed or increasing the sample size of observations to capture more ER occasions.

Overall, the results of testing specific hypotheses related to emotion appraisals and ER suggest that the strongest predictor of an individual's typical ER use is their average level of negative affect during the same time period. However, the best predictor of an individual's momentary ER (relative to their regular use) is their current appraisal of the importance of changing their mood. This pattern of effect seems to be the same for both engagement and disengagement ER.

4.4 Insights from Exploratory Analyses

The final aim of the current study was to examine the effect of momentary emotion appraisals on the likelihood of reporting specific ER strategies. Because I used a more stringent alpha level for these analyses, only the most robust effects reached significance. Where between-person effects of appraisals were present, they were better explained by average negative affect. Within-person, momentary ER importance was most strongly associated with acceptance, reappraisal, avoidance, and suppression. Consistent with my other findings, momentary ER importance is associated with a mix of engagement and disengagement strategies. The weakest effects in terms of magnitude were those for distraction and problem solving. It's possible this is because these two ER strategies are also behaviors that can occur outside of emotional contexts, whereas some of the others are specific to emotional contexts (for example suppression and reappraisal, which had the strongest effects). Thus, they may be less tightly linked to ER importance.

Though there were no effects of momentary ER self-efficacy that were significant at $p < .001$, there were some trends in these effects that I will note cautiously in order to highlight methodological difficulties in predicting ER strategies. Across the specific ER strategies modeled, momentary ER self-efficacy trended toward predicting a lower probability of most strategies. However, this was not true for suppression; results trended toward higher momentary ER self-efficacy being associated a higher chance of suppression. This points to the possibility that some emotion appraisals may be differentially related to specific strategies within the same broader category such as 'engagement' or 'disengagement.' For example, if someone believes their mood is changeable in the moment, this could make them simultaneously less likely to avoid the situation *and* more likely to attempt to suppress their emotions. Future studies should

be thoughtful when combining ER strategies to make sure their outcomes are sensitive to these potential differences, if they are relevant to the research question.

One specific hypothesis I made was that acceptance would be predicted by lower ER importance. Instead, acceptance was predicted by higher momentary ER importance, even at our more stringent alpha level. This may again be because the current analyses were not designed to predict the *relative* selection of certain strategies over others, but the likelihood of using the strategy versus not using it. Future studies may consider using analytic methods more tailored to examining which strategies are chosen *when* there is a goal to regulate to better understand processes related to strategy selection. I hope that these exploratory analyses can help inform future hypotheses that seek to understand how emotion appraisals relate to ER behaviors.

4.5 Limitations and Future Directions

Though this study has many strengths, there are also notable limitations in the approaches used – some of which have already been mentioned in the context of interpreting this study’s findings. An important limitation of the psychometric component of this study is the lack of trait-level measurement of emotion beliefs. Because we did not measure beliefs directly, it is not possible to describe the relation between momentary emotion appraisals and the trait-level constructs they were inspired by. However, it is well established that global self-reports do not consistently capture differences in state-level phenomena (see Feil et al., 2020 & Koval et al., 2020 for two examples), and in particular we may not expect global self-report of beliefs to directly track with averages of momentary appraisals, given that the manifestation of belief-congruent appraisals may be highly situation specific. Nonetheless, future psychometric work on these items would benefit greatly from comparing average emotion appraisals to their corresponding emotion beliefs.

To satisfy the first aim of this study, I reported on various within-person and temporal dynamics of these measures. However, my ability to fully characterize these dynamics is naturally limited by our sampling frequency. It's possible that meaningful trends in these appraisals were not captured by my analyses because they play out on a shorter time scale than is represented by our 5-times-per-day protocol. Sampling frequency could also have an impact on the correlations presented when there is a time-lag between the two variables, and in the rest of the analyses which have ER behaviors being predicted at the next time point. In this study, the average distance between observations within the same day was 3 hours and 7 minutes, and participants report on emotion regulation that happened over that entire period. While it seems reasonable that emotion appraisals could have an impact on ER behaviors within this time scale, it's possible that either a shorter or longer lag between observations would have generated different results. Many process-oriented models of emotion regulation theorize that emotion regulation is a recursive process involving continued feedback and adjustment of appraisals, goals, and behaviors (Ford & Gross, 2019). This suggests more temporal and directional nuance than what was modeled in the current study, which only looked at appraisals impacting ER behavior. However, it's equally likely that ER behaviors – and their emotional outcomes – impact appraisals. For example, the use of effective ER at the previous time point might lead to decreased ER importance and increased ER self-efficacy. Testing these more complex models would likely require more frequent within-day sampling.

Another potential limitation of the current study is the way in which the ER behavior outcome variables were measured and calculated. Because individual strategies were measured as binary, there is a significant amount of information missing about the nature of the regulation individuals did. For example, endorsing 'distraction' could describe someone taking a short

break to take their mind off a problem, or it could describe someone who spent hours watching TV to avoid thinking about a problem. It could be argued that the later individual is doing ‘more’ distraction than the former – in which case it might be appropriate for ER strategies to be measured on a scale that represents intensity of the ER behaviors in addition to simply whether they did it or not. Additionally, there’s no information captured in these measures as to whether the ER strategy was used effectively. Together, these measurement limitations make it somewhat difficult to interpret the meaning of a calculated variable such as ‘total ER.’ I’ve characterized the sum scored used in this study as a ‘variety’ score which captures the number of different strategies an individual uses during a given assessment period. However, a high number could represent someone effectively and competently deploying a range of strategies, or it could represent someone who is using multiple strategies out of desperation because none are particularly effective. The present study was not concerned as much with these nuances, but to integrate the present results into larger theories of how emotion appraisals contribute to psychopathology, understanding the precursors of *effective* versus *ineffective* ER may be particularly important.

Another potential limitation of this study is the use of single-item scales for the appraisal items. There is active debate within EMA research as to the benefits of single-item measures versus multiple item-scales (Diamantopoulos et al., 2012; Gardner et al., 1998). Single items have the benefit of being low burden and having clear construct coverage when the construct is thought to be narrow and homogenous across individuals (the item essentially *is* the construct). The appropriateness of using a single item for specific emotion appraisals depends partially on how complex we believe this construct to be – some of which comes down to semantic considerations. For example, it could be argued that the language ‘how important is it to you to

changing your mood' doesn't cleanly capture either valuation appraisals (which have been at times used to describe whether emotions are desirable, harmful, unwanted, and appropriate, among others) or ER importance, which may imply an explicit desire to enact change. Is saying that something is 'important to change' the same as saying you don't like it or that you want it to change? These are empirical questions, and if researchers believe that broader coverage is needed to fully characterize appraisal dimensions, then development of a multi-item scales may be a productive direction for future psychometric work on momentary appraisals.

Lastly, this study was conducted in a non-clinical population of undergraduate students. These patterns may look different in clinical population, particularly in populations that are characterized by specific patterns in emotion regulatory difficulties. Future studies may find it fruitful to look for different appraisal and ER patterns *within* individuals that have high trait negative emotionality, since that ended up being a powerful predictor of almost all ER behaviors. The correlation between ER importance and ER self-efficacy was weak at the trait-level, suggesting that within the group of individuals with high negative emotionality and high ER use, varying levels of average ER self-efficacy could be represented. For example, some may be using ER strategies while feeling confident in their abilities to regulate, while others may be using many strategies while having low confidence in their abilities to effectively change their mood. These differences may be more clinically relevant than the difference between how someone with generally low negative affect differs in their regulation from someone who is generally high in NA, as the goal of therapy is often not to reduce the experience of negative affect directly, but to help individuals who are predisposed to negative emotionality learn to cope effectively with their emotions. As an extension, examining these patterns within clinical populations – and within individuals who have been successfully treated for mental health

disorders – may help connect patterns of emotion appraisal and regulation to specific psychological outcomes as well as effective components of treatment.

4.6 Strengths, Clinical Implications, and Conclusions

The current study has many strengths, and the results have important implications for both research and treatment. This study provides the first thorough psychometric account of EMA items measuring momentary emotion appraisals and to test hypotheses about their interaction. It is also one of the first studies to examine prospective associations between emotional appraisals and emotion regulation in day-to-day life. I hope that the findings from this study may encourage other EMA researchers interested in emotion-behavior dynamics to consider the inclusion of appraisals – and in particular ER importance – in their models. These items could be helpful for moving forward research on emotion-related processes and how they contribute to psychopathology. Given the brief nature of the ER importance item and its associations with ER behaviors, use of this measure may be useful for more prediction-oriented work in particular. There has been a rise in interest in idiographic methods and individualized assessment and treatment approaches that could use EMA-like methods to tailor interventions to individuals. Measuring relevant appraisals in a low-burden way may be useful in advancing the precision of this work.

Engaging in ‘unhealthy’ ER strategies was most strongly related to a combination of trait emotionality and momentary ER importance. Given this, interventions which seek to reduce the desire to change one’s emotion could theoretically produce healthier coping responses. For example, acceptance and mindfulness based approaches seek to reduce distress by changing appraisals of negative emotions to be more neutral (Hayes, 2004; Hayes et al., 2006). However, our findings suggest that the same processes promote ‘healthier’ ER behaviors as well. This

highlights the clinical struggle to define what a ‘healthy’ set of emotion appraisals may look like. Further, some research suggests that psychological flexibility and fitting emotion regulation attempts to the situation is key to psychological health (Haines et al., 2016), such that disengagement strategies may be more appropriate in some situations, and engagement strategies more appropriate in others. Other studies have found that person-level factors may moderate whether acceptance-based or control-based regulation strategies are more effective (Forman et al., 2007), indicating that different appraisals may be more or less useful for different individuals. The appraisal items presented in this paper could be used in future studies to examine this type of contextual nuance.

This study provides preliminary evidence that emotion appraisals can be measured in EMA and capture enough within-person variance to be used in models of emotion-behavior dynamics. It also provided evidence for the importance of measuring emotion appraisals in addition to more traditional components of emotion such as valence and discrete emotion terms. These results also highlight the importance of differentiating between appraisal tendencies and momentary appraisals, and provide preliminary evidence that appraisals may be more important at the within-person level than the between-person level. This is a particularly novel finding considering that the bulk of the research on emotion beliefs to date has focused exclusively on the trait level.

Lastly, I hope that these results support the integration of emotion appraisals into future work that examines how individuals make meaning of their emotional experiences, and how that meaning guides their behavior. Ultimately, the goal of integrating emotion appraisals into models of emotion-behavior associations is to understand how individuals can most adaptively interact with their own internal experiences in order to promote psychological health and wellbeing.

References

- Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review, 30*(2), 217–237. <https://doi.org/10.1016/j.cpr.2009.11.004>
- Bandura, A., Caprara, G. V., Barbaranelli, C., Gerbino, M., & Pastorelli, C. (2003). Role of affective self-regulatory efficacy in diverse spheres of psychosocial functioning. *Child Development, 74*(3), 769–782. <https://doi.org/10.1111/1467-8624.00567>
- Barrett, L. F., Mesquita, B., Ochsner, K. N., & Gross, J. J. (2007). The Experience of Emotion. *Annual Review of Psychology, 58*(1), 373–403. <https://doi.org/10.1146/annurev.psych.58.110405.085709>
- Bartsch, A., Vorderer, P., Mangold, R., & Viehoff, R. (2008). Appraisal of Emotions in Media Use: Toward a Process Model of Meta-Emotion and Emotion Regulation. *Media Psychology, 11*(1), 7–27. <https://doi.org/10.1080/15213260701813447>
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software, 67*(1), 1–48. <https://doi.org/10.18637/jss.v067.i01>
- Brooks, M. E., Kristensen, K., Benthem, K. J. van, Magnusson, A., Berg, C. W., Nielsen, A., Skaug, H. J., Maechler, M., & Bolker, B. M. (2017). GlmmTMB Balances Speed and Flexibility Among Packages for Zero-inflated Generalized Linear Mixed Modeling. *The R Journal, 9*(2), 378–400.
- Bylsma, L. M., & Rottenberg, J. (2011). Uncovering the Dynamics of Emotion Regulation and Dysfunction in Daily Life with Ecological Momentary Assessment. In I. Nyklíček, A.

- Vingerhoets, & M. Zeelenberg (Eds.), *Emotion Regulation and Well-Being* (pp. 225–244). Springer New York. https://doi.org/10.1007/978-1-4419-6953-8_14
- Carver, C. S., Johnson, S. L., & Timpano, K. R. (2017). Toward a Functional View of the p Factor in Psychopathology. *Clinical Psychological Science, 5*(5), 880–889. <https://doi.org/10.1177/2167702617710037>
- Chawla, N., & Ostafin, B. (2007). Experiential avoidance as a functional dimensional approach to psychopathology: An empirical review. *Journal of Clinical Psychology, 63*(9), 871–890. <https://doi.org/10.1002/jclp.20400>
- Colombo, D., Fernández-Álvarez, J., Suso-Ribera, C., Cipresso, P., Valev, H., Leufkens, T., Sas, C., Garcia-Palacios, A., Riva, G., & Botella, C. (2020). The need for change: Understanding emotion regulation antecedents and consequences using ecological momentary assessment. *Emotion, 20*(1), 30–36. <https://doi.org/10.1037/emo0000671>
- Coxe, S., West, S. G., & Aiken, L. S. (2009). The Analysis of Count Data: A Gentle Introduction to Poisson Regression and Its Alternatives. *Journal of Personality Assessment, 91*(2), 121–136. <https://doi.org/10.1080/00223890802634175>
- Daros, A. R., Daniel, K. E., Boukhechba, M., Chow, P. I., Barnes, L. E., & Teachman, B. A. (2020). Relationships between trait emotion dysregulation and emotional experiences in daily life: An experience sampling study. *Cognition and Emotion, 34*(4), 743–755. <https://doi.org/10.1080/02699931.2019.1681364>
- De Castella, K., Goldin, P., Jazaieri, H., Ziv, M., Dweck, C. S., & Gross, J. J. (2013). Beliefs About Emotion: Links to Emotion Regulation, Well-Being, and Psychological Distress. *Basic and Applied Social Psychology, 35*(6), 497–505. <https://doi.org/10.1080/01973533.2013.840632>

- De Castella, K., Platow, M. J., Tamir, M., & Gross, J. J. (2018a). Beliefs about emotion: Implications for avoidance-based emotion regulation and psychological health. *Cognition and Emotion*, 32(4), 773–795. <https://doi.org/10.1080/02699931.2017.1353485>
- De Castella, K., Platow, M. J., Tamir, M., & Gross, J. J. (2018b). Beliefs about emotion: Implications for avoidance-based emotion regulation and psychological health. *Cognition and Emotion*, 32(4), 773–795. <https://doi.org/10.1080/02699931.2017.1353485>
- De Vaus, J., Hornsey, M. J., Kuppens, P., & Bastian, B. (2018). Exploring the East-West Divide in Prevalence of Affective Disorder: A Case for Cultural Differences in Coping With Negative Emotion. *Personality and Social Psychology Review*, 22(3), 285–304. <https://doi.org/10.1177/1088868317736222>
- Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: A predictive validity perspective. *Journal of the Academy of Marketing Science*, 40(3), 434–449. <https://doi.org/10.1007/s11747-011-0300-3>
- Dvorak, R. D., Pearson, M. R., & Day, A. M. (2014). Ecological momentary assessment of acute alcohol use disorder symptoms: Associations with mood, motives, and use on planned drinking days. *Experimental and Clinical Psychopharmacology*, 22(4), 285–297. <https://doi.org/10.1037/a0037157>
- Dweck, C. S., Chiu, C., & Hong, Y. (1995). Implicit Theories and Their Role in Judgments and Reactions: A World from Two Perspectives. *Psychological Inquiry*, 6(4), 267–285. JSTOR.
- Edwards, E. R., & Wupperman, P. (2019). Research on emotional schemas: A review of findings and challenges. *Clinical Psychologist*, 23(1), 3–14. <https://doi.org/10.1111/cp.12171>

- Ekman, P. (1999). Basic Emotions. In *Handbook of Cognition and Emotion*. John Wilen & Sons Ltd.
- Feil, M., Halvorson, M., Lengua, L., & King, K. M. (2020). A state model of negative urgency: Do momentary reports of emotional impulsivity reflect global self-report? *Journal of Research in Personality*, *86*, 103942. <https://doi.org/10.1016/j.jrp.2020.103942>
- Fisher, A. J., Medaglia, J. D., & Jeronimus, B. F. (2018). Lack of group-to-individual generalizability is a threat to human subjects research. *Proceedings of the National Academy of Sciences*, *115*(27), E6106–E6115. <https://doi.org/10.1073/pnas.1711978115>
- Ford, B. Q., & Gross, J. J. (2019). Why Beliefs About Emotion Matter: An Emotion-Regulation Perspective. *Current Directions in Psychological Science*, *28*(1), 74–81. <https://doi.org/10.1177/0963721418806697>
- Ford, B. Q., Lwi, S. J., Gentzler, A. L., Hankin, B., & Mauss, I. B. (2018). The cost of believing emotions are uncontrollable: Youths' beliefs about emotion predict emotion regulation and depressive symptoms. *Journal of Experimental Psychology: General*, *147*(8), 1170–1190. <https://doi.org/10.1037/xge0000396>
- Forman, E. M., Hoffman, K. L., McGrath, K. B., Herbert, J. D., Brandsma, L. L., & Lowe, M. R. (2007). A comparison of acceptance- and control-based strategies for coping with food cravings: An analog study. *Behaviour Research and Therapy*, *45*(10), 2372–2386. <https://doi.org/10.1016/j.brat.2007.04.004>
- Gardner, D. G., Cummings, L. L., Dunham, R. B., & Pierce, J. L. (1998). Single-Item Versus Multiple-Item Measurement Scales: An Empirical Comparison. *Educational and Psychological Measurement*, *58*(6), 898–915. <https://doi.org/10.1177/0013164498058006003>

- Garnefski, N., Kraaij, V., & Spinhoven, P. (2001). Negative life events, cognitive emotion regulation and emotional problems. *Personality and Individual Differences, 30*(8), 1311–1327. [https://doi.org/10.1016/S0191-8869\(00\)00113-6](https://doi.org/10.1016/S0191-8869(00)00113-6)
- Gottman, J. M., Katz, L. F., & Hooven, C. (1996). Parental meta-emotion philosophy and the emotional life of families: Theoretical models and preliminary data. *Journal of Family Psychology, 10*(3), 243–268. <https://doi.org/10.1037/0893-3200.10.3.243>
- Greeley, J., & Oei, T. (1999). Alcohol and tension reduction. In *Psychological theories of drinking and alcoholism, 2nd ed* (pp. 14–53). The Guilford Press.
- Grice, J. W., Cohn, A., Ramsey, R. R., & Chaney, J. M. (2015). On Muddled Reasoning and Mediation Modeling. *Basic and Applied Social Psychology, 37*(4), 214–225. <https://doi.org/10.1080/01973533.2015.1049350>
- Gross, J. J. (2015). The Extended Process Model of Emotion Regulation: Elaborations, Applications, and Future Directions. *Psychological Inquiry, 26*(1), 130–137. <https://doi.org/10.1080/1047840X.2015.989751>
- Haedt-Matt, A. A., & Keel, P. K. (2011). Revisiting the Affect Regulation Model of Binge Eating: A Meta-Analysis of Studies using Ecological Momentary Assessment. *Psychological Bulletin, 137*(4), 660–681. <https://doi.org/10.1037/a0023660>
- Haines, S. J., Gleeson, J., Kuppens, P., Hollenstein, T., Ciarrochi, J., Labuschagne, I., Grace, C., & Koval, P. (2016). The Wisdom to Know the Difference: Strategy-Situation Fit in Emotion Regulation in Daily Life Is Associated With Well-Being. *Psychological Science, 27*(12), 1651–1659. <https://doi.org/10.1177/0956797616669086>
- Halvorson, M. A., Pedersen, S., Feil, M., Lengua, L., Molina, B., & King, K. M. (2019). *Impulsive states and impulsive traits: A study of the multilevel structure and validity of a*

multifaceted measure of impulsive states [Preprint]. Open Science Framework.

<https://doi.org/10.31219/osf.io/nyevc>

- Hamaker, E. L., & Wichers, M. (2017). No Time Like the Present: Discovering the Hidden Dynamics in Intensive Longitudinal Data. *Current Directions in Psychological Science*, 26(1), 10–15. <https://doi.org/10.1177/0963721416666518>
- Hayes, S. C. (2004). Acceptance and commitment therapy, relational frame theory, and the third wave of behavioral and cognitive therapies. *Behavior Therapy*, 35(4), 639–665. [https://doi.org/10.1016/S0005-7894\(04\)80013-3](https://doi.org/10.1016/S0005-7894(04)80013-3)
- Hayes, S. C., Luoma, J. B., Bond, F. W., Masuda, A., & Lillis, J. (2006). Acceptance and Commitment Therapy: Model, processes and outcomes. *Behaviour Research and Therapy*, 44(1), 1–25. <https://doi.org/10.1016/j.brat.2005.06.006>
- Hayes, S. C., Wilson, K. G., Gifford, E. V., Follette, V. M., & Strosahl, K. (1996). Experiential Avoidance and Behavioral Disorders: A Functional Dimensional Approach to Diagnosis and Treatment. *Journal of Consulting and Clinical Psychology*, 64(2).
- Haynos, A. F., & Fruzzetti, A. E. (2011). Anorexia Nervosa as a Disorder of Emotion Dysregulation: Evidence and Treatment Implications. *Clinical Psychology: Science and Practice*, 18(3), 183–202. <https://doi.org/10.1111/j.1468-2850.2011.01250.x>
- Hu, M.-C., Pavlicova, M., & Nunes, E. V. (2011). Zero-Inflated and Hurdle Models of Count Data with Extra Zeros: Examples from an HIV-Risk Reduction Intervention Trial. *The American Journal of Drug and Alcohol Abuse*, 37(5), 367–375. <https://doi.org/10.3109/00952990.2011.597280>

- Izard, C. E. (2007). Basic Emotions, Natural Kinds, Emotion Schemas, and a New Paradigm. *Perspectives on Psychological Science*, 2(3), 260–280. <https://doi.org/10.1111/j.1745-6916.2007.00044.x>
- Izard, C. E. (2010). The Many Meanings/Aspects of Emotion: Definitions, Functions, Activation, and Regulation. *Emotion Review*, 2(4), 363–370. <https://doi.org/10.1177/1754073910374661>
- Johnson-Laird, P. N., Mancini, F., & Gangemi, A. (2006). A hyper-emotion theory of psychological illnesses. *Psychological Review*, 113(4), 822–841. <https://doi.org/10.1037/0033-295X.113.4.822>
- Kämpfe, N., & Mitte, K. (2009). What you wish is what you get? The meaning of individual variability in desired affect and affective discrepancy. *Journal of Research in Personality*, 43(3), 409–418. <https://doi.org/10.1016/j.jrp.2009.01.007>
- Karnaze, M. M., & Levine, L. J. (2018). Data versus Spock: Lay theories about whether emotion helps or hinders. *Cognition and Emotion*, 32(3), 549–565. <https://doi.org/10.1080/02699931.2017.1326374>
- Kazdin, A. E. (2007). Mediators and Mechanisms of Change in Psychotherapy Research. *Annual Review of Clinical Psychology*, 3(1), 1–27. <https://doi.org/10.1146/annurev.clinpsy.3.022806.091432>
- King, R. B., & dela Rosa, E. D. (2019). Are your emotions under your control or not? Implicit theories of emotion predict well-being via cognitive reappraisal. *Personality and Individual Differences*, 138, 177–182. <https://doi.org/10.1016/j.paid.2018.09.040>
- Klonsky, E. D. (2007). The functions of deliberate self-injury: A review of the evidence. *Clinical Psychology Review*, 27(2), 226–239. <https://doi.org/10.1016/j.cpr.2006.08.002>

- Kneeland, E. T., Goodman, F. R., & Dovidio, J. F. (2020). Emotion Beliefs, Emotion Regulation, and Emotional Experiences in Daily Life. *Behavior Therapy, 51*(5), 728–738.
<https://doi.org/10.1016/j.beth.2019.10.007>
- Kneeland, E. T., Nolen-Hoeksema, S., Dovidio, J. F., & Gruber, J. (2016a). Emotion Malleability Beliefs Influence the Spontaneous Regulation of Social Anxiety. *Cognitive Therapy and Research, 40*(4), 496–509. <https://doi.org/10.1007/s10608-016-9765-1>
- Kneeland, E. T., Nolen-Hoeksema, S., Dovidio, J. F., & Gruber, J. (2016b). Beliefs about emotion's malleability influence state emotion regulation. *Motivation and Emotion, 40*(5), 740–749. <https://doi.org/10.1007/s11031-016-9566-6>
- Koval, P., Butler, E. A., Hollenstein, T., Lanteigne, D., & Kuppens, P. (2015). Emotion regulation and the temporal dynamics of emotions: Effects of cognitive reappraisal and expressive suppression on emotional inertia. *Cognition and Emotion, 29*(5), 831–851.
<https://doi.org/10.1080/02699931.2014.948388>
- Koval, P., Kalokerinos, E. K., Greenaway, K. H., Medland, H., Kuppens, P., Nezlek, J. B., Hinton, J., & Gross, J. (2020). *Emotion Regulation in Everyday Life: What Can We Learn from Global Self-Reports?* [Preprint]. PsyArXiv. <https://doi.org/10.31234/osf.io/cav54>
- Kuppens, P. (2019). Improving theory, measurement, and reality to advance the future of emotion research. *Cognition and Emotion, 33*(1), 20–23.
<https://doi.org/10.1080/02699931.2018.1536037>
- Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010). Emotional Inertia and Psychological Maladjustment. *Psychological Science, 21*(7), 984–991.
<https://doi.org/10.1177/0956797610372634>

- Lane, A. M., Beedie, C. J., Devonport, T. J., & Stanley, D. M. (2011). Instrumental emotion regulation in sport: Relationships between beliefs about emotion and emotion regulation strategies used by athletes. *Scandinavian Journal of Medicine and Science in Sports*, *21*(6), 445–451. <https://doi.org/10.1111/j.1600-0838.2011.01364.x>
- Larson, R. W., & Lampman-Petratis, C. (1989). Daily emotional states as reported by children and adolescents. *Child Development*, *60*(5), 1250–1260. <https://doi.org/10.2307/1130798>
- Leahy, R. L. (2002). A model of emotional schemas. *Cognitive and Behavioral Practice*, *9*(3), 177–190. [https://doi.org/10.1016/S1077-7229\(02\)80048-7](https://doi.org/10.1016/S1077-7229(02)80048-7)
- Luong, G., Wrzus, C., Wagner, G. G., & Riediger, M. (2016). When bad moods may not be so bad: Valuing negative affect is associated with weakened affect–health links. *Emotion*, *16*(3), 387–401. <https://doi.org/10.1037/emo0000132>
- Maio, G. R., & Esses, V. M. (2001). The Need for Affect: Individual Differences in the Motivation to Approach or Avoid Emotions. *Journal of Personality*, *69*(4), 583–614. <https://doi.org/10.1111/1467-6494.694156>
- Manser, R., Cooper, M., & Trefusis, J. (2012). Beliefs about Emotions as a Metacognitive Construct: Initial Development of a Self-Report Questionnaire Measure and Preliminary Investigation in Relation to Emotion Regulation. *Clinical Psychology and Psychotherapy*, *19*(3), 235–246. <https://doi.org/10.1002/cpp.745>
- Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. *Cognition & Emotion*, *23*(2), 209–237. <https://doi.org/10.1080/02699930802204677>
- Moumne, S., Hall, N., Böke, B. N., Bastien, L., & Heath, N. (2020). Implicit Theories of Emotion, Goals for Emotion Regulation, and Cognitive Responses to Negative Life

- Events. *Psychological Reports*, 003329412094211.
- <https://doi.org/10.1177/0033294120942110>
- Nock, M. K. (2007). Conceptual and Design Essentials for Evaluating Mechanisms of Change. *Alcoholism: Clinical and Experimental Research*, 31(s3), 4s–12s.
- <https://doi.org/10.1111/j.1530-0277.2007.00488.x>
- Nock, M. K., Wedig, M. M., Holmberg, E. B., & Hooley, J. M. (2008). The Emotion Reactivity Scale: Development, Evaluation, and Relation to Self-Injurious Thoughts and Behaviors. *Behavior Therapy*, 39(2), 107–116. <https://doi.org/10.1016/j.beth.2007.05.005>
- Ortner, C. N. M., & Pennekamp, P. (2020). Emotion malleability beliefs and event intensity and importance predict emotion regulation in daily life. *Personality and Individual Differences*, 159, 109887. <https://doi.org/10.1016/j.paid.2020.109887>
- Porat, R., Halperin, E., Mannheim, I., & Tamir, M. (2016). Together we cry: Social motives and preferences for group-based sadness. *Cognition and Emotion*, 30(1), 66–79.
- <https://doi.org/10.1080/02699931.2015.1039495>
- R Core Team. (2020). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Ridout, M., Demetrio, C. G. B., & Hinde, J. (1998). *Models for count data with many zeros*. 13.
- Robinson, M. D., & Clore, G. L. (2002). Belief and feeling: Evidence for an accessibility model of emotional self-report. *Psychological Bulletin*, 128(6), 934–960.
- <https://doi.org/10.1037//0033-2909.128.6.934>
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161–1178. <https://doi.org/10.1037/h0077714>

- Sander, D., Grandjean, D., & Scherer, K. R. (2018). An Appraisal-Driven Componential Approach to the Emotional Brain. *Emotion Review*, *10*(3), 219–231.
<https://doi.org/10.1177/1754073918765653>
- Sher, K. J., & Grekin, E. R. (2007). Alcohol and Affect Regulation. In *Handbook of emotion regulation* (pp. 560–580). The Guilford Press.
- Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology*, *4*, 1–32.
- Silk, J. S., Steinberg, L., & Morris, A. S. (2003). Adolescents' Emotion Regulation in Daily Life: Links to Depressive Symptoms and Problem Behavior Author (s): Jennifer S. Silk , Laurence Steinberg and Amanda Sheffield Morris Published by: Wiley on behalf of the Society for Research in Child Develop. *Child Development*, *74*(6), 1869–1880.
<https://doi.org/10.1046/j.1467-8624.2003.00643.x>
- Simons, J. S., Dvorak, R. D., Batien, B. D., & Wray, T. B. (2010). Event-level associations between affect, alcohol intoxication, and acute dependence symptoms: Effects of urgency, self-control, and drinking experience. *Addictive Behaviors*, *35*(12), 1045–1053.
<https://doi.org/10.1016/j.addbeh.2010.07.001>
- Simons, J. S., & Gaher, R. M. (2005). The Distress Tolerance Scale: Development and Validation of a Self-Report Measure. *Motivation and Emotion*, *29*(2), 83–102.
<https://doi.org/10.1007/s11031-005-7955-3>
- Smith, R., & Lane, R. D. (2015). The neural basis of one's own conscious and unconscious emotional states. *Neuroscience & Biobehavioral Reviews*, *57*, 1–29.
<https://doi.org/10.1016/j.neubiorev.2015.08.003>

- Tamir, M., & Ford, B. Q. (2009). Choosing to be afraid: Preferences for fear as a function of goal pursuit. *Emotion, 9*(4), 488–497. <https://doi.org/10.1037/a0015882>
- Tamir, M., & Ford, B. Q. (2012). When feeling bad is expected to be good: Emotion regulation and outcome expectancies in social conflicts. *Emotion, 12*(4), 807–816. <https://doi.org/10.1037/a0024443>
- Tamir, M., & Gutentag, T. (2017). Desired emotional states: Their nature, causes, and implications for emotion regulation. *Current Opinion in Psychology, 17*, 84–88. <https://doi.org/10.1016/j.copsyc.2017.06.014>
- Tamir, M., John, O. P., Srivastava, S., & Gross, J. J. (2007). Implicit theories of emotion: Affective and social outcomes across a major life transition. *Journal of Personality and Social Psychology, 92*(4), 731–744. <https://doi.org/10.1037/0022-3514.92.4.731>
- Tan, P. Z., Forbes, E. E., Dahl, R. E., Ryan, N. D., Siegle, G. J., Ladouceur, C. D., & Silk, J. S. (2012). Emotional reactivity and regulation in anxious and nonanxious youth: A cell-phone ecological momentary assessment study. *Journal of Child Psychology and Psychiatry and Allied Disciplines, 53*(2), 197–206. <https://doi.org/10.1111/j.1469-7610.2011.02469.x>
- Trull, T. J., & Ebner-Priemer, U. (2014). The role of ambulatory assessment in psychological science. *Current Directions in Psychological Science, 23*(6), 466–470. <https://doi.org/10.1177/0963721414550706>
- Tsai, J. L. (2007). Ideal Affect: Cultural Causes and Behavioral Consequences. *Perspectives on Psychological Science, 2*(3), 242–259. JSTOR.

- Tsai, J. L. (2017). Ideal affect in daily life: Implications for affective experience, health, and social behavior. *Current Opinion in Psychology*, *17*, 118–128.
<https://doi.org/10.1016/j.copsyc.2017.07.004>
- Veilleux, J. C., Hill, M. A., Skinner, K. D., Pollert, G. A., Baker, D. E., & Spero, K. D. (2018). The dynamics of persisting through distress: Development of a Momentary Distress Intolerance Scale using ecological momentary assessment. *Psychological Assessment*, *30*(11), 1468–1478. <https://doi.org/10.1037/pas0000593>
- Werner, K., & Gross, J. J. (2010). Emotion regulation and psychopathology: A conceptual framework. In *Emotion regulation and psychopathology: A transdiagnostic approach to etiology and treatment* (pp. 13–37). The Guilford Press.
- Whiteside, S. P., & Lynam, D. R. (2001). The Five Factor Model and impulsivity: Using a structural model of personality to understand impulsivity. *Personality and Individual Differences*, *30*(4), 669–689. [https://doi.org/10.1016/S0191-8869\(00\)00064-7](https://doi.org/10.1016/S0191-8869(00)00064-7)
- Williams, K. E., Chambless, D. L., & Ahrens, A. (1997). Are emotions frightening? An extension of the fear of fear construct. *Behaviour Research and Therapy*, *35*(3), 239–248.
[https://doi.org/10.1016/S0005-7967\(96\)00098-8](https://doi.org/10.1016/S0005-7967(96)00098-8)
- Wray, T. B., Merrill, J. E., & Monti, P. M. (2014). Using Ecological Momentary Assessment (EMA) to Assess Situation-Level Predictors of Alcohol Use and Alcohol-Related Consequences. *Alcohol Research : Current Reviews*, *36*(1), 19–27.
- Yoon, S., Dang, V., Mertz, J., & Rottenberg, J. (2018). Are attitudes towards emotions associated with depression? A Conceptual and meta-analytic review. *Journal of Affective Disorders*, *232*, 329–340. <https://doi.org/10.1016/j.jad.2018.02.009>

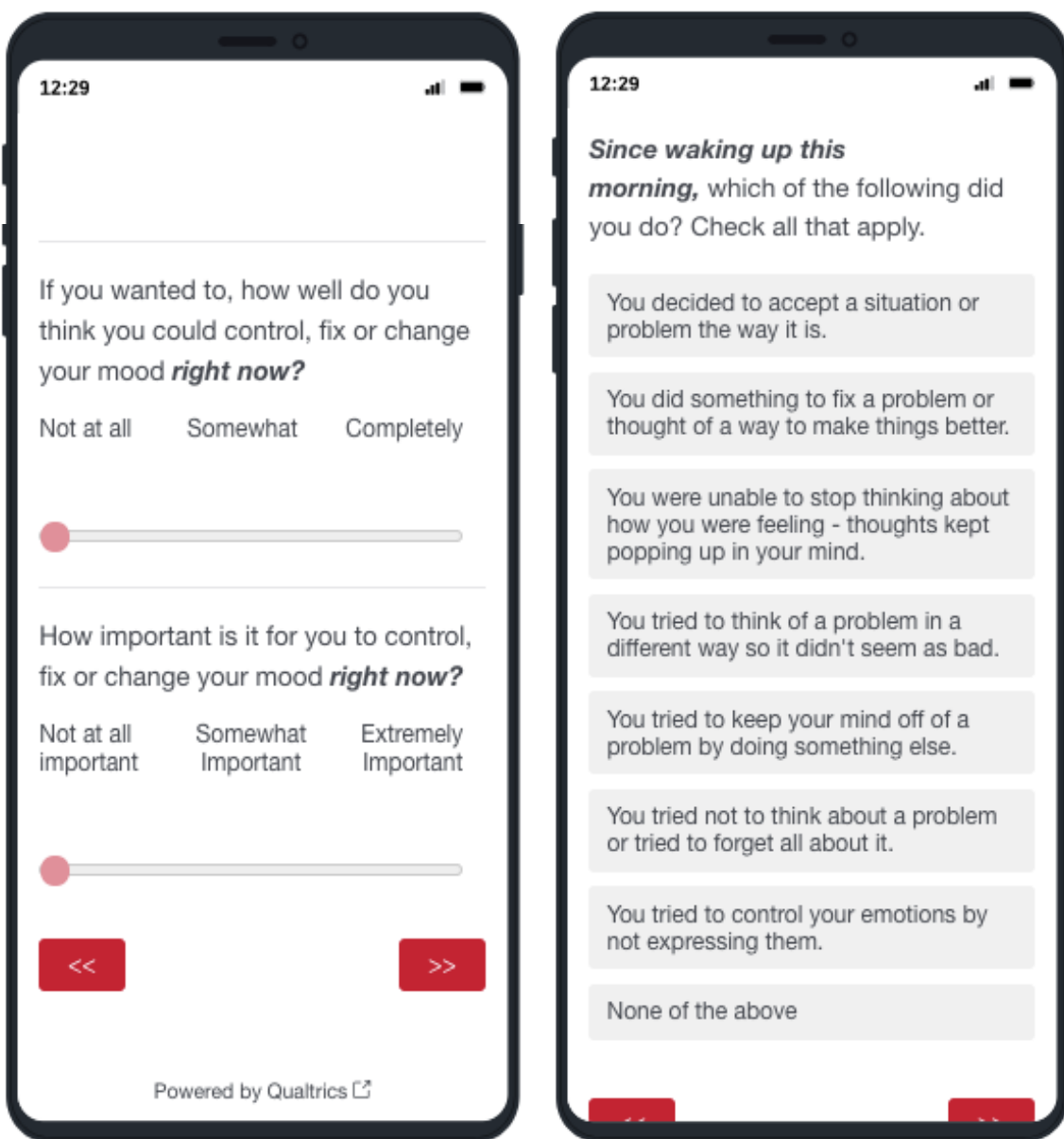
Zorn, C. J. W. (1998). An Analytic and Empirical Examination of Zero-Inflated and Hurdle Poisson Specifications. *Sociological Methods & Research*, 26(3), 368–400.

<https://doi.org/10.1177/0049124198026003004>

Appendix 1

Figure 12

Emotion appraisal and emotion regulation items as they appear to participants in EMAs



Appendix 2

Table 7

Descriptive statistics for all study variables

	<i>Ecological Momentary Assessment</i>		<i>Person-Level EMA Average</i>		<i>Baseline Variables</i>	
	Mean	SD	Mean	SD	Mean	SD
ER Importance	21.67	24.99	22.02	14.66	-	-
ER Self-Efficacy	56.12	27.36	55.46	18.50	-	-
Negative Affect	13.23	15.30	14.14	10.43	-	-
Positive Affect	53.94	22.26	53.97	53.97	-	-
Total ER	0.74	1.08	0.778	0.64	-	-
Engagement ER	0.37	0.64	0.39	0.35	-	-
Disengagement ER	0.26	0.59	0.27	0.27	-	-
Negative Urgency (UPPS)	19.07	22.17	19.35	15.45	2.54	0.49
Persistence (UPPS)	51.53	18.20	51.38	9.03	2.07	0.35
Planning (UPPS)	62.10	19.93	61.84	12.67	1.95	0.51
Emotion Reactivity Scale (ERS)	-	-	-	-	2.33	2.33
Self-Blame (CERQ)	-	-	-	-	2.87	0.84
Other-Blame (CERQ)	-	-	-	-	1.97	0.54
Rumination (CERQ)	-	-	-	-	3.22	0.90
Catastrophizing (CERQ)	-	-	-	-	2.03	0.72
Reframing (CERQ)	-	-	-	-	2.37	0.85
Planning (CERQ)	-	-	-	-	3.24	0.79
Reappraisal (CERQ)	-	-	-	-	3.36	0.89
Perspective Taking (CERQ)	-	-	-	-	3.26	0.83
Acceptance (CERQ)	-	-	-	-	3.23	0.74
Depression (PROMIS)	-	-	-	-	1.97	0.93
Anxiety (PROMIS)	-	-	-	-	2.53	0.93
Anger (PROMIS)	-	-	-	-	2.32	0.78
Marijuana Problems (PROMIS)	-	-	-	-	1.73	1.03
Alcohol Problems (PROMIS)	-	-	-	-	2.70	1.10

Appendix 3

Table 8

Bivariate Correlations of EMA emotion appraisals and other EMA study variables

	1	2	3	4	5	6	7	8	9	10	11
1. ER Importance											
2. ER Self-Efficacy	0.11										
3. Valence	0.24	-0.17									
4. Arousal	-0.12	0.14	-0.34								
5. Negative Affect	0.43	-0.20	0.42	-0.24							
6. Positive Affect	-0.21	0.29	-0.52	0.48	-0.37						
7. Total ER	0.20	-0.09	0.05	-0.07	0.22	-0.06					
8. Engagement ER	0.14	-0.07	0.03	-0.02	0.14	0.00	0.75				
9. Disengagement ER	0.16	-0.05	0.03	-0.07	0.16	-0.07	0.74	0.19			
10. Acting on Impulse	0.20	-0.17	0.04	-0.05	0.20	-0.13	0.16	0.06	0.15		
11. Persistence	-0.02	0.14	-0.06	0.06	-0.03	0.15	-0.04	0.03	-0.06	-0.01	
12. Planning	-0.06	0.20	-0.08	0.09	-0.10	0.19	-0.06	0.03	-0.09	-0.39	0.22

Note: Correlations significant at $p < .05$ are bolded.

Table 9

Bivariate correlations of person-level average emotion appraisals and person-level and trait emotion variables

	1	2	3	4	5	6	7	8	9
1. Average ER Importance									
2. Average ER Self-Efficacy	-0.15								
3. Average Valence	0.21	-0.19							
4. Average Arousal	-0.17	0.14	-0.38						
5. Average Negative Affect	0.54	-0.20	0.37	-0.31					
6. Average Positive Affect	-0.17	0.34	-0.64	0.55	-0.26				
7. PROMIS Anxiety	0.41	-0.18	0.34	-0.19	0.47	-0.39			
8. PROMIS Anger	0.35	-0.17	0.19	-0.22	0.47	-0.19	0.52		
9. PROMIS Depression	0.40	-0.23	0.30	-0.26	0.45	-0.34	0.78	0.56	
10. Emotion Reactivity Scale (ERS)	0.27	-0.23	0.15	-0.05	0.36	-0.21	0.54	0.42	0.43

Note: Correlations significant at $p < .05$ are bolded.

Table 10*Bivariate correlations of person-average emotion appraisals and person-average and trait-level ER variables*

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Average ER Importance													
2. Average ER Self-Efficacy	-0.15												
3. Self-Blame (CERQ)	0.28	-0.13											
4. Other-blame (CERQ)	0.05	-0.14	0.05										
5. Rumination (CERQ)	0.19	-0.28	0.48	0.23									
6. Catastrophizing (CERQ)	0.32	-0.21	0.31	0.42	0.45								
7. Reframing (CERQ)	-0.07	0.10	-0.22	0.03	0.02	-0.16							
8. Planning (CERQ)	0.19	0.03	0.16	0.02	0.17	-0.14	0.35						
9. Reappraisal (CERQ)	-0.01	0.13	-0.16	-0.17	-0.10	-0.33	0.42	0.63					
10. Perspective Taking (CERQ)	-0.07	0.04	-0.12	0.03	-0.08	-0.17	0.32	0.41	0.50				
11. Acceptance (CERQ)	0.00	-0.03	0.30	-0.11	0.22	0.11	0.08	0.14	0.15	0.11			
12. Average Total ER	0.35	-0.18	0.31	0.03	0.31	0.19	-0.03	0.24	-0.01	-0.06	0.16		
12. Average Disengagement ER	0.39	-0.15	0.35	0.06	0.30	0.17	-0.04	0.14	-0.10	-0.14	0.22	0.81	
13. Average Engagement ER	0.24	-0.14	0.21	0.01	0.26	0.16	0.04	0.34	0.13	0.04	0.11	0.87	0.47

*Note: Correlations significant a $p < .05$ are bolded.***Table 11***Bivariate correlations of person-average emotion appraisals and person-average and trait impulsivity and substance use problems*

	1	2	3	4	5	6	7	8	9
1. ER Importance									
2. ER Self-Efficacy	-0.15								
3. Acting on Impulse (EMA)	0.36	-0.28							
4. Persistence (EMA)	-0.10	0.39	-0.12						
5. Planning (EMA)	-0.07	0.37	-0.53	0.52					
6. Urgency (UPPS)	-0.24	0.15	-0.35	0.01	0.29				
7. Planning (UPPS)	-0.06	-0.07	0.28	0.04	-0.34	-0.31			
8. Persistence (UPPS)	0.00	-0.20	0.27	-0.27	-0.35	-0.03	0.41		
9. Marijuana Problems (PROMIS)	-0.04	0.12	0.08	0.09	-0.03	-0.04	0.16	0.04	
10. Alcohol Problems (PROMIS)	0.23	-0.19	0.22	-0.05	-0.23	-0.46	0.16	0.04	0.01

Note: Correlations significant a $p < .05$ are bolded.