8-2021

Individual Differences and Ecological Validity of Emotion Regulation in Response to Sadness

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INDIVIDUAL DIFFERENCES AND ECOLOGICAL VALIDITY OF EMOTION REGULATION IN RESPONSE TO SADNESS

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A THESIS

Submitted in Partial Fulfillment of the

Requirements of the Degree of

Doctor of Philosophy

(in Psychology)

The Graduate School

University of Maine

August 2021

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An Abstract of the Dissertation Presented
in Partial Fulfillment of the Requirements for the
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The majority of research on emotion regulation processes has been restricted to controlled laboratory settings that use experimental paradigms to investigate short-term outcomes (Berking & Wupperman, 2012). A true understanding of emotion regulation requires an unobtrusive, ecologically valid assessment of the construct as it naturally unfolds in the environment. Digital phenotyping, or moment-by-moment quantification of individual level human behavior using data from smartphone sensors (Torous & Onnela, 2016), is a novel method for evaluating human behavior in naturalistic settings. The present project is the first to implement digital phenotyping in the investigation of emotion regulation.

The central aim of the study was to evaluate whether smartphone-based digital phenotyping data predicted individual differences in emotion regulation in both in-lab and naturalistic settings. During an in-lab session, unselected adult participants ($N = 69$) completed self-report questionnaires measuring trait emotion regulation as well as state affect/emotion regulation following a neutral mood induction, negative mood induction, and recovery period. Smartphone-based digital phenotyping data were collected during a 7-day follow-up period using the Beiwe Research Platform (Onnela & Rauch, 2016), an open-access mobile- and cloud-based research tool for collecting digital data via smartphones.

Results showed that variation in mobile power state level and GPS distance were significantly associated with variation in negative state affect and state cognitive reappraisal over time. Clustering and classification analyses showed power state level and GPS distance over time to accurately, and with high sensitivity and specificity, classify two trait emotion clusters. Variation in power state level and GPS distance together with trait and state emotion regulation was not associated with current depressive symptoms. Overall, the findings provide initial data on the use of digital phenotyping data in predicting individual differences in state and trait emotion regulation in both in-lab and naturalistic settings. The results suggest that operationalizations of digital phenotyping data and modeling approaches are particularly important factors to consider when implementing digital phenotyping methodology in the study of mental health processes such as emotion regulation.

ACKNOWLEDGEMENTS

I would like to express my sincerest gratitude for the chair of the committee, my graduate advisor and mentor, Dr. Emily Haigh. When I think of who fully embodies what it means to be a strong clinical psychologist, you are the one who comes to mind. You are inspiring and I am grateful to have you as a mentor. Your guidance has been instrumental in my growth as a clinical psychologist. I am excited for future chapters in our work together. Thank you for everything.

I would like to thank graduate committee members for their time, energy, and dedication through this process. Your expertise, intellect, and support strengthened this investigation and pushed me to grow as a scientist. I am incredibly grateful for your advice and guidance on this project.

To my phenomenal lab mates Dr. Rachel Goetze, Dr. Olivia Bogucki, Dr. Victoria Quinones, Liv Valo, and Aubrey Lagasse: thank you for your hard work, collaboration, and encouragement. You all have so much wisdom and I look forward to continuing to be your colleague and friend. To the undergraduate research assistants in the Maine Mood Lab (William O'Neil, Neil Rafferty, Evan Vidas, Mikayla Padilla, Gabrielle Sands, Dorien Baudewyns, Sabrina Paetow, Heather Andrews, Steven Santiago, Maggie White, Ethan Seymour, Lydia Lavoie, Chris Carey, Alex Paradis, Maliyan Binette, Ryan Boucher): thank you for your eagerness to learn about psychology research, for your intellectual contributions, and your dependability. This project would not have been possible without the time and energy you devoted to it. To my friends and colleagues in the graduate program: thank you for your support and for all of the enjoyable experiences we shared. Thank you, David Smith, for always being up for going to the gym, going on hikes, or camping, and thank you for pushing my ability as researcher by being enthusiastic about learning new skills with me.

To my dear friend, Dr. Silas Tittes: thank you for being on this journey into research with me since high school. It has been an exceptional experience growing with you as a scientist and as a person. Silas, you are indeed a gentleman and scholar. To my mentor, colleague, and friend Dr. Francesco Pagnini: I want to express my thanks for all that you have taught me and for our adventures around the world. To my first mentors in psychology, Dr. Shaw Ketels and Dr. Sam Hubley: you two have always been there to guide me through my journey in academia and instilled in me the values I now hold as a clinical psychologist. Thank you for the opportunities and mentorship. I would not be where I am today if not for you. To my previous mentor, Dr. Ellen Langer: thank you for your guidance and support. Your wisdom expanded my perspectives on mindfulness and on pursuing a career in psychology.

To my family: thank you for unwavering support throughout this process. You have been incredibly patient and supportive during the tough times and have also been there to celebrate my accomplishments. I love you. Finally, I want to thank Aeleah Granger. You have been the most amazing partner in this process. You are remarkable in your unfailing support. I am so appreciative of you.

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LIST OF ABBREVIATIONS

ANS	Anatomic nervous system
CFA	Confirmatory factor analysis
DERS	Difficulties in Emotion Regulation Scale
DSM-5	Diagnostic and Statistical Manual, 5th Edition
EMA	Ecological momentary assessment
ERQ	Emotion Regulation Questionnaire
ERQ-R	Emotion Regulation Questionnaire cognitive reappraisal subscale
ERQ-S	Emotion Regulation Questionnaire expressive suppression subscale
GPS	Global position system
HF-HRV	High frequency heart rate variability
I-PANAS-SF	The International Positive and Negative Affect Schedule Short Form
IAPS	International Affective Picture System
ICD-10	International Classification of Disease and Related Health, 10th Edition
IDE	Integrated development environment
MICE	Multiple Imputation via Chained Equations
PANAS	Positive and Negative Affective Scale
PANAS-X	The Positive and Negative Affect Schedule – Expanded Form
PHQ-9	The Patient Health Questionnaire 9
RDoC	Research Domain Criteria
RRS	Ruminative Response Scale
RSQ	Ruminative Styles Questionnaire
SARS	Spontaneous Affect Regulation Scale
SARS-R	Spontaneous Affect Regulation Scale cognitive reappraisal subscale
SARS-S	Spontaneous Affect Regulation Scale expressive suppression subscale
VAS	Visual Analog Scale

CHAPTER 1

INTRODUCTION

Emotion regulation refers to the strategic and automatic processes that impact the magnitude, occurrence, and duration of emotional responses (Gross, 2014). The ability to regulate emotion is important for well-being, as dysregulation of emotion is associated with the development and maintenance of mental health problems (Aldao et al., 2016). For instance, mood disorders like depression are characterized by dysregulated emotional responses (e.g., negative repetitive thought) that contribute to low positive and excessive negative affect (Joormann & Vanderlind, 2014). Our current understanding of emotion regulation is limited by an almost exclusive reliance on tightly-controlled laboratory-based paradigms and measurement of short-term outcomes (Aldao, 2013; Gross, 2015). It is unclear how directing participants to elicit or regulate emotions impacts subjective reporting, or how accurately these findings predict real-world consequences (Berking & Wupperman, 2012). Indeed, recent research has suggested that depressed populations exhibit a recall bias for negative affective experiences, while a positive recall bias is associated with non-psychiatric populations (Colombo et al., 2020). Although ecological momentary assessment (EMA), or the repeated sampling of participants' current behaviors and experiences in real time and in their natural environments, is an important advancement for improving ecological validity in psychological research, the findings are often limited by an exclusive reliance on self-report ratings of emotional experiences, goals, and behaviors. A true understanding of emotion regulation requires integration of data across multiple levels of analysis.

Progress in emotion regulation research depends upon our ability to use innovative interdisciplinary methodology to advance our understanding of subjective experiences. Recent

developments in metrics and approaches to collecting data derived from digital devices have emerged and provide exciting opportunities to evaluate human behavior in naturalistic settings. Digital devices allow for continuous telemetry of key parameters of psychological health, generating comprehensive longitudinal data. Daily use of digital devices such as smartphones generate a significant amount of social and behavioral data. This moment-by-moment quantification of individual-level human behavior using data from smartphone sensors generates a digital profile of human behavior, or a digital phenotype (Torous, Kiang, Lorme, & Onnela, 2016). An important advantage of digital data is that it is exceptionally granular, and therefore sensitive to individual differences in trajectories, compared to traditional longitudinal sampling methods such as ecological momentary assessment (EMA).

Digital phenotyping data from smartphones is a tool that captures behavioral units of analysis of psychological phenomena in line with the National Institute of Mental Health's Research Domain Criteria (RDoC) framework (Insel et al., 2010; Onnela & Rauch, 2016; Torous et al., 2016). The RDoC initiative is a strategic plan for classifying mental illness based on dimensions of observable behavior and neurobiological measures (Insel et al., 2010). RDoC is intended to overcome the unreliability associated with traditional, category-based systems of psychopathology, such as the Diagnostic and Statistical Manual, 5th Edition (DSM-5: American Psychiatric Association, 2013) and International Classification of Disease and Related Health, 10th Edition (ICD-10; World Health Organization, 1992).

Consistent with the aims of RDoC, the goal of this project is to leverage digital phenotyping data to expand the nomological network, or the representation of concepts by respective observable manifestations (Cronbach & Meehl, 1955), of emotion regulation and create new knowledge. Specifically, this project will evaluate digital phenotyping as an

assessment of individual differences in emotion regulation. The application of smartphone-based digital phenotyping to emotion regulation research is poised to make important contributions to the identification of impaired emotional processing and maladaptive regulation strategies. In turn, this new knowledge has the potential to improve clinical decision-making for identifying and treating a range of psychopathology.

Emotion Regulation

Emotion regulation was first introduced as a construct in developmental literature as part of a framework for evaluating emotion as a dynamic rather than discrete process (Thompson, 1994). From this perspective the aim of emotion regulation is to influence the dynamics of emotion, negative or positive, to produce an adaptive response to the emotion eliciting stimuli. Further, the goal of the emotion regulatory process is to experience optimal levels of emotion dynamics (i.e., not too much positive, not too much negative) so that emotions can motivate appropriate behaviors in response to the environment.

In the 1990s, James Gross developed a construct of emotion regulation from a social psychology perspective. According to Gross (1998b) emotion regulation processes refer to an individual's ability to influence how and when emotions are experienced, as well as how emotions are expressed. Gross specifies three core features of emotion regulation including activation of a goal, engagement of the processes responsible for altering the emotion, and emotion dynamics (Gross, 2014). The first feature involves the activation of a goal to modify emotions as they are generated, where the goal of regulation can occur intrinsically, on the individual level, extrinsically, on an interpersonal level, or co-occur (Gross, Sheppes, & Urry, 2011). The goal for modifying emotions is motivated by the demands of the environment. A straightforward example would be to generally regulate mood by down-regulating negative

emotions (e.g., sadness, anger, disgust) and up-regulating positive emotions (e.g., happiness, euphoria, pleasure, etc.). However, goals for regulating emotions can be more nuanced, such as being motivated to down-regulate positive emotions to maintain a professional stance at work, to up-regulate negative emotions to evaluate a situation with skepticism, or to hide one's emotions from peers.

The second core feature of Gross's emotion regulation construct (2014) refers to the engagement of the various processes that influence the trajectory of emotion, or emotion regulation strategies. These regulatory processes have historically involved conscious effort (i.e., explicit) or occur effortlessly (i.e., implicit) depending on the context. Although previous research conceptualized these processes as discrete, recent research takes a more dimensional perspective, spanning conscious, effortful, and controlled regulation to unconscious and automatic regulation of emotions.

The third core feature of emotion regulation refers to the relationship between regulatory processes and emotion dynamics (Gross, 2014). As emotions are processed over time, emotion regulation involves changes in emotion dynamics, or modifications in the latency, speed of formation, magnitude, and duration of emotions behaviorally, physiologically, and subjectively (Thompson, 1990). Emotion dynamics are influenced by emotion regulation processes, which depend on the goal of the individual. Without the activation of a goal, and the implementation of emotion regulation, the trajectory of the emotion dynamics in response to the emotion-eliciting context would unfold as it would without the presence of emotion regulation processes (Gross, 2014).

Gross's conceptualization of emotion regulation (1998a) also makes a distinction between antecedent-focused and response-focused emotion regulation strategies. Antecedent-

focused emotion regulation is implemented during the input phase of emotion processing, before the emotion is generated, and response-focused emotion regulation occurs at the output phase of emotion processing, during the formation of an emotion. Gross developed a framework, the process model of emotion regulation, to organize the various forms of emotion regulation into a theoretical model (Gross, 1998b).

Process Model of Emotion Regulation

Gross's (1998b) process model of emotion regulation is an information-processing model based on the sequence of emotion generation, with emotion regulation processes occurring at each step of the emotion generation process. The steps of the emotion-generative process used in the process model of emotion regulation involve situation selection, attending to the situation, and appraising the situation, which results in expressed emotions. Notably, the emotion-generative process is not circumscribed to a single instance or episode but is ongoing, iterative, and contributes to the dynamic nature of emotion and emotion regulation. The resulting emotion from one instance of the emotion-generative process can feedback to the selected situation or appraisal step of a new emotion-generative process. For example, if one becomes anxious about an upcoming presentation (result of one emotion-generative process) the anxiety may engage one's attention and be appraised as negative in another emotion-generative process, which may potentially lead to the emotion of anger over feeling anxious in the first place. Both the anxiety and the anger can then become targets for emotion regulation.

According to Gross (1998b), there are five points in the emotion-generative process where individuals can regulate their emotions, and each point represents a separate emotion regulation process. The five regulatory processes in the process model of emotion regulation

include situation selection, situation modification, attentional deployment, cognitive change, and response modulation, respectively. Each of these regulatory processes will be described below.

Situation selection is an emotion regulation process that is implemented before the emotion-generative process begins (Gross, 1998b). Emotion regulation at this stage involves taking action to select situations to either increase or decrease the likelihood of an emotion being generated. For example, increasing the possibility of experiencing positive emotions by choosing to eat at a favorite restaurant, or decreasing the possibility of experiencing negative emotions by avoiding arguments with a romantic partner. It is notable, however, that situation selection is not always an explicit emotion regulation strategy and one cannot always predict which emotions they will elicit or avoid based on situation selection (e.g., new experiences or environments).

Situation modification is an emotion regulation strategy that refers to directly modifying a situation to impact the emotion-generative process and subsequent emotions (Gross, 1998b). This regulatory process refers only to modifying the external or physical environments. To illustrate, situation modification could involve decorating your house with pictures of loved ones to evoke positive emotions when you come home. Another example would be to prepare comfort food when one is feeling sick.

The third regulatory process is attentional deployment (Gross 1998b). During the attentional deployment phase of the emotion-generative process, attentional deployment can be implemented as a specific emotion regulation strategy. Attentional deployment refers to directing attention with the purpose of influencing emotion. For example, a typical attentional deployment strategy is distraction (Ochsner & Gross, 2005). Through distraction, one directs their attention to a different aspect of a situation or fully away from the situation. Distraction can also be used

to direct attention internally, such as thinking about something to facilitate a positive emotion when in a situation that would otherwise evoke negative emotions.

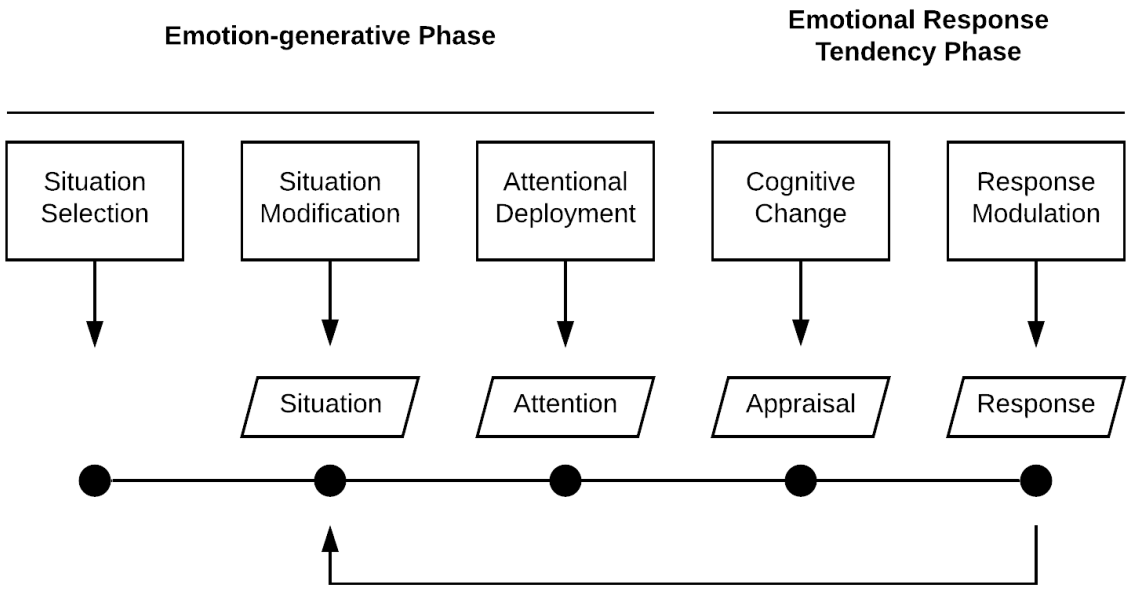
The fourth emotion regulation process of the process model, cognitive change, is an internal form of situation modification (Gross, 1998b). Since cognitive change occurs after response tendencies have been initiated, this emotion regulation process influences subjective, behavioral, and physiological aspects of emotion expression. Cognitive change is an internal process that can be applied to both external and internal situations. For example, applying cognitive change to an external situation could be to change one's perspective of going to the dentist from dread to an important aspect of maintaining dental hygiene and even overall physical health. Applying cognitive change to an internal situation could take the form of perceiving anxiety related to giving a presentation as a way of your body preparing to perform well. A well-studied form of cognitive change is cognitive reappraisal, an emotion regulation strategy that involves reinterpreting the meaning of an emotional stimulus (Gross, 2002).

Response modulation, the fifth part of Gross's process model, refers to direct modification to the experiential, behavioral, or physiological aspects of an emotional response (Gross, 1998b). Response modulation occurs after emotion tendencies begin and later in the emotion-generative process. For example, diaphragmatic breathing can be used during the response modulation phase of the process model to down-regulate the physiological and behavioral experiences that correspond with a negative emotion such as anxiety (Manzoni et al., 2008). Broadly, external stimuli such as substances, food, music, and social interactions can be used to modify emotional responses. An example of a cognitive response modulation strategy is expressive suppression, or the conscious process where an individual actively inhibits negative or positive expressions of emotions (Gross & John, 2003).

The five parts of the process model of emotion regulation are nested between two areas of emotion regulation based on whether emotions are modified during the emotion-generative phase or during the emotional response tendency phase (see Figure 1; Gross, 1998b). Regulatory processes occurring before an emotion is generated, including situation selection, situation modification, and attentional deployment are considered to be antecedent emotion regulation. Strategies implemented after an emotion is generated, such as cognitive change and response modulation, are conceptualized as response-focused emotion regulation in the process model. Thus, the process model of emotion regulation is based on the assumption that emotions unfold over time, and that emotions can be modified at different time points during the emotion-generative and response processes, leading to different emotional outcomes.

Figure 1

Diagram based on Gross's (1998b) process model of emotion regulation including illustration of which components are part of the emotion-generative phase and the emotional response tendency phase



Extended Process Model of Emotion Regulation

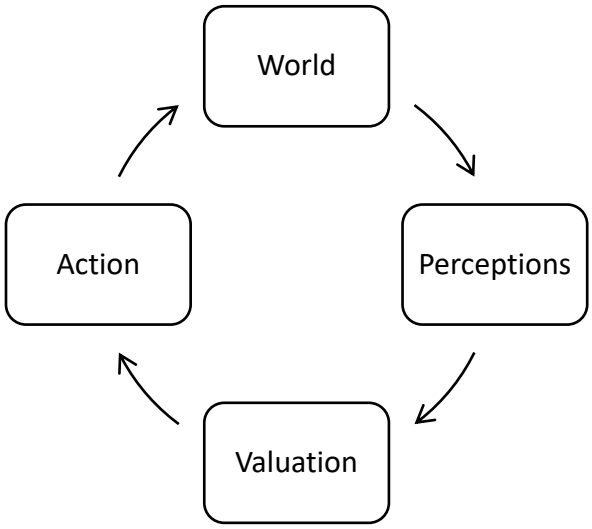
Building upon these conceptual foundations of emotion regulation, Gross introduced the extended process model of emotion regulation to provide more granularity to the original theoretical model (Gross, 2015a, 2015c). The extended process model of emotion regulation reflects a theoretical framework for understanding; 1) what initiates emotion regulation, 2) what influences which emotion regulation strategy is implemented and, 3) why there are individual differences in individuals' ability to regulate their emotions successfully.

The extended process model of emotion regulation posits that emotions involve valuation, or the simple judgement of good or bad (Gross, 2015a). According to this theoretical model, there is a 4-component schematized valuation system involved in emotion regulation (see Figure 2). The first component is the *world*, or how an individual conceptualizes both their internal and external reality. The second component is *perception*, which capture's the impact of past experience on the valuation system. The third component is *valuation*; specifically, whether the emotion is determined to be good or bad. The valuation is based on whether the emotion fits when a representation of the world and a representation of a desired state of the world (i.e., the individuals' goal) are compared. The fourth component is *action*, which refers to the action impulses, or behaviors and cognitions, generated by the valuation. Each component is processed sequentially, creating a valuation cycle, from the world to perception, perception to valuation, followed by action. These four components map onto the original process model of emotion regulation, with situation onto *world*, attention onto *perception*, appraisal onto *valuation*, and response onto *action*. For example, when you receive news that a loved one has been diagnosed with a terminal illness (situation and *world*), it draws your attention because you perceive the situation to be negative based on previous experiences (attention and *perception*), your

perception leads to feelings of sadness (appraisal and *valuation*), and you distract yourself with tasks at work to experience less intense feelings of sadness (response and *action*).

Figure 2

Diagram based on Gross's (2015a) conceptual illustration of the four-component valuation system cycle



An important aspect of valuation cycles in the extended process model of emotion regulation is that they are dynamic (Gross, 2015a). Valuation cycles are dynamic in that they unfold over time, with each valuation cycle leading to a new valuation cycle with the *world* as its target. The valuation cycles end when the discrepancy between an individual's goal and the world that instigated the initial valuation cycle is below the threshold for the respective valuation system. This reconciliation is achieved when either the representation of the goal has changed, or the representation of the world has changed as a result of the valuation cycles.

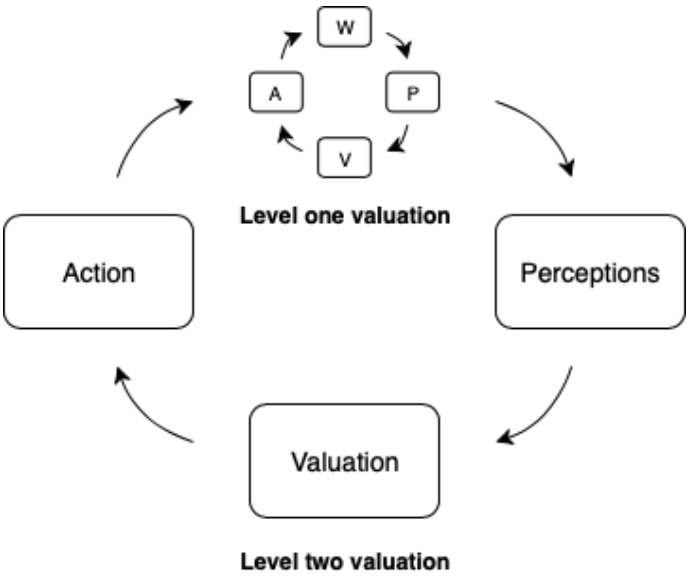
Different valuation systems are simultaneously active and interact as we navigate our lives (Gross, 2015a). An example of when two valuation systems interact is when two emotion-evoking situations are positively reinforced, such as eating your favorite meal with good friends. Valuations systems can also interact in ways that are not reinforcing. For example, when you

need to complete an activity but desire the positive emotions associated with something else, such as completing homework when you want to go hiking because the weather is nice. Valuation systems can interact in a nested, or hierarchical fashion.

The hierarchical interactions of valuations systems is integral to the conceptualization of emotion regulation in Gross's extended process model (Gross, 2015a). According to Gross's extended model, emotion regulation occurs when two valuation systems interact, with one valuation system generating an emotion (i.e., level one) and the other valuating the generated emotion as either fitting or not fitting their goal (i.e., level two). When this occurs, the second-level valuation system generates action that is intended to regulate the activity, or the emotion generated, from the first-level valuation system. For example (see Figure 3), a level one valuation system can involve a significant other that is sad (*world*) and you perceive that they are sad (*perception*). At this point a *valuation* is initiated as there is a discrepancy between how the *world* is represented (perception of significant other as sad) and your desired representation of the *world*, which is for your significant other to not be sad, leading to a negative valuation. The negative valuation then evokes an emotional response (*action*), which may be experienced mentally as well as physiologically. In this example, a level two valuation would involve awareness of the negative valuation from level one, which becomes the target of the new valuation. The emotion (*world*) and the perception of the emotion (*perception*) may lead to a determination that it would be better to not express the emotion (*valuation*), resulting in an effort to suppress the potential expression of the emotion (*action*). The second-level valuation can influence the first-level valuation through any of the five phases of the original process model of emotion regulation delineated above, including situation selection, situation modification, attentional deployment, cognitive change, and response modulation (Gross, 1998b, 2015a).

Figure 3

Diagram based on Gross's (2015a) conceptual illustration of a level one valuation system nested in a level two valuation system



Note. W = *world* (e.g., friend lost their job), P = *perceptions* (e.g., is it bad that my friend lost their job?), V = *valuation* (e.g., yes, it is bad that my friend lost their job), A = *action* (e.g., encouraging your friend to engage in a fun activity to help them feel better).

Gross suggests that deficits in emotion regulation are associated with valuations systems that correspond with three different stages of the over-arching emotion regulation cycle (Gross, 2015a, 2015c). The three stages include the identification, selection, and the implementation stage. These stages operate as a third-level valuation system, with level two (valuation of whether there is a target emotion) and level one (valuation of whether an emotion will be generated) valuation systems as nested targets. Each of the three emotion regulation stages are also comprised of a respective valuation system. During the identification stage, a valuation is made to determine whether the goal is to regulate an emotion. The identification stage takes

place when an emotion is generated by a level one valuation system. When the emotion is detected, a determination is made on whether to regulate the emotion. Since emotion awareness is an important aspect of emotion regulation (Chambers et al., 2009), deficiencies in the identification stage can negatively impact an individual's ability to successfully regulate their emotions (Gross, 2015a).

Similarly, the degree to which someone believes their emotions are malleable impacts whether they make a determination at the selection stage that their emotion can be modified. This determination may result in inaction or less action directed toward regulating emotions in general. The selection stage is triggered by the identification stage and the focus of the stage is to determine which emotion regulation strategy to implement. In the selection stage, potential emotion regulation strategies are represented and considered, then the feasibility of implementing them is evaluated based on the availability of cognitive and physiological resources. The result of this stage is a determination of which emotion regulation strategy should be implemented.

Several types of emotion regulation deficiencies have been associated with the selection stage. Individuals, given the context, may perceive that they have fewer emotion regulation strategies to choose from, or believe that they have fewer strategies in their repertoire to choose from. The perception of having fewer emotion strategies to choose from, or actually having a smaller repertoire, can lead to an over-reliance on particular strategies or the inability to flexibly implement emotion regulation strategies that best fit the situation. Another difficulty associated with the selection stage is low self-efficacy of implementing an emotion regulation strategy because the strategy is evaluated to not be effective enough given the situation. Another potential problem is that individuals may not evaluate contextual factors (e.g., cognitive and physiological

resources, perception of the world, goals, etc.) in an adaptive manner which can lead to biases in emotion regulation implementation choice. For example, an individual with Generalized Anxiety Disorder may attribute more importance to the goal of wanting to reduce feelings of anxiety in the short-term, which leads the individual to select avoidance as an emotion regulation strategy. In this scenario, the individual may have initially had a deficit in their repertoire of emotion regulation strategies (i.e., history of using avoidance and distraction and little practice with other strategies) and, therefore, found avoidance was effective in meeting their goal to reduce anxiety in the moment. In turn this may lead to an over-reliance on avoidance to regulate anxiety. Developing an over-reliance on few emotion regulation strategies across situations is an example of a deficit in emotion regulation in the context of anxiety disorders, as consistently relying on a strategy such as avoidance can lead to negative long-term consequences, such as impairment in functioning (Cisler et al., 2010). To illustrate, someone with generalized anxiety may avoid reading their emails regularly, as they have learned that avoiding this task alleviates anxiety about potential work-related obligations. However, by not regularly checking their email, they might miss important or time-sensitive emails that can lead to negative long-term consequences. Selection of an emotion regulation strategy triggers the implementation stage (Gross, 2015a), which involves the execution of the selected emotion regulation strategy in a given context.

The implementation stage involves translating the representation, or the idea, of an emotion regulation strategy into action given the valuation of the current situation. Deficits associated with the implementation stage include a lack of skill in implementing emotion regulation strategies in novel situations, as well as the perception that few strategies are available. Both deficits impede the ability to translate an emotion regulation strategy into a corresponding action. In addition, if an individual gives too little or too much importance to the

target emotion given the context, it will affect whether an appropriate emotion regulation strategy will be implemented. For example, in response to a perceived slight, the determination that feeling angry is the primary goal, may outweigh the goal to downregulate their anger. In this case, the individual may choose to implement cognitive reappraisal in a superficial way. Each of the deficits in the implementation stage can lead to poor execution of the action impulses associated with an emotion regulation strategy.

The schematic valuation system in the extended process model and the associated emotion regulation stages are hierarchical and dynamic (Gross, 2015a, 2015c). Valuation systems operate concurrently, interactively on different levels, and unfold over time. Level one valuation systems can generate emotions, which in turn become the target of level two valuation systems, where the valuations determine whether the emotion should be regulated. Level three valuation systems target both level one and two valuations systems, regulating emotion through the identification, selection, and implementation stages. All levels of valuation systems are iterative, with the valuation cycles unfolding over time until the discrepancy between the individual's goal and the representation of a desired *world,* instigated by the level of valuation cycle, falls below a threshold where the representation of the goal or the representation of the *world* has sufficiently changed. Gross's addition of a schematic valuation system in the extended process model of emotion regulation provides a framework for scientists to investigate with more granularity what initiates emotion regulation, what influences which emotion regulations strategy is implemented, and individual differences in emotion regulation ability (Gross, 2015a, 2015c).

Over the past several decades, the field of emotion regulation has developed a strong theoretical foundation. With few exceptions the majority of emotion regulation research has yet to test the dynamic unfolding of Gross's extended process model of emotion regulation (Gross,

2015c). Rather, extant research on emotion regulation has generally focused on self-report, trait-like descriptors of specific strategies and how they relate to outcomes and psychopathology.

Emotion Regulation and Psychopathology

Historically, emotion regulation strategies have been grouped into two major categories: adaptive or maladaptive. Adaptive emotion regulation strategies engender favorable emotional reactivity (e.g., reappraising an anxiety-provoking situation to feel less anxious), whereas maladaptive emotion regulation strategies prolong, produce, or intensify unwanted emotional responses (e.g., ruminating about a speech and becoming too anxious to give the speech) (Gross, 2014). Emotion regulation strategies that are generally considered to be adaptive in the literature include cognitive reappraisal, distraction, decentering, and acceptance. Strategies that are generally regarded as maladaptive include expressive suppression, rumination, and avoidance. In reality, the adaptiveness of an emotion regulation strategy is likely more complex and depends on an interaction among contextual factors, such as the novelty of the situation, the emotion to be regulated, and the individual's mental and physiological resources (Bonanno et al., 2004; Gross, 2014).

It is widely agreed upon that mental health disorders are largely characterized by deficits in emotion regulation processes (Aldao et al., 2016; Joormann & Siemer, 2014; Mennin & Fresco, 2015; Sheppes, Suri, & Gross, 2015). Indeed, research supports the transdiagnostic role of emotion regulation such that both negative affect and deficits in emotion regulation cut across psychopathology.

A rigorous meta-analysis examined whether emotion regulation strategies predict risk of mental health problems (Aldao et al., 2010). The authors combined 241 effect sizes from 114 studies that examined the relationships between trait emotion regulation and symptoms of

anxiety, depression, eating, and substance abuse-related mental health disorders. Higher levels of the tendency to use expressive suppression, rumination, and avoidance as well as the decreased tendency to use cognitive reappraisal together have been found to best predict psychopathology, broadly. The tendency to engage in rumination independently best predicted psychopathology across studies. Overall, maladaptive strategies [rumination ($r = .49$), suppression ($r = .34$), and avoidance ($r = .38$)] were more strongly related to psychopathology than adaptive strategies [problem-solving ($r = -.31$), cognitive reappraisal ($r = -.14$), and acceptance ($r = -.19$)]. Findings from the meta-analysis also indicated deficiencies in emotion identification, emotion regulation implementation, emotion regulation flexibility, and emotion monitoring to be significantly associated with the development and maintenance of psychopathology. Finally, the results showed that emotion regulation strategies better predict internalizing symptoms than externalizing symptoms.

In terms of specificity of cognitive emotion regulation strategies predicting mental health disorders, a follow-up review of Aldao and colleague's (2010) meta-analysis indicated that greater tendencies to engage in rumination and expressive suppression best characterized depressive and anxiety disorders (Aldao, 2014). Other cognitive emotion regulation profiles, however, were mixed in terms of specificity of mapping onto psychopathology.

A recent review of emotion regulation as a transdiagnostic factor in the development of psychopathology found that emotion regulation strategies were involved in the development of both internalizing and externalizing mental health symptoms (Aldao et al., 2016). Specifically, this research found that trait-level emotion regulation abilities, such as habitual use of rumination and inflexibility with respect to implementing strategies predicted the development of mental

health disorders over time (Aldao et al., 2015a, 2016). Overall, the evidence suggests that emotion regulation is key to understanding the onset and course of psychopathology.

Overview of Emotion Regulation Methodology

Researchers have developed a number of methodological approaches to studying individual differences in emotion regulation. By far the most common method of assessment is the use of subjective self-report questionnaires (John & Eng, 2014). Other methods include physiological data, such as measures of the anatomic nervous system (ANS; Gross, 1998), neural (Etkin et al., 2015; Mauss et al., 2007), genetic (Johnstone & Walter, 2014), and behavioral indices, such as facial expressions (Cohn et al., 2002; Donato et al., 1999). Several lab-based paradigms use standardized emotion-eliciting stimuli to manipulate emotion regulation and measure affective experience. While a complete review of emotion regulation methodology is beyond the scope of this project, interested readers should refer to Appelhans & Luecken (2006); Fernandez, Jazaieri, & Gross, (2016); and Gross, (2014). The following review describes several of the most common approaches to studying emotion regulation under the following, overlapping domains: self-report questionnaires, experimental paradigms, and ecological momentary assessment.

Self-report Questionnaires

The popularity of emotion regulation research has led to a proliferation of self-report measures. Emotion regulation processes commonly measured with self-report questionnaires include; acceptance (Hofmann & Asmundson, 2008), problem-solving (Aldao et al., 2010), mindfulness (Chambers et al., 2009), interpersonal aspects (Hofmann, 2014), difficulties with emotion regulation (Gratz & Roemer, 2004), and cognitive strategies (e.g. reappraisal, suppression, rumination, distraction). Select self-report measures of cognitive strategies are

reviewed in more detail below, while measurement of affect is discussed in the experimental paradigm section.

Empirical research on individual differences in emotion regulation has largely focused on two cognitive emotion regulation processes, cognitive reappraisal and expressive suppression (Gross, 2015a). Cognitive reappraisal refers to the process of generating an alternate perspective in response to emotion-eliciting stimuli with the purpose of changing its emotional impact. To illustrate, when a student takes an exam, they may choose to view the exam as an opportunity to demonstrate their mastery of the material rather than an unfair assessment of their knowledge or merely a means to an end. Expressive suppression refers to the process of actively inhibiting the emotion-generative process as a way to modulate the emotional impact of a emotion-eliciting stimuli (Gross & John, 2003). An example of expressive suppression would be to purposely appear professional and polite while interacting with a boss that just implemented a policy you vehemently disagree with or acting as though you are happy after finding out about terrible news because it would be inappropriate to express negative emotions in the current social context. Individual differences in one's tendency to implement cognitive reappraisal and expressive suppression is typically assessed using the Emotion Regulation Questionnaire (ERQ; Gross & John, 2003).

The ERQ was developed to assess individual differences in the tendency of two cognitive regulation strategies based on Gross's process model of emotion regulation. The ERQ is a 10-item, rationally derived measure with two factors: cognitive reappraisal and expressive suppression (Gross & John, 2003). The response format for each item is a 7-point Liker-type scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*) to indicate the degree to which one implements each emotion regulation strategy. The items pertain to regulating both positive

emotion and negative emotion. The measure is scored by summing the total of each item corresponding to the cognitive reappraisal scale and expressive suppression scale, with higher scores indicating greater tendencies to implement the respective emotion regulation strategy. Gross and John (2003) conducted a series of confirmatory factor analyses (CFA) using a combined sample (N = 1,483) to evaluate the factor structure of the ERQ and found the two-factor model with the factors cognitive reappraisal and expression suppression to provide the best fit across all standard fit indexes. Initial psychometric evaluations of the ERQ indicate adequate internal consistency for the cognitive reappraisal (r = .79) and expressive suppression (r = .73) scales and adequate test-retest reliability across 3 months for both scales (r = .69). Gross and John evaluated the construct validity of the ERQ developing a nomological net with theoretically related and discriminant constructs (2003). Convergent validity with constructs including regulation success, inauthenticity, coping, rumination, and negative mood regulation was in an appropriate range (β = -.47 to β = .47) between the two scales. Discriminant validities with measures of broad personality, impulse control, cognitive ability, and desirability ranged from moderately associated (β = -.47) to appropriate (β = -.20 to β = .15). The internal consistencies and subscale intercorrelations indicate the cognitive reappraisal and expressive suppression scales of the ERQ are internally consistent and adequately assess distinct constructs.

A substantial body of research on individual differences in emotion regulation using self-report has also focused on another emotion regulation process, rumination, or the tendency to engage in negative repetitive thought about the causes and consequences of negative mood (Nolen-Hoeksema, 1991). For example, in response to a negative comment by one's supervisor they may proceed to persistently think about the remark, why their boss made the remark, and the potential consequences for the rest of the day. Individual differences in the subjective

experience of rumination was initially measured using the Response Styles Questionnaire (RSQ; Nolen-Hoeksema, 1991). The RSQ was originally developed to investigate individual differences in rumination as a predictor for the onset and duration of depressed mood; however, the scale was criticized for having several items that confounded with depressive symptoms. In response, the Ruminative Response Scale (RRS; Treynor, Gonzalez, & Nolen-Hoeksema, 2003) was derived from a secondary analysis of the RSQ to provide a measure of rumination that is not confounded with depression symptoms. The RRS is a 10-item questionnaire designed to measure an individual's tendency to ruminate; that is, engage in repetitive and passive thinking about problems, negative events, and negative feelings. Participants respond using a scale from 1 (*almost never*) to 4 (*almost always*) indicating the frequency with which they endorse rumination items. The RSS demonstrated good internal consistency ($\alpha = .90$) and moderate test-retest reliability ($r = 67$). A more recent psychometric investigation of the RRS supported the original bi-factor structure of the RRS [i.e., pondering and brooding, and that the brooding subscale had stronger predictive validity for depressive symptoms (Armey et al., 2009)].

Experimental Paradigms

A common paradigm used to study emotion regulation involves a procedure to induce an emotion (i.e., mood induction) followed by an emotion regulation strategy implementation or measurement (Fernandez et al., 2016). This general framework for emotion regulation research paradigms can take on various forms and complexity. Mood inductions use emotion-eliciting stimuli, such as images, film clips, text, and music (Aldao, 2013; Gross, 2014). For images, it is common for researchers to use the International Affective Picture System (IAPS; Lang, Bradley, & Cuthbert, 1999), a database comprised of 956 images designed to provide standardized images for emotion-related research in psychology. The IAPS database includes normative ratings

indicating the average rating of emotional valence of each image, thus standardizing whether each image is generally considered to have a neutral, negative, or positive valence. Similarly, film clips have been standardized to elicit specific emotions and valences to improve replication across studies. Building on past standardization efforts (i.e., Gross & Levenson, 1995), Rottenberg, Ray, and Gross (2007) developed a library of recommended emotion eliciting films and instructions for using them that are widely used in emotion-related research. Mood-induction procedures using music, typically asks participants to focus on a time or event in their lives when they felt sad while listening to a piece of sad music, commonly the orchestral introduction by Prokofiev, "Russia Under the Mongolian Yoke" played at half-speed (van der Does, 2002). This paradigm was popularized by Segal, Gemar, and Williams (1999) in a study investigating cognitive reactivity following a sad mood induction in individuals who underwent either cognitive therapy or medication treatment for Major Depressive Disorder. Although the Emotional Stroop Task, an adapted version of the Stroop Task using emotionally-valenced words, is not used to induce emotions, it is commonly used in emotion regulation research to evaluate attentional biases related to emotion, which can have implications for attention-related emotion regulation processes (Fernandez et al., 2016).

In the context of mood induction procedures, emotion regulation is often examined by instructing the participant to engage in a specific emotion regulation strategy during the induction (e.g., suppression, cognitive reappraisal, distraction, etc.) or asked to report how they are regulating their emotions before, during, or after the mood induction (Fernandez et al., 2016). For example, participants may be asked to engage in distraction (e.g., shift attention from emotion-evoking stimuli or it can involve changing one's internal focus) (Sheppes, 2014). In one such study, researchers evaluated the relationship between retrospectively self-reported emotion

regulation strategy use and cortisol during an evaluative speech task designed to elicit negative emotion (Lam et al., 2009). Higher levels of both trait expressive suppression and cognitive reappraisal predicted exaggerated cortisol responses to the speech task, and those with higher expressive suppression had a greater degree of cortisol reactivity.

More typically, emotion regulation paradigms examine change in self-reported state affect in response to a mood induction (Fernandez et al., 2016). Changes in affective experiences can be considered indicative of mood repair. For example, if individuals are instructed to up regulate during a negative affective experience, such as a negative mood induction, the effectiveness of each strategy is determined by the degree of change in the individuals' affective self-report. State affect is typically measured before and after a mood induction in order to measure change in emotion in response to the mood induction. To examine the longitudinal trajectory of emotions, participants may complete multiple assessments of state emotion across the paradigm. For example, state emotion can be measured during a baseline period, a period where participants are shown neutrally-valenced stimuli or none at all, pre-mood induction, post-mood induction, and following a recovery period where participants are again shown neutrally-valenced stimuli or none at all.

Two commonly used self-report measures of current affective experiences are the Visual Analog Scale (VAS; Aitken, 1969) and the Positive and Negative Affect Scale (PANAS; Watson, Clark, & Tellegen, 1988). By convention, the VAS is a horizontal 100mm line with anchor words or images on either side of the line with the extremes of the emotion, such as happy on one end and sad on the other (Feinstein, 1987). Participants indicate where on the line best represents their present affective experience. The test-retest reliability of the VAS has been shown to vary across early psychometric studies, ranging from poor in long intervals (r = .32-

.48; Ahearn & Carroll, 1996) to good in short intervals (r = .82-.89; Folstein & Luria, 1973). Concurrent validity of the VAS is similarly mixed across studies. For example, coefficients comparing the VAS to the original Beck Depression Inventory (BDI) ranged from r = .30 (Faravelli et al., 1986) to r = .76 (Little & McPhail, 1973). On other measures, concurrent validity coefficients ranged from very poor (Hamilton Depression Rating Scale; r = 0.14) (Faravelli et al., 1986) to adequate (Clyde Clear Thinking Scale; r = 0.86) (Luria, 1975). Nyenbuis and colleages (1997) evaluated the construct validity of VAS for mood using a multi-trait, multimethod approach, as well as principal components analysis. The VAS correlation coefficients with other measures of mood ranged from poor to adequate (r = .55-.80). The principle component analysis revealed a two-component solution that accounted for 61.8% of the variance, with the components being negative mood and energy. Although the reliability and validity of the VAS is not consistently robust, the scales are simple to complete and are associated with a high rate of compliance, making them a valuable tool for the assessment of mood, especially for shorter intervals such as within a laboratory visit (Ahearn, 1997).

The PANAS was designed to measure the degree of positive and negative affective experiences for any combination of seven timeframes, including in the moment, today, the past few days, the past week, the past few weeks, the past year, and generally (Watson et al., 1988). A separate score is calculated for positive affect and negative affect by summing the rating of all respective mood terms. Researchers have developed variations of the PANAS for use in different settings. The Positive and Negative Affect Schedule – Expanded Form (PANAS-X) developed by Watson and Clark (1999) features 40 additional mood terms, allowing for more comprehensive assessment of positive and negative affect. The International Positive and Negative Affect Schedule Short Form (I-PANAS-SF; Thompson, 2007) is an abbreviated version

of the PANAS containing mood terms that can be understood cross-culturally. Additional psychometric evaluations by Watson and colleagues (1988) of the PANAS showed good internal consistency across all seven timeframes (PA scale Cronbach's α = 0.86-0.90; NA scale Cronbach's α = 0.84-0.87) with a more recent replication (Crawford & Henry, 2004) supporting good consistency of both scales across timeframes (PA scale Cronbach's α = 0.89, 95% *CI* = 0.88-0.90; NA scale Cronbach's α = 0.85, 95% *CI* = 0.84-0.87). Evaluations of test-retest reliability of the PANAS showed the positive affect scale ranged from poor to moderate (*r* = 0.47-0.68) and from weak to acceptable for the NA scale (*r* = 0.39-0.71) (Watson et al., 1988), with test-retest reliability increasing as the timeframes increased. In terms of the validity of the factor structure of the PANAS, Watson and colleagues conducted an initial principal component analysis, which showed two dimensions (i.e., positive and negative affect) accounting for the majority of the common variance, ranging from 87.4% (in the moment) to 96.1% (in general time frame). A more recent confirmatory factor analysis supported the two-factor, positive and negative affect model of the PANAS (comparative fit index = .99; Tuccitto, Giacobbi, & Leite, 2009).

Affective experiences measured by scales such as the VAS and PANAS can be mapped out onto two dimensions: valence and arousal (Feldman, 1995). This approach captures the degree to which individuals attend to the valence of the affective experience (i.e., negative, neutral, positive) and the degree of arousal from the affective experience (i.e., intensity). Combining valence and arousal on the same plane allows researchers to operationalize the dimensional aspects of both components of an affective experience together. For example, when affective experiences are operationalized in this way, each data point accounts for two values

(valence and arousal) on an x and y axes. In emotion regulation research, changes in valence and arousal are hypothesized to reflect the effectiveness of the emotion regulation strategy.

A recent study by Stange and colleagues (2017a) validated the use of a new measure designed to capture spontaneous emotion regulation, the Spontaneous Affect Regulation Scale (SARS; Egloff, Schmukle, Burns, & Schwerdtfeger, 2006). As part of a larger study, participants watched a sad film clip, validated to produce transient sad mood, and completed a measure of spontaneous emotion regulation (i.e., cognitive reappraisal, expressive suppression) using a self-report questionnaire. Results showed that, in response to the sad mood induction, the spontaneous use of cognitive reappraisal and distraction was associated with more mood repair while greater use of expressive suppression was associated with less mood repair.

Ecological Momentary Assessment

An important methodological advance in emotion regulation research is ecological momentary assessment (EMA), or experiential sampling. Experimental assessment of emotion regulation using EMA allows researchers to conduct longitudinal investigations outside of laboratory settings, expanding to naturalistic settings. In line with more recent theoretical conceptualizations, an EMA approach increases the ecological validity of emotion regulation research by better capturing the impact of environmental context on emotion-related processes (Aldao, 2013). Although the field of emotion regulation has emphasized the need for more research in naturalistic settings (e.g., Aldao, 2013; Gross, 2015a), few studies have investigated the ecological validity of emotion regulation in adults using EMA methodology. EMA methods used in emotion regulation research typically include self-report of affective states and self-report of emotion regulation strategies often via electronically delivered questionnaires.

Research conducted by Fichman and colleagues (1999) represents one of the earliest studies to use EMA to evaluate the relationship between mood symptoms and daily emotion regulation. The researchers instructed 95 non-psychiatric undergraduate women to complete assessments of depressive symptoms, affect, and retrospective use of emotion regulation strategies, twice per day over a two-week period. Findings indicated that engaging in behavioral activation (i.e., engaging in activities that elicit pleasure or mastery) was associated with reductions in negative affect, whereas interpersonal venting and self-criticism were associated with poorer regulation of negative affect. More recently, Gruber and colleagues (2015) used an EMA approach to investigate whether parasympathetic reactivity (HF-HRV), a putative maker of emotion regulation, predicted positive mood disturbance during one-week period in individuals with Bipolar I Disorder, Major Depressive Disorder, and non-psychiatric controls. Although the authors found participants with Bipolar I Disorder had greater overall HF-HRV variability during the EMA period, parasympathetic reactivity was not associated with ratings of positive affect. In another study, Tan and colleagues (2012) employed an EMA approach to evaluate emotion regulation and reactivity among youth with Generalized Anxiety Disorder and Social Anxiety Disorder and matched healthy controls. Participants were periodically called 14 times using answer-only mobile phones over five days and asked to complete a brief structured interview. Results indicated that youth with Generalized Anxiety Disorder and Social Anxiety Disorder experienced more frequent and heightened emotional reactivity and were less effective at implementing emotion regulation strategies for down regulating negative emotions compared to the healthy control group. Silk and authors (Silk et al., 2011) used mobile phones to track participant's daily emotion expression and regulation during an 8-week cognitive-behavioral intervention among youth with Major Depression Disorder and non-psychiatric controls.

Compared to the non-psychiatric controls, depressed youth participants experience more intense and variability in negative emotions over time. Nezlek and Kuppens (2008) used an EMA approach to investigate emotion regulation in daily lives by instructing non-psychiatric undergraduate participants to describe the extent to which they regulated their positive and negative emotional experiences in terms of implementing cognitive reappraisal and expressive suppression once a day for three weeks. Results indicated that participants used cognitive reappraisal more frequently than expressive suppression and that cognitive reappraisal was associated with better maintenance of positive emotion.

Research using EMA has also specifically evaluated individual differences in which emotion regulation strategies people implement as well as how many and how often they implement these strategies in naturalistic settings. In one project, researchers used two experiencing sampling studies (Ns = 46 and 95), with the latter serving as an independent replication study (Brans et al., 2013). A non-psychiatric, community sample recruited from a university employment office was instructed to use a Palmtop PC (a small, portable computer) to complete self-report questionnaires 10 times a day for 7 consecutive days. In both studies, participants reported state positive and negative affect by indicating the degree to which they were experiencing emotions using 2 positive affect and 4 negative affect adjectives from the PANAS. Participants also reported the extent to which they had engaged in each of 6 emotion regulation strategies (i.e., distraction, reflection, expressive suppression, rumination, social sharing, and cognitive reappraisal) since the last alert from the Palmtop PC. In both studies, expressive suppression and rumination were significantly associated with increases in negative affect and decreases in positive affect over time. In the replication study, reappraisal, distraction, and social sharing were significantly associated with increases in positive affect over time.

Consistent across both studies, participants implemented distraction the most, while social sharing and cognitive reappraisal were used the least. The design, which allowed for frequent sampling, provided more sensitive evaluations of the trajectory of emotion regulation strategy use and affective experiences was further strengthened by the inclusion of a replication study. In a similar EMA study, Heiy and Cheavens (2014) investigated the associations between 40 regulatory strategies and affective experiences. The authors assessed cognitive (e.g., expressive suppression) and behavioral (e.g., behavioral activation, sleep, substance use, exercise) emotion regulation strategies. Ninety-two non-psychiatric undergraduate students were recruited to use a personal device assistant (i.e., Palm Pilot) preprogrammed to alert participants 3 times a day at 4-hour intervals to complete questionnaires over 10 consecutive days. Participants completed measures of positive and negative affect (i.e., VAS) and the degree to which they implemented 40 emotion regulation strategies. Results showed that participants implemented an average of 15 emotion regulation strategies in response to negative emotions and most frequently used acceptance, behavioral activation, and rumination. Findings with respect to positive emotions, revealed that participants used an average of 16 strategies, primarily relying on savoring, future focus, and behavioral activation. It is notable, however, that in both of these studies the authors did not collect context-related information, such as what the participants were doing in between alerts or what were they doing when they were reporting their state affect. Connecting affect ratings to context would provide better ecological validity.

Brockman and colleagues (2017) used a daily diary approach to investigate emotion regulation strategies and change in affect with the longest monitoring period to date. Participants were 187 non-psychiatric undergraduate students who completed trait assessments of cognitive reappraisal, expressive suppression (i.e., ERQ), and mindfulness (i.e., Langer Mindfulness Scale;

Pirson, Langer, Bodner, & Zilcha, 2012) during an initial laboratory session. During the EMA portion of the study, participants completed modified versions of the ERQ and the Mindful Attention and Awareness Scale (MAAS; Brown & Ryan, 2003), and state positive and negative affect each evening for 21 consecutive days. Results revealed that higher levels of daily state mindfulness were significantly associated with less negative and greater positive affect over time. Conversely, higher daily state expressive suppression was significantly associated with lower positive affect and higher negative affect over time. Further, greater use of cognitive appraisal was significantly associated with lower negative affect, but only in younger participants (ages 17-19). While this study included the longest EMA period to date, and is one of few studies to measure of mindfulness as an emotion regulation strategy, this work was limited by the fact that participants were instructed to complete questionnaires only once per day and at the same time each day. An advantage of this approach is likely improved adherence; however, it limits inference for these relationships at other times during the day when people are also engaged in emotion-eliciting situations.

Compared to other emotion regulation studies using EMA methods, English et al., (2017) incorporated context by examining how social context and individual goals influence emotion regulation strategy selection in naturalistic settings. As part of a larger study, the authors recruited 136 non-psychiatric first-year undergraduate students to participate in a 7-day daily diary study. Each day, participants were prompted to report either a positive or negative event, the extent to which they regulated their emotions, their goal for regulation of their emotions (e.g., to keep up appearances), and the specific emotion regulation strategies they used (i.e., distraction, expressive suppression, and cognitive reappraisal). Results revealed that participants were more likely to use expressive suppression when others were present, especially with non-

close partners and when people had interpersonal goals (e.g., avoiding conflict) associated with regulating their emotions. Participants were also more likely to implement distraction and cognitive reappraisal when the emotion regulation goal was to make oneself feel better (i.e., hedonic) or when the goal was not interpersonal, such as needing to get work done. In terms of the frequency and degree, emotion regulation strategies were more frequently implemented and with greater effort during negative events (73%) than positive events (43%). This study was novel in terms of investigating emotion regulation choice in naturalistic settings and examining these constructs in the context of interpersonal factors. One limitation is that the study did not examine whether the selected emotion regulation strategy was effective in terms of impacting participant's affective experience or other measures of well-being.

Although EMA has been helpful in overcoming some methodological shortcomings (e.g., measurement at only one time-point), relatively few emotion regulation studies have used this approach, and those that employ EMA still rely on participants' retrospective self-report of their emotion experiences, goals, and behaviors. With the exception of Gruber et al. (2015) which incorporated a psychophysiological measure of emotion regulation, the studies reviewed above relied on self-report measures, limiting the ecological validity of the findings. Self-report measures, which require participants to recall their subjective experiences, are subject to reporting biases (Stone & Shiffman, 2002). The act of recalling one's behavior may impact the phenomena being measured, particularly when participants are instructed to engage in emotion regulation (Berking & Wupperman, 2012; Gross, 2015b). Moreover, while a number of the studies assess variation in state affect over time, the majority of the studies have relied upon a trait measure of emotion regulation (i.e., one's tendency to use a particular strategy such as

cognitive reappraisal, expressive suppression) rather than what participants actually did in the moment (i.e., a state measure of emotion regulation).

In summary, lab-based emotion regulation research has advanced the field's foundational knowledge, as well as provide validation of specific methods for investigating emotion regulation and related constructs. EMA studies have advanced this work by providing valuable insights into emotion regulation as it occurs in naturalistic settings. Although there is a large body of rigorous research on emotion regulation, progress is constrained by several methodological considerations reviewed below.

Limitations of Emotion Regulation Methodology

Methods for measuring and evaluating emotion regulation have continued to advance as the field has progressed over the past several decades (Aldao, 2013; Gross, 2015a). The field utilizes self-report, behavioral, neurological, genetic, and physiological assessments of emotion regulation. Further, experimental paradigms use a wide range of methods and instruments, including self-report questionnaires, behavioral observation and coding, mood inductions using standardized emotion-eliciting stimuli, neurological imaging, and ecological momentary assessment. Despite the breadth of methodology employed in emotion regulation research, the field is limited by an excessive reliance on laboratory-based paradigms and self-report measures (Aldao, 2013; Gross, 2015a). Though self-report measures can be developed with strong psychometric properties, they are prone to recall bias and distortion (Stone & Shiffman, 2002). Findings from laboratory-based paradigms lack ecological validity, with the majority of emotion regulation research confined to controlled laboratory settings, measuring short-term outcomes (Aldao, 2013). Moreover, it is unclear how instructions to elicit or regulate emotions impact participants subjective reporting, or how well these findings from controlled laboratory settings

predict real-world consequences (Berking & Wupperman, 2012). While ecological momentary assessment (EMA) is an important advancement for understanding emotion regulation in naturalistic settings, results are often limited by an exclusive reliance on participants' self-report of their emotional experiences, goals, and behaviors (Berking & Wupperman, 2012). Although behavioral coding, neural, genetic, and physiological address this limitation, these approaches do so at the expense of ecological validity as they are almost exclusively employed in laboratory settings. A complete understanding of emotion regulation requires an unobtrusive, ecologically valid assessment of the construct as it occurs in the environment. New developments in metrics and approaches to collecting data derived from digital devices have emerged and are well-poised to enhance our ability to evaluate emotion regulation in naturalistic settings. Digital sensors in smartphones enable the collection of data from individuals in their naturalistic settings, and with high accuracy (Torous, Onnela, & Keshavan, 2017; Torous et al., 2016).

Digital Phenotyping and Emotion Regulation

Digital phenotyping, or moment-by-moment quantification of individual level human behavior using data from smartphone sensors (Onnela & Rauch, 2016), is a novel method for evaluating human behavior in naturalistic settings. Continuous data of metrics from smartphones can provide accurate predictions of psychopathology in relation to naturalistic behavioral patterns. Digital devices allow for continuous telemetry of key parameters of psychological health, generating rich data sets of continuous metrics.

Our culture has acclimated to the pervasiveness of personal computing devices such as smartphones for organizing and navigating our daily lives, with >75% of US adults regularly using smartphones (Baker et al., 2018). Smartphones generate abundant social and behavioral data as a byproduct of this daily use. Specifically, digital sensors in smartphones enable the

collection of data from individuals in their daily lives, and with high resolution as data can be collected every few seconds rather than a few times a day (Onnela & Rauch, 2016). Smartphone data reflect the lived experiences of people in their real-world environment; thus, it is possible to use these data to develop precise markers of well-being and illness at the individual and population level. For example, data such as GPS for temporal mobility patterns and call and text logs can reflect degrees of social interaction. Experimental designs using smartphone-based digital phenotyping open the gateway to more sophisticated assessments of the characteristics of individuals with varying levels of emotion regulation implementation style and ability, and their impact on well-being.

Continuous data of metrics from smartphones can provide accurate predictions of psychopathology in relation to naturalistic behavioral patterns. For example, Saeb and colleagues (Saeb et al., 2015) conducted an exploratory study using GPS smartphone data to distinguish between participants with depressive symptoms and healthy controls. The results showed that mobility between favorite locations and location variance (mobility independent of location) to classify those with significant depressive symptoms from those without with 86.5% accuracy. These findings suggest that smartphone data, such as GPS, can be an accurate behavioral marker of depressive symptom severity. Other research using sensor data from smartphones found total duration of phone use predicted ratings on the warning signs scale for psychosis in individuals with schizophrenia (Torous et al., 2017), and differences in reported affect, anxiety, and energy over time among individuals diagnosed with bipolar disorder compared to healthy controls (Ortiz et al., 2017).

The application of smartphone-based digital phenotyping to emotion regulation research can contribute to a better understanding of how context impacts individual differences in one's

ability to implement adaptive emotion regulation and, thus, overall well-being. To date, no research has specifically examined the relationship between emotion regulation indices and digital phenotyping. Importantly, digital phenotyping data from smartphones is an approach that captures behavioral units of analysis of psychological phenomena in line with the National Institute of Mental Health's Research Domain Criteria (RDoC) framework (T. Insel et al., 2010; Torous, Onnela, et al., 2017). Digital phenotyping is a promising methodological approach that can help accurately identify individual differences in emotion regulation implementation, which can improve our ability to identify and treat emotion regulation deficits and promote or teach adaptive emotion regulation skills.

Overview and Statement of Purpose

The ability to effectively regulate our emotions is critical to well-being, as emotion dysregulation has been shown to increase the likelihood of developing and maintaining a range of mental health problems (Aldao et al., 2016, 2010; Joormann & Vanderlind, 2014). While our understanding of emotion regulation has benefited from a strong theoretical framework (e.g., the extended process model; Gross, 2014, 2015a, 2015b), that has generated an impressive body of research (Aldao et al., 2010, 2016; Sheppes et al., 2015), significant gaps remain. The majority of research on emotion regulation has been circumscribed to controlled laboratory settings that use experimental paradigms to investigate short-term outcomes. It is unknown how instructions to elicit or regulate emotions impact participants' subjective reporting, or how these findings generalize to naturalistic settings (Berking & Wupperman, 2012). Ecological momentary assessment is helpful in addressing some methodological issues with longitudinal investigations of emotion regulation; however, the majority of research remains reliant on participants' self-report of their emotion experiences, goals, and behaviors. There are numerous well-validated

self-report measures used in emotion regulation research (Fernandez et al., 2016; Mauss & Robinson, 2009) that have been instrumental in advancing our conceptual understanding of emotion regulation; these measures have typically been administered in a cross-sectional fashion which prevents a comprehensive evaluation of emotion regulation processes as they unfold over time. Moreover, our more traditional approaches to measurement fail to assess variability in dynamic processes associated with emotion regulation. As the field of emotion regulation has established foundational knowledge of how individuals regulate emotions in laboratory settings, a true understanding of emotion regulation must leverage an unobtrusive, ecologically valid assessment of the construct as it occurs in real-world settings. The future of emotion regulation assessment depends on our ability to harness innovative interdisciplinary methodology to advance our understanding of implicit and passive experience. Digital sensors in smartphones enable the collection of moment-by-moment data from individuals in naturalistic settings (Onnela & Rauch, 2016; Torous et al., 2016). Digital phenotyping, or the moment-by-moment quantification of individual level human behavior using data from smartphone sensors is a novel method for evaluating human behavior, such as emotion regulation, in naturalistic settings (Onnela & Rauch, 2016).

The central aim of this project is to employ digital phenotyping methodology to expand the nomological network of emotion regulation. Research to date has focused on the behavioral, cognitive, and biological components of emotion regulation (Gross, 2015a; Mendes, 2014). The next horizon for emotion regulation research is to use digital data to characterize and predict emotion regulation processes, ultimately in service of providing personalized treatment for mental health problems. The first step is to investigate the associations between state and trait self-report measures of emotion regulation and digital phenotypes, and how these patterns relate

to well-being. To expand the nomological network of emotion regulation, it is necessary to validate multiple indices of a construct. Given emotion regulation is conceptualized at both the state- and trait-level, both forms of assessment are needed to understand how emotion regulation is associated with digital phenotypes. This project will evaluate whether digital phenotyping can improve accurate predictions of individual differences in emotion regulation and emotion regulation implementation. This new method may ultimately enhance therapists' ability to accurately identify and respond to fluctuations in emotion regulation associated with mental well-being.

Research Aims and Hypotheses

This study will contribute to new knowledge of the relationships between emotion regulation, digital behaviors, and depressive symptoms both in response to a sad mood induction and in naturalistic settings. Digital phenotyping data included GPS and mobile phone power state as both types of data can be used to produce a respective index, represented by a single value per observation over time. Specifically, GPS was used to calculate a distance index (meters) and power state level index (mobile phone battery level ranging from 0% to 100%). Relative to other digital phenotyping data, GPS distance and mobile phone power state are more accessible and practical to acquire and compute; thus, future research can more feasibly build on the findings this project. Further, variation in GPS distance and power state level may be sensitive to changes in behavior consistent with the behavioral theory of depression, such as when individuals experience greater depressive symptoms, they are more likely to maintain positive activities for general emotional regulation (Dimidjian et al., 2011). Based on an emotion dynamics framework, which conceptualizes emotion variability as the range and amplitude of emotion and emotion regulation processes occurring over time (Gross, 2014; Kuppens & Verduyn, 2015,

2017), state emotion regulation was operationalized as variation in state negative affect as well as variation in spontaneous emotion regulation implementation over time. As digital phenotyping is a novel approach for examining psychological phenomena, and this is the first project to date to evaluate the correlations between digital phenotyping and emotion regulation, the proposed aims are exploratory. Based on a pilot study of digital phenotyping methodology and a review of the relevant research, the following aims and hypotheses were proposed:

Aim 1: Investigate the digital behavior correlates of self-report emotion regulation (state and trait). Using a statistical learning approach, it was hypothesized that:

H_1 Trait emotion regulation (cognitive reappraisal, expressive suppression, rumination, and difficulties in emotion regulation) would be related to power state level and GPS distance over time.

H_2 State emotion regulation over time (variation in negative affect and spontaneous emotion regulation) would be related to power state level and GPS distance over time.

Aim 2: Building upon aim 1, the second aim sought to investigate whether self-reported emotion regulation (state and trait) interacted with digital behaviors (variation in power state level and GPS distance over time) to predict emotional well-being at baseline. Accordingly, the following exploratory hypothesis were proposed:

H_3 Trait emotion regulation and digital phenotyping data together would predict baseline depressive symptoms.

H_4 State emotion regulation in response to a negative mood induction and digital phenotyping data together would predict baseline depressive symptoms.

CHAPTER 2

METHODS AND PROCEDURES

The writing author was the primary experimenter for the study. Undergraduate and graduate research assistants in Dr. Emily Haigh's Maine Mood Lab assisted with conducting the study. All research assistants had completed the required training for the Institutional Review Board (IRB) for Protections of Human Subjects. Undergraduate research assistants were trained on standardized study procedures for participant recruitment and conducting the in-lab and follow-up phases of the experiment.

The current project is part of a larger study for which participants were assessed using continuous physiological data. The results of this data collection will be reported elsewhere.

Participant Recruitment

Participants ($N = 69$; age range: 18 - 28 years; $M_{age} = 19.70$ years) were recruited from introductory psychology courses at a mid-sized New England university from 02/12/2020 to 03/10/2020 and were compensated with course credit in their respective courses (see Appendix A for the recruitment materials). Eligible participants were at least 18 years of age or older and owned a smartphone with either Apple iOS or Android operating systems. All participants completed the same experimental paradigm, serving as their own controls. A power analysis was conducted using G*Power version 3.1.9.3 (Faul et al., 2007) and indicated that approximately 68 participants would be sufficient to find a medium effect size (e.g., $f^2 = .15$) with sufficient power (e.g., $\beta = .80$) for multiple regression with two predictors. Although it was expected that a sample of 100 participants would be recruited to account for attrition and non-compliance , participant recruitment ended early due to COVID-19-related university closures. See Table 1 for sample demographic characteristics.

Table 1

Sample Demographic Characteristics

Variable	*M*	*SD*
Age (N = 69)	19.70	1.72
Variable	*n*	*%*
Gender Identity		
Male	33	48
Female	36	52
Race		
Asian	1	1.44
Black	1	1.44
Multiple	2	2.9
Native American	2	2.9
White	62	89
Relationship Status		
Never Married/Single	69	100
Education Level		
High School	43	62
1 Year of College	14	20
2 Years of College	9	13
Bachelors	1	1.44
Associates or Other	1	1.44

Measures

See Appendix C for full measures.

Demographic information

Participants were asked to provide information about their age, gender identity, race/ethnicity, and level of education.

Trait Emotion Regulation

Cognitive Reappraisal and Expressive Suppression. Participants completed the Emotion Regulation Questionnaire (ERQ; Gross & John, 2003) to assess individual differences in the tendency to use two emotion regulation strategies: cognitive reappraisal and expressive

suppression. This 10-item self-report questionnaire has a subscale for cognitive reappraisal (six items) and expressive suppression (four items). The response format of each item is a 7-point Likert-type scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*) indicating the degree to which they tend to implement the content of each item. The items pertain to regulating both positive emotion and negative emotion. Scoring yields separate sum scores for the cognitive reappraisal and expressive suppression subscales, with higher scores indicating greater tendencies to implement the emotion regulation strategy. Initial psychometric evaluations of the ERQ (Gross & John, 2003) indicate adequate internal consistency for the cognitive reappraisal (α = .79) and expressive suppression (α = .73) scales and adequate test-retest reliability across three months for both scales (α = .69). Initial psychometric evaluations also demonstrated adequate convergent validity with specific measures of inauthenticity, coping, rumination, and negative mood regulation, as well as adequate discriminant validity with measures of broad personality, impulse control, cognitive ability, and desirability. Subsequent psychometric research has demonstrated the ERQ to be internally consistent and to adequately assess cognitive reappraisal and expressive suppression as distinct constructs (Melka et al., 2011). Internal reliability for the full scale in the present sample was acceptable (α = .79), cognitive reappraisal subscale was good (α = .89) and expressive suppression subscale acceptable (α = .70). Scores on the ERQ were utilized to determine individual differences in trait emotion regulation of cognitive reappraisal and expressive suppression. ERQ scores were used as the dependent variable and as part of the cluster and classification analyses in Hypothesis 1, as well as a predictor variable in Hypothesis 3.

Trait Rumination. The Ruminative Responses Scale (RRS; Treynor, Gonzalez, & Nolen-hoeksema, 2003) was used to assess trait rumination. The RRS is a widely used 10-item

questionnaire designed to measure individual differences in rumination, or the tendency to engage in repetitive and passive thinking about problems, negative events, and negative feelings. A meta-analysis found rumination to be the most predictive emotion regulation strategy of emotion disorders (Aldao et al., 2010). The response format of each item is a 4-point Likert-type scale ranging from 1 (*almost never*) to 4 (*almost always*) indicating the frequency with which an individual endorses each item. The measure is scored by a total sum of all items or the sum of each item corresponding to a pondering subscale (5 items) and a brooding subscale (5 items). Initial psychometric evaluations demonstrated the RRS to have good internal consistency (α = .90) and moderate test-retest reliability (r = 67). Internal reliability for the present sample was acceptable (α = .70). Subsequent psychometric research has also found the RRS to have good internal consistency and to adequately assess pondering and brooding as distinct constructs (Armey et al., 2009). RRS scores were used as the dependent variable and as part of the cluster and classification analyses in Hypothesis 1, as well as a predictor variable in Hypothesis 3.

Trait Difficulty Regulating Emotions

The Difficulties in Emotion Regulation Scale **(**DERS; Gratz & Roemer, 2004) was used to measure trait difficulties with implementing emotion regulation. The DERS was designed to assess trait-level perceived emotion regulation ability across four domains, including awareness and understanding of emotions, acceptance of emotions, the ability to control impulses and behave in accordance with goals in the presence of negative affect, and access to emotion regulation strategies that are perceived to be effective for feeling better. Items are rated on a scale of 1 (*almost never* [0-15%]), 2 (*sometimes* [11-35%]), 3 (*about half the time* [36-65%]), 4 (*most of the time* [55-90%]), to 5 (*almost always* [91-100%]). The DERS can be interpreted as a total score or each subscale can be scored separately. Higher scores indicate more difficulty in

emotion regulation. Development of the DERS demonstrated strong internal consistency (α = .83 to .90; Gratz & Roemer, 2004). The full-scale internal reliability for the present sample was excellent (α = .96). DERS scores were used as part of the clustering and classification analyses in Hypothesis 1.

State Emotion Regulation Use

The Spontaneous Affect Regulation Scale (SARS; Egloff, Schmukle, Burns, & Schwerdtfeger, 2006) is a self-report questionnaire based on the format of the ERQ (Gross & John, 2003) and designed to measure the degree to which individuals spontaneously (i.e., without instruction) implemented emotion regulation strategies during a specified time. The SARS is comprised of six items and two subscales, including cognitive reappraisal and expressive suppression. Higher scores on the subscales represent a greater degree of implementation of that emotion regulations strategy. The SARS subscales have demonstrated adequate internal consistency in previous studies (Egloff et al., 2006; Gruber, Harvey, & Gross, 2012; Stange et al., 2017). Scores from the SARS were used to assess spontaneous implementation of emotion regulation strategies during the sad mood induction and the EMA phase of the study. SARS scores will be the dependent variable in Hypotheses 2 and 4.

State Affect. A visual analog scale (VAS; Feinstein, 1987) was used to assess state negative affect. Using horizontal 100 count lines with anchors at the 0 (*not at all*) and 100 (*extremely*) endpoints, participants rated the degree to which they were currently experiencing sadness. Although the results of studies evaluating the validity and reliability of the VAS have been mixed, the scales are useful for capturing state affective experiences because of their simplicity, especially for paradigms with short intervals between assessments (Ahearn, 1997). VAS ratings were used to assess change in state affect in response to a sad mood induction, as

well as state affect during a 7-day EMA/digital phenotyping phase. VAS change scores were the dependent variable in Hypothesis 2 and a predictor in Hypothesis 4. Changes in VAS ratings were also used to complete a manipulation check for the negative mood induction.

Severity of Depressive Symptoms

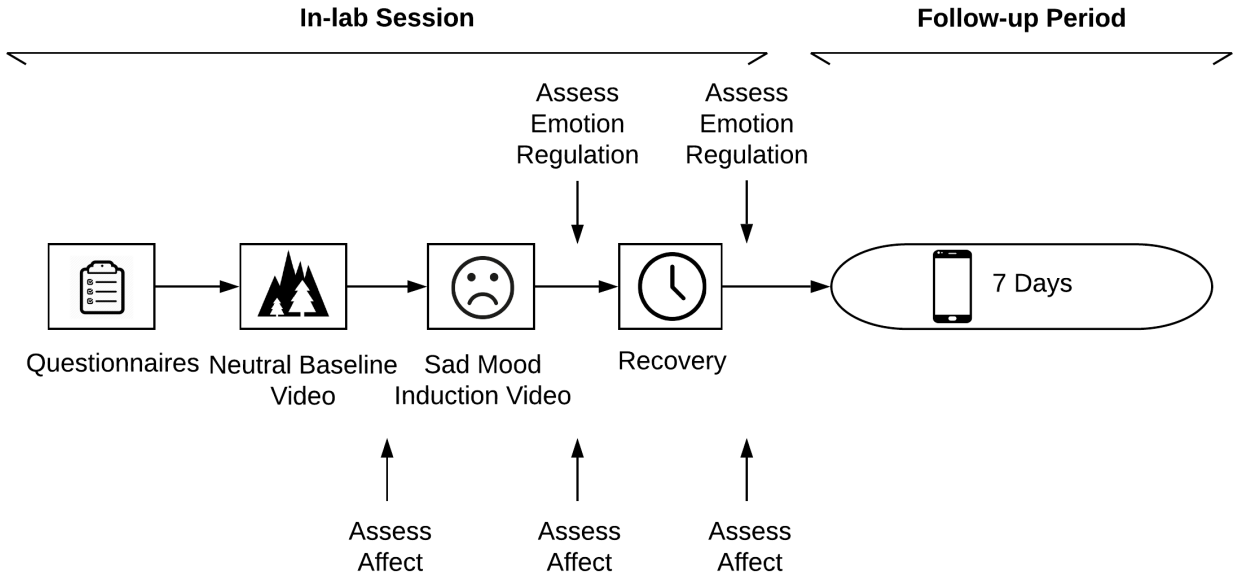
The Patient Health Questionnaire 9 (PHQ-9; Kroenke et al., 2001; Appendix C) was used to measure current depressive symptoms. The PHQ-9 is a widely used, 9-item, multipurpose instrument for screening, diagnosing, monitoring, and measuring the severity of depression. The response format of each item is a 4-point Likert-type scale ranging from 0 (*not at all*) to 3 (*nearly every day*) indicating the frequency with which an individual endorses each item for the previous 2 weeks. Higher scores indicate greater depressive symptom severity. The PHQ-9 had demonstrated strong internal reliability (α = .89; Kroenke et al., 2001). The internal reliability for the present sample was excellent (α = .91). PHQ-9 total scores were used as the dependent variable in hypotheses 3 and 4.

Data Collection

Participants completed a 1-hour laboratory session consisting of questionnaire completion, baseline assessment, a sad mood induction, a recovery period, and a 7-day follow-up EMA/digital phenotyping period. Affect ratings and spontaneous ratings of emotion regulation were obtained following a neutral mood induction, a sad mood induction, a recovery period, and twice a day during the 7-day follow-up period (see Figure 4). After installing the digital phenotyping application, participants were debriefed (Appendix E) and compensated with course credit.

Figure 4

Diagram of Study Procedure



After providing informed consent, participants completed battery of questionnaires on Qualtrics©. The questionnaires were administered in a randomized order, assessing demographic information, trait emotion regulation strategy use (i.e., ERQ, DERS, and RRS; Appendix C), and emotional well-being (i.e., PHQ-9; Appendix C).

Mood Inductions

After completing the questionnaires, participants watched a series of video clips on a desktop computer, presented approximately 24 inches in front of them. To establish a neutral baseline, participants viewed an emotionally neutral 3-minute nature film clip from Alaska's Denali National Park. For the sad mood induction, the neutral film was followed by a 2-minute and 51-second film depicting a boy who is distraught at the death of his father from the movie "The Champ." This paradigm has been validated in previous research to elicit transient sadness (Rottenberg et al., 2007). After the sad mood induction, participants were instructed to sit quietly

for a 5-minute recovery period. To ensure procedural standardization, directions, videos, and audio were presented on a computer using E-Prime 2.0 (2015) computer software.

Digital Phenotype Acquisition

At the end of the in-lab session, participants were instructed how to install the Beiwe mobile device application on their smartphones to collect digital phenotyping data.

The Beiwe mobile device application, part of the Beiwe research platform and a cloud-based research platform developed and maintained by the Onnela Lab at the Harvard T.H. Chan School of Public Health, is designed for collecting digital phenotyping data. The Beiwe mobile device application is installed using the Apple App Store or the Google Play Store and requires cellular and location services. The application collects anonymous data from the sensors in smartphones. The types of digital phenotype data to be collected include the following: accelerometer data, GPS data, device motion, frequency of Wi-Fi use, frequency of Bluetooth use, and mobile phone power state. The Beiwe mobile application semi-continuously collects digital phenotype data in the background as the individual uses the smartphone. The GPS data and power state data were used as digital phenotyping data in the present study. The accuracy of GPS data on smartphone devices is on average withing 4.9 meters and is impacted by satellite geometry, atmospheric conditions, receiver design and quality, and the position of buildings (United States Government, 2020). The granularity of power state level collected by the Beiwe Research Platform was to the percentage point. Based on pilot testing, the sampling rate for GPS position and power state ranged from approximately 10-second to 15-minutes, with GPS data sampled more frequently on average.

To reassure the participants that their privacy was and will be protected, participants were informed that the data collected by the mobile application are secure and would not be shared. It

was also be made clear to participants that the mobile application does not collect private content, such as the actual content of their texts, recordings of their conversations, content of files stored on their phones, or internet browsing history. To standardize instructions for using the Beiwe application during the follow-up period, a script was used (Appendix D). The script was implemented as a Qualtrics© survey for participants to follow along as research assistants read the instructions, and to document that they received and understood the instructions.

Participants were asked to keep the application on their smartphone for seven consecutive days following the in-lab session. Participants were able to send transcribed voicemails through the Beiwe application using Google Voice in case they needed to contact research personnel with any questions. Participants were prompted about their phone use 14 times (once in the morning and once in the evening) over the course of the EMA phase. After the seven days, participants were sent an email indicating they should uninstall the Beiwe application from their smartphone. In the same email, participants were also sent a list of local counseling services (Appendix F). Participants earned additional course credit for completing the follow-up period of the study.

The Beiwe Research Platform collects data on a continuous basis, sampling each index on average of every 10 seconds. Sampling of each index at this rate generates a substantial amount of data. Therefore, the data were pre-processed to generate a summary statistic for each index (i.e., GPS distance and power state level). A summary statistic in the context of Beiwe data is data processed and formatted into a standard one-variable, one-column format for each variable of interest. Digital phenotyping data included in the present study were GPS data, power state data, and time stamp. GPS and power state data were pre-processed to create a GPS distance summary statistic (in meters) and a power level summary statistic (0%-100%). Distance was calculated as the difference between one GPS coordinate and its preceding coordinate using

a great circle distances approach which accounts for the curvature of the earth. Both GPS distance and power level observations were time stamped. The code for pre-processing the digital phenotyping data collected using the Beiwe Research Platform is available on a public repository that is being maintained by the writing author (https://github.com/cmbosma/beiwe-scripts).

Data Diagnostics

Prior to analyses, self-report measures and digital phenotyping summary statistic variables were inspected for univariate outliers. Outliers were defined as z-score values exceeding +/- 3.0 standard deviations as well as impossible values (i.e., values outside of the range of the measure) (Daszykowski et al., 2007). There was one instance where GPS distance exceeded the 3.0 standard deviations. This instance was replaced with the 3rd quartile value (i.e., 668.42 meters) as it was not an impossible value. Univariate normality was inspected using boxplots and kurtosis values. Although numerous variables were either positively or negatively sckewed, none of the distributions of the variables of interest exceeded the recommended acceptable kurtosis range of -2 to 2 (Gravetter et al., 2020).

Given the longitudinal design of the research project, attrition was expected. To reduce bias and increase efficiency in statistical modeling, a multiple imputation approach was implemented for missing values using the Multivariate Imputation via Chained Equations R package (MICE; Buuren & Groothuis-Oudshoorn, 2010). Multiple imputation is a Bayesian-based method for addressing missing values by generating several possible imputed data sets and combining the results from each of them (White et al., 2011).

To determine whether participants used their phones in an atypical way during the 7-day ecological momentary assessment (EMA) phase, each time the participants completed the self-

report emotion regulation and affect items, they were also prompted with questions about their phone use. For those who indicated they had used their phone in an atypical way, there were four responses to the prompt "please describe what was atypical about how you used your phone today." The responses included the following: "I used it"; "I used it too much"; "I came home to Portland"; and "My phone was dead for half of my day". There were 55 responses to the prompt, "please describe what it was about your day that was atypical." The content of the descriptions was generally related to social behaviors (e.g., "drove home", "saw my girlfriend at lunch", "went skiing with friends", "got in a fight with my sister"), academic behaviors (e.g., "I skipped class", "I got a 0/10 on a homework with no explanation", "I only had one class"), and sleep behaviors (e.g., "I slept all morning", "couldn't fall asleep until 5am"). There were a number of responses describing stress-related events, such as "I dropped my coffee right outside my class and I'm so mad" and "I pulled myself out of two stressful situations". Compliance for responding to the phone use prompts was relatively low (~50% missing). Descriptive statistics on self-report of phone use are presented in Table 2.

Table 2

Ecological Momentary Assessment Self-Report Phone Use

Variable	*n*	%
Atypical phone use		
Yes	10	3.76
No	122	45.86
Missing	134	50.38
Anything Atypical Occurred Today		
Yes	43	7.19
No	255	42.64
Missing	300	50.17

Data Analytic Strategy

Analyses were conducted using the R statistical programing language, version 4.0.3, in RStudio, an integrated development environment (IDE) for R, as well as using Python 3.9.0 in the Jupyter Notebooks IDE.

Descriptive analyses were first conducted to provide information on primary study variables. A manipulation check was conducted to ensure the induction had its intended effects. Participants reported significantly higher state negative affect after the sad mood induction (M = 58.81, SD = 29.18) compared to before the sad mood induction (M = 5.26, SD = 10.36), $t(68) = -14.38$, $p < .001$.

Primary analyses for each aim were conducted using both supervised (i.e., test an expected pattern in the data) and unsupervised (i.e., detecting patterns in the data) learning approaches where appropriate given the aims and nature of the data. Supervised learning approaches included simple linear regression to test for the presence of directional relationships and multiple regressions to evaluate both directional relationships and interactions. Unsupervised learning approaches included cluster analysis to determine grouping patterns in numerous continuous variables followed by classification analysis to determine whether digital phenotyping data accurately predicted the groups identified in the cluster analysis. All reported model coefficient 95% CIs were bootstrapped with 2000 bootstrap replicates.

CHAPTER 3

RESULTS

The purpose of this project was to investigate the digital behavior correlates of state and trait emotion regulation (Aim 1) and whether the relationships between digital behavior and emotion regulation predict emotional distress (Aim 2). Self-report measures completed during an in-lab phase of the study were used to assess trait emotion regulation and state emotion regulation in response to a sad mood induction. Digital behaviors using smartphone sensors and self-report state affect and state emotion regulation were collected using the Beiwe Research Platform on mobile devices for seven days following the in-lab phase.

Broadly, emotion regulation variables were operationalized as the *SD* of the values over time to capture the range and amplitude of emotion and emotion regulation processes occurring longitudinally (Kuppens & Verduyn, 2015, 2017). Specifically, variation in state emotion regulation across time during the 7-day follow-up phase was operationalized as the *SD* of the cognitive appraisal and expressive suppression subscales of the SARS, as well as the *SD* of sadness VAS ratings (i.e., Hypothesis 2). Digital behaviors were operationalized as GPS distance (meters) power state level (0%-100). Variation in digital behaviors over time was operationalized as the *SD* of GPS distance and power state level values across all time points (i.e., Hypotheses 1, 2, 3, and 4). When investigating the relationship between digital behaviors over time and trait emotion regulation using an unsupervised learning statistical analysis (cluster and classification analyses), the time stamps of each GPS distance and power state level entry was used to evaluate variation in digital behaviors over time (i.e., Hypothesis 1). State emotion regulation in response to a negative mood induction was operationalized as the *SD* of the cognitive appraisal and

expressive suppression subscales of the SARS, as well as the *SD* of sadness VAS ratings (i.e., Hypothesis 4).

Descriptive Analyses

First, descriptive analyses were performed for each lab phase self-report measure and are presented in Table 3.

Table 3

Sample In-Lab Phase Self-Report Measure Characteristics

In-lab Self-Report Measure Characteristics

			Range	
Variable	*M*	*SD*	Potential	Actual
ERQ				
Cognitive Reappraisal	28.26	7.64	6-42	7-42
Expressive Suppression	15.53	4.41	4-28	4-24
RRS	27.09	6.08	10-40	12-40
DERS	80.32	27.05	36-180	48-153
SARS Cognitive Reappraisal Sub-scale				
Post Neutral Mood Induction	11.29	3.99	4-24	4-19
Post Negative Mood Induction	13.30	3.82	4-24	4-22
Post Recovery	12.70	4.63	4-24	4-24
Across All Time Points	12.36	2.45	4-24	4-24
SARS Expressive Suppression Sub-scale				
Post Neutral Mood Induction	6.35	2.81	2-14	2-14
Post Negative Mood Induction	7.58	2.46	2-14	2-14
Post Recovery	7.49	2.76	2-14	2-14
Across All Time Points	7.19	1.56	2-14	2-14
Negative Affect VAS				
Post Neutral Mood Induction	5.26	10.36	0-100	0-50
Post Negative Mood Induction	58.81	29.18	0-100	0-100
Post Recovery	20.54	27.10	0-100	0-94
Across All Time Points	27.29	30.80	0-100	0-100
PHQ9	13.24	7.40	0-27	2-27

Note. ERQ = Emotion Regulation Questionnaire, RRS = Ruminative Responses Scale, DERS = Difficulties in Emotion Regulation Scale, SARS = Spontaneous Affect Regulation Scale. VAS = Visual Analog Scale. PHQ-9 = Patient Health Questionnaire 9.

Descriptive statistics for self-report state emotion regulation questionnaires completed during the 7-day EMA phase are presented in Table 4. Descriptive statistics for the digital phenotyping data collected during the EMA phase are presented in Table 5. It is notable that 22% of the power level data were missing. Upon investigation of any existing patterns related to the missing data, it was determined that 16 participants did not have power level data. All 16 of the participants with missing power level data had Android operating systems including Android versions 7, 8, 8.1, 9, and 10. The model of phones included the Google Pixel 2 XL, Samsung Galaxy S6, Samsung Galaxy S8, Samsung Galaxy Note 8 (n = 3, Samsung Galaxy S9 (n = 4), Motorola Moto X4, OnePlus 7, Google Pixel 2 XL, and the Xaomi Mi A1. Review of the installation logs did not indicate issues during the installation or registration of the Beiwe 2 mobile application. Since there are more global options for mobile application permissions available to Android operating system users, it is possible that participants had permission settings that prevented the collection of power level state data, even when granting permissions for the Beiwe 2 mobile application during installation.

Table 4

Ecological Momentary Assessment Self-Report Measure Characteristics

Variable	*M*	*SD*	Range
SARS			
Cognitive Reappraisal Subscale	2.46	1.78	0-6
Expressive Suppression Subscale	3.13	1.59	0-6
Negative Affect VAS	6.23	14.96	0-90

Note. SARS = Spontaneous Affect Regulation Scale. VAS = Visual Analog Scale.

Table 5

Digital Phenotyping Data Characteristics

Variable	*N Observations*	% Missing	*M*	*SD*	Range
Power state					
Power State level	186593	22	0.48	0.27	0-1
GPS					
Distance	1789156	0	33.2	1108.38	0-485472

Note. GPS distance was transformed to meters. Power level was measured in percentage of battery level ranging from 0% to 100%.

Hypothesis 1: Trait Emotion Regulation and Digital Phenotyping

Hypothesis 1 analyses evaluated whether trait emotion regulation (cognitive reappraisal, expressive suppression, rumination, and difficulties in emotion regulation) would be related to power state level and GPS distance over time.

Supervised Learning: Regression analysis

Variation in power state level and GPS distance was operationalized as the *SD* of each variable across each observation over the 7-day follow-up period.

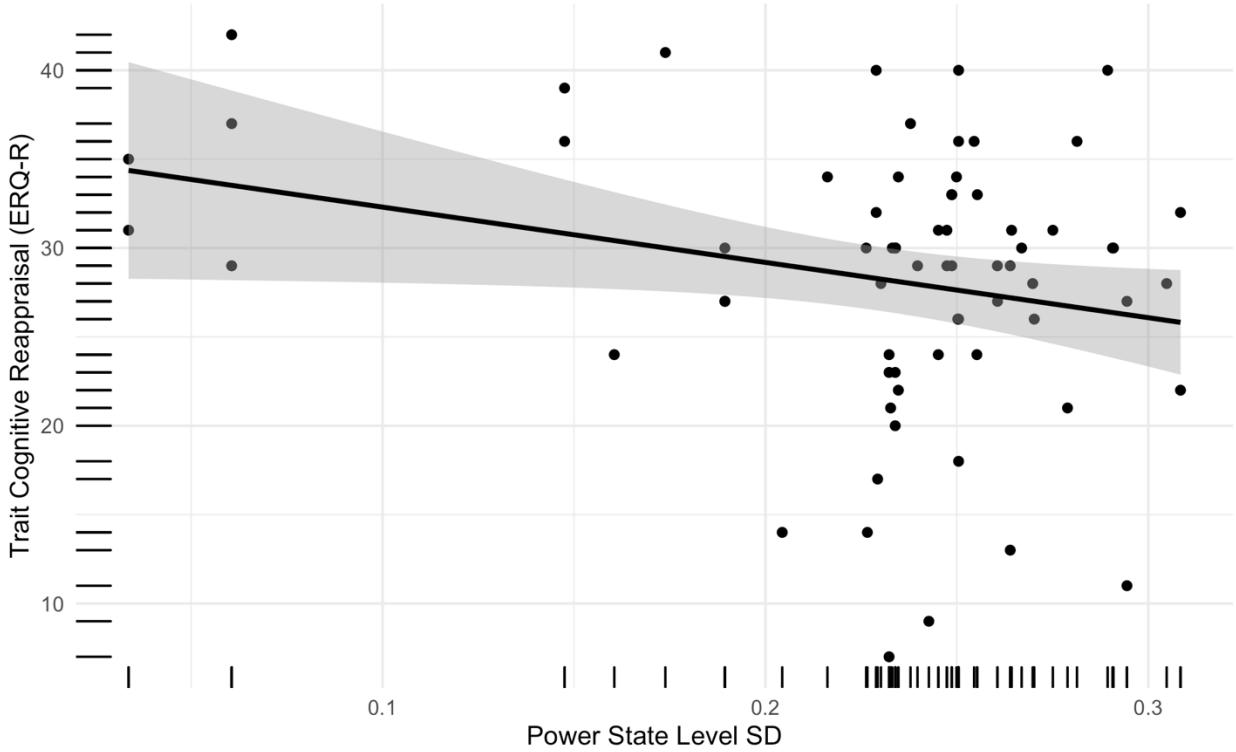
Power State Level Analyses

Hypothesis 1 simple linear regression results with power state level *SD* as the predictor variable are displayed in Table 6.

Trait Cognitive Reappraisal. Variation in power state level did not predict trait cognitive reappraisal and explained less than one percent of the variance in trait cognitive reappraisal ($_{adj}R^2$ = -.005, $F(1, 67) = 0.65$, $p = .42$). The linear regression is displayed in Figure 5.

Figure 5

Power State Level SD Regressed on Trait Cognitive Reappraisal

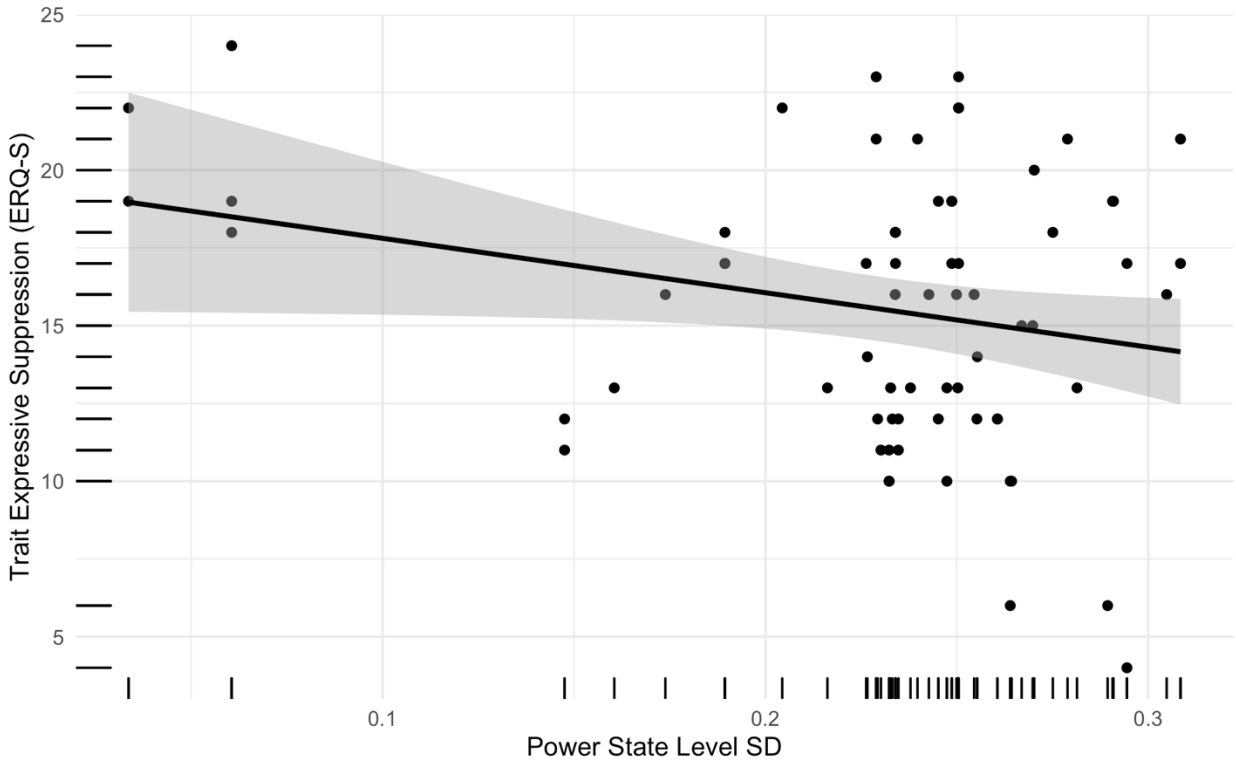


Note. ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale. Band width represents 95% CI for predictions from the linear model.

Trait Expressive Suppression. Variation in power state level did not predict trait expressive suppression and explained less than one percent of the variance in trait cognitive reappraisal ($_{adj}R^2$ = -.003, $F(1, 67) = 0.81$, $p = .37$). The linear regression is displayed in Figure 6.

Figure 6

Power State Level SD Regressed on Trait Expressive Suppression

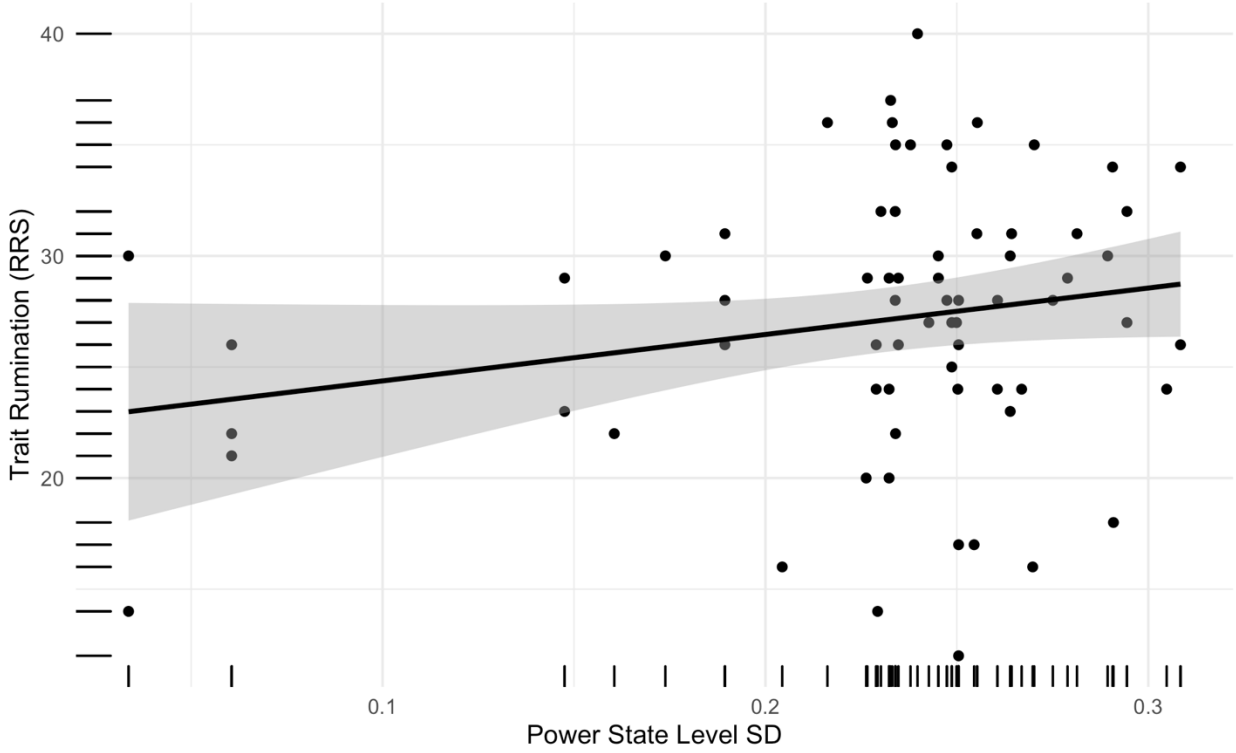


Note. ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale. Band width represents 95% CI for predictions from the linear model.

Trait Rumination. Variation in power state level did not predict trait rumination and explained less than one percent of the variance in trait cognitive reappraisal ($_{adj}R^2$ = .01, $F(1, 67)$ = 0.04, p = .85). The linear regression is displayed in Figure 7.

Figure 7

Power State Level SD Regressed on Trait Rumination



Note. RRS = Ruminative Responses Scale. Band width represents 95% CI for predictions from the linear model.

Table 6

Results of Trait Emotion Regulation and Variance in Power State Level Regression Models

Predictor	Model 1: Cognitive Reappraisal			
	b	*SE*	95% CI	*p*
(Intercept)	32.30	5.08	17.11, 39.34	<.0001
Power Level SD	-16.58	20.53	-45.30, 39.55	.42
	Model 2: Expressive Suppression			
(Intercept)	18.12	2.93	10.74, 22.65	<.0001
Power Level SD	-10.64	11.84	-30.86, 18.64	.37
	Model 3: Rumination			
(Intercept)	26.34	4.07	18.15, 31.24	<.0001
Power Level SD	3.05	16.43	-16.35, 34.39	.85

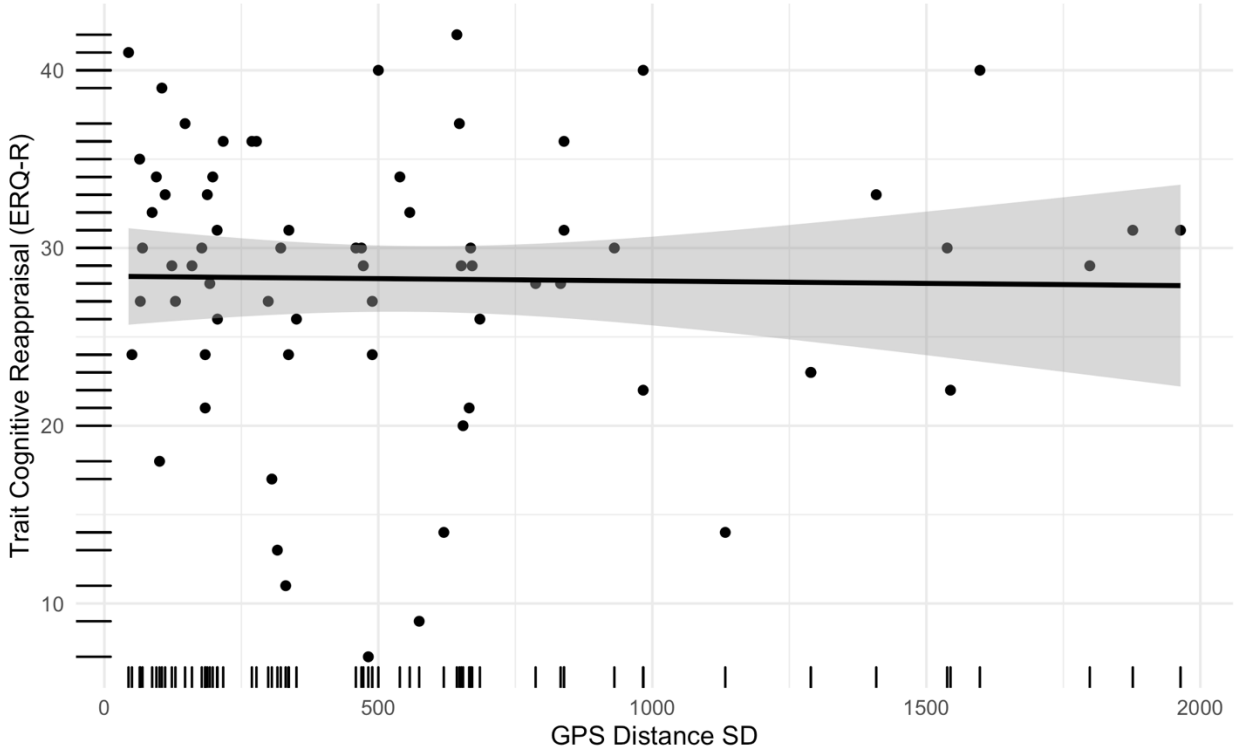
GPS Distance Analyses

Hypothesis 1 simple linear regression results with GPS distance SD as the predictor variable are displayed in Table 7.

Trait Cognitive Reappraisal. Variation in GPS distance did not predict trait cognitive reappraisal and explained less than one percent of the variance in trait cognitive reappraisal ($_{adj}R^2$ = -.02, $F(1, 67) = 0.02$, $p = .89$). The linear regression is displayed in Figure 8.

Figure 8

GPS Distance SD Regressed on Trait Cognitive Reappraisal

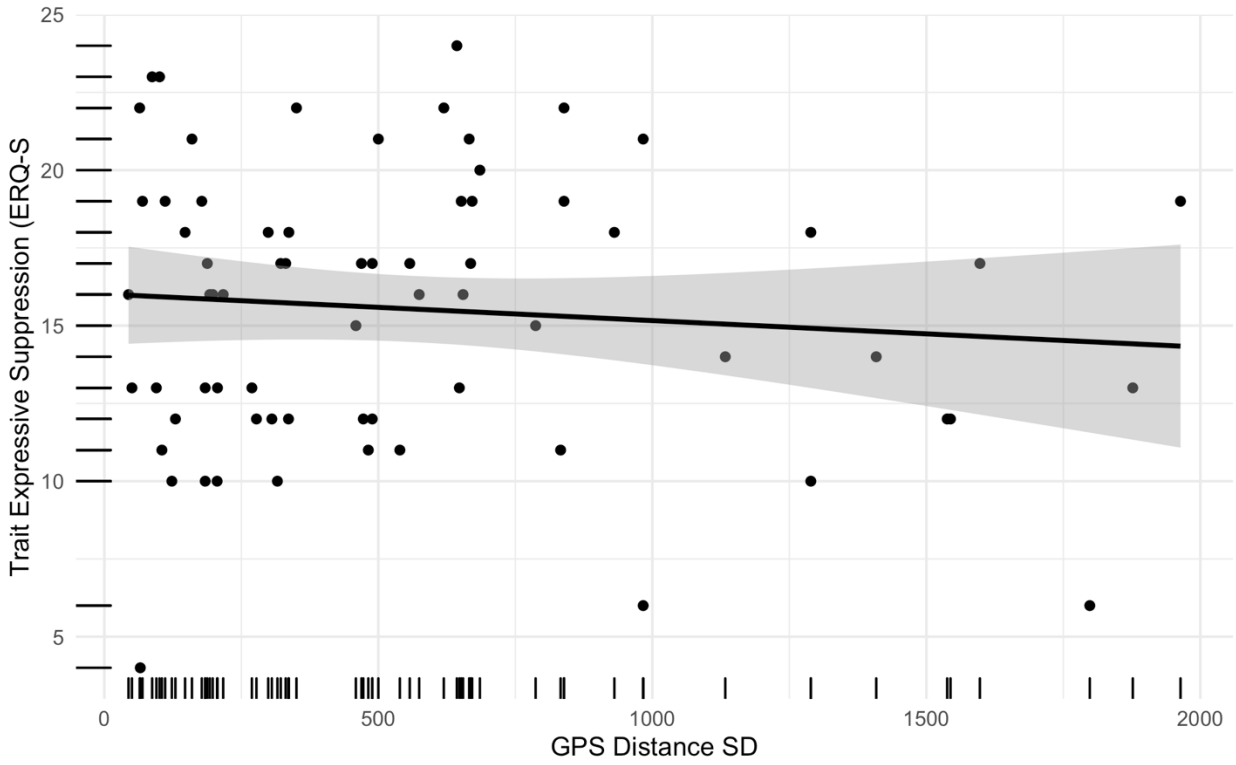


Note. ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale. Band width represents 95% CI for predictions from the linear model.

Trait Expressive Suppression. Variation in GPS distance did not predict trait expressive suppression and explained less than one percent of the variance in trait cognitive reappraisal ($_{adj}R^2$ = -.006, $F(1, 67) = 0.60$, $p = .44$). The linear regression is displayed in Figure 9.

Figure 9

GPS Distance SD Regressed on Trait Expressive Suppression

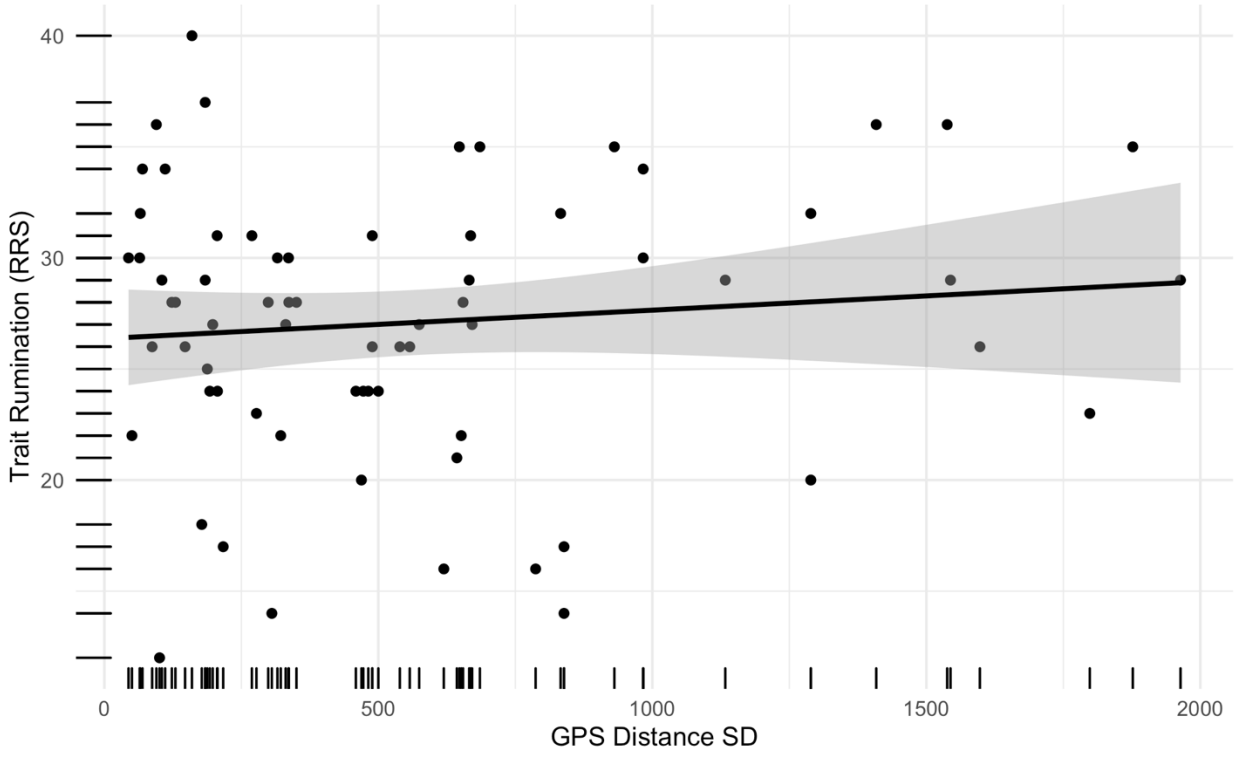


Note. ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale. Band width represents 95% CI for predictions from the linear model.

Trait Rumination. Variation in GPS distance did not predict trait rumination and explained less than one percent of the variance in trait cognitive reappraisal ($_{adj}R^2$ = -.004, F(1, 67) = 0.71, p = .40). The linear regression is displayed in Figure 10.

Figure 10

GPS Distance SD Regressed on Trait Rumination



Note. RRS = Ruminative Responses Scale. Band width represents 95% CI for predictions from the linear model.

Table 7

Results of Trait Emotion Regulation and Variance in GPS Distance Regression Models

Predictor	Model 1: Cognitive Reappraisal			
	b	*SE*	95% CI	*p*
(Intercept)	28.41	1.40	25.95, 30.73	<.0001
Distance SD	-0.0002	0.002	-0.004, 0.002	.89
	Model 2: Expressive Suppression			
(Intercept)	16.01	0.81	14.30, 17.50	<.0001
Distance SD	-0.001	0.001	-0.003, 0.002	.44
	Model 3: Rumination			
(Intercept)	26.36	1.12	24.18, 28.60	<.0001
Distance SD	0.001	0.002	-0.001, 0.004	.40

Unsupervised Learning: Cluster and Classification Analyses

Cluster Analysis

K-means clustering analysis was conducted to examine how self-reported trait cognitive emotion regulation scores grouped together. Scores from the ERQ-R, ERQ-S, RRS, and the DERS were included in the clustering analysis. As *K*-means clustering requires *k* to be specified, the optimal *k* was determined through observing results from the Elbow method, Silhouette method, and the gap statistic (James et al., 2013). Across optimal *k* methods, $k = 2$ was optimal (2 clusters). Scaled mean trait emotion regulation and difficulties in emotion regulation scores are displayed in Table 8. Distributions of each trait emotion regulation measure by cluster are displayed in ridgeline plots (see Figure 11) and layered density plots (see Figure 12). The 2 trait emotion regulation clusters were used as the dependent variable in subsequent *K*-nearest neighbors classification analyses.

Table 8

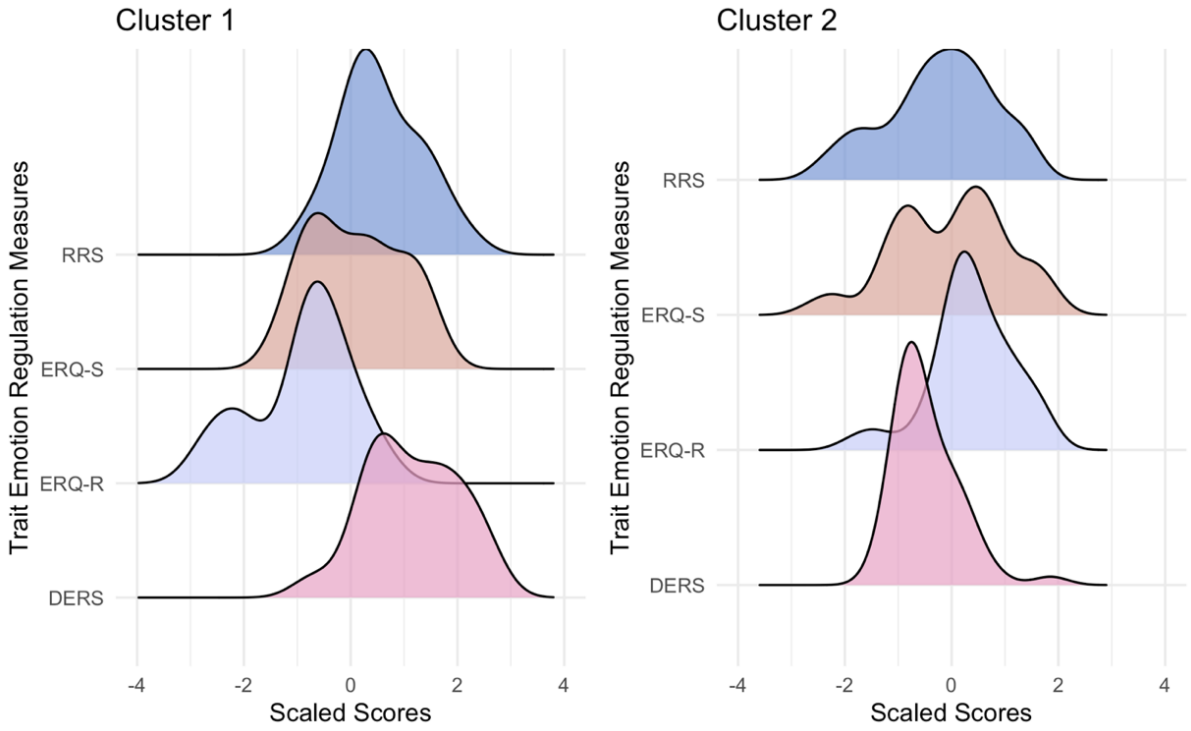
Scaled Mean Trait Emotion Regulation and Difficulties in Emotion Regulation Scores

	Measure			
Cluster	ERQ-R *M*	ERQ-S *M*	RRS *M*	DERS *M*
1	-0.69	0.49	0.05	1.11
2	0.34	-0.24	-0.02	-0.55

Note. ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale, ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale, RRS = Ruminative Responses Scale, DERS = Difficulties in Emotion Regulation Scale.

Figure 11

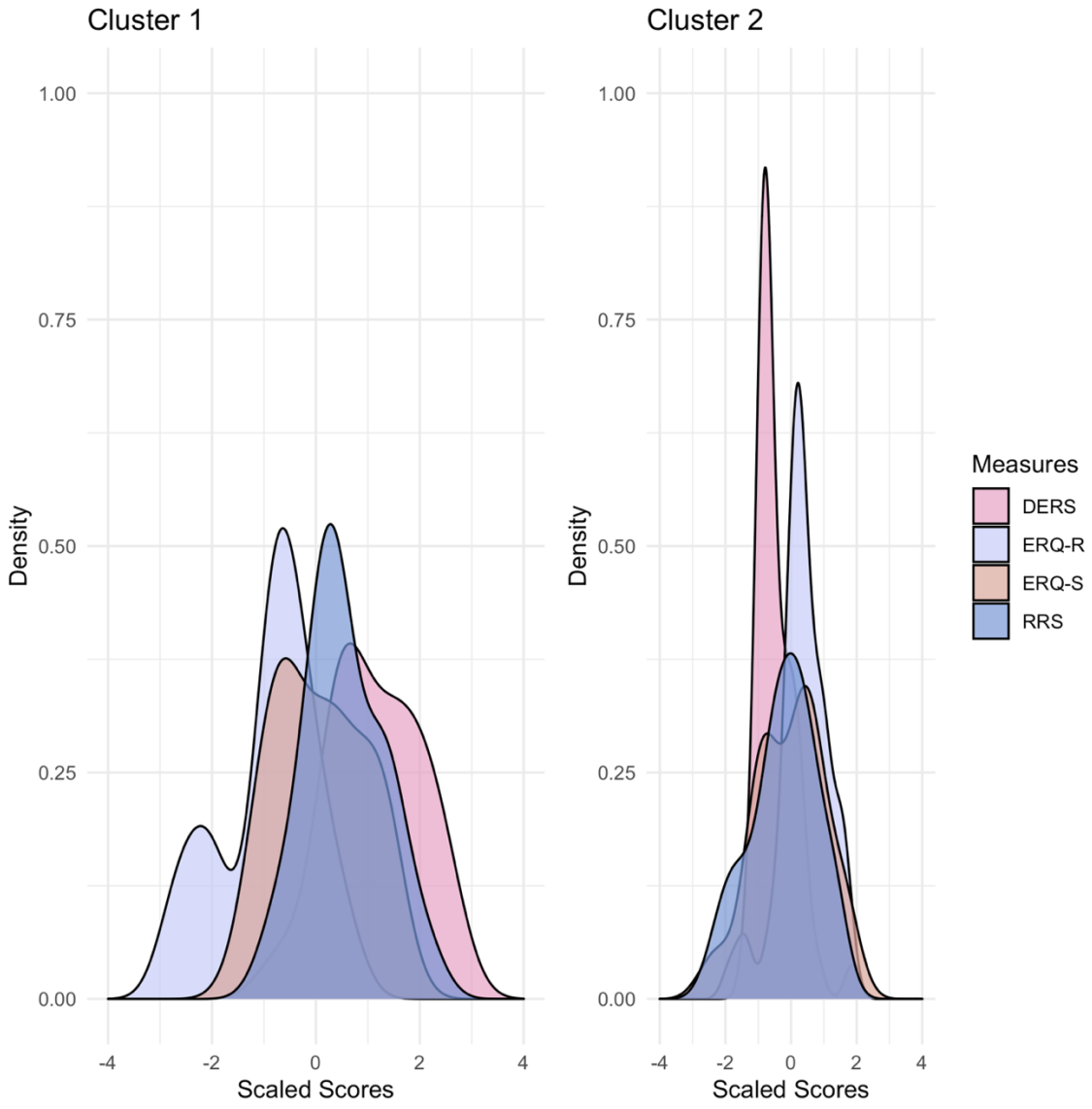
Trait Emotion Regulation Cluster Analysis Results Ridgeline Plots



Note. ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale, ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale, RRS = Ruminative Responses Scale, DERS = Difficulties in Emotion Regulation Scale.

Figure 12

Trait Emotion Regulation Cluster Analysis Results Density Plots



Note. ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale, ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale, RRS = Ruminative Responses Scale, DERS = Difficulties in Emotion Regulation Scale.

k-Nearest Neighbor Classification Analyses

Two k-Nearest Neighbor Classifier models were conducted to examine the extent that digital phenotyping data predicted the previously determined two trait emotion regulation

clusters from the *k*-means cluster analysis. The first model evaluated power state level and time as classifiers, and the second model evaluated GPS distance and time as classifiers. Model performance indices including accuracy, specificity, and sensitivity for both *k*-Nearest Neighbors models are presented in Table 9. Optimal *k*-neighbors were selected for each model based on maximizing specificity and sensitivity. The Matthews correlation coefficient for the power state level and time classification analysis was .82. The Matthews correlation coefficient for the GPS distance and time classification analysis was .96. Confusion matrices showing the number of true-positive and false-positive predictions of each model are presented Table 10 (power state level and time) and Table 11 (GPS distance and time).

Table 9

Results of Trait Emotion Regulation K-Nearest Neighbors Classification Models

Classifiers	*k* Neighbors	Accuracy	Specificity	Sensitivity
Phone State Level and Time	5	.93	.86	.95
GPS Distance and Time	8	.98	.97	.96

Table 10

Power State Level and Time Confusion Matrix

	Predicted		
Actual	Cluster 1	Cluster 2	% Correct
Cluster 1	19653	893	95.65
Cluster 2	997	6171	86.03

Note. Matthews correlation coefficient = .82.

Table 11

GPS Distance and Time Confusion Matrix

	Predicted		
Actual	Cluster 1	Cluster 2	% Correct
Cluster 1	272550	2611	99.01
Cluster 2	2993	79677	96.37

Note. Matthews correlation coefficient = .96.

Hypothesis 2: State Emotion Regulation and Digital Phenotyping

Hypothesis 2 analyses evaluated whether digital phenotyping data predict changes in state negative affect and state emotion regulation strategy implementation over time. For hypothesis 2 analyses, variation in power state level and variation in GPS distance were operationalized as the *SD* of each variable across each observation over the 7-day follow-up period. Variation in state negative affect and variation in spontaneous emotion regulation strategy implementation (SARS cognitive reappraisal and expressive suppression subscales) were also operationalized as *SD* of each respective variable across each observation over the 7-day follow-up period. Hypothesis 2 simple linear regression results with power state level SD as the predictor variable are displayed in Table 12.

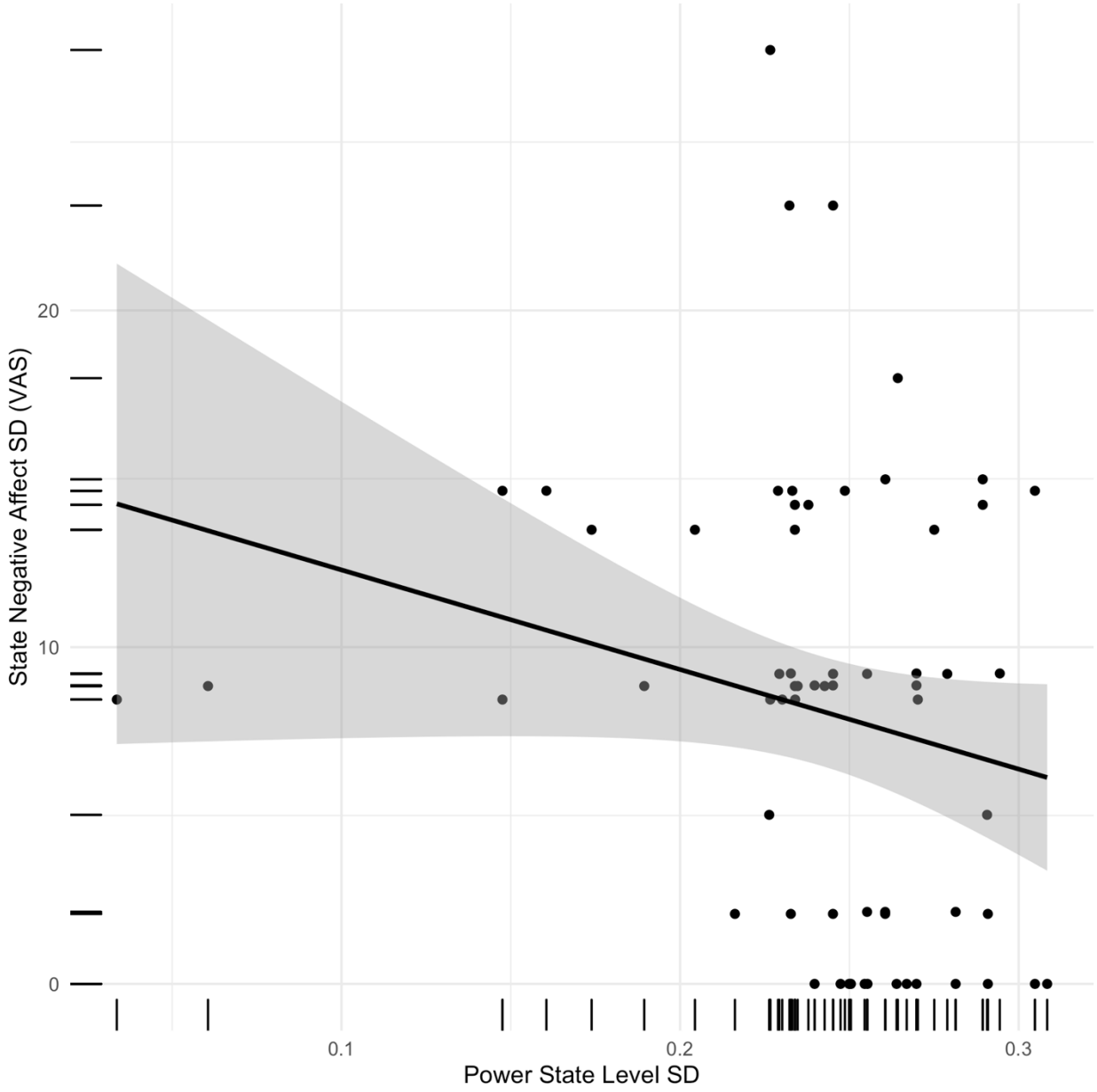
Power State Level Analyses

Variation in State Negative Affect

Variation in power state level marginally predicted variation in negative affect (b = -29.58, $t(67)$ = -1.76, p = .08, 95% CI [-66.47, -6.72]) and explained three percent of the variance in state negative affect over time ($_{adj}R^2$ = .03, $F(1, 67)$ = 3.13, p = .08). The linear regression is displayed in Figure 13.

Figure 13

Power State Level SD Regressed on State Negative Affect SD



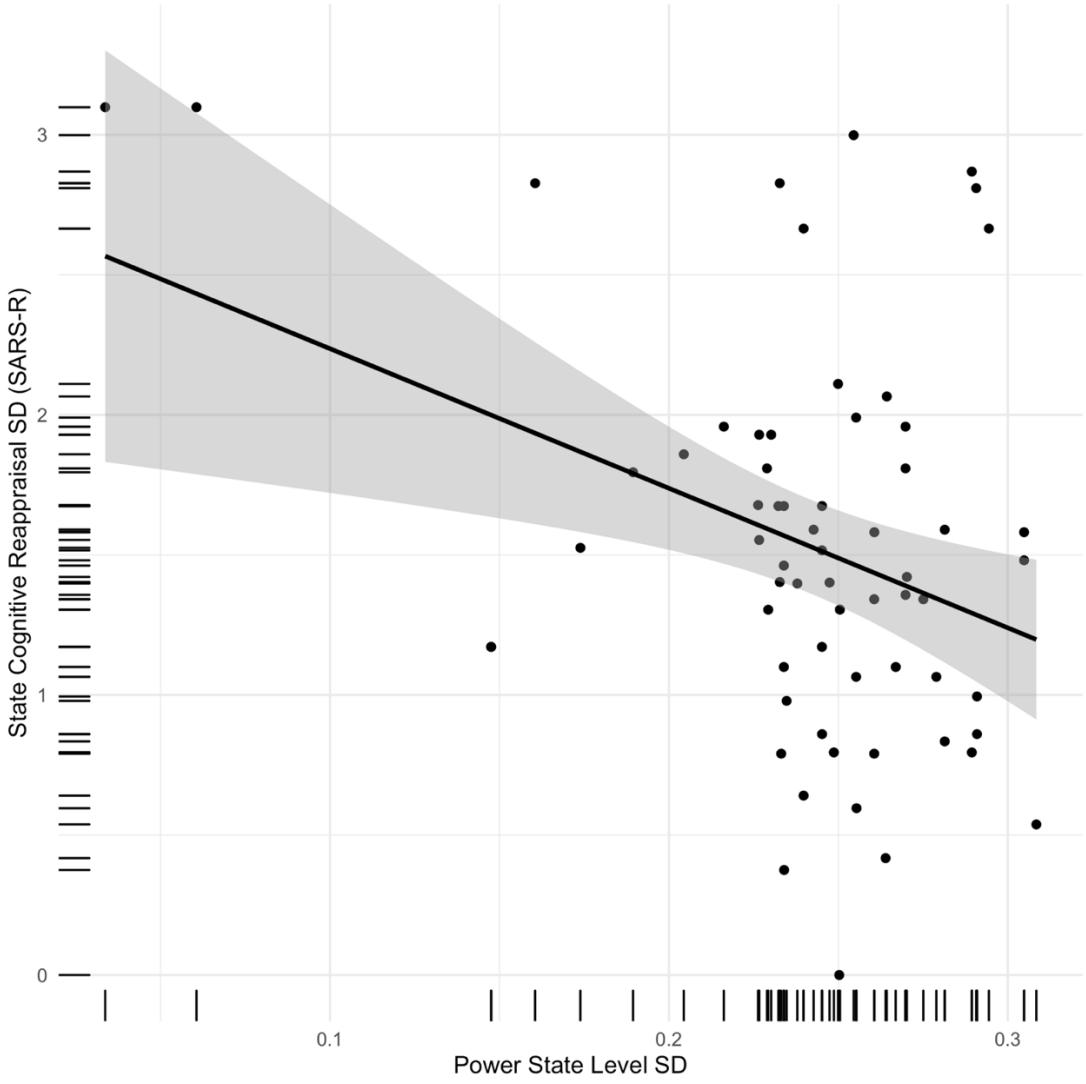
Note. VAS = Visual Analog Scale. Band width represents 95% CI for predictions from the linear model.

State Cognitive Reappraisal

Variation in power state level over time significantly predicted variation in state cognitive reappraisal (b = -4.98, $t(67)$ = -2.89, p = .005, 95% CI [-8.09, -0.21]) and explained eleven percent of the variance in state cognitive reappraisal over time ($_{adj}R^2$ = .11, $F(1, 67)$ = 8.37, p = .005). The linear regression is displayed in Figure 14.

Figure 14

Power State Level SD Regressed on State Cognitive Reappraisal SD



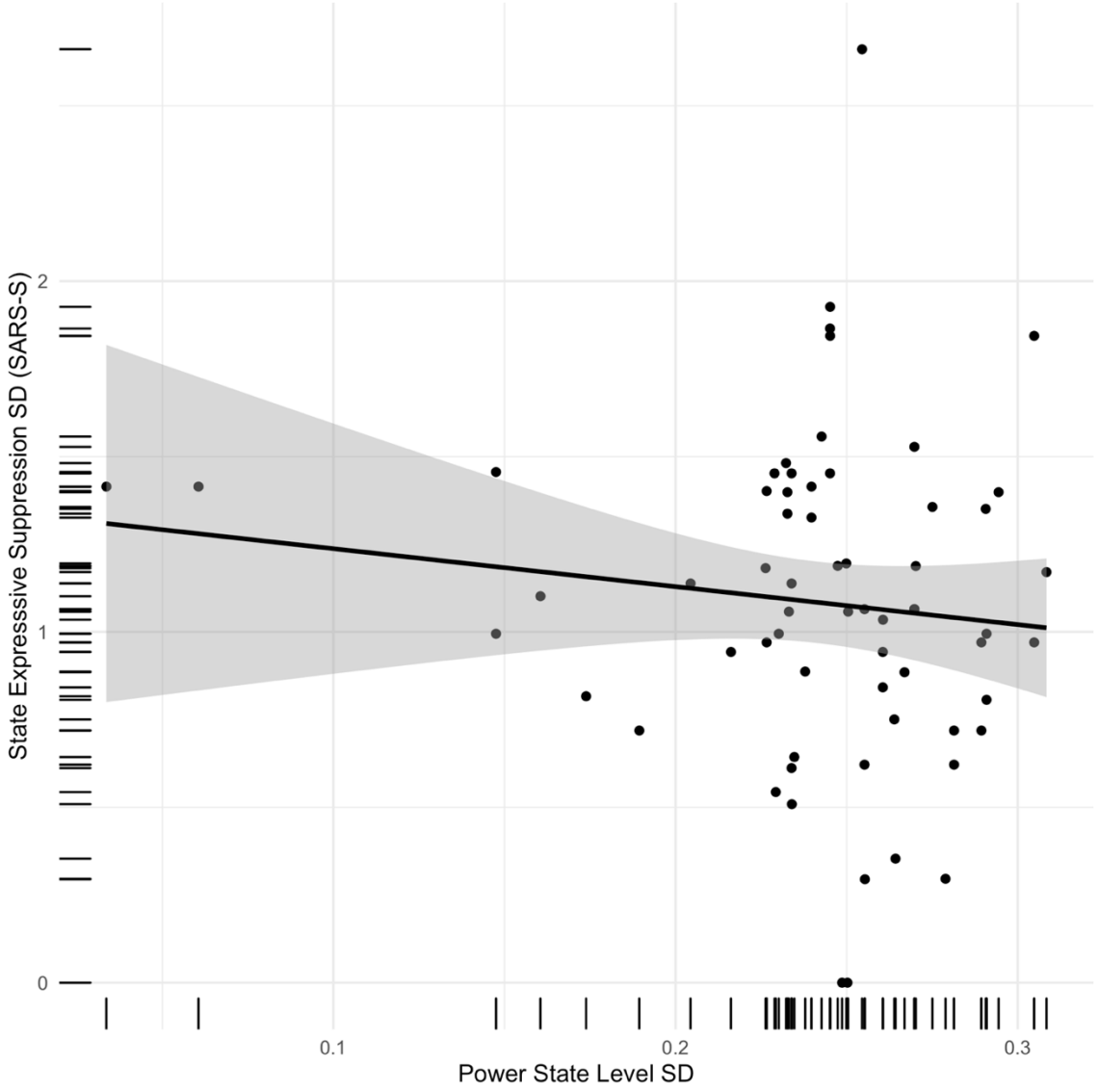
Note. SARS-R = Spontaneous Affect Regulation Scale cognitive reappraisal subscale. Band width represents 95% CI for predictions from the linear model.

State Expressive Suppression

Variation in power state level over time did not predict variation in state expressive suppression and explained less than percent of the variance in state expressive suppression over time ($_{adj}R^2$ = -.003, $F(1, 67) = 0.82$, $p = .37$). The linear regression is displayed in Figure 15.

Figure 15

Power State Level SD Regressed on State Expressive Suppression SD



Note. SARS-S = Spontaneous Affect Regulation Scale expressive suppression subscale. Band width represents 95% CI for predictions from the linear model.

Table 12

Results of Variance in State Emotion Regulation and Variance in Power State Level Regression Models

Predictor	Model 1: State Affect SD			
	b	*SE*	95% CI	*p*
(Intercept)	15.25	4.12	10.20, 24.51	<.0001
Power Level SD	-29.58	16.73	-66.47, -6.72	.08
	Model 2: State Cognitive Reappraisal SD			
(Intercept)	2.73	0.42	1.53, 3.47	<.0001
Power Level SD	-4.98	1.72	-8.09, -0.21	.005
	Model 3: State Expressive Suppression SD			
(Intercept)	1.35	0.29	0.85, 1.62	<.0001
Power Level SD	-1.08	1.19	-2.31, 0.98	.37

GPS Distance Analyses

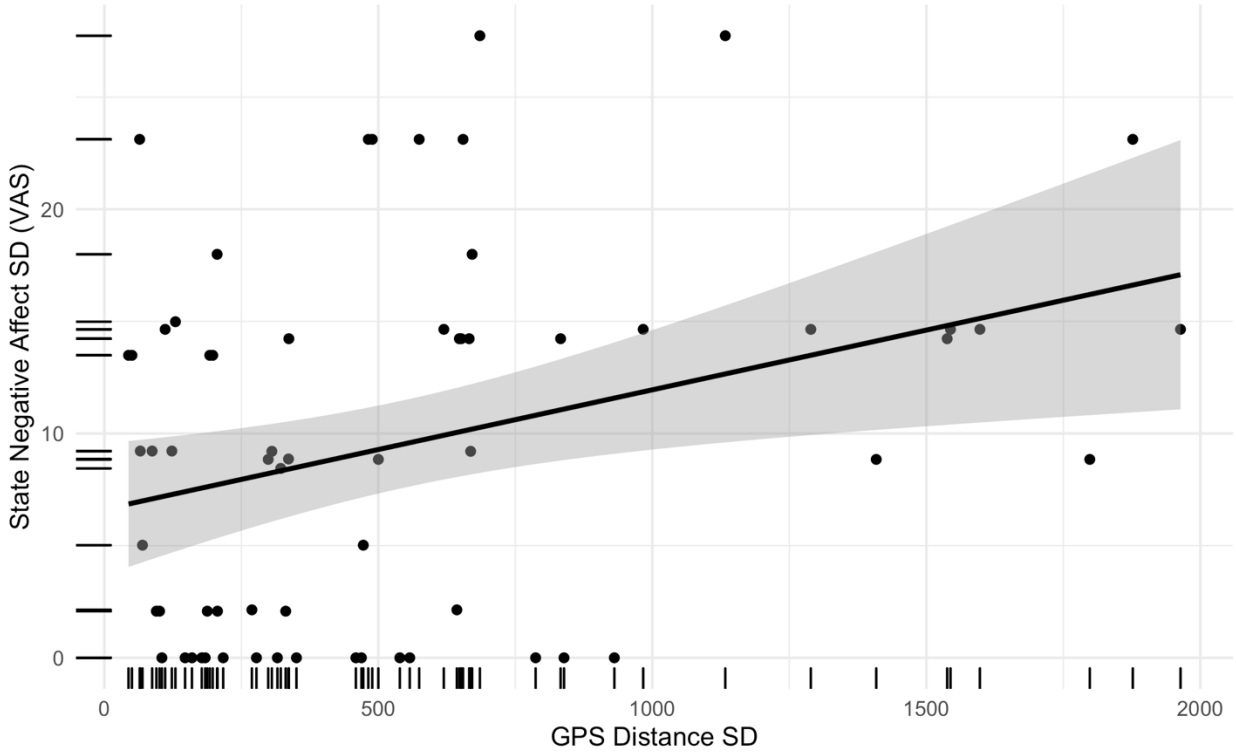
Hypothesis 2 simple linear regression results with GPS distance SD as the predictor variable are displayed in Table 13.

State Negative Affect

Variation in GPS distance over time significantly predicted variation in state negative affect ($b = 0.005$, $t(67) = 2.66$, $p = .01$, 95% CI [0.002, 0.009]) and explained nine percent of the variance in state negative affect ($_{adj}R^2 = .09$, $F(1, 67) = 7.05$, $p = .01$). The linear regression is displayed in Figure 16.

Figure 16

GPS Distance SD Regressed on State Negative Affect SD



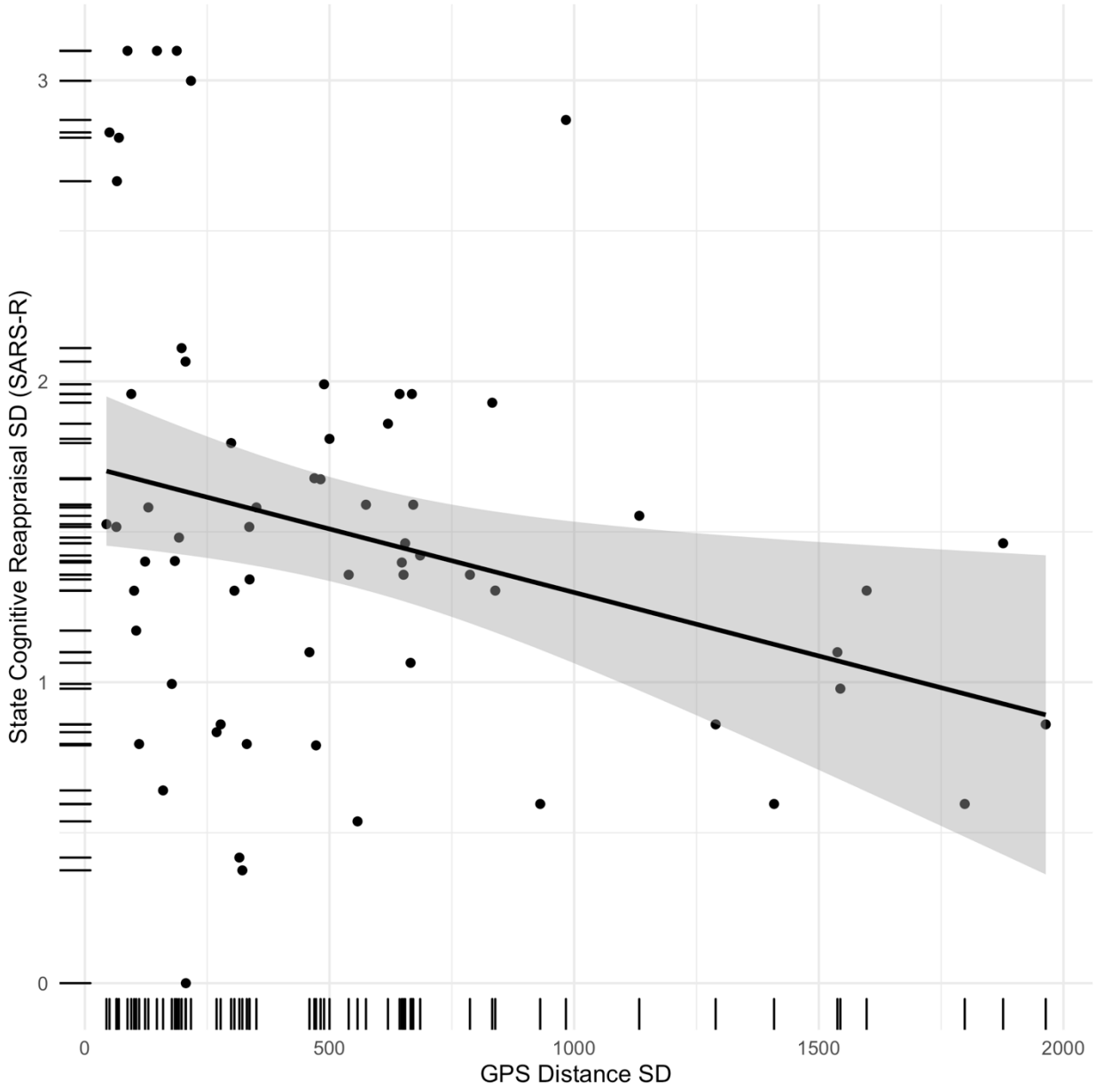
Note. VAS = Visual Analog Scale. Band width represents 95% CI for predictions from the linear model.

State Cognitive Reappraisal

Variation in GPS distance over time significantly predicted variation in state cognitive reappraisal over time (b = 0.0004, $t(67)$ = -2.38, p = .02, 95% CI [-0.0007, -0.0001]) and explained seven percent of the variance in state cognitive reappraisal over time ($_{adj}R^2$ = .07, $F(1, 67)$ = 5.68, p = .02). The linear regression is displayed in Figure 17.

Figure 17

GPS Distance SD Regressed on State Cognitive Reappraisal SD



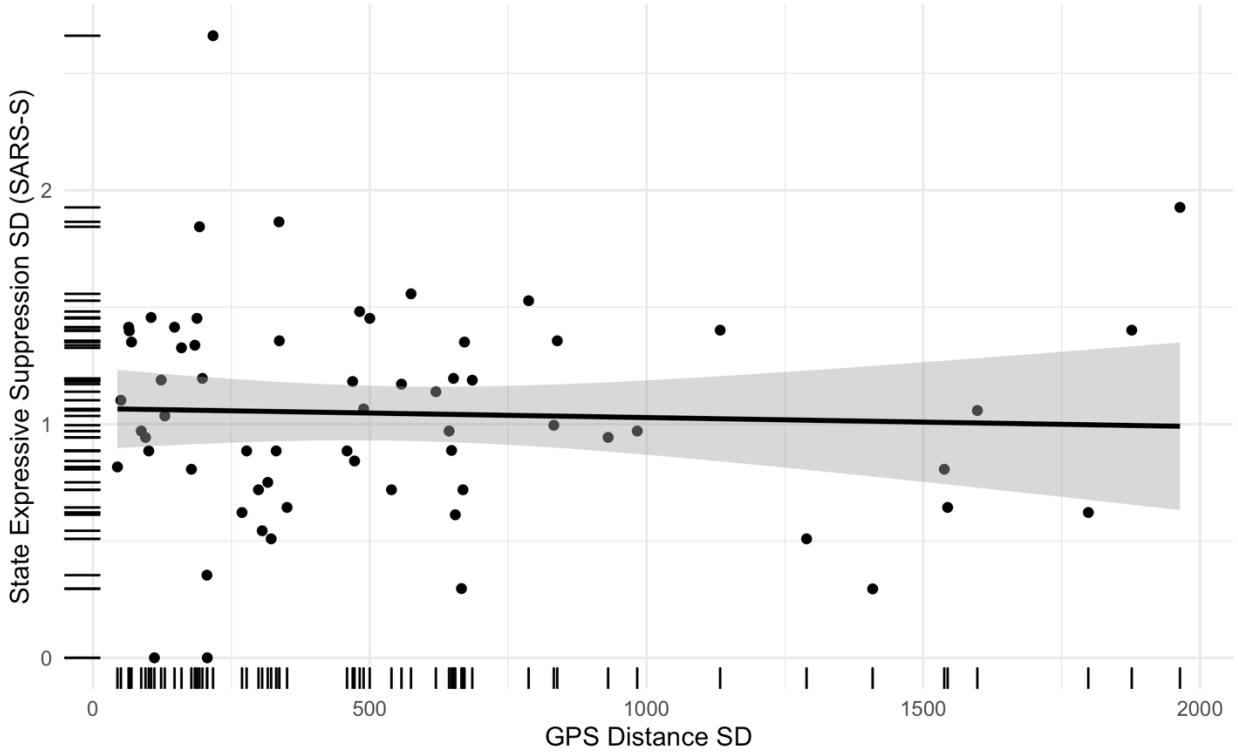
Note. SARS-R = Spontaneous Affect Regulation Scale cognitive reappraisal subscale. Band width represents 95% CI for predictions from the linear model.

State Expressive Suppression

Variation in GPS distance over time did not predict variation in state expressive suppression over time and explained less than one percent of the variance in state expressive suppression over time ($_{adj}R^2$ = -.01, $F(1, 67) = 0.10$, $p = .75$). The linear regression is displayed in Figure 18.

Figure 18

GPS Distance SD Regressed on State Expressive Suppression SD



Note. SARS-S = Spontaneous Affect Regulation Scale expressive suppression subscale. Band width represents 95% CI for predictions from the linear model.

Table 13

Results of Variation in State Emotion Regulation and Variance in GPS Distance Regression Models

Predictor	Model 1: State Affect SD			
	b	*SE*	95% CI	*p*
(Intercept)	6.62	1.47	4.22, 9.53	<.001
GPS Distance SD	0.005	0.002	0.002, 0.009	.01
	Model 2: State Cognitive Reappraisal SD			
(Intercept)	1.72	0.13	1.44, 2.00	<.001
GPS Distance SD	-0.0004	0.0002	-0.0007, -0.0001	.02
	Model 3: State Expressive Suppression SD			
(Intercept)	1.07	0.09	0.89, 1.26	<.0001
GPS Distance SD	0.0000	0.0000	-0.0003, 0.0002	.75

Hypothesis 3: Depressive Symptoms, Trait Emotion Regulation, and Digital Phenotyping

Hypothesis 3 analyses evaluated whether digital phenotyping data and trait emotion regulation together predict general depressive symptoms (i.e., PHQ-9 sum scores) using multiple regressions with an interaction term. Variation in power state level and variation in GPS distance were again operationalized as the *SD* of each variable across each observation over the follow-up period. All predictor variables were mean-centered to improve interpretability. Hypothesis 3 simple multiple regression results with power state level *SD* as one of the predictor variables are displayed in Table 14.

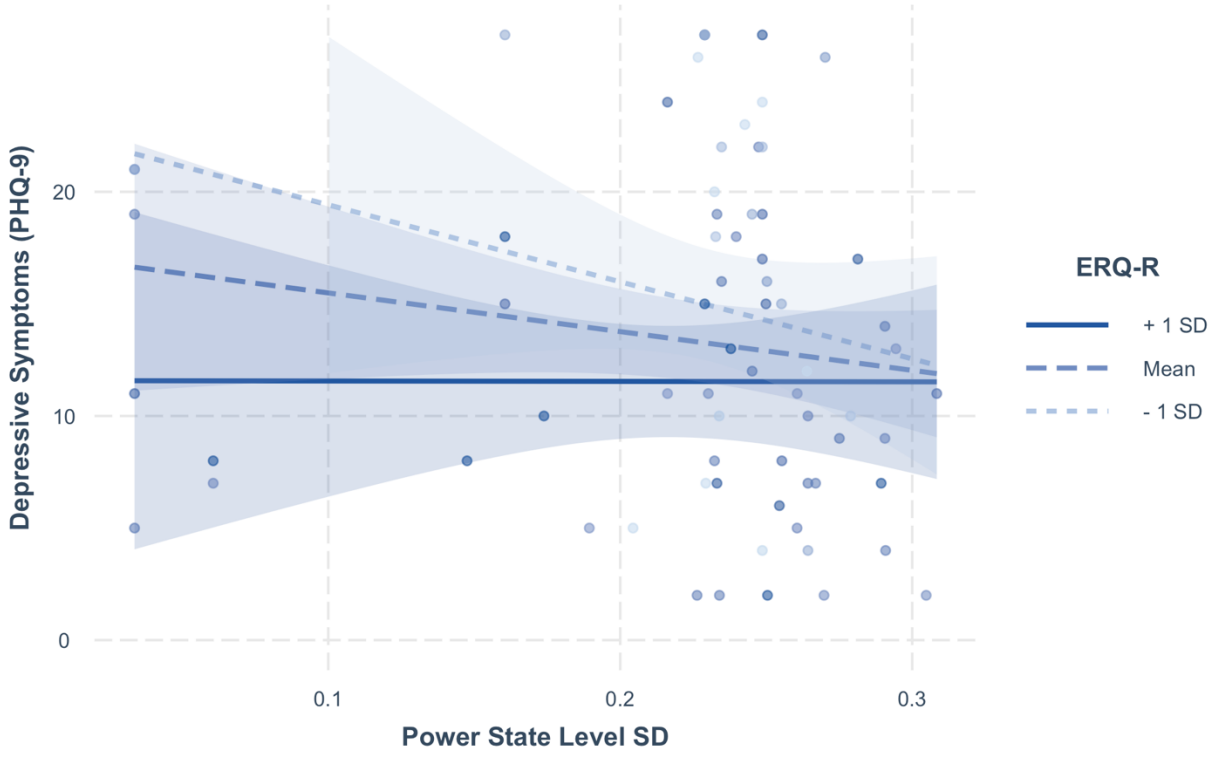
Power State Level Analyses

Trait Cognitive Reappraisal

Higher trait cognitive reappraisal significantly predicted depressive symptoms (b = -0.24, $t(65)$ = -2.06, p = .04, 95% CI [0.02, 0.04]). Variation in power state level over time, nor did the interaction term, predict depressive symptoms ($_{adj}R^2$ = .03, $F(3, 65)$ = 1.83, p = .15). The multiple regression is displayed in Figure 19.

Figure 19

Trait Cognitive Reappraisal and Power Level SD Regressed on PHQ-9



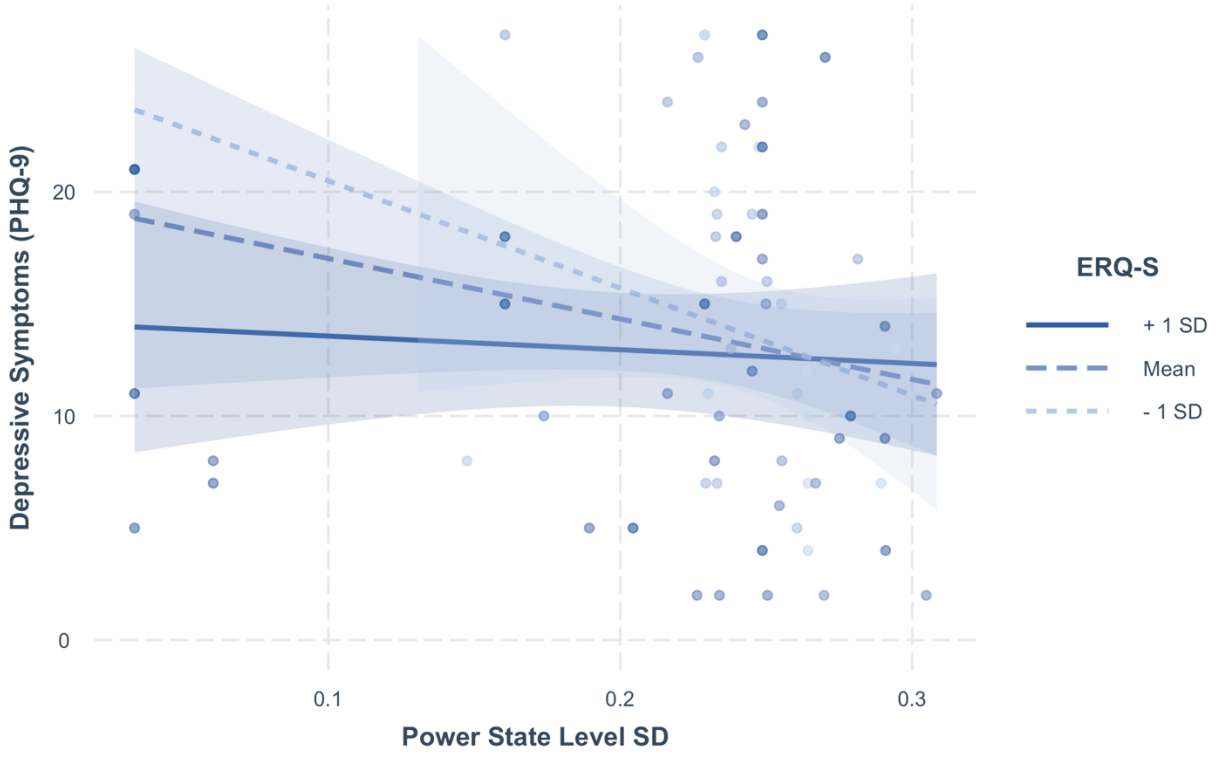
Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale. Band width represents 95% CI for predictions from the multiple regression model.

Trait Expressive Suppression

Variation in power state level over time and trait expressive suppression did not independently, nor did the interaction term, predict depressive symptoms ($_{adj}R^2$ = -.01, $F(3, 65)$ = 0.79, p = .51). The multiple regression is displayed in Figure 20.

Figure 20

Trait Expressive Suppression and Power Level SD Regressed on PHQ-9



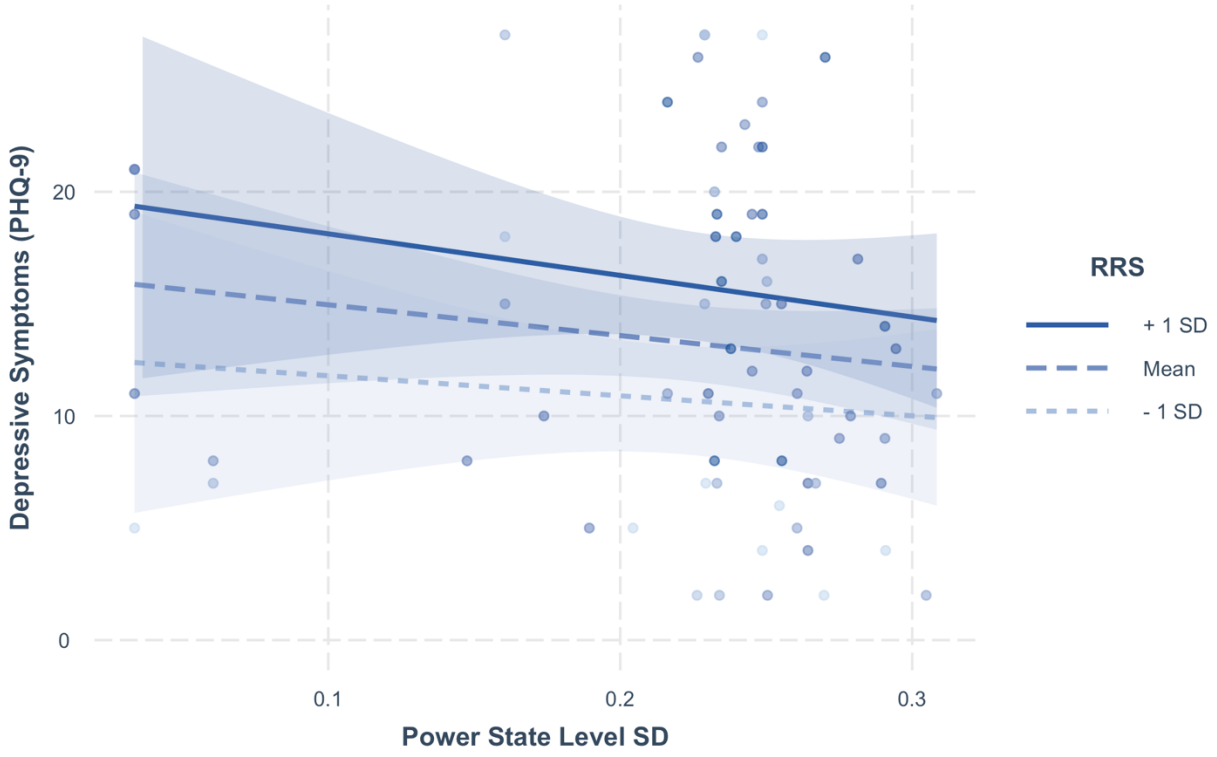
Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale. Band width represents 95% CI for predictions from the multiple regression model.

Trait Rumination

Trait rumination significantly predicted depressive symptoms (b = 0.42, $t(67)$ = 3.00, p = .004, 95% CI [0.06, 0.66]). Variation in power state level over time and the interaction term did not predict depressive symptoms. The full model significantly predicted depressive symptoms, explaining nine percent of the variance in depressive symptoms ($_{adj}R^2$ = .09, $F(3, 65)$ = 3.29, p = .51). The multiple regression is displayed in Figure 21.

Figure 21

Trait Rumination and Power State Level SD Regressed on PHQ-9



Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, RRS = Ruminative Responses Scale. Band width represents 95% CI for predictions from the multiple regression model.

Table 14

Results of Depressive Symptoms, Trait Emotion Regulation, and Variation in Power State Level Multiple Regression Models

Predictor	Model 1: Cognitive Reappraisal			
	b	*SE*	95% CI	*p*
(Intercept)	13.37	0.89	11.65, 15.25	<.0001
ERQ-R	-0.24	0.12	-0.45, 0.02	.04
Power Level SD	-17.27	13.56	-40.61, 16.96	.21
ERQ-R*Power Level SD	2.23	2.51	-3.11, 6.10	.38
	Model 2: Expressive Suppression			
(Intercept)	13.72	0.98	11.75, 15.76	<.0001
ERQ-S	-0.20	0.23	-0.70, 0.27	.38
Power Level SD	-26.97	18.11	-66.63, 6.85	.14
ERQ-S*Power Level SD	4.73	3.97	-2.99, 14.41	.23
	Model 3: Rumination			
(Intercept)	13.27	0.85	11.63, 15.05	<.0001
RRS	0.42	0.14	0.06, 0.66	.004
Power Level SD	-13.74	12.4	-37.61, 9.46	.27
RRS*Power Level SD	-0.79	2.15	-4.41, 6.40	.71

Note. ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale, ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale, RRS = Ruminative Responses Scale.

GPS Distance Analyses

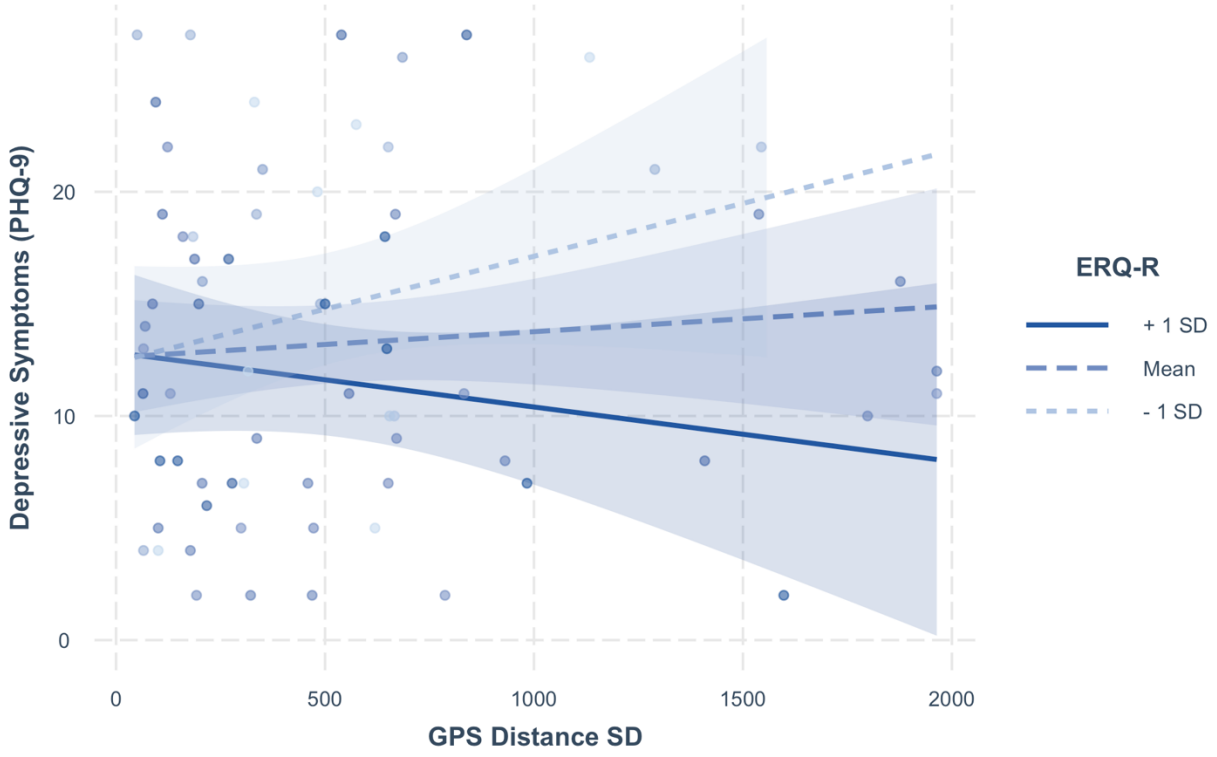
Hypothesis 3 simple multiple regression results with GPS distance SD as one of the predictor variables are displayed in Table 15.

Trait Cognitive Reappraisal

Trait cognitive reappraisal marginally predicted depressive symptoms (b = -0.23, $t(67)$ = -2.00, p = .05, 95% CI [-0.43, 0.009]). Variation in GPS distance over time the interaction term did not predict depressive symptoms ($_{adj}R^2$ = .04, $F(3, 65) = 2.00$, p = .12). The multiple regression is displayed in Figure 22.

Figure 22

Trait Cognitive Reappraisal and GPS Distance SD Regressed on PHQ-9



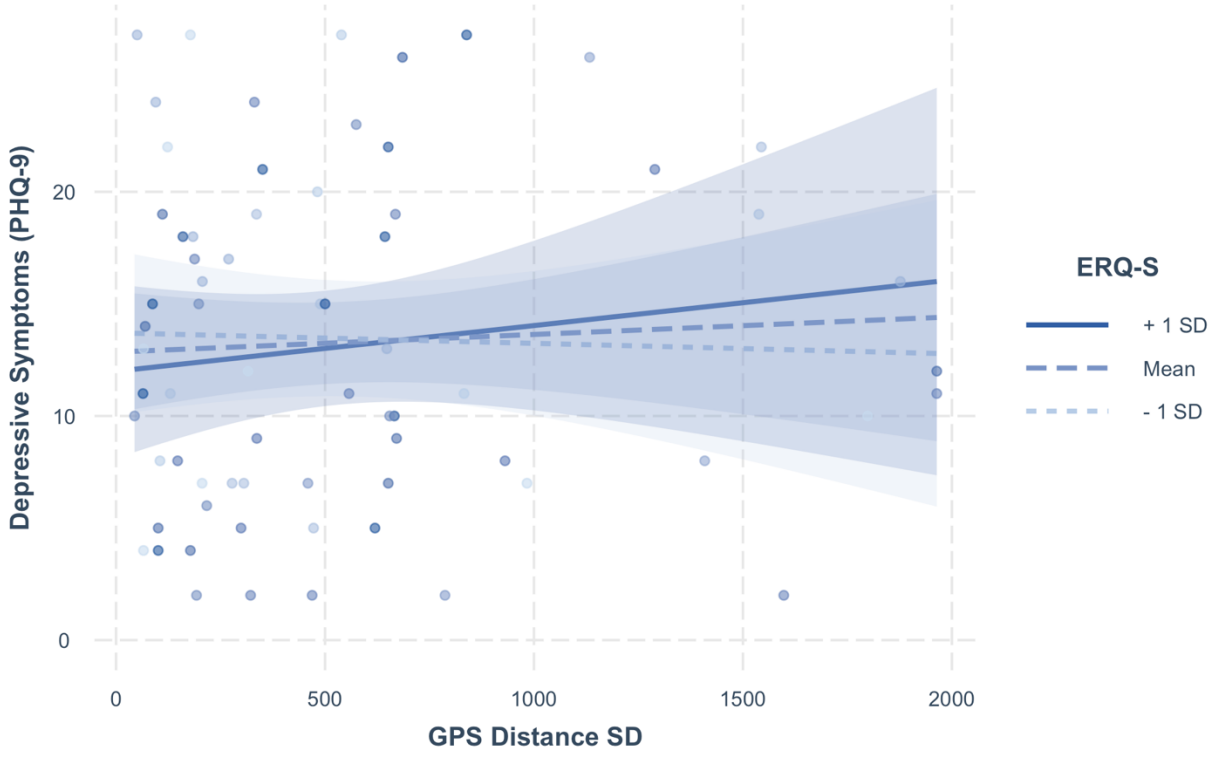
Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale. Band width represents 95% CI for predictions from the multiple regression model.

Trait Expressive Suppression

Variation in GPS distance over time and trait expressive suppression did not independently, nor did the interaction term, predict depressive symptoms ($_{adj}R^2$ = -.04, $F(3, 65)$ = 0.21, p = .89). The multiple regression is displayed in Figure 23.

Figure 23

Trait Expressive Suppression and GPS Distance SD Regressed on PHQ-9



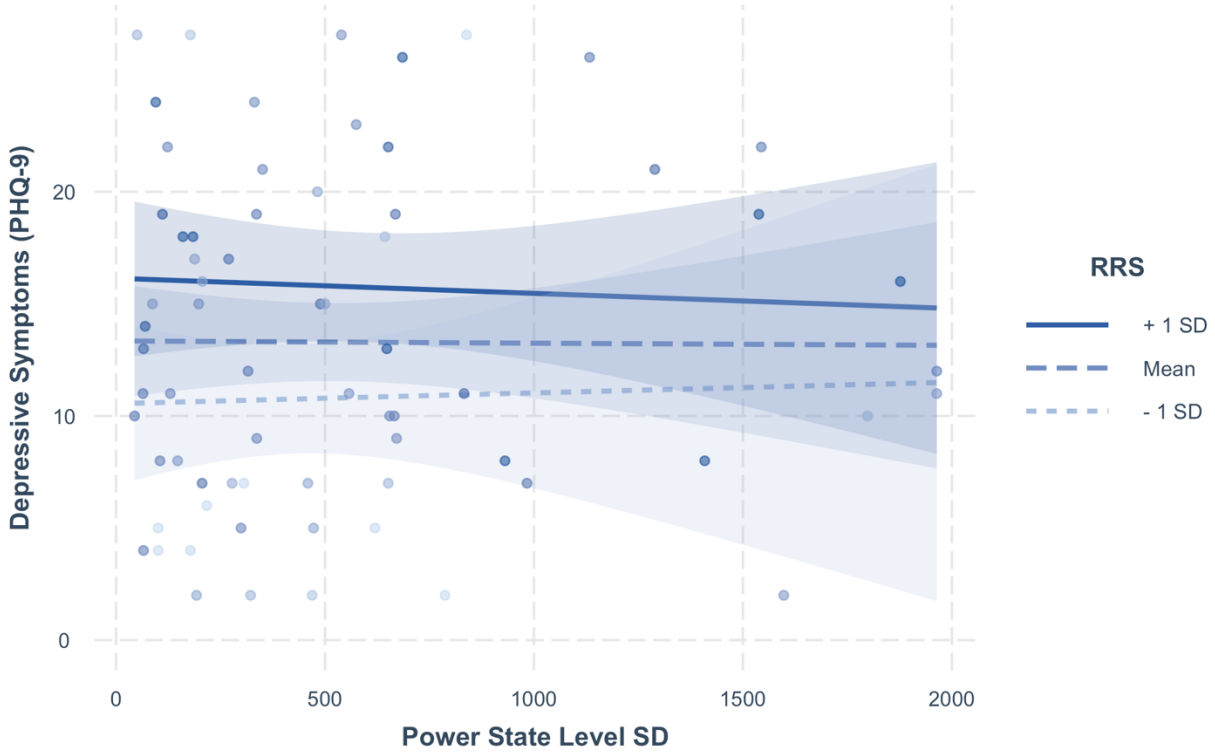
Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale. Band width represents 95% CI for predictions from the multiple regression model.

Trait Rumination

Trait rumination significantly predicted depressive symptoms (b = 0.41, $t(67) = 2.78$, p = .007, 95% CI [0.06, 0.66]). Although the full model was significant ($_{adj}R^2$ = .07, $F(3, 65) = 2.85$, p = .04), variation in power state level over time and the interaction term did not independently predict depressive symptoms. The multiple regression is displayed in Figure 24.

Figure 24

Trait Rumination and GPS Distance SD Regressed on PHQ-9



Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, RRS = Ruminative Responses Scale. Band width represents 95% CI for predictions from the multiple regression model.

Table 15

Results of Depressive Symptoms, Trait Emotion Regulation, and Variation in GPS Distance Multiple Regression Models

Predictor	Model 1: Cognitive Reappraisal			
	b	*SE*	95% CI	*p*
(Intercept)	13.25	0.87	11.61, 15.08	<.0001
ERQ-R	-0.23	0.11	-0.43, 0.009	.05
Distance SD	0.001	0.002	-0.002, 0.004	.52
ERQ-R*Distance SD	-0.0005	0.0003	-0.009, 0.0003	.14
	Model 2: Expressive Suppression			
(Intercept)	13.28	0.91	11.62, 14.93	<.0001
ERQ-S	-0.04	-.21	-0.44, 0.01	.86
Distance SD	0.001	0.002	-0.002, 0.004	0.67
ERQ-S*Distance SD	0.0001	0.0004	-0.0009, 0.0003	0.49
	Model 3: Rumination			
(Intercept)	13.29	0.87	11.77, 15.29	<.0001
RRS	0.41	0.15	0.06, 0.66	.007
Distance SD	0.00	0.002	-0.004, 0.005	.96
RRS*Distance SD	0.00	0.00	-0.0009, 0.0005	.77

Note. ERQ-R = Emotion Regulation Questionnaire cognitive reappraisal subscale, ERQ-S = Emotion Regulation Questionnaire expressive suppression subscale, RRS = Ruminative Responses Scale.

Hypothesis 4: Depressive Symptoms, State Emotion Regulation, and Digital Phenotyping

Hypothesis 4 analyses evaluated whether digital phenotyping data and state emotion regulation together predict general depressive symptoms using multiple regressions with an interaction term. For all hypothesis 4 analyses, variation in power state level and variation in GPS distance were again operationalized as the *SD* of each variable across each observation over the follow-up period. State emotion regulation was operationalized as variation (*SD*) in negative state affect, spontaneous cognitive reappraisal (SARS-R), and spontaneous expressive suppression (SARS-S) across the in-lab neutral mood induction, sad mood induction, and recovery period. All predictor variables tested for hypothesis 4 were mean-centered to improve

interpretability. Hypothesis 4 simple multiple regression results with power state level SD as one of the predictor variables are displayed in Table 16.

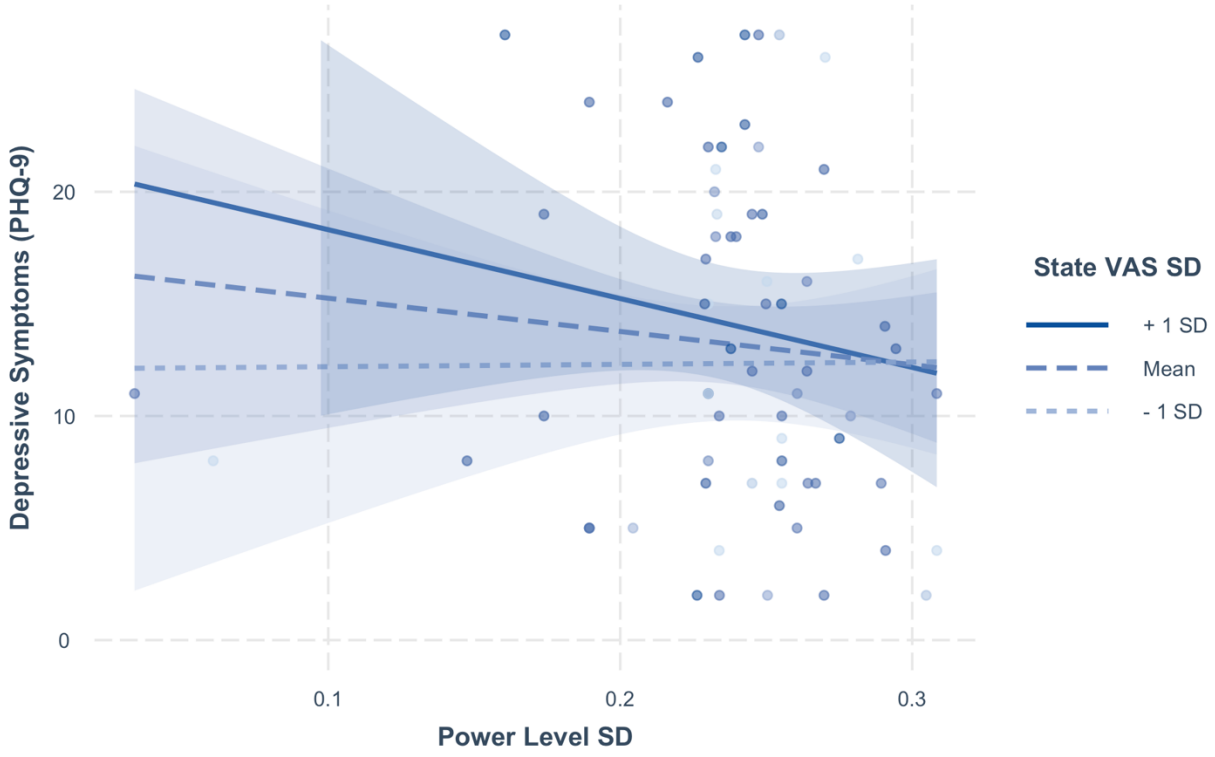
Power State Analyses

Variation in State Negative Affect

Variation in power state level over time and variation in state negative affect did not independently, nor did the interaction term, predict depressive symptoms ($_{adj}R^2$ = -.01, $F(3, 65)$ = 0.77, p = .52). The multiple regression is displayed in Figure 25.

Figure 25

State Negative Affect SD and Power State Level SD Regressed on PHQ-9



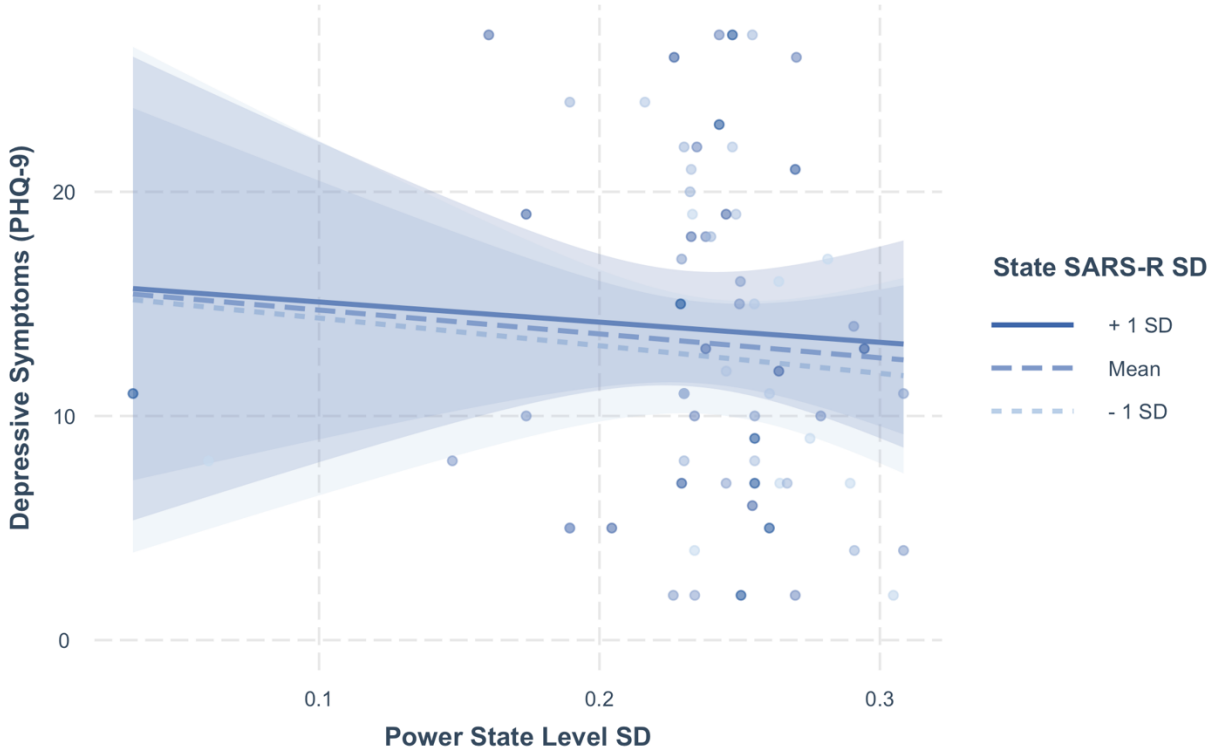
Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, VAS = Visual Analog Scale. Band width represents 95% CI for predictions from the multiple regression model.

State Cognitive Reappraisal

Variation in power state level over time and state cognitive reappraisal did not independently, nor did the interaction term, predict depressive symptoms ($_{adj}R^2$ = -.03, $F(3, 65)$ = 0.26, p = .86). The multiple regression is displayed in Figure 26.

Figure 26

State Cognitive Reappraisal SD and Power State Level SD Regressed on PHQ-9



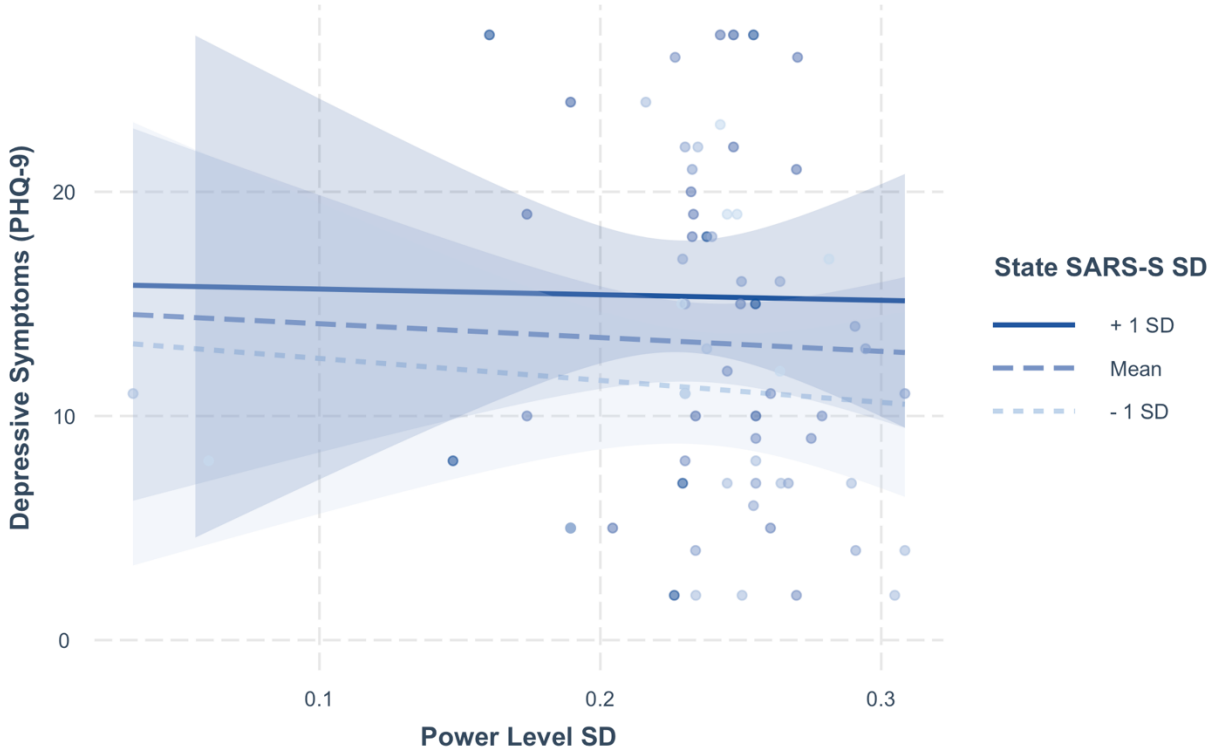
Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, SARS-R = Spontaneous Affect Regulation cognitive reappraisal subscale. Band width represents 95% CI for predictions from the multiple regression model.

State Expressive Suppression

Variation in power state level over time and state expressive suppression did not independently, nor did the interaction term, predict depressive symptoms ($_{adj}R^2$ = .04, $F(3, 65)$ = 1.85, p = .15). The multiple regression is displayed in Figure 27.

Figure 27

State Expressive Suppression SD and Power State Level SD Regressed on PHQ-9



Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, SARS-S = Spontaneous Affect Regulation expressive suppression subscale. Band width represents 95% CI for predictions from the multiple regression model.

Table 16

Results of Depressive Symptoms, State Emotion Regulation, and Variation in Power State Level Multiple Regression Models

Predictor	Model 1: State Negative Affect SD			
	b	*SE*	95% CI	*p*
(Intercept)	16.74	4.84	6.91, 30.57	.001
VAS Negative SD	0.30	0.27	-0.73, 1.32	.27
Power Level SD	-14.85	20.02	-71.00, 24.72	.46
VAS SD*Power Level SD	-1.02	1.12	-5.19, 3.16	.37
	Model 2: State Cognitive Reappraisal SD			
(Intercept)	15.79	4.81	5.59, 29.20	.002
SARS-R SD	0.11	2.36	-8.11, 8.06	.96
Power Level SD	-10.66	19.82	-63.62, 33.68	.59
ERQ-S SD*Power Level SD	0.98	9.75	-33.33, 31.86	.92
	Model 3: State Expressive Suppression SD			
(Intercept)	14.73	4.82	4.59, 27.46	.003
SARS-S SD	0.86	3.26	-9.19, 9.49	.79
Power Level SD	-6.16	20.01	-55.63, 37.00	.76
SARS-S SD*Power Level SD	2.65	14.01	-35.60, 43.77	.85

Note. VAS = Visual Analog Scale, SARS-R = Spontaneous Affect Regulation cognitive reappraisal subscale, SARS-S = Spontaneous Affect Regulation expressive suppression subscale.

GPS Distance Analyses

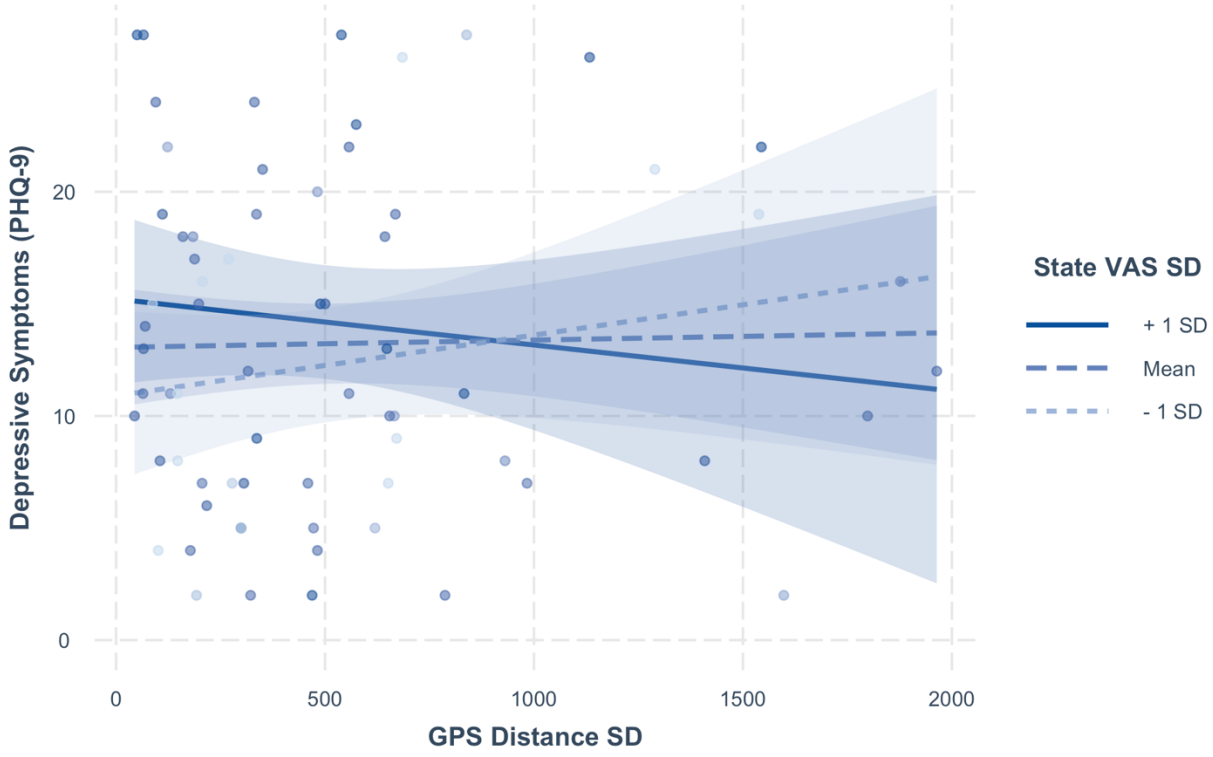
Hypothesis 4 simple multiple regression results with GPS distance SD as one of the predictor variables are displayed in Table 17.

Variation in State Negative Affect

Variation in GPS distance over time and variation in state negative affect over time did not independently, nor did the interaction term, predict depressive symptoms ($_{adj}R^2$ = -.006, $F(3, 65) = 0.86$, $p = .46$). The multiple regression is displayed in Figure 28.

Figure 28

State Negative Affect SD and GPS Distance SD Regressed on PHQ-9



Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, VAS = Visual Analog Scale. Band width represents 95% CI for predictions from the multiple regression model.

State Cognitive Reappraisal

Variation in state cognitive reappraisal marginally predicted depressive symptoms (b = 1.40, $t(65) = 1.68$, $p = .09$, 95% CI -0.27, 3.04]). Variation in GPS distance over time and the interaction term did not predict depressive symptoms ($_{adj}R^2 = -.001$, $F(3, 65) = 0.98$, $p = .41$). The multiple regression is displayed in Figure 29.

Figure 29

State Cognitive Reappraisal SD and GPS Distance SD Regressed on PHQ-9

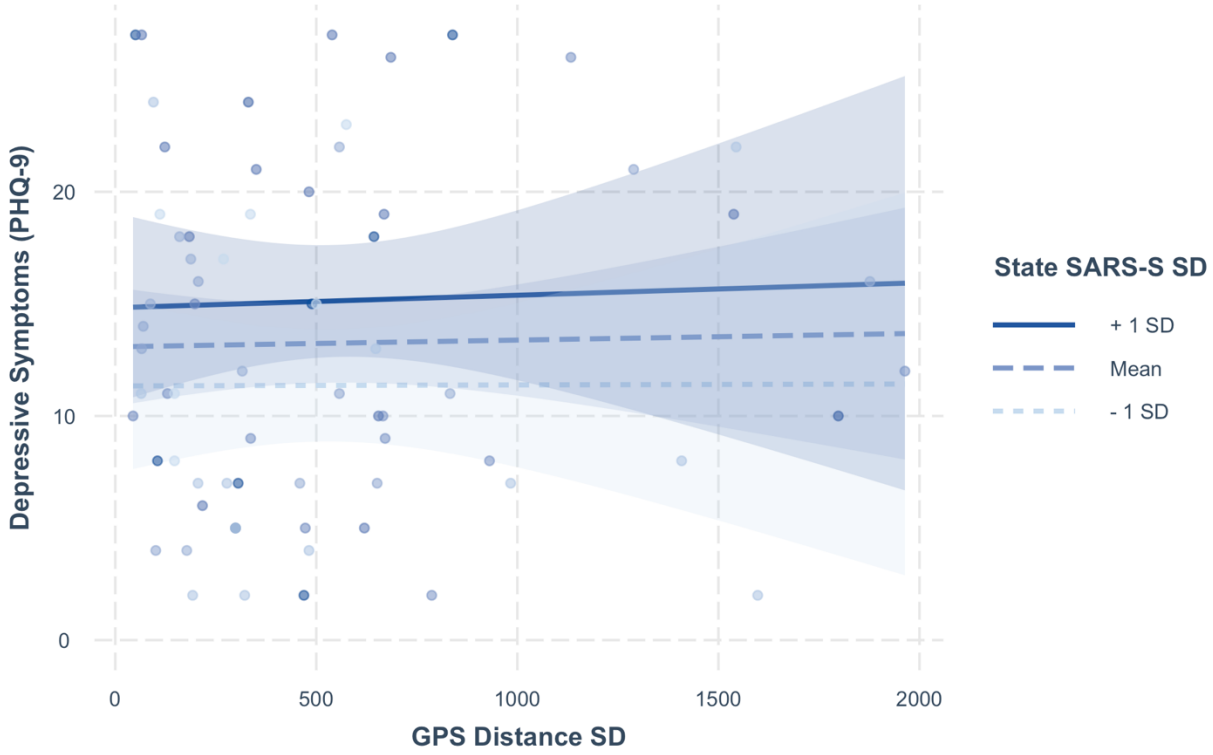
Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, SARS-R = Spontaneous Affect Regulation cognitive reappraisal subscale. Band width represents 95% CI for predictions from the multiple regression model.

State Expressive Suppression

Variation in GPS distance over time and variation in state expressive suppression over time did not independently, nor did the interaction term, predict depressive symptoms ($_{adj}R^2$ = .02, $F(3, 65) = 1.52$, $p = .22$). The multiple regression is displayed in Figure 30.

Figure 30

State Expressive Suppression SD and GPS Distance SD Regressed on PHQ-9



Note. PHQ-9 = Patient Health Questionnaire depressive symptoms items, SARS-S = Spontaneous Affect Regulation expressive suppression subscale. Band width represents 95% CI for predictions from the multiple regression model.

Table 17

Results of Depressive Symptoms, State Emotion Regulation, and Variation in GPS Distance Multiple Regression Models

Predictor	Model 1: State Negative Affect SD			
	b	*SE*	95% CI	*p*
(Intercept)	13.06	1.34	10.54, 15.49	<.0001
VAS Negative SD	0.14	0.09	-0.02, 0.31	.11
Distance SD	0.0003	0.002	-0.003, 0.004	.86
VAS SD*Distance SD	0.0002	0.0001	-0.0004, 0.0002	.25
	Model 2: State Cognitive Reappraisal SD			
(Intercept)	13.57	1.38	11.10, 16.28	<.0001
SARS-R SD	1.40	0.88	-0.27, 3.04	.09
Distance SD	-0.001	0.002	-0.004, 0.004	.76
ERQ-S SD*Distance SD	-0.002	0.001	-0.004, 0.001	.14
	Model 3: State Expressive Suppression SD			
(Intercept)	13.09	1.33	10.61, 15.83	<.0001
SARS-S SD	1.28	1.14	-1.82, 3.50	.26
Distance SD	0.00	0.002	-0.004, 0.004	.87
SARS-S SD*Distance SD	0.00	0.002	-0.005, 0.005	.91

Note. VAS = Visual Analog Scale, SARS-R = Spontaneous Affect Regulation cognitive reappraisal subscale, SARS-S = Spontaneous Affect Regulation expressive suppression subscale.

CHAPTER 4

DISCUSSION

The central aim of this study was to evaluate smartphone-based digital phenotyping data to generate new knowledge of the nomological network of emotion regulation. As research in this area has conventionally focused on the behavioral, cognitive, and biological underpinnings of emotion regulation (Gross, 2015a; Mendes, 2014), digital phenotyping data provide a potential new index for characterizing individual differences in emotion regulation processes. Improving our ability to accurately predict emotion regulation processes is essential for ultimately providing personalized treatment for mental health problems. The present study set out to expand the nomological network of emotion regulation through foundational evaluations of the associations between digital phenotyping data and emotion regulation, guided by two principle aims. The first was to examine the digital behavior correlates of self-report emotion regulation (state and trait). The second aim was to evaluate whether self-reported emotion regulation (state and trait) interacts with digital phenotypes to predict emotional well-being.

Results showed that variation in mobile power state level and GPS distance were associated with variation in negative state affect and state cognitive reappraisal over time, with greater variation in these digital behaviors possibly reflecting less successful down regulation of negative emotions. Power state level and GPS distance across time accurately classified two trait emotion regulation clusters. Variation in mobile phone power level and GPS distance over time together with state and trait emotion regulation did not predict current depressive symptoms. To date, the modeling approaches and operationalizations of digital phenotyping data have resulted in mixed findings in terms of predicting psychopathology. The present study demonstrates that digital phenotyping is both a promising approach to assessing emotion regulation in naturalistic

settings and that future research can build on how to best apply digital phenotyping. Overall, the findings from this study provide initial data on the use of digital phenotyping methodology in predicting individual differences in emotion regulation, contributing to our understanding of normative ranges of markers of emotion regulation processes.

Digital phenotyping is a novel method for assessing passive digital behaviors in naturalistic settings (Insel, 2017; Onnela & Rauch, 2016). Thus, there are few studies that have implemented digital phenotyping to examine psychopathology in relation to naturalistic behavioral patterns. None to date have explicitly investigated the relationship between smartphone-based digital phenotyping data and emotion regulation. A recent pilot project examined digital phenotyping data quality and psychopathology symptoms in a sample of 16 outpatients diagnosed with Schizophrenia Spectrum Disorder (Barnett et al., 2018; Torous et al., 2018). Similar to the present project, the authors used the Beiwe Research Platform to examine accelerometer, GPS, and survey timing data collected over a 90-day period. All indices were operationalized as frequency of unique daily measurements. Lower frequency of accelerometer and GPS data was weakly associated with higher (worse) scores on psychopathology outcomes and slower survey completion rates was associated with worse psychopathology symptom outcomes. Compared to the present study, the operationalizations of digital phenotypes used by the authors may have been more reflective of amount of on-person phone use (i.e., accelerometer, or device movement) or general study adherence, as they used frequency of data point acquisition.

In line with the present study, Saeb et al. (2015) used GPS data operationalized as favorite locations and location variance to accurately classify individuals with significant depressive symptoms from those without. Digital phenotyping data has been shown to predict

differences in reported positive and negative affect, anxiety, and energy over time between individuals with Bipolar Disorder and non-psychiatric controls (Ortiz et al., 2017). Although the short psychiatric report did not specify which digital phenotype indices were used, the authors noted the relationship between digital phenotyping data and psychological variables were not linear, which is consistent with the classification analysis results of the present study and number of non-significant linear evaluations. Previous research using smartphones has found 5 distinct classifications of suicidal thinking patterns across both psychiatric inpatients with a history of suicide attempts and a non-psychiatric sample (Kleiman et al., 2018). It is notable, however, that the design of the study uses the term "digital phenotype" while the design of the study used EMA methodology, solely using self-report data pushed to smartphones.

Although previous research using digital phenotyping data has not explicitly examined emotion regulation, the present study aligns with previous work by demonstrating that digital phenotyping is associated with clinical psychology phenomena. Given the data driven nature of digital phenotyping, the present study builds on previous research by contributing to our understanding of implementing digital phenotyping as an assessment tool and in the emotion regulation domain.

Trait Emotion Regulation and Digital Phenotyping

Variation in mobile power state level over time nor variation in GPS distance over time predicted trait cognitive reappraisal, expressive suppression, or rumination. *K*-means clustering analyses identified two clusters consisting of trait cognitive reappraisal, expressive suppression, rumination, and overall difficulties in emotion regulation. *K*-nearest neighbor classification results showed mobile power state level over time to have high accuracy (93%), specificity (86%), and sensitivity (95%) with $k = 5$ neighbors. Similarly, *k*-nearest neighbor classifications

showed GPS distance and time to have high accuracy (98%), specificity (97%), and sensitivity (97%) with $k = 8$ neighbors. Juxtaposing the linear association analysis results and the clustering/classification results, it appears that power state level and GPS distance do not accurately predict individual differences in trait emotion regulation when operationalized as variation over time (i.e., *SD*) and that a more flexible, non-linear, approach allowed for considerably more accurate predictions. The *k*-means cluster analysis showed individuals with less difficulties in emotion regulation on average were more likely to implement more cognitive reappraisal and less expressive suppression, with the opposite pattern for those with greater difficulties with emotion regulation implementation. Additionally, individuals belonging to both groups used rumination to a similar degree. The classification findings are in line with foundational research indicating that individuals with higher trait cognitive reappraisal experience greater positive emotion, less negative emotion, better interpersonal functioning, and greater well-being, whereas individuals with higher trait expressive suppression experience less positive emotion, greater negative emotion, worse interpersonal functioning, and worse well-being (Aldao, 2014; Aldao et al., 2010; Gross & John, 2003). As previously discussed, the field of emotion regulation has evolved to conceptualize adaptive emotion regulation as the ability to flexibly implement different strategies (Aldao et al., 2015b; Bonanno & Burton, 2013; Sheppes et al., 2011) in response to context (Aldao, 2013; Aldao & Nolen-Hoeksema, 2013). Therefore, future research can further examine the role of context in the relationship between emotion regulation and digital phenotypes, such as investigating psychophysiological variables, clinical populations, or specific environmental contexts.

Using a cluster/classification analysis approach introduces bias, as this approach ignores the nuance of a percentage of the data that is incorrectly classified (James et al., 2013). The two

clusters were relatively easy to interpret as the individuals in one group had high difficulties in emotion regulation and the other low difficulties on average. The incorrectly classified data points (i.e., false positives/negatives), however, may not closely resemble the patterns of trait emotion regulation scores associated with the two clusters. For example, the *k*-means clustering optimal *k* indices (i.e., Elbow method, Silhouette method, and the gap statistic) showed $k = 3$ as a potentially optimal clustering value. Although increasing *k* introduces greater variance in possible classifications, and can thus reduce bias in the model, increasing *k* clusters makes the results of the classification models more challenging to interpret (James et al., 2013). Since it appears that digital phenotyping data may not always have a linear relationship with psychological data, future research using non-linear modeling will benefit from carefully considering the bias/variance trade-off.

State Emotion Regulation and Digital Phenotyping

Results of associations between state emotion regulation and digital phenotyping were mixed. Variation in mobile phone power state level over time significantly predicted variation in state negative affect over time as well as variation in state cognitive reappraisal over time. Greater variation in mobile phone power state level over time was significantly associated with less variation in state negative affect over time, as well as variation in state cognitive reappraisal over time. Greater variation in mobile phone power state level may be indicative of behaviors such as charging one's phone at regular intervals, whereas less variation in power state level over time may be reflective of intermittent, frequently not charging, or forgetting to charge one's phone. Greater variation in negative affect may reflect greater emotional reactivity and less, or unsuccessful, implementation of emotion regulation strategies (Kuppens & Verduyn, 2017; Rottenberg & Hindash, 2015). How an individual interacts with their phone in terms of charging

and battery use may reflect changes in behaviors related to mood. For example, if an individual becomes more depressed and emotionally reactive, they may disengage from habitual behaviors that help to maintain and regulate mood (Dimidjian et al., 2011). This change in behaviors in response to dysregulated mood could manifest in changes in phone power level such as charging one's phone on an as-needed basis compared to routinely charging one's phone every night.

Greater variation in GPS distance significantly predicted greater variation in state negative affect over time and less variation in state cognitive reappraisal over time. More variation in distance can be reflective of numerous behavioral patterns. For example, regularly commuting from home to work or school from a neighboring city could indicate similar variation as an individual who lives closer to their place of work or school and is frequently mobile in a smaller geographic area. Another example would be an individual who is relatively less mobile during the work week and typically takes a relatively long trip during the weekend to a different geographical area. The range in variability in the present study, however, demonstrates that operationalizing GPS data as variation in distance over time did capture individual differences in this particular digital phenotype. Although the GPS distance data could not capture granular enough data to assess movement within relatively small area (e.g., within one's living space), the frequency of GPS data was approximately every 1-10 minutes. Future research using mobile phone GPS data can develop research questions based on these GPS data sampling limitations. For example, at this level of GPS data granularity, research can be conducted on the speed of movement between geographic locations (i.e., individual differences in acceleration), or time spent at different geographical locations, potentially identifying individual differences time spent in "favorite" locations. Additionally, specifying research questions based on the granularity of the digital phenotyping data will help identify other behaviors that covary with digital behaviors.

Depressive Symptoms, Emotion Regulation, and Digital Phenotyping

Examinations of the interactions between both state and trait emotion regulation and digital phenotyping indices did not predict current depressive symptoms. Consistent with previous research, lower trait cognitive reappraisal (Joormann & Siemer, 2014) and higher trait rumination (Nolen-Hoeksema et al., 2008) independently predicted current depressive symptoms. Further, variation in mobile phone power state level over time and variation in GPS distance over time did not independently predict current depressive symptoms. As trait emotion regulation was not associated with digital phenotypes, and the strength of the significant associations between state emotion regulation and digital phenotypes were relatively small (b = -.003 to .11), it is unsurprising that there were no interaction effects for emotion regulation and digital phenotype on current depressive symptoms. These findings provide clarification that operationalizing mobile phone power state level and GPS distance as variation over time may not adequately capture how these indices relate to emotion regulation and symptoms of psychopathology.

Strengths

The present study has several strengths that meaningfully contribute to previous findings as well as methodology. The current study addressed methodological issues present in previous research. Although prior research has employed self-report, behavioral, neurological, genetic, and physiological assessments of emotion regulation, the majority of research on emotion regulation has been circumscribed to controlled laboratory settings that use experimental paradigms to investigate short-term outcomes, and EMA studies largely rely on self-report of emotional experiences (Berking & Wupperman, 2012). To date, the present study is the first to apply digital phenotyping methodology to the investigation of emotion regulation phenomena.

Using a digital phenotyping approach, the current study concurrently collected passive behavioral data and subjective affective experiences in naturalistic settings. One strength of this approach is that it is consistent with the RDoC framework for capturing individual differences in psychological phenomena (Cuthbert, 2014; Torous, Onnela, et al., 2017). Furthermore, the high sampling rate of digital phenotyping data allowed for moment-by-moment quantification of digital behavior and higher fidelity of changes in behavioral patterns (Insel, 2017). Since digital phenotyping acquisition is passive, it addressed potential participant burden from too frequently responding to self-report inquiries.

Another strength of the current study was the incorporation of measuring spontaneous cognitive emotion regulation strategies. The majority of prior research conventionally operationalizes spontaneous emotion as change in state affect or by instructing participants to engage in a particular strategy following exposure to an emotion-eliciting stimuli (Dixon-Gordon et al., 2015). Spontaneous emotion regulation was measured using both change in affect and spontaneous cognitive emotion regulation strategy implementation (i.e., cognitive reappraisal and expressive suppression) in response to a validated negative mood induction as well as sampled in naturalistic settings using EMA methodology. Building on recent research on spontaneous emotion regulation (e.g., Gruber et al., 2012; Stange et al., 2017), this is the first study to incorporate spontaneous emotion regulation strategy implementation using EMA.

An additional strength of the current study is that it was conducted following open-science practices. The project was pre-registered on the Open Science Framework (registration URL: https://osf.io/zth8d). The open-access version of the Beiwe Research Platform was used for collecting digital phenotyping data. In addition, the code for processing data collected using the Beiwe Research Platform is hosted on a public repository with supporting documentation

(GitHub URL: https://github.com/cmbosma/beiwe-scripts). Implementing digital phenotyping methodology requires a number of computer science components. For example, the open-access, single-deployment version of the Beiwe Research Platform requires knowledge of command line/prompt languages, using virtual machines for processing and storage, and website security. Given the challenges with implementing digital phenotyping methodology and that digital phenotyping is in early stages of investigation, open-science practices enable researchers to more easily conduct future research using digital phenotyping methods, as they are freely accessible.

Limitations and Future Directions

Despite the noted strengths, the present study had limitations that can be addressed in future research. Participants were recruited from a mid-sized university undergraduate subject pool. As a result, participants were not fully representative of the general U.S. population as they were predominantly young, Caucasian, never married, college students. Future research should attempt to recruit from more diverse sample populations. Regarding sample size, an a priori power analysis was conducted based on limited prior research and indicated a sample of 68 would be sufficient for a medium effect size ($f^2 = .15$) with sufficient power ($\beta = .80$) for multiple regressions with two predictors. Although participant recruitment ended early due to COVID-19 precaution-related university closures, 69 participants were recruited. However, the intended sample size of 100 would have better accounted for data attrition during the 7-day follow up period and, given the operationalizations of digital phenotypes in the present study, would have increased power to better detect the effects of the digital behaviors.

There were several limitations to using an exploratory approach in the study. The application of digital phenotyping to clinical psychology is a nascent area of research and to our knowledge, this is the first study to investigate the relationship between digital phenotyping and

emotion regulation. Accordingly, it was not possible to rely on previous research to inform hypotheses-testing. Thus, multiple statistical models were conducted to systematically test each relationship of interest without correction, increasing the possibility of type 1 errors. It is important to note, that applying a correction for multiple comparisons to address researcher degrees of freedom and to reduce the possibility of false positives (i.e., type 1 errors), may be at the expense of increasing false negatives (type 2 errors) (Rothman, 1990) and penalizes larger, multifaceted studies (Althouse, 2016), such as the present study. Indeed, there is no consensus on whether applying a correction for multiple comparisons adequately addresses the issue it purports to target, as researcher degrees of freedom ranges from needing to correct within a reported study to across every statistical test a researcher conducts (Gelman et al., 2012; Reinhart, 2015). Until clinical psychology as a field accumulates a research base using digital phenotyping to inform subsequent research, multiple comparison issues can be addressed using statistical methods that are more robust to type 1 error, such as structural equation modeling or multilevel modeling using a Bayesian framework (Gelman et al., 2012).

The current study also revealed the limitations of GPS acquisition technology in investigating human behavior. As GPS technology cannot detect whether an individual is inside or outside a building and is not accurate enough to detect movement within a small space, it may not be sensitive enough measurement index to capture individual differences in behavior associated with psychopathology. For example, GPS data may not differentiate between someone who is mostly sedentary within their home due to low mood and someone who is experiencing euthymia and normal activity within their home. Moreover, when operationalizing GPS as distance (subtracting a GPS coordinate from the preceding coordinate and accounting for the curvature of the earth), distance traveled due to elevation, such as walking up hills or stairs, is

not captured. Future work that plans to use GPS data from digital phenotyping platforms would benefit from developing research questions that take into account the inherent limitations of GPS data acquisition in smartphone technology. For example, future research could use GPS data to calculate acceleration to differentiate among individuals who are engaging in different types of travel or transport, such as walking or driving. Since GPS is not sensitive to within building movement, researchers can create algorithms to detect when and for how long individuals are in certain geographical areas and determine whether the individual is likely at home, work, or another frequently visited location.

There were limitations associated with using the Beiwe Research Platform for digital phenotyping data acquisition. Even though power state level and GPS digital phenotyping data were sampled at a high rate, operationalizing variation over time as *SD* limited the sample used in the regression models to 69 observations. The thousands of digital phenotyping observations, however, contributed to better estimations of *SD* for each participant. The juxtaposition in number of observations obtained through digital phenotyping and self-report pose a methodological challenge for future research. Digital phenotyping data indices are sampled at different rates and at different times, generating variables of varying lengths and time stamps that do not match. To illustrate, there were far more GPS distance observations (n = 1,789,156) than power state (n = 186,593), regardless of the missing the power state level data. The differences in observations between digital phenotyping indices and non-matching time stamps precludes the ability to conduct direct time series analyses comparing digital phenotype indices. The same issue exists when attempting to conduct time series analyses comparing self-report measures collected concurrently with digital phenotyping data. Future studies can take further advantage of

the longitudinal nature of digital phenotyping data by creating time index variables to approximately match observations for time series analyses.

Another limitation of the Beiwe Research Platform was that the types of digital phenotyping data collected by the platform were not the same between phones with an Apple iOS operating system and phones with an Android operating system. Of the total 10 digital raw phenotyping data types that can be collected by the Beiwe Research Platform, 5 types are consistent across the two operating systems. Since inconsistent variable types across the two operating systems can limit which data can be analyzed, future research should aim to investigate digital phenotyping data that are collected by both operating systems, or compensate by recruiting more individuals using the operating system with the data type of interest while accounting for possible sample bias. There appeared to be a data collection issue unique to phones using Android operating systems, as there were 16 cases with no power state data acquisition. A useful feature of the Beiwe Research Platform is that it generates output with identifiers for each registered participant, including the version of the Beiwe Research Platform installed on the phone, phone model, and phone operating system and version. Future researchers can also contribute to the continued development of the Beiwe Research Platform by documenting issues in data collection and reporting them on the Onnela Lab GitHub webpage (https://github.com/onnela-lab).

A notable limitation of the Beiwe Research Platform is that it is not designed for real time monitoring of data acquisition. For example, the backend user interface does not immediately allow for the researcher to know whether data is actively being collected or which data types are being collected, such as tracking which pushed self-report questions have been answered. The backend user interface is limited to solely indicating which Beiwe usernames have been

registered on a device. The data have to be downloaded and inspected to ascertain the degree of use on the participant's end. This research platform limitation restricts the researcher's ability to monitor for participation compliance or acquisition issues while a study is currently running. The Onnela Lab at the Harvard T.H. Chan School of Public Health offers a paid version of the Beiwe Research Platform that can run an automated pipeline for downloading and processing data collected from the platform. Future researchers can address this limitation using the open-access version of the Beiwe Research Platform by regularly downloading participant data and automating data processing workflows to routinely inspect the data. I created data processing workflows for the digital phenotyping variables collected by both Apple and Android operating systems and posted them to an online repository with documentation to guide implementation (https://github.com/cmbosma/beiwe-scripts). The workflows include documentation, such as how to manually download digital phenotyping data using the open-access version of the Beiwe Research Platform, as well as functions written in the R programming language for wrangling data to a tidy format (i.e., one column representing one variable in a data frame), working with time stamps, a framework for processing survey data, and computing basic summary statistics for the digital phenotyping indices collected by the platform (e.g., GPS, power state level, gyro, and accelerometer). It is possible to independently create one's own pipeline using virtual machines, or computing using servers (e.g., Amazon Web Services), to automate running the data processing workflows at a frequency that would enable monitoring of data acquisition using the Beiwe Research Platform. It can be advantageous to automate data processing workflows, as each participant generated approximately two gigabytes of digital phenotyping data over a 7-day collection period. Particular to larger-scale studies, automating data processing workflows to

wrangle data, compute variables, and complete pre-determined data analyses as data are collected would help decrease the amount of time associated with these computational tasks.

Despite limitations with Beiwe platform, a strength in the study was that the results suggested people used their phones as they typically do, as few respondents indicated that they used their phones in an atypical manner. As the nature of typical phone use was not observed or assessed in the present study, it is recommended that future research using smartphones for digital phenotyping data collect information on participants' typical phone use to better learn how to detect atypical phone use.

Conclusions

Emotion regulation has been proposed as an RDoC domain for transdiagnostic criteria for psychopathology (Fernandez et al., 2016). As the field of emotion regulation has relatively robust foundational knowledge of individual differences in emotion regulation in laboratory settings, a complete understanding of normative ranges in emotion regulation requires an unobtrusive, ecologically valid assessment of the construct as it occurs in real-world settings. Therefore, comprehensive emotion regulation assessment depends on our ability to harness innovative interdisciplinary methodology to advance our understanding of implicit and passive experience of emotion. The present study addressed this aspect of extending the nomological network of emotion regulation by being the first to implement digital phenotyping to the investigation of emotion regulation. Results from the current investigation suggest that digital behavior can predict individual differences in trait emotion regulation implementation patterns. GPS distance and mobile phone power over time accurately classified individuals into two trait emotion regulation clusters. One cluster was characterized by less difficulty in implementing emotion regulation strategies, greater cognitive reappraisal use, and less expressive suppression

use. The other cluster was characterized by greater difficulty with implementing emotion regulation strategies, low cognitive reappraisal use, and high expressive suppression. Both clusters were characterized by relatively low use of rumination on average. Variation in mobile phone use and GPS distance over time predicted trait cognitive reappraisal, variation in state cognitive reappraisal over time, and variation in negative affect over time. Interestingly, these two digital phenotype indices did not predict other forms of trait and state emotion regulation and did not interact with emotion regulation to predict depressive symptoms. These findings indicate that operationalizations of digital phenotyping data and modeling methods are especially important to consider when using digital phenotyping methodology. The results further demonstrate the promising potential of digital phenotyping data in further expanding the nomological network of emotion regulation. Building on the findings of this study, future research can investigate additional digital phenotyping indices, alternative operationalizations of digital phenotyping data, and the relationships between digital phenotyping data and other markers of emotion regulation (e.g., physiology). Data from a digital phenotyping platform such as the Beiwe Research Platform can be examined in concert with other technologies that collect passive data. For example, additional digital phenotyping indices could be collected using wearable devices that can acquire psychophysiological data or by connecting supplementary sensors to the outside of smartphones. The findings from this project provide foundational knowledge on the use of digital phenotyping to investigate the ecological validity of emotion regulation, contributing to our understanding of individual differences in implicit and passive experiences of emotion. In line with the RDoC initiative (Insel et al., 2010; Torous et al., 2017) these findings provide a foundation for future research using digital phenotyping with the

ultimate goal of being able to accurately identify normative ranges in emotion regulation associated with mental well-being.

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APPENDICES

Appendix A: Sona Advertisement and Recruitment Email

SONA Systems Advertisement

Study Name: Emotion in Context Study

Study Type: Multi-Part Standard Study (Two-Part)

Duration: 60 minutes (in-lab); 7-day (follow-up period)

Credits: 1 (in-lab); 2 (follow-up period)

Description: The study will take place at 329 Corbett Hall (near Wells Central Dining and Memorial Gym; map: https://goo.gl/maps/S54AFjHFm9r). First, you will complete a series of surveys asking questions about how you are feeling and different types of thoughts that people sometimes about how they manage their emotions. Next, a trained female research assistant will place sensors on your body in order to record electrical activity of the heart and skin. Once the sensors are placed on your body, you will be asked to sit comfortably in front of a computer in a small room. You will then be asked to complete the following: sit quietly for 5 minutes, answer questions about how you are feeling, watch a short video about a mountain, and a short video designed to induce a brief sad mood. This portion of the study will take approximately 50 minutes.

Next, you will be instructed to download and activate a mobile application on your smartphone. You will be asked to keep your phone with you during the day for a 7-day period. You will be asked to keep your smartphone charged during the 7-day period. Each day, you will complete two surveys on your smartphone when the application prompts you to do so. The surveys include questions about how you are currently feeling (e.g., rating how sad or happy), about thoughts you were having, and about activities you were engaged in. Each survey will take approximately 5 minutes to complete. In addition, the smartphone application will be collecting anonymous data (e.g., GPS, frequency of texting, frequency of calls, WIFI usage) from sensors in your phone. At the end of the 7-day period, you will be asked to delete the application from your smartphone.

Eligibility Requirements: You must be at least 18 years or older, fluent in English, and own a smartphone with either the Apple iOS or Android operating system to participate.

Appendix B: Consent Form

Emotion in Context Study
The University of Maine
Informed Consent Document (PSY 100, 212)

You are invited to participate in a research project being conducted by Colin Bosma, M.A., in the Department of Psychology at the University of Maine. The faculty sponsor is Dr. Emily Haigh. The purpose of the research is to learn more about how individuals regulate their emotions in different contexts. You must be at least 18 years to participate, fluent in English, and own a smartphone with either the Apple iOS or Android operating system.

What Will You Be Asked to Do?
If you decide to participate, you will complete a series of questionnaires. As part of the survey you will answer questions about how you are feeling (e.g., "to what extent in the last week have you felt nervous?"), different types of thoughts that people sometimes have (e.g., "to what extent do you think about how you don't feel up to doing anything?"), and questions about how your life has changed in response to the COVID-19 epidemic (e.g., Since the coronavirus disease pandemic began, what has changed for you or your family?"). This portion of the study will take about 30 minutes.

Next, a trained female research assistant will place sensors on your body in order to record electrical activity of the heart and skin.

- Once the sensors are placed on your body, you will be asked to sit comfortably in front of the computer in a small room. The equipment used for psychophysiological recordings is not medical grade and is not meant to be diagnostic.
- You will then be asked to complete the following tasks: sit quietly for 5 minutes, answer questions about how you are feeling, watch a short video about a mountain and a short video designed to induce a brief sad mood.
- This portion of the study will take approximately 20 minutes.

Next, you will be instructed to download and activate the "Beiwe2" application on your smartphone.

- The "Beiwe2" application is free to install and does not require a paid subscription. The application will require the notifications to be enabled and access to location services at all times for the application to work.
- You will be asked to keep your phone with you during the day for a 7-day period. You will be asked to keep your smartphone charged during the 7-day period. Each day, you will complete two surveys on your smartphone when the application prompts you to do so.
- The surveys include questions about how you are currently feeling (e.g., rating how sad or happy), about thoughts you were having (e.g., to what extent did you change the way you were thinking to feel more positive emotion?"), and about activities you were engaged in (e.g., "are you currently socializing with anyone?").
- Each survey will take approximately 5 minutes to complete. In addition, the smartphone application will be collecting data from sensors in your phone, including 1) location, 2)

device movement, 3) reachability, and phone usage (e.g., number of texts, number of calls, WIFI usage, power state).
- Actual content of phone calls (i.e., recordings of conversations) and text messages (i.e., text) is not collected through the mobile application. At the end of the 7-day period, you will receive a list of counseling resources and be asked to delete the application from your smartphone.

Risks
The risks involved in this study are minimal. It is possible that you may feel uncomfortable when answering questions about yourself in the lab and via your smartphone for a 7 days. At any point during the study, you have the right to skip questions you do not wish to answer or stop the session and choose not to participate in the remainder of the study. You will not need to provide a reason for stopping the session. As part of the psychophysiological recording process, it is possible you will experience skin irritation upon removal of the sensors, similar to the removal of a large band-aid. This irritation may leave initial red marks on the skin, which should go away a few hours after removal. You may experience slightly more (10-20%) battery usage on your phone, meaning you might need to charge your phone earlier in the day than your previous habit. You may experience some worry about a loss of privacy as a result of revealing your location and daily activities during the study or answering survey questions. However, the data from the Beiwe2 application does not record the content of smartphone usage, nor does it track one's location in buildings. In addition, both the survey responses and GPS location from the Beiwe2 app will not be monitored. You will be provided with a list of local counseling resources and hotlines at the end of the study.

Benefits
While this study will have no direct benefit to you, this research will help us understand how our ability to regulate our negative emotions is related to well-being.

Compensation
Students will receive 1 research credit for each hour of participation during the in-lab portion of the study. Since the survey is expected to take 30 minutes and computer task 20 minutes, it is likely that you will earn 1 credit today. Students will receive 2 credits for completing the 7-day follow-up phase. If students no longer require research points for course credit (e.g., have already earned 5 research credits as required by PSY 100) students will receive $15 for the laboratory portion and/or a $20 Amazon gift card via email for the 7-day follow-up phase, accordingly. You will be fully compensated even if you choose to withdraw from the study at any point.

Confidentiality
To protect your confidentiality, your name will not appear on any of the documents associated with the study. A code number will be used to protect your identity. The code is stored on a file with software designed to provide added security. Data will only be accessible to the principal investigator, graduate students who have been trained to deal with sensitive material, and the sponsoring faculty member, Dr. Emily Haigh. Your name or other identifying information will not be reported in any publications. The key linking your name to the data will be destroyed June 2021, after primary analyses are expected to be completed. All data will be kept indefinitely by the investigators.

Voluntary

Participation is voluntary. If you choose to participate in this study, you may change your mind and stop at any time. You may also skip any questions you do not wish to answer.

Contact Information

If you have any questions about the study, please contact Colin Bosma at colin.bosma@maine.edu. If you have any questions about your rights as a research participant, please contact the Office of Research Compliance, University of Maine, (207) 581-2657 (or email umric@maine.edu).

Adhesive Allergy
Are you allergic to adhesives?

☐ Yes ☐ No

Future Studies
Would you be interested in being contacted for future studies conducted in the lab for monetary compensation?

☐ Yes ☐ No

Your signature below indicates that you have read and understand the above information and agree to participate. You will receive a copy of this form.

_____ _____

Signature Date

Appendix C: Self-report Questionnaires

Demographic Information

To start with, we would like to get some background information from you.

1. What is your age? ___

2. Gender? _____

3. What is your date of birth? ____/ ____ / ____

4. What is your current marital situation (please check one)?

_____ Married _____ Separated _____ Never married/Single
_____ Common law marriage_____ Divorced _____ Widowed

5. Do you consider yourself to be Hispanic or Latino (see definition below)?
Hispanic or Latino. A person of Mexican, Puerto Rican, Cuban, South or Central American, or other Spanish culture of origin, regardless of race.

☐ Yes ☐ No

6. Do you consider yourself to be Franco-American ?

☐ Yes ☐ No

7. What is your race? (please check one)

☐	Native American or Alaska Native	A person having origins in any of the original peoples of North, Central, or South America.
☐	Asian	A person having origins in any of the original peoples of the Far East, Southeast Asia, or the Indian subcontinent including, for example, Cambodia, China, India, Japan, Korea, Malaysia, Pakistan, the Philippine Islands, Thailand, and Vietnam.
☐	Black or African American	A person having origins in any of the black racial groups of Africa.

	Native Hawaiian or Other Pacific Islander	A person having origins in any of the original peoples of Hawaii, Guam, Samoa, or other Pacific Islands.
	White	A person having origins in any of the original peoples of Europe, the Middle East, or North Africa.
	Multiple races	
	None of the above	

7. What is the highest grade in school you have completed (please check one)?

____Less than High School (**record actual grade**)

____4 years of college with degree

____High School

____Postgraduate, M.D., Ph.D.

____1 year of college or technical school

____A.A. or other degree that is not a B.A. or B.S.

____2 or more years of college but did not graduate

Emotion Regulation Questionnaire (ERQ)

INSTRUCTIONS:
We would like to ask you some questions about your emotional life, in particular, how you control (that is, regulate and manage) your emotions. The questions below involve two distinct aspects of your emotional life. One is your emotional experience, or what you feel like inside. The other is your emotional expression, or how you show your emotions in the way you talk, gesture, or behave. Although some of the following questions may seem similar to one another, they differ in important ways. For each item, please answer using the following scale:

1----------2----------3----------4----------5----------6----------7
strongly disagree **neutral** **strongly agree**

1. ____ When I want to feel more *positive* emotion (such as joy or amusement), I *change what I'm thinking about*.
2. ____ I keep my emotions to myself.
3. ____ When I want to feel less *negative* emotion (such as sadness or anger), I *change what I'm thinking about*.
4. ____ When I am feeling *positive* emotions, I am careful not to express them.
5. ____ When I'm faced with a stressful situation, I make myself *think about it* in a way that helps me stay calm.
6. ____ I control my emotions by *not expressing them*.
7. ____ When I want to feel more *positive* emotion, I *change the way I'm thinking* about the situation.
8. ____ I control my emotions by *changing the way I think* about the situation I'm in.
9. ____ When I am feeling *negative* emotions, I make sure not to express them.
10. ____ When I want to feel less *negative* emotion, I *change the way I'm thinking* about the situation.

Ruminative Response Scale (RRS)

INSTRUCTIONS:
People think and do many different things when they feel sad, blue, or depressed. Please indicate for each possibility if you never, sometimes, often, or always think or do each one. Please indicate what you generally do, not what you think you should do.

1	2	3	4
Almost never	sometimes	often	almost always

_____ 1. Think “What am I doing to deserve this?”

_____ 2. Analyze recent events to try to understand why you are depressed.

_____ 3. Think “Why do I always react this way?”

_____ 4. Go away by yourself and think about why you feel this way.

_____ 5. Write down what you are thinking and analyze it.

_____ 6. Think about a recent situation, wishing it had gone better.

_____ 7. Think “Why do I have problems other people don’t have?”

_____ 8. Think “Why can’t I handle things better?”

_____ 9. Analyze your personality to try to understand why you are depressed.

_____ 10. Go someplace alone to think about your feelings.

Difficulties in Emotion Regulation Scale (DERS)

Please indicate how often the following statements apply to you by writing the appropriate number from the scale below on the line beside each item.

1----------2----------3----------4----------5

almost never	sometimes	about half the time	most of the time	almost always
(0-10%)	(11-35%)	(36-65%)	(66-90%)	(91-100%)

_____1) I am clear about my feelings.
_____2) I pay attention to how I feel.
_____3) I experience my emotions as overwhelming and out of control
_____4) I have no idea how I am feeling.
_____5) I have difficulty making sense out of my feelings.
_____6) I am attentive to my feelings.
_____7) I know exactly how I am feeling.
_____8) I care about what I am feeling.
_____9) I am confused about how I feel.
_____10) When I'm upset, I acknowledge my emotions.
_____11) When I'm upset, I become angry with myself for feeling that way.
_____12) When I'm upset, I become embarrassed for feeling that way.
_____13) When I'm upset, I have difficulty getting work done.
_____14) When I'm upset, I become out of control.
_____15) When I'm upset, I believe that I will remain that way for a long time.
_____16) When I'm upset, I believe that I will end up feeling very depressed.
_____17) When I'm upset, I believe that my feelings are valid and important.
_____18) When I'm upset, I have difficulty focusing on other things.
_____19) When I'm upset, I feel out of control.
_____20) When I'm upset, I can still get things done.
_____21) When I'm upset, I feel ashamed at myself for feeling that way.
_____22) When I'm upset, I know that I can find a way to eventually feel better.
_____23) When I'm upset, I feel like I am weak.
_____24) When I'm upset, I feel I can remain in control of my behaviors.
_____25) When I'm upset, I feel guilty for feeling that way.
_____26) When I'm upset, I have difficulty concentrating.
_____27) When I'm upset, I have difficulty controlling my behaviors.
_____28) When I'm upset, I believe there is nothing I can do to make myself feel better.
_____29) When I'm upset, I become irritated at myself for feeling that way.
_____30) When I'm upset, I start to feel very bad about myself.
_____31) When I'm upset, I believe that wallowing in it is all I can do.
_____32) When I'm upset, I lose control over my behavior.
_____33) When I'm upset, I have difficulty thinking about anything else.
_____34) When I'm upset, I take time to figure out what I'm really feeling.
_____35) When I'm upset, it take me a long time to feel better.
_____36) When I'm upset, my emotions feel overwhelming.

Spontaneous Affect Regulation Scale (SARS)

INSTRUCTIONS:
Indicate to what extent you used each of the following strategies to regulate, or alter, your emotional experience.

Use the following scale to record your answers:

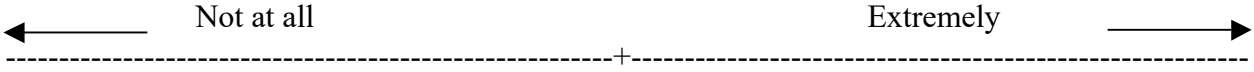
0 = strongly disagree
1 = disagree
2 = slightly disagree
3 = neutral
4 = slightly agree
5 = agree
6 = strongly agree

1. _____Changing the way I was thinking to feel more positive emotion.
2. _____Changing the way I was thinking to feel less negative emotion.
3. _____Changing the way I was thinking to feel less positive emotion.
4. _____Changing the way I was thinking to feel more negative emotion.
5. _____Keeping my emotions to myself.
6. _____Being careful not to express my negative emotions.

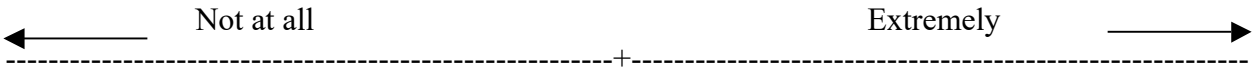
Visual Analog Scale VAS

INSTRUCTIONS:
We are interested in knowing about your current mood. Please mark an 'X' on the line below to indicate how you feel right now. Use the labels above the line to help you in your judgment.

Sadness



Happy



Appendix D: Beiwe Mobile Application Use Script

Beiwe Mobile Application Use Script

What am I being asked to do?

For the follow-up portion of the study, you will install a mobile application on your phone called Beiwe2 and register for this study on the application. The application requires that notifications and access to your location are enabled. You will keep the mobile application on your phone for 7 days. Each day, you will be prompted to complete two surveys, one in the morning and one in the evening. The surveys take approximately 5 minutes to complete.

How much space does the app take up?

The Beiwe2 app is a small program and will use 40MB on your phone.

Do I have to respond right away?

You should not respond to prompts from the application when you are driving, taking an exam, or any other activity where it would be detrimental to divert your attention. When prompted, complete the survey as soon as it is safe, or possible, for you to do so.

What if I miss a survey?

If you miss a survey, it will remain in your queue until it is completed. Please complete any surveys you missed and do not fill out several back-to-back. Leave at least one hour between completing each survey.

What data are you collecting?

In addition, the smartphone application will be collecting data from sensors in your phone, including your location, device movement, reachability, and phone usage. For example, number of texts, number of calls, WIFI usage, and power state.

Will you see my personal content (e.g. texts, pictures, emails, photos, web browsing history, tinder etc.)?

The mobile application does not collect private content, such as the actual content of your texts, recordings of your conversations, content of the files stored on your phone, or your internet browsing history. Furthermore, the data collected by the mobile application is secure and will not be shared.

Will my name or any personal identifying information be associated with the data?

No, it will not. We receive a spreadsheet of coded variables and numeric data that have no identifiable information. This data will be analyzed using advanced statistical techniques so that general patterns can be identified and summarized.

What do I do at the end of the study?

After the 7-day period, you will receive an email from us reminding you to delete the Beiwe2 mobile application from your phone. It is important that you delete the application from your phone after the 7-day period, as the application will continue collecting data from the sensors in your smartphone, even if you do not open or actively use the application.

Any questions? [if none] Please provide acknowledgement on the tablet [orient participant to question on Qualtrics survey] that you received and understand the instructions for using the Beiwe2 mobile application. [researcher indicates on Qualtrics that they witnessed the participant's acknowledgment]

Wording for Qualtrics Questions:

I have been instructed on the use of the Beiwe2 mobile application as part participating in the follow-up portion of the Emotion in Context Study, including that I should not respond to prompts when I am driving, taking an exam, or any other activity where it would be detrimental to divert my attention.

Yes No

[ ] [ ]

Researcher Name: _____

Witnessed acknowledgement by the participant?

Yes No

[ ] [ ]

Appendix E: Debriefing Form

Debriefing Form for Participation in a Research Study
University of Maine

Thank you for participation in our study. Your participation is greatly appreciated.

Purpose of the Study

The purpose of this study is to examine how individual's thoughts, physiological responses, and digital behaviors relate to regulating emotions (i.e., feeling less negative emotion or more positive emotion). This study is important as it may help us understand how emotion regulation is related to well-being, as well as improve our ability to measure individual differences in how people regulate their emotions.

In this study you completed a series of questionnaires about how you think and feel. Using sensors to detect electrical impulses, we measured physiological arousal (e.g., heart rate) as you watched short film clips designed to make you feel sad or no change in mood. You also completed a 7-day follow-up with surveys asking about your current mood, thinking, and your activities. During this period, data was collected from sensors on your smartphone.

We expect to find that participants' behaviors and physiological responses will predict the style of thinking they implement when regulating their emotions in response to emotional stimuli, and that these patterns will be associated with different levels of depressive and anxiety symptoms. Previous research has shown certain emotion regulation strategies and physiological responses to sad mood to be associated with higher levels of depression and anxiety. However, little research has examined how these factors are related to behaviors outside of laboratory settings.

Do you have any questions about the study? When you were doing the study what did you think the study was about? Was there any part of the study that was difficult? How is your mood now? We realize that some of the questions asked may have provoked an emotional reaction.

Confidentiality

You may decide that you do not want your data used in this research. If you would like your data removed from the study and permanently deleted, please email your request to the principal investigator, Colin Bosma at colin.bosma@maine.edu.

Whether you agree or do not agree to have your data used for this study, you will still receive compensation for your participation.

Final Report

If you would like to learn about the results of the study, let the researcher know and we will email you a summary of the results at the end of the study.

Further Reading(s)

Berking, M., & Wupperman, P. (2012). Emotion regulation and mental health: Recent findings, current challenges, and future directions. *Current Opinion in Psychiatry*, *25*(2), 128–134. https://doi.org/10.1097/YCO.0b013e3283503669

Fernandez, K. C., Jazaieri, H., & Gross, J. J. (2016). Emotion regulation: a transdiagnostic perspective on a new RDoC domain. *Cognitive Therapy and Research*, *40*(3), 48–56. https://doi.org/10.1007/s10608-016-9772-2

Onnela, J. P., & Rauch, S. L. (2016). Harnessing Smartphone-Based Digital Phenotyping to Enhance Behavioral and Mental Health. *Neuropsychopharmacology*, *41*(7), 1691–1696. https://doi.org/10.1038/npp.2016.7

Useful Contact Information

If you have any questions or concerns regarding this study, its purpose or procedures, or if you have a research-related problem, please feel free to contact the Principal Investigator, Colin Bosma at colin.bosma@maine.edu.

If you have any questions concerning your rights as a research subject, you may contact the University of Maine Institutional Review Board for the Protection of Human Subjects at (207) 581-1498 or (207) 581-2657 (or email umric@maine.edu).

Appendix F: Counseling Services

Counseling Services		
ON-CAMPUS RESOURCES Available for UMaine Faculty, Staff, and Students		
Counseling Center **Cutler Health Building (Gannet Hall side)** **(FREE to UMaine students)**	**207-581-1392** **http://www.umaine.edu/counseling/**	Weekdays 8:00 am-4:30 pm After business hours, call UMaine Police, 581-4040 or 911
Psychological Services Center **330 Corbett Hall** (Sliding fee scale; costs are your responsibility)	**207-581-2034** **http://umaine.edu/clinicalpsychology/psychological-services-center/**	Weekdays 8:00 am – 4:30 pm
COMMUNITY RESOURCES Available to Anyone		
Community Health & Counseling Services **42 Cedar Street** **Bangor, ME 04401** (Any costs are your responsibility)	**207-947-0366** http://www.chcs-me.org/	Weekdays 8:00 am-5:00 pm
Maine Warm Line (Any costs are your responsibility)	**1-888-771-9276** **http://www.thecommunityconnector.org/directory/profile/maine-warm-line**	7 days/week 5:00 pm – 8:00 am
Maine Suicide and Crisis Hotline (Any costs are your responsibility)	**1-888-568-1112** **http://www.maine.gov/suicide/youth/index.htm**	7 days/week 24 hours
Psychological Services Center **330 Corbett Hall** (sliding fee scale)	**207-581-2034** **http://umaine.edu/clinicalpsychology/psychological-services-center/**	Weekdays 8:00 am – 4:30 pm
Contact Your Primary Care Provider (Any costs are your responsibility)		
NATIONAL RESOURCES		
Mental Health Services Locator http://store.samhsa.gov/mhlocator		
National Suicide Prevention Lifeline, Toll-Free, 24-hour Hotline, 1-800-273-TALK (1800-273-8255)		