Using Bayesian mixed-effects models to predict self-injurious thoughts in intensive longitudinal data

Kevin S. Kuehn

A dissertation

submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

University of Washington

2021

Reading Committee:

Kevin M. King, Chair

Melanie S. Harned

Katherine T. Foster

Program Authorized to Offer Degree:

Psychology

University of Washington

Abstract

Using Bayesian mixed-effects models to predict self-injurious thoughts in intensive longitudinal data

Kevin S. Kuehn

Chair of Supervisor Committee:

Kevin M. King, Ph.D.

Department of Psychology

Suicide is a leading cause of death in the United States and around the world. Despite decades of research aimed at improving the understanding of self-injurious thoughts and behaviors (SITBs), researchers are not currently able to reliably predict when someone is at high-risk for suicide. This might be due to methodological limitations of prior studies which relied on retrospective recall of distal SITB risk factors (e.g., temperamental characteristics, mental health diagnoses, etc.). Research focused on proximal risk-factors (e.g., momentary emotional states, environmental contexts, stressful events, etc.) is likely to lead to a better understanding of SITBs given their dynamic nature. The current study used ecological momentary assessment to examine proximal relations between negative emotions, coping behaviors, impulsivity, and real-time SITBs among youth (N = 60) at high-risk for suicide. Bayesian multi-level models revealed

associations between negative emotions and suicidal thoughts. There was some evidence that specific emotions, as well as particular coping strategies, were weakly correlated with suicidal thoughts. Disengagement coping strategies strengthened the association between negative emotions and suicidal thoughts. There was no evidence that coping strategies or impulsivity attenuated the relation between negative emotions and thoughts of non-suicidal self-injury. Due to the large degree of heterogeneity present in the data, more research concentrated on understanding subject-level predictors of SITBs is needed to precisely predict when individuals are at elevated risk for suicide. This type of research could be crucial to improving behavioral treatments through the discovery of person-specific treatment targets.

Table of Contents

Acknowledgements

Who could have predicted my path? My mom, Kathy Kuehn, must have known as she argued for me be moved up to honor's math in elementary school and as she had a "discussion" with the music teacher for leaving me out of honor's choir (my singing voice was, and still is, like a mule on the verge of their last breath). Thank you, mom, for continuing to believe in my potential when it was not a popular opinion, and for never losing faith in me (or at least for saying the right things that made me think you believed in me). Thank you for showing me how to be persistent, for fostering in me a love of reading, and for sacrificing so much for your children to be successful. My dad, Jeff Kuehn, who howled like a coyote when I was a goaltender for the Royal Oak (Michigan) Coyotes, who was the only parent present for sixth grade election speeches in my bid for class Vice President (I won that one), and who was the most competitive 40-year-old elementary school soccer player as a lunch aid. He is the only dad to earn the award, "Best Dad Ever". Thank you, "Vern", for always being there for your kids and for loving us all unconditionally. Speaking of Vern, Baba and Papa, thank you for always picking up the phone, especially after I earned my first 4.0 in college. Your relentless faith in me encouraged me to do better. I wish I could have a Zoom call with you now to let you know how graduate school went.

My siblings, Joel Kuehn and Lindsey Doughty, will never call me Dr. Kuehn, and I guess that is something I will learn to accept. Thank you, Joel and Lindsey for supporting me these past 31 years. I am especially grateful that you now provided me with nieces and nephews, so thanks to Dyl Pickle (Meatball, Jr.), Chase Man, Baby Reid, Cassie (Dino Princess), and Gavin for all the joy you bring to our family, and for writing this dissertation.[1]

[1] Surprisingly, no children wrote any part of this dissertation

I would also like to acknowledge all the academic mentors that have been instrumental in keeping me moving towards the finish line of my non-linear journey ($time^6$; -2logLik = 249.04, x^2 (df = 8) = 15.77, $p < .001$): Annmarie Caño, Rich Slatcher and Paul Toro at Wayne State for providing me with initial research opportunities and academic guidance which then steered me in the right direction. Cheryl King at the University of Michigan for taking me on as a volunteer assistant and for continuing to open many doors these past 12 years. Shirley Yen at Brown for taking a chance on me as a Research Assistant. And the cadre of mentors at the University of Washington: Melanie Harned and Katie Korslund for their continued guidance; Kevin King for taking me on as a student and tolerating a few of my ideas, Jen Mankoff and Paula Nurius for the opportunity to assist with the UWEXP project, and Kate Foster for the conversations and amazing collaborations. Thank you all for walking (sometimes running) with me during a few challenging parts of this passage.

I would also like to acknowledge all the undergraduate research assistants and volunteers in assisting with this project. I could not have collected this data without your efforts. Similarly, I greatly appreciate the participants of this study for sharing their stories through their data. Finally, thank you to my husband, Nick Albanese, who has been by my side every step of the way. I cannot wait for the beaches, sunshine, and breweries in our near future.

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Self-Injurious Thoughts and Behaviors (SITBs) as a Public Health Concern

Self-injurious thoughts and behaviors (SITBs), a broad term referring to both non-suicidal and suicidal thoughts and behaviors, are common in the United States and internationally. Non-suicidal self-injury (NSSI) is defined as the deliberate damage to an individuals' bodily tissue without the intention for a fatal outcome (Nock & Favazza, 2009), while suicidal thoughts and behaviors are delineated by an intention to end one's own life (Posner et al., 2014). According to the 2019 Youth Risk Behavior Surveillance Survey, a nationally representative survey administered in U.S. schools, an estimated 19% of youth reported they seriously considered attempting suicide in the prior year (Ivey-Stephenson et al., 2020). In that same time period, an estimated 9% of the adolescents sampled reported they made a suicide attempt[2]. Although the suicide rate stabilized beginning in 2019 (Hedegaard, Curtin, & Warner, 2021), mortality increased 35% from 1999 to 2018 (Hedegaard et al., 2021), with approximately 14.5 per 100,000 people currently dying by suicide per year in the United States (CDC, 2020).

1.2 Theories of SITBs

There are many theories regarding the etiology and phenomenology of SITBs. While an individual can have multiple reasons for engaging in NSSI, most researchers believe that NSSI is primarily developed and maintained through a process of affect regulation (Nock & Prinstein, 2004; Taylor et al., 2017) in which NSSI behaviors help to down-regulate from intense and aversive emotions. This relief from distress is thought to negatively reinforce NSSI behaviors

[2]Likely an overestimate due to the use of a single-item, self-report suicide attempt measure in the YRBS survey (see Millner et al., 2015 for problems in using single-item measures to assess suicidal behaviors)

(Vansteelandt et al., 2017), thereby increasing the likelihood someone will engage in NSSI in the future when experiencing similar levels of distress. Though this affect regulation hypothesis was initially developed to explain NSSI behaviors (Nock & Prinstein, 2004), there is emerging evidence to suggest that other SITBs, such as suicidal cognitions, may also be negatively reinforced by distressing emotions (Kleiman, Coppersmith, et al., 2018; Mou et al., 2018).

Theories of suicidal behaviors (i.e., suicide attempts, suicide deaths) emphasize an "ideation-to-action" framework in which an individual transitions from suicidal thinking to suicidal behaviors through a complex interplay of higher-order cognitions (Joiner, 2005; Klonsky & May, 2015). These ideation-to-action theories posit that the development of suicidal thoughts differs substantially from suicidal behaviors. Therefore, these models first offer explanations as to how individuals initially start to think about suicide, and then hypothesize how individuals transition to attempting. The two leading paradigms within this domain are the Interpersonal Psychological Theory of Suicide (Joiner, 2005) and the 3-Step Theory of Suicide (Klonsky & May, 2015). Both theories highlight a combination of intrapersonal (e.g., perceived burdensomeness, psychological pain, hopelessness) and interpersonal dynamics (e.g., thwarted belongingness, connectedness) leading to the development of suicidal thoughts. These two theories also hypothesize that an "acquired capability" likely explains the transition to suicidal behavior in which an individual prepares themselves to engage in lethal behavior and/or their environmental circumstances allow for a suicide attempt to occur (e.g., acquisition of lethal means). These explanations offer insights as to the possible etiology of suicidal thoughts, as well as how someone escalates from thinking about suicide to attempting, but they are limited by a focus on distal risk-factors. That is, both theories do not explain how suicidal thoughts are maintained in the short-term nor how SITBs operate under real-world conditions.

1.3 Limitations of Prior SITB Research and Incorporation of New Methods

Despite the high rate of suicide death worldwide and in the United States, researchers and clinicians are largely unable to reliably predict when someone is at imminent risk for suicide (Franklin et al., 2017). A few reasons for the poor predictive models to date are 1) suicidal thoughts and behaviors, although prevalent at a population-level, are relatively rare at any one-point in time; 2) prior studies relied on retrospective self-reports in which participants recalled the precipitants to SITBs they experienced months and/or years ago; 3) studies were mostly cross-sectional limiting the ability to detect temporal associations and 4) studies largely focused on distal as opposed to proximal risk-factors. To address these limitations, researchers seeking to improve the understanding and prediction of short-term risk have recently incorporated new research methods.

Intensive longitudinal data is a way of collecting information in which participants are repeatedly sampled over a relatively short period (Hamaker & Wichers, 2017). This type of data allows a researcher to understand temporal patterns between variables as well how these processes change over time. Ecological momentary assessment (EMA), one way to collect intensive longitudinal data, is a data collection method in which surveys are delivered to an individual’s web-enabled mobile device multiple times per day (Shiffman et al., 2008). In daily diary designs, another way to collect intensive longitudinal data, surveys are distributed once per day. Although the content of the questionnaires used in both daily diary and EMA studies varies across disciplines, in psychological research, both are predominately used to assess thoughts, emotions, and behaviors as they occur in real-time. While some researchers have recently argued that ecological momentary assessment is not used enough in SITB research (Davidson et al., 2017), intensive longitudinal studies of SITBs are becoming increasingly more common (Kleiman & Nock, 2018).

There are many benefits to intensive longitudinal data. One of the most crucial advantages is the ability to tease apart within- and between-person variance (Enders & Tofighi, 2007), that is distinguishing how unique individuals change over time (i.e., *within-person*) from how they differ across people (i.e., *between-person*). For SITB research, intensive longitudinal data can help to identify *who* is most at-risk for suicide (e.g., whether between-person differences in mental health diagnoses differentiate individuals at high from low risk) as well as *how* suicidal thoughts are maintained for individual people (whether or not within-person changes in depressive symptoms are associated with imminent suicide risk). A more complete assessment of these dynamics is critical to improving researchers' ability to predict imminent risk, and to provide insights as the psychological processes that likely contribute to the development and maintenance of SITBs.

1.4 Intensive Longitudinal Studies of SITBs Highlight the Role of Negative Affect

Three systematic reviews summarized the findings from intensive longitudinal studies of NSSI behaviors (Hamza & Willoughby, 2015; Hepp et al., 2020; Rodríguez-Blanco et al., 2018), while one study critically reviewed intensive longitudinal studies of suicidal thoughts (Rabasco & Sheehan, 2021). For the reviews of NSSI behaviors, all three narrowed in on the affect regulation hypothesis, largely concluding there is strong evidence for increased negative affect prior to NSSI behaviors. These reviews, however, determined there was mixed evidence for decreased negative following NSSI behaviors. Meanwhile, intensive longitudinal studies of suicidal thoughts found these cognitions were short-lived and highly variable in daily life (Rabasco & Sheehan, 2021). Similar to intensive longitudinal studies of NSSI behaviors, reports of suicidal thoughts also converged on the importance of affective dynamics in predicting near-term escalation of suicidal thoughts (e.g., Hallensleben et al., 2017; Kleiman, Coppersmith, et al., 2018; Mou et al., 2018; Victor et al., 2019).

1.4.1 Predictors of NSSI Thoughts in Intensive Longitudinal Data

To date, seven studies measured NSSI thoughts with an intensive longitudinal design (Andrewes et al., 2017; Bresin et al., 2013; Hochard et al., 2015; Kiekens et al., 2020; Lear et al., 2019; Selby et al., 2019; Victor et al., 2019). Kiekens et al. (2020) used an EMA design with 30 young adults, finding both concurrent and prospective associations between mean levels of negative affect and NSSI thoughts. Lear et al. (2019) found the association between trait self-criticism and NSSI thoughts was explained by higher same-day levels of punishment beliefs (e.g., "I deserved to be treated badly"), meaning that individuals who commonly engaged in negative self-talk were more likely to think about NSSI on days they believed they deserved punishment. Victor et al. (2019) examined both internalizing (e.g., anxiety, sadness) and externalizing (e.g., anger) negative emotions in an EMA design, reporting that within-day changes in internalizing emotions prospectively predicted NSSI thoughts. These internalizing emotions also explained the association between daily interpersonal processes and NSSI thoughts.

Even though the remaining studies (Andrewes et al., 2017; Hochard et al., 2015; Selby et al., 2019) measured NSSI thoughts, the main analyses of these articles focused on NSSI behaviors. Findings from these studies largely supported the role of negative emotion in predicting and maintaining self-harm. A recent meta-analysis pooled data from all seven studies measuring both NSSI thoughts and negative affect within an intensive longitudinal design. Results from this analysis found that negative affect was increased by about .70 standard deviations in the observation prior to an NSSI thought as compared to observations prior to a non-NSSI thought (Kuehn, Harned, Foster, Song, Smith & King, 2020*)*, suggesting negative affect is a robust proximal predictor of NSSI thoughts.

1.4.2 Predictors of Suicidal Thoughts in Intensive Longitudinal Data

About twenty-eight articles examined suicidal thoughts in an intensive longitudinal design (e.g., Czyz et al., 2019; Czyz et al., 2018; Czyz et al., 2019; Hallensleben et al., 2019; Husky et al., 2017; Kaurin et al., 2020; Peters et al., 2020; Salim et al., 2019; Victor & Klonsky, 2014; Vine et al., 2020; Wolford-Clevenger et al., 2019). See Rabasco & Sheehan (2021) for a full review of these articles. In general, intensive longitudinal studies of suicidal thoughts found suicidal cognitions were highly variable across timepoints (Forkmann et al., 2018; Hallensleben et al., 2017; Kleiman et al., 2017; Peters et al., 2020), and that a range of risk-factors were associated with suicidal thoughts (Hallensleben et al., 2019; Hallensleben et al., 2017; Kleiman, Turner, et al., 2018; Rath et al., 2019). For example, Czyz et al., in a series of analyses from a daily diary study of 34 youth recently discharged from psychiatric hospitalization, reported that intensive longitudinal data was a safe and feasible data collection method, and identified several factors associated with near term suicide risk. (Czyz et al., 2019a; Czyz et al., 2018; Czyz et al., 2019b). Specifically, connectedness, burdensomeness, and hopelessness were associated with same-day suicidal thoughts. Additional analyses found an interaction between connectedness with both burdensomeness and hopelessness, that is those who were low in connectedness and high in either burdensomeness or hopelessness experienced more severe suicidal thoughts on that same day, as well as on the next day (Czyz et al., 2019a). Czyz et al. (2019b) focused on the co-occurrence of NSSI with suicidal thoughts, reporting that youth used NSSI as a way to cope with suicidal thoughts. In the same study, these authors found that youth who used more coping strategies on average also had a lower likelihood of self-harming over the month-long study (Czyz et al., 2019b).

Hallensleben et al. (2018) used an EMA design with 74 participants, differentiating between active suicidal thoughts (e.g., “I have a plan to die by suicide”) and passive cognitions (e.g., “I want to die but will not act”). The authors found that hopelessness, depression, perceived burdensomeness, and thwarted belongingness were all related to both concurrent passive and active thoughts, while only hopelessness, perceived burdensomeness, and an interaction between burdensomeness and belongingness predicted future suicidal thoughts. Husky et al. (2017) used an EMA design to study 42 adults immediately following discharge from psychiatric hospitalization, finding that a number of contextual influences (e.g., being at home or work) increased the likelihood of suicidal thoughts.

To date, intensive longitudinal studies of suicidal thoughts largely examined interpersonal variables (e.g., connectedness, burdensomeness, belongingness). Although the most common intrapersonal variables studied were hopelessness and depressive symptoms (i.e., non-affective variables), other studies have assessed links between emotions and suicidal thoughts. For example, Kleiman, Coppersmith, et al. (2018) studied the affect regulation hypothesis in suicidal thoughts, finding evidence that affect was increased prior to suicidal thoughts and decreased following. Mou et al. (2018) discovered participants diagnosed with borderline personality disorder exhibited stronger associations between negative affect and suicidal thoughts. Mirroring their findings on NSSI thoughts, Victor et al. (2019) found that internalizing forms of negative affect were associated with suicidal thoughts, and this link explained how interpersonal variables (such as rejection) were associated with suicidal thoughts.

In the meta-analysis described above (Kuehn, Harned, Foster, Song, Smith & King, 2020), affective dynamics pre- and post-suicidal thoughts were also tested in the thirteen unique intensive longitudinal datasets that measured negative affect and suicidal thoughts. Once again, there was robust evidence for increased negative affect pre-suicidal thoughts (d = .84) and some evidence for decreased negative affect following a suicidal thought (d = -.23). Taken together, there appears to be broad evidence for increased negative affect prior to both NSSI and suicidal thoughts. Across intensive longitudinal studies, there is also evidence that negative affect is reduced following SITBs. However, the similar effect sizes across various forms of SITBs indicates that affect alone likely does not differentiate NSSI thoughts from NSSI behaviors, nor does it likely distinguish non-suicidal from suicidal thoughts and behaviors. A greater focus on the interplay between cognitive, behavioral, and affective processes in close proximity to SITBs is needed to best understand how SITBs operate in daily life.

1.5 Moderators of the Negative Affect and SITB Association

Knowledge of a person's emotional state is likely insufficient to predict SITBs. Negative emotional states are a universal experience, yet most people do not think about, let alone attempt, suicide. Thus, understanding when and for whom negative emotions lead to SITBs is paramount to better prevent youth SITBs. Emotion regulation, or the broad ability for individuals to identify their emotions and/or the possible strategies they use to modify affective states (Gross & Thompson, 2007; Sheppes et al., 2015), may explain how affective experiences confer risk for SITBs (Neacsiu et al., 2018). While emotion regulation specifically refers to how individuals manage their emotions, coping generally refers to individuals' responses to specific stressors (e.g., school or work; Compas et al., 2017).

Disengagement coping (e.g., denial, wishful thinking, distraction, avoidance suppression) may prolong negative emotions (Hong, 2007), and make SITBs more likely (Horwitz et al., 2011). A few studies showed that individuals who tended to use disengagement coping strategies were more likely to have a history of self-injurious behavior (Mahtani et al., 2018; O'Connor et al., 2012), and these individuals also exhibited stronger associations between emotional expression and NSSI (Mahtani et al., 2018). Within intensive longitudinal data, Czyz et al. (2018) found that individuals who used fewer coping strategies overall were more likely to engage in NSSI over the month-long follow-up period. However, as most of the research to date relied on retrospective reports of coping, or studied coping strategies in general, it remains unclear whether individuals are also more prone to SITBs in the face of negative emotions when they use disengagement coping strategies.

Negative urgency, or a tendency towards impulsive action in response to negative emotions (Cyders & Smith, 2008) may make SITBs more likely because it reflects general dysregulation in the face of negative affect, with one consequence possibly being NSSI. A recent meta-analysis suggested that negative urgency was more strongly associated with self-injurious behavior (r = .25) than other facets of impulsivity (Berg et al., 2015). Specifically in intensive longitudinal data, negative urgency strengthened the relation between one specific negative emotion (i.e., sadness) and NSSI behavior (Bresin et al., 2013).

A few studies tested moderators of the negative emotion-SITB relation in intensive longitudinal data. Kleiman, Turner, et al. (2018) found that fatigue moderated the association between stress and suicidal thoughts, while Bresin et al. (2013) discovered that trait urgency moderated the association between sadness and NSSI thoughts. That is daily sadness was associated with thoughts of NSSI, but only for individuals high in trait negative urgency. No studies examined whether or not momentary urgency, or momentary coping behaviors, moderated the within-person association between negative affect and SITBs.

1.6 Aims and Hypotheses of Dissertation Study

The present study uses EMA to examine the direct and indirect relations between negative emotions, coping behaviors, and levels of impulsivity with SITBs among a high-risk for suicide sample. Specifically, this study tested the following aims and hypotheses (see **Figure 1** for the theoretical model):

Aim 1: To prospectively examine the main effects of an individual's daily experience of emotions and use of disengagement coping on SITBs.

I used Bayesian mixed-effect models (Vasishth et al., 2018) to examine whether mean levels of negative emotions and disengagement coping behaviors predicted NSSI thoughts or suicidal thoughts. To do this, I disaggregated within and between person variance (Enders & Tofighi, 2007) in both the negative emotion and disengagement coping variables and scaled these variables so that the coefficients reflected standard deviation units.

Hypothesis 1 for Aim 1: The intensity of negative emotions would prospectively predict SITBs in youth at-risk for suicidal behaviors.

I specifically hypothesized that higher levels of negative emotion at timepoint *t-1* would be associated with a higher likelihood of experiencing a NSSI thought or a suicidal thought at timepoint *t*. To test this, models with and without negative emotions were compared using model fit indices (i.e., PSIS-LOO, WAIC, and Pseudo-BMA) to determine whether negative emotions improved the posterior prediction of either NSSI or suicidal thoughts.

Hypothesis 2 for Aim 1: Higher use of disengagement coping behaviors, as well as higher levels of acting on impulse, would prospectively predict SITBs.

A higher number of disengagement coping behaviors relative to the number of adaptive coping behaviors, and higher levels of impulsivity, both at timepoint *t* was hypothesized to be associated with a higher likelihood of experiencing an NSSI thought and/or a suicidal thought. First, models with and without disengagement coping were compared using model fits indices to determine whether disengagement coping improved the posterior prediction (Vehtari et al., 2017). Then, models with and without a disaggregated and scaled impulsivity variable were compared to determine if levels of momentary impulsivity improved the prediction of SITBs.

Exploratory Hypothesis 3 for Aim 3: Specific emotions (such as shame) would be more strongly associated with SITBs than negative emotions in general

To test this hypothesis, the specific emotions of anger, guilt, fear, shame, and sadness were used as predictors of NSSI thoughts and suicidal thoughts. Within- and between-person variance was disaggregated for all variables which were then scaled to reflect standard deviation units. Separate models were then compared against each other to see if any of the specific emotions improved model fit.

Aim 2: To test whether state or trait level of disengagement behaviors or negative urgency moderated the association between negative emotions and SITBs.

I then added a product term between within-person negative emotions and baseline levels of both disengagement coping and negative urgency to determine whether either of these variables strengthened the association between negative emotions and NSSI thoughts or suicidal thoughts. Separate models tested for an interaction between within-person negative emotions and within-person disengagement coping or within-person impulsivity to determine if the association between negative emotions and SITBs was strengthened when individuals used either more disengagement coping strategies or felt more impulsive. All models were compared with and without the product term to determine if including these interactions significantly improved model fit.

Hypothesis 1 for Aim 2: Individuals who report more trait disengaged coping or negative urgency would exhibit stronger within-person associations between momentary negative emotions and SITBs.

For this hypothesis, models were compared with an interaction between within-person negative emotions and baseline levels of disengagement coping to determine if models with an interaction improved model fit. Conditional effects were plotted at +/- one standard deviation.

Hypothesis 2 for Aim 2: The relation between momentary associations of negative emotions and SITBs would be stronger when individuals reported higher levels of disengagement coping or more acting on impulse.

Similar to Hypothesis 1 for Aim 2, I tested for an interaction between within-person negative emotions and within-person disengagement coping. I compared this model without the interaction term (i.e., with just negative emotions) to determine if this model improved fit. In a separate analysis, I also tested for an interaction between within-person negative emotions and within-person urgency, comparing this model to one without an interaction. For both models, the conditional effects of the interaction terms were plotted at +/- one standard deviation.

1.7 Innovation and Public Health Impact

SITBs are a major public health concern. Despite these elevated rates, researchers and clinicians are currently unable to reliably predict when someone is most at-risk of dying by suicide. This is likely due, in part, to limitations of prior research designs. The present study aims to add to a growing body of literature focusing on better understanding proximal risk for SITBs and to test whether two modifiable strategies strengthen the association between negative emotions and SITBs. This type of information could help tailor treatments, potentially making them more effective in reducing the frequency of SITBs. An improved ability to predict imminent risk of suicide could help treatment providers prioritize individuals at the most elevated risk so these individuals are prioritized in receiving services.

Chapter 2: Methods

2.1 Procedures

See **Figure 2** for a CONSORT flow diagram of participant progression through the study. All study procedures and confirmatory hypotheses were pre-registered on the Open Science Framework (Kuehn, 2020). Interested potential participants (*N* = 1,435) first completed an online screening form which assessed eligibility criteria (**Table 1;** e.g., the presence of self-harm in past two weeks, a suicide attempt in the past year, and/or past-month suicidal ideation, etc.). Eligible participants (*N* = 304) were contacted to schedule a baseline session. During the baseline session, either adult consent (18+), or parental consent and youth assent (for 16–17-year-old participants), was obtained. Additional baseline tasks included an online self-report survey, along with a semi-structured assessment covering prior mental health treatment, lifetime suicide and self-harm history, and mental health diagnoses. This assessment was conducted by a doctoral-level assessor. At baseline, eligible participants were trained in the EMA procedure by completing a sample survey, were instructed to store a link to initiate an event-contingent survey in their smartphone, and downloaded the AWARE framework, a mobile phone application, which collected passive data (*see* https://www.awareframework.com).

Participants confirmed to be eligible during the baseline evaluation (*N* = 62)[3] completed 14 days of surveys (observation period commenced the day following the baseline session). Assessments were delivered five times per day. Participants were also asked to complete event-contingent surveys when experiencing a significant increase in SITBs. At baseline, participants verified their cell phone number and enrolled in an automated platform which was used to

[3]Two participants completed less than 25% of surveys over the two weeks and were dropped from analysis. The reasons for missing data from these two participants are explained in study compliance and missing data section (p. 10).

deliver signal-contingent surveys (Hofmann & Patel, 2015). Once verified and enrolled, this service delivered EMA prompts via text message containing the hyperlink to an online survey. Participants were given unique four letter codewords which were used to link survey responses to individual participants. Surveys were scheduled to be delivered between the hours of 8am and 10pm daily and were sent in a random interval between these hours with a minimum of one hour in between. Participants had one hour to respond and were sent a reminder text message if they did not click on the link within 30 minutes of receiving the initial prompt. Participants were compensated $25 in either cash (in-person) or gift card (online) and were paid $1 for each signal-contingent survey (up to $70; participants were not paid for event-contingent responses so as not to inadvertently reinforce SITBs). Those completing more than 80% of the signal-contingent surveys were compensated an additional $30. Participants could earn a maximum of $125 for completing the study. All study procedures were approved by the Institutional Review Board at the University of Washington.

2.2 Participants

Participants (N = 60) were recruited on the basis of high-suicide risk. The mean age of the sample was 18.58 (SD = 1.25). 53.33% of the sample self-identified as White; 11.67% Hispanic/Latinx; 10% reported a mixed ethnicity; 20% Asian, 3.33% Black/African American; and 1.67% Middle Eastern. See **Table 2** for demographic and descriptive data. Surprisingly, about 70% of the sample identified as non-heterosexual (e.g., Gay, Lesbian, Bisexual or other). Within sexual minorities, lesbian/bisexual females accounted for the largest sub-group (50% of the overall sample).

Subject recruitment occurred through online social media advertisement, referrals from local treatment providers, and flyers posted around the community. Prior to 03/05/2020, participants were required to live within commuting distance of the research office to attend an in-person baseline session. Due to the COVID-19 global pandemic and the restriction of in-person research, on 03/05/2020 and thereafter, participants were recruited nationally. During this time, baseline interviews were conducted virtually via the Zoom video conferencing service. Inclusion criteria for the full 14-day study were: 1) Recent SIB defined as a SA in the past year OR NSSI in past two weeks with current SI; 2) 16-20 years old; 3) easy access to a smartphone; 4) English speaking; 5) Parental consent if 16-17 years old. Participants were excluded from the study if they did not provide an emergency contact who study staff could contact in the event that participants were unreachable following a report of imminent suicide risk. **Table 1** lists the inclusion and exclusion criteria in more detail.

2.3 Measures

2.3.1 Baseline Self-Report Measures

See **Table 3** for means and standard deviations of baseline measures. The following questionnaires were administered at the baseline interview:

Responses to Stress Questionnaire – Child Self Report Peer Stress (RSQ). The RSQ (Connor-Smith et al., 2000) is a 57-item Likert style self-report measure (scored 1 – 4; 1 = “Not at all”; 4 = “Very Much”) which gauged the frequency of coping responses used to manage stressful social interactions in the peer domain over the previous six-months. There are five subscales to the RSQ including: 1) Primary coping (α = .64, M = 0.16, SD = 0.03), which measures an individual’s effortful attempts to engage in problem-solving or to directly change the stressor (sample item: “I try to think of different ways to change or fix the situation”); 2) Secondary coping (α = .78, M = 0.19, SD = 0.04) or attempts to change emotional consequences of the stressor (sample item: “I realize that I just have to live with things the way they are”); 3)

Disengagement coping (α = .74, M = 0.16, SD = .02), which is a participants' deliberate attempt to avoid or withdraw from experiencing stressful events (sample item: "When I'm around other people I act like the problems with peers never happened"); 4) Involuntary engagement coping (α = .87, M = 0.29, SD = 0.04) or reactionary/physiological stress responses (sample item: "When dealing with the stress of problems with peers, I feel sick to my stomach or get headaches") and; 5) Involuntary disengagement coping (α = .84, M = 0.21, SD = 0.03), defined as reactionary behavioral withdraw, numbness, or avoidance (sample item: "When faced with the stress of problems with peers, I don't feel anything at all, it's like I have no feelings"). Subscales were calculated by deriving a proportion score, reflecting an individuals' relative proportion in coping strategies (e.g., .29 in involuntary engagement indicates that 29% of the coping strategies participants used were characterized by type of coping).

UPPS-P Impulsive Behavior Scale. The UPPS-P (Whiteside & Lynam, 2001) is a 59-item questionnaire that measured trait based impulsive personality characteristics. The UPPS-P, scored on a 1 ("Agree Strongly") to 4 ("Disagree Strongly") scale, is composed of five subscales including 1) Negative Urgency (α = .89; M = 2.92; SD = 0.67) defined as rash action in the face of negative emotions (sample item: "I have trouble controlling my impulses"); 2) Premeditation (α = .87; M = 2.87; SD = 0.58) or not thinking through consequences before acting impulsively (sample item: "I have a reserved and cautious attitude toward life"); 3) Sensation-seeking (α = .88; M = 2.64; SD = 0.62), or deliberately seeking out impulsive situations (sample item: "I generally seek new and exciting experiences and sensations"); 4) (lack of) Perseverance (α = .82; M = 2.71; SD = 0.55) or prematurely giving up (sample item: "I generally like to see things through to the end"); and Positive Urgency (α = .96, M = 2.32; SD = 0.83), or impulsive behavior due to positive emotions (sample item: "When I am very happy, I can't seem to stop myself from doing things that can have bad consequences").

Cognitive Emotion Regulation Questionnaire (CERQ). The CERQ (Garnefski et al., 2001) is a 36-item self-report measure of common cognitive strategies employed to regulate affective states. Participants were asked to rate the strategies they generally used on a scale from 1 ("Almost Never") to 5 ("Almost Always"). There are 9 subscales of the CERQ (M α = .78, α's ranged from .58 to .90). The 9 subscales included: 1) Self-blame (α = .87, M = 3.92, SD = 0.96), the tendency to blame oneself for the situation (sample item: "I feel that I am the one to blame for it"); 2) Positive refocusing (α = .86, M = 2.02, SD = 0.98), characterized by shifting thoughts away from the stressor towards ones that elicit positive emotions (sample item: "I think of nicer things than what I have experienced") 3) Refocus on planning (α = .74, M = 2.92, SD = 0.91), or the ability to shift towards future oriented positive aspects (sample item: "I think of what I can do best") 4) Positive reappraisal (α = .90, M = 2.63, SD = 1.13), or the ability to change interpretations about the stressor from negative towards positive thoughts (sample item: "I think I can learn something from the situation"); 5) Putting into perspective (α = .84, M = 2.83, SD = 1.04; sample item: "I think that it all could have been much worse") measures an individuals' ability to make positive meaning out of stressful situations; 6) Catastrophizing (α = .76, M = 2.70, SD = 0.90) or assuming the worst of a situation (sample item: "I often think that what I have experienced is much worse than what others have experienced"); 7) Blaming others, or putting the responsibility for negative emotions onto others, (α = .82, M = 2.25, SD = 0.91; sample item: "I feel that others are to blame for it"); 8) Acceptance, or the ability to believe in the reality of the stressor (α = .58, M = 3.35, SD = 0.82; sample item: "I think that I have to accept that this has happened”); 9) Rumination (α = .66, M = 3.70, SD = 0.84) or the tendency to repetitively think about the stressor in negative ways.

PROMIS Anxiety, Depression, and Anger Subscales. Anxiety (α = .85; M *t*-score = 66.2; SD = 7.56), depressive (α = 0.89; M *t*-score = 66.74; SD = 6.44), and anger (α = 0.82; M *t*-score = 60.89; SD = 9.80) symptoms experienced in the seven days prior to the baseline were assessed using the corresponding subscales from the PROMIS measures, part of the National Institutes of Health toolkit (Broderick et al., 2013). All three measures allow for the calculation of *t*-scores, which indicate an individuals’ relative position compared to a normative sample. For all measures, a *t*-score of 50 represented anxiety levels similar to the reference population, while an increase of 10 marked a one-standard deviation departure from the mean. For the current sample, anxiety and depression levels were more than 1.5 standard deviations above the reference, while anger was elevated by about one-standard deviation compared to the general population.

Medical Outcomes of Sleep Scale (MOS). The MOS (Hays et al., 2005) was used to measure sleep difficulties in the past month. The MOS subscales include sleep disturbance (α = 0.76; M = 62.10; SD = 23.91), sleep adequacy (α = 0.74; M = 32.67; SD = 25.90), and somnolence (i.e., “drowsiness”; α = 0.66; M = 36.00; SD = 30.76). The MOS also includes two general sleep indices to capture overall sleep quality (Index I α = 0.74; M = 59.38; SD = 20.12; Index II α = 0.81; M = 63.05; SD = 18.85).

Self-Report Family Inventory (SFI). Participants’ current perceived family functioning was measured using the SFI (Beavers & Hampson, 1990). The SFI is a 36-item self-report measure (response options are 1 = “fits my family well” to 5 = “does not fit my family”) and evaluates the following domains of family functioning: health competence (α = 0.94; M = 3.12;

SD = 0.94), conflict (α = 0.88; M = 2.82; SD = 0.90), cohesion (α = 0.78; M = 3.30; SD = 0.68), leadership (α = 0.24; M = 2.78; SD = 0.79), and expressiveness (α = 0.87; M = 2.99; SD = 0.80).

2.3.2 Baseline Semi-Structured Assessments

See **Table 4** for descriptive data from the semi-structured assessments. The following assessments were administered at the baseline interview:

Treatment History Interview (THI). Treatment history was obtained using the Treatment History Interview (THI; Linehan & Heard, 1987). A trained doctoral-level assessor used this semi-structured interview to collect information regarding outpatient mental health services, crisis psychiatric services, and currently prescribed psychotropic medications.

Suicide Attempt Self-Injury Interview (SASII). The SASII (Linehan et al., 2006) is a semi-structured assessment measure used to obtain lifetime history of suicide attempts and non-suicidal self-injurious behaviors. When suicidal behavior was present (differentiated based on the item, "Did you intend to die as a result of this behavior") necessary information was obtained to classify the attempt based on CDC definitions of aborted, interrupted, or actual suicide attempts (Posner et al., 2014).

Structured Clinical Interview for DSM-5 (SCID-5). The SCID-5 (First, 2014; Shankman et al., 2018) is a structured assessment used to diagnose and characterize psychopathology along DSM-5 dimensions (American Psychiatric Association, 2013). A trained doctoral-level student completed all assessments, and the following diagnoses were considered: 1) Major Depressive Episode; 2) Manic Episodes/Bipolar Disorder; 3) Substance Use Disorders; 4) Generalized Anxiety Disorder; 5) Post-Traumatic Stress Disorder; and 6) Obsessive-Compulsive Disorders.

2.3.3 Ecological Momentary Assessment Items:

Descriptive data from the EMA items are presented in **Table 5.** The following constructs were measured in EMA:

Positive and Negative Emotions. Participants were asked about negative and positive emotions experienced *in the past 10 minutes.* Items from the Positive-Affect Negative-Affect Scale (PANAS; Watson et al., 1988) were adapted to reflect negative and positive emotionality due to the brief EMA assessment window. Negative emotion indices included anger, sadness, shame, guilt, and fear (R_{KF} = .99; R_{1R} = .33; R_{KR} = .98), whereas positive emotionality included the following emotions: happy, confident, attentive, joyful, and loving (R_{KF} = 1.00; R_{1R} = .53; R_{KR} = .99). Participants rated these emotional experiences using a 0 (“low”) - 100 (“high”) visual analogue scale.

Coping Strategies. Items assessed the presence of coping strategies used *since the last assessment*. These strategies, measured in a binary yes or no fashion, included: 1) Cognitive reappraisal (Intra-class coefficient [ICC] = .31); 2) Self-Invalidation (ICC = .32); 3) Rumination (ICC = .16); 4) Suppression (ICC = .31); 5) Problem-Solving (ICC = .25); 6) Social Support (ICC = .02); 7) Distraction (ICC = .24); 8) Acceptance (ICC = .25) and 9) Avoidance (ICC = .04). Disengagement coping was calculated by summing across the avoidance, suppression and distraction items (maximum = 3) and subtracting by the number of adaptive strategies used (i.e., acceptance, problem-solving and re-appraisal).

Daily Stressful Events. Stressful events were measured similar to coping strategies. A list of 5 daily events were presented to participants who checked whether any of the following occurred *since the last assessmen*t. These scenarios were 1) Argument/disagreement with anyone (ICC = .09); 2) Work or school related stressful events (ICC = .19); 3) Perceived discrimination on the basis of race, age, or sex (ICC =.04); 4) Close friend or relative event that was stressful (ICC = .07); 5) "Anything else that people would consider stressful" (ICC = .26). Participants that endorsed one of these items were asked to provide more details about the event.

Impulsivity. Negative urgency was assessed in global self-report for all participants (e.g., "When I am upset, I often act without thinking"); however, it was intended to be measured in a momentary fashion (e.g., "Since the last assessment, I acted without thinking"). Halfway through data collection, the momentary item was added such that the latter half of the participants were asked about both global self-report urgency (R_{KF} = 1.00; R_{1R} = .26; R_{KR} = .97) as well as momentary urgency (R_{KF} = 1.00; R_{1R} = .60; R_{KR} = .99). Global self-report items were measured from 1 ("Strongly disagree) to 4 ("Strongly agree"). Momentary measures were assessed on a 100-point (0 = "low"; 100 = "high) visual analogue scale. To combine these scales, global self-reports were multiplied by 25.

Self-Injurious Thoughts and Behaviors. SITBs were assessed with an item, "Since the last assessment, have you thought about harming yourself?" Response options were "Yes" or "No". Participants who answered yes were then asked the strength of their intention of harming themselves in the past 30 minutes (ICC = .34), the strength of their intention to kill themselves in the past 30 minutes (ICC = .19), the current strength of their intention to kill themselves (ICC = .20), and whether or not they engaged in any self-harm behavior in the past 30 minutes (ICC = .02). Those who engaged in any self-injurious behavior were then asked if they had an intention to die as a result (to differentiate between NSSI and suicidal behavior), the method used (e.g., cutting, burning, scratching), the function (e.g., "to get rid of a thought or feeling"), and whether or not they sought medical or mental health treatment for SITBs. These items were adapted from

Nock et al., 2009 and were similar to other EMA studies of SITBs. See **Table 6** for descriptive information of the SITBs reported.

Chapter 3: Data Analysis Plan

3.1 Analytic Strategy

I conducted two sets of correlational analyses between baseline and EMA variables to determine the predictive, discriminant, and convergent validity of baseline and EMA variables. These analyses are presented in **Table 7 and Table 8** and **Figures 3** and **Figures 4** respectively. Additionally, I examined the frequencies for each of the SITB variables (see **Table 6**). Notably, there were only 23 instances of self-injurious behavior, which limited my ability to model this as a dependent variable. Thus, the present analyses examined NSSI thoughts and suicidal thoughts. For hypothesis testing, I constructed Bayesian multi-level models using the ‘brms’ package (Bürkner, 2017), while I used the ‘lme4’ package (a maximum likelihood approach) for some model building exercises (Bates et al., 2015). Both packages rely on the R statistical environment (R Core Team, 2013).

There are two main approaches for nomothetic-based analysis: frequentist and Bayesian methods (Bayarri & Berger, 2004). Frequentist techniques are predominant in psychological research and usually include maximum-likelihood based estimation (e.g., regression, multi-level models) to conduct null-hypothesis significance testing. In frequentist analysis, parameters are generated from the sample used for data collection and then generalized to estimate population-level effects (e.g., an intervention is evaluated based on differences in the efficacy between two randomly selected groups, a binary “effective” versus “not-effective” decision is made based on statistical significance). Bayesian analysis, instead, relies less on null hypothesis significance testing, but attempts to estimate the full range plausible outcomes (e.g., what is the probability that an intervention is efficacious under a range of various scenarios?). Comparisons between frequentist and Bayesian-based approaches, specifically within the context of multi-level models, tend to suggest that Bayesian-based approaches provide less biased estimates, especially when used with smaller datasets (Stegmueller, 2013). Bayesian analysis also allow for improved communication regarding uncertainty of effects (Hamaker & Klugkist, 2011). As the current study is based on a relatively small number of participants (N = 60) and the distribution of SITBs was expected to be heavily skewed (potentially leading to biased estimates), I used Bayesian analyses to model the probability someone experienced a SITB given varying levels of negative emotions, emotion regulation strategies, and levels of impulsivity.

The ‘brms’ package incorporates R syntax from ‘lme4 but translates this input to “Stan” programming language for analyzing data and generating output. Stan uses Hamiltonian Monte Carlo (Carpenter et al., 2017) and the No-U-Turn Sampler (Hoffman & Gelman, 2014) algorithms, both of which are extensions of Markov Chain Monte Carlo estimation (MCMC; Hastings, 1970). Compared to frequentist-based mixed-models, which provide a single estimate of the coefficient based on the observed data, Hamiltonian Monte Carlo and MCMC algorithms are designed to run regression models thousands of times, with the parameters converging around a range of values (i.e., a “credible interval”). The credible interval is somewhat similar to a confidence interval in frequentist analysis but represents an observed interval in a Bayesian framework (based on the output of MCMC chains), rather than an estimate in frequentist-based methods. In ‘brms’, as in any Bayesian modeling, the distribution of these coefficients is a function of the observed probability of the outcome variable (i.e., the average likelihood), a-priori expectations of the relations between the model coefficients and the outcome variable (i.e., prior information), and the probability of the outcome variable under different scenarios of the independent variable (i.e., the likelihood). Predictions for the outcome variable, the output of

Bayesian modeling, is called the posterior. This is explained in a bit more detail below (*see* **section 3.8**).

3.2 Survey Compliance and Missing Data

Out of 4,200 possible responses (70 responses per 60 participants), a total of 3,671 were submitted (87.40%). Survey responses were cleaned in which duplicates (first survey preserved), incomplete, and responses with a duration longer than one hour were deleted to keep the temporal structure of the data and to maintain surveys that reflected momentary emotions, cognitions, and behaviors. 238 responses were deleted using these criteria, such that there were 3,414 valid responses (81.29% of the possible 4,200). See **Table 9** for response rates based on daily assessment period. Rates of missingness per participant ranged from 45.71% to 100% (median = 84.29%). There were 19 complete event-contingent responses. Thus, there were a total of 3,433 signal- and event-contingent responses for analyses. The average response duration was 2 minutes 54 seconds. While no participants withdrew from the study following enrollment, two participants did stop responding to surveys at some point during the follow-up period[4]. No data from these two participants were analyzed and two additional participants were enrolled to compensate for these "dropped" participants.

Generalized linear mixed models (GLMMs; McCulloch & Neuhaus, 2005), a form of multi-level models, were conducted to predict missingness from both baseline and EMA data. Three patterns emerged, such that 1) baseline suicidal ideation differentiated participants with a higher proportion of missingness from those with less missingness (b = -0.01; OR = 0.99, 95% CI OR = 0.97 – 0.99; p = .01), such that individuals who reported higher ideation scores at

[4] One participant stopped responding due to an unexpected family emergency during the peak of the COVID-19 global pandemic. The other participant had their cell-phone privileges revoked by their parent due to increased mental health concerns unrelated to study participation.

baseline were less likely to miss surveys; 2) A linear effect of daily assessment period was predictive of missingness (b = -0.33; OR = 0.72; 95% CI OR = 0.67 – 0.76; $p < .001$), such that reports were less likely to be missing as the day progressed. When examining categorical differences, morning signals (i.e., the first survey of the day) were more likely to be missing than other periods; 3) Missingness was more likely to occur over time such that participants were more likely to miss surveys later in the study compared to the earlier days (b = .05; OR = 1.05; 95% CI OR = 1.03 – 1.08; $p < .001$). Previous reports of suicidal thoughts did not predict missingness at the next period, and number of baseline self-injurious behavior, disengagement coping, self-blame emotion regulation strategies, and negative urgency at baseline all did not predict proportion of missingness in EMAs.

3.3 Identifying Auxiliary Variables

As described above, baseline suicide ideation, daily assessment period, and day of the study all predicted missing SITB observations. Additional preliminary analyses examined trajectories of suicidal thoughts over time, both within and across days. A pattern emerged similar to missingness, such that time of the survey prompt (b = 0.14; OR = 1.15; 95% CI OR = 1.02 – 1.30, $p = .02$), day of the study (b = -.06, OR = 0.94; 95% CI OR = 0.91 – 0.98; $p < .001$), and baseline ideation scores (b = 1.29, OR = 3.63; 95% CI OR = 1.92 –7.94; $p < .001$) also predicted an increased likelihood of someone experiencing a suicidal thought. These patterns indicated that suicidal thoughts were more likely in the evening, earlier in the 14-day observation period, and among people who reported higher levels of ideation at baseline. No other variables were significantly associated with suicidal thoughts. Due to these patterns, these variables were included in the imputation models (described below). Since the associations between these variables and suicidal thoughts were handled through imputation, these auxiliary variables were not included as covariates in the confirmatory models.

3.4 Imputation Approach

Generally, there are three main patterns to missing data in any study (Enders, 2010; Schafer & Graham, 2002); missing at random (MAR), missing completely at random (MCAR), and missing not at random (MNAR). These three patterns are differentiated based the cause of missingness, which is rarely known. In MAR, the probability of missing data for the dependent variable is related to other observed variables, but not to the dependent variable itself. One possibility for missing data in the current study was that participants did not complete surveys when they were experiencing elevated levels of negative affect. Under a MAR scenario, participants would be equally likely to experience a suicidal thought even when they were experiencing elevated negative emotions, implying distress was not the cause of missingness. In a MCAR scenario, the probability of missing data for the dependent variable is unrelated to any of the measured variables (i.e., there are no observable patterns in missingness) while in MNAR, the probability of missing data in the dependent variable is due to the dependent variable itself (i.e., someone did not fill out a survey because they were thinking about suicide). As previously mentioned, there *were* observable missing patterns in the present analysis, with participants more likely to not complete morning surveys or prompts during the later days of the study. Therefore, I could rule out that missing SITB data was MCAR. It was nearly impossible to know whether participants did not complete surveys because they were thinking about suicide, but this explanation was unlikely given the inverse association between the predictors of missingness and suicidal thoughts (people more likely to think about suicide in the evening while more likely to miss surveys in the morning) and due to the inverse association between baseline ideation and missing data (those higher in ideation scores were less likely to miss surveys).

As there were observable patterns to missingness, listwise deletion (i.e., ignoring missing observations and using only complete cases) seemed to be an inappropriate solution because of the rigid MCAR assumption when using this approach (Bell et al., 2009). Due to the missingness patterns described above (also see **Figure 5)** and because 'brms' excludes missing data at Level 2 (Bürkner, 2017)**,** I used a multi-level, Bayesian, multiple imputation strategy to account for the missing data. These analyses used the "Amelia" package (Honaker et al., 2011) in R. Amelia was chosen over other imputation approaches, such as multiple imputation by chain equations ("MICE"), for two main reasons: 1) Amelia is was developed within a Bayesian framework, meaning it is theoretically similar to the main confirmatory analyses described below and; 2) the Amelia package allows for the appropriate specification of time-series data (for a tutorial *see* Zhang [2016]).

Auxiliary variables (i.e., factors that predicted missingness such as suicidal ideation at baseline, day of the study, and time of day) were included in the imputation predictor matrix. Missing Level 2 outcome variables (i.e., NSSI thoughts and suicidal thoughts) were imputed from all predictor variables with a binary logistic regression while missing Level 2 predictor variables were imputed by specifying a normal distribution (there were no missing data at Level 1). 15 different data files were imputed and multi-level models, which tested the main hypotheses, pooled across these 15 datasets. Differences between the observed and imputed datasets are presented in **Table 10** and **Figure 6**. The imputed datasets appeared to keep the associations between the covariates and the dependent variables in-tact as the predictor variables were centered around 0 with a mean of 1 following imputation. Missing observations were somewhat more likely to include a SITB response as the average proportion of both NSSI thoughts and suicidal thoughts were increased in the imputed datasets (**Table 10**).

Initially, the MCMC algorithm used for the Bayesian mixed-effects models struggled to pool estimates across the imputed datasets. The resulting models all had convergence errors (Rhat > 1.05 for individual parameters and low Bulk Effective Sample Sizes), appearing to suggest unreliable estimates. However, these errors were likely false positives and generated due to how “brms” models imputed datasets (Bürkner, 2021). Indeed, estimates derived from individual datasets (as opposed to the single pooled estimate) suggested these individual models converged (Rhats = 1.00). Examination of the trace plots and the MCMC chains (**Figure 7, Figure 8, and Figure 9**) also suggested the models converged normally.

3.5 Approach to Model Comparisons

There are many approaches to model comparisons in a Bayesian framework (*see* Vehtari, Gelman, & Gabry, 2017 for an overview). Model comparisons can be conducted based on the observed data or using randomly generated data (i.e., out-of-sample predictions). For the purposes of the present analysis, model comparisons were used primarily to determine whether one model was superior to another in predicting either NSSI thoughts or suicidal thoughts. Given the increased computational needs of Bayesian models, I prioritized an approach that was both computationally efficient and accurate. Pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO) and Watanabe-Akaike information criterion (WAIC; Watanabe, 2010) achieved both of the aims (Vehtari et al., 2017). PSIS-LOO is an approximation for assessing out-of-sample predictive performance and uses the posterior replications of the pooled coefficients (Vehtari et al., 2017), while WAIC is a complementary estimate of the predictive performance (the predictive performance is also called the expected log predictive density; ELPD).

Generally, a difference in ELPD/WAIC of 4 or less between models is considered small (Vehtari, 2020). Models can also be compared using a ratio of the difference between models and the standard errors, with a difference of two times the standard error generally being considered a significant difference. On the other hand, some argue for a more conservation ratio of five times the standard errors. As PSIS-LOO and WAIC can sometimes provide conflicting information, I also used Pseudo-Bayesian model averaging (Pseudo-BMA) with bootstrapping (Yao, Vehtari, Simpson & Gelman, 2018) as a supplemental method to compare models.

3.6 Unconditional Growth Modeling: Specifying Change Over Time

To model change over time, I initially conducted unconditional growth models (Verbake, 1997) in which I compared various models with EMA observation number (e.g., 1 – 70+) specified as a fixed versus a random effect and as a linear versus quadratic effect. Results from these model comparisons indicated a fixed and random effect of time best fit the data in which suicide risk decreased as the study unfolded. This pattern also varied significantly from person-to-person (i.e., the association between time and suicide risk differed between people). One limitation to this model is that it assumes a linear association between suicidal thoughts and prompt number. As previously described, the association between observation number and suicidal thoughts was not linear as people were more likely to think about suicide in the evening, thus suggesting within-day variation. Therefore, results were compared in which observation number was included as a fixed and random effect (along with the within- and between-person predictors) and in which change over time was ignored. As there were no differences between the two models in terms of model fit or the parameter estimates, all subsequent analyses did not include observation number as either a fixed or random effect.

3.7 Impulsivity Measurement in EMA

As described in the measures section, there was a researcher error in the ecological assessment of negative urgency. About half the prompts measured urgency by asking participants how impulsive they generally felt, while half the observations measured urgency in a more momentary fashion. To tease apart measurement differences, I combined the two measures by multiplying the GSR variable (measured on a scale from 1 to 4) by 25. I then tested for moderation in a GLMM model with an interaction between question type (i.e., a categorical variable indicating if urgency asked in a GSR or momentary fashion) and the centered-within-person urgency variable. For NSSI thoughts, there were no differences in model fit, suggesting that this measurement difference did not attenuate findings. However, for suicidal thoughts, there was evidence of moderation as the model with the interaction term suggested superior model fit (Δ logLik = 3.34, x^2 (df = 2) = 6.68, p = .04). Additionally, momentary urgency was correlated with suicidal thoughts (r = .25), while the global self-report form of urgency was not (r = .01), again suggesting a moderating effect. Urgency models predicting NSSI thoughts therefore did not include question type as a moderator, while models predicting suicidal thoughts did.

3.8 Specifying the Prior

Frequentist based methods, which are traditionally used to analyze mixed effects models, are largely constrained to the dataset used for analysis. This often means that traditional analyses do not incorporate known information, which could potentially lead to more extreme estimates. On the other hand, Bayesian models incorporate prior information as part of the modeling procedure (*see* Equation 1 in which *P(A)* represents the prior). Priors articulate the known information within a particular field of study and constrain coefficients in the equation to an expected distribution based on previous studies. Uniform or weakly informative priors can be used when a field is relatively young and there is little relevant data to incorporate.

$$\text{Eq 1. Bayes' Theorem} = P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Posterior = P(A|B), Probability of *A* given the probability of *B*

Likelihood = P(B|A), Probability of *B* given the probability of *A*

Prior = P(A), Probability of *A*

Average Likelihood = P(B), Probability of *B*

Researchers can use a few different types of priors for analysis (for an overview *see* Gelman et al. [2017]). The most common prior is called a "weakly informative prior" in which expectations for the intercept and the variance parameters of the model are specified, but not the coefficients of the predictors. These types of priors are mostly used to help with the convergence of the MCMC chains and the scaling of the posterior, as opposed to informing the posterior predictions. In the present analysis, I used the following weakly informative priors for the intercept of the multi-level regression, standard deviation, standard errors (i.e., the variation in regression coefficients across individual participants, and a zero-inflated distribution ("Zi").

$$Intercept \sim Student\ t(3, 0\ , 2.5)$$

$$\sigma^2 \sim Student\ t(3, 0, 2.5)$$

$$SE \sim Student\ t(3, 0, 2.5)$$

$$Zi \sim Beta(1, 1)$$

Weakly informative priors are used most often in Bayesian analyses as researchers ordinally do not have much access to relevant prior studies useful in building an "informed" prior. After all, funding organizations are unlikely to pay much money to study a topic that already has a wealth of knowledge. However, as I recently conducted a meta-analysis of previous intensive longitudinal studies testing the association between negative affect and SITBs (Kuehn et al., 2020*)*, I did have access to information that could inform expectations for the present analysis. Specifically, I had access to six intensive longitudinal datasets that measured both NSSI thoughts and negative affect (Bresin et al., 2013; Selby et al., 2019; Vansteelandt et al., 2017, Lear et al., 2019; Hochard et al., 2015) and ten datasets (Bresin et al., 2013; Czyz et al., 2018; Forkmann et al., 2018; Husky et al., 2017; Kiekens et al., 2020; Kleiman et al., 2017; Kleiman & Nock, 2018) that measured suicidal thoughts and negative affect. For both SITB outcomes, I first standardized the composite negative affect variables and then disaggregated within- and between- person variance. I then used GLMMs to test time lagged centered-within-person and grand-mean-centered negative affect as predictors of NSSI or suicidal thoughts in each dataset[5] (*see* **Figure 10** and **Figure 11**). For NSSI thoughts, the pooled within-person coefficient was 0.29 (95% CI = -0.08 – 0.65; p = .10), while the between-person coefficient was 1.14 (95% CI = 0.61 – 1.68, p < .01).

I used the “lme4” and “meta” (Schwarzer, 2007) packages in R to calculate effects. To calculate the pooled estimates, I used a random-effects meta-analysis rather than fixed-effects due to the expected between-stud heterogeneity. I used “lme4” instead of “brms” to calculate individual study effects due to the increased computation efficiency of “lme4”. There are some drawbacks to this approach, such as the inability to specify a zero-inflated distribution or to appropriately model the autoregressive parameter. Differences between the two strategies for analyzing results could artificially bias the coefficients and provide an overly optimistic expectation for the current study. In an attempt to account for these differences, I compared the

[5] Meta-analysis did not include data from the present study. All predictor variables from other studies were also scaled to reflect standard deviation units to allow for comparisons to the present study.

coefficients derived from a GLMM model using “lme4” to a zero-inflated auto-regressive model with a weakly informative prior in “brms using data from the current study. I adjusted the pooled coefficients derived from the meta-analysis based on these differences. For NSSI thoughts, the within-person coefficient was nearly identical in both “lme4” and “brms”. Therefore, I kept the prior for the within-person coefficient at .29. The difference in the between-person coefficient between “lme4” and “brms” was 10%. Therefore, I reduced my expectations for this coefficient from 1.14 to 1.04.

To calculate the standard errors for the prior I subtracted the lower-bound of the confidence intervals from the upper-bound and divided this sum by 3.92 (e.g., [1.68 – 0.61]/3.92 = 0.27). Based on this information, I expected the regression coefficients in my models to be normally distributed around the pooled estimate, with the variance of the distribution equivalent to the pooled standard error. Thus, I specified the following prior for the models predicting NSSI thoughts:

$$\beta_1 \sim Normal(0.29, 0.19)$$

$$\beta_2 \sim Normal(1.04, 0.27)$$

$$\beta_1 = \text{CWP negative emotions}; \beta_2 = \text{GMC negative emotions}$$

For suicidal thoughts, the within-person effect size was 0.36 (95% CI = 0.14 – 0.58, p < .01) and the between-person effect size was 1.50 (95% CI = 0.72 – 2.27, p = .001). The resulting estimate from “brms” was 65% of the coefficient from “lme4”. I decreased the expectation for the within-person effect from .36 to .23. Similarly, the between-person result of “brms” was 47% of the “lme4” coefficient; I adjusted the expectation of the between-person coefficient for suicidal thoughts from 1.04 to 0.71. Therefore, for models predicting suicidal thoughts, I specified the following prior (in addition to the defaults mentioned above).

$$\beta_1 \sim Normal(0.23, 0.11)$$

$$\beta_2 \sim Normal(0.71, 0.40)$$

To determine how results changed when using a weakly informative prior I conducted sensitivity analyses comparing an informative prior to a weakly informative one. The result from one of these models (negative emotions predicting suicidal thoughts) is presented in **Table 11**. As model comparisons between the two did not suggest significant differences in model fit (PSIS-LOO slightly preferred a weakly informative prior, difference in ELPD = -0.3, SE = 0.5), I used an informative prior for all analyses that included within- and between-person emotions as a predictor.

3.9 Specifying the Outcome Distribution

There were a few distributions I considered to best represent the NSSI and suicidal thought outcome variables. A priori, I knew that both outcomes were likely to be “zero-inflated” with “no” accounting for a large percentage of responses. Additionally, both NSSI thoughts and suicidal thoughts were measured in an ordinal fashion with higher levels suggesting more severe thoughts. Therefore, one option to model this zero-inflated, count data was a Poisson Hurdle model (Neelon et al., 2013) in which the zeros are modeled separately from the non-zero responses. Non-zero responses are then modeled as count data reflecting the entire range of the positive responses (e.g., suicidal thoughts ranging from 1 “mild” to 4 “imminent risk”). Differences between “severe” suicidal thoughts and “benign” cognitions could then be determined. Another approach would be to test for category specific effects of predictor variables where estimates would be derived for each of the various ordinal levels.

There were extremely few observations of SITBs. This was particularly true in the higher levels of both outcome variables (e.g., only 71 responses that were 2 or higher, out of a possible

4, in the severity of suicidal thoughts; *see* **Table 6** and **Figure 12**). Additionally, category specific effects suggested there were minimal differences in the predictor variables at increasingly higher levels of the outcome responses. Together, this suggested that both NSSI thoughts and suicidal thoughts should be treated as a dichotomous variable, with 1 indicating the presence of NSSI/suicidal thoughts and 0 representing an absence of SITBs. A zero-inflated binomial model (Diop et al., 2016) was thus a logical choice as this model combines aspects of the hurdle model (i.e., modeling zeros separately from non-zeros) while also specifying a Bernoulli distribution, thus treating the outcome variables as binary.

3.10 Autocorrelation of the Dependent Variable

Researchers are typically interested in understanding the stability, or inertia, of the dependent variable (e.g., does a suicidal thought at the previous timepoint predict whether or not someone will experience a suicidal thought at the next timepoint?). In an attempt to model this, researchers often include a lagged dependent variable (e.g., suicidal thoughts at *t-1*) as a covariate to predict suicidal thoughts at timepoint *t*. A compelling argument is that someone who thought about suicide just a few hours earlier is perhaps more likely to still be experiencing a suicidal thought at the next assessment. Therefore, the lagged dependent variable may be a confound accounting for the relations between the independent (negative affect) and dependent (SITBs) variables. Others argue that including the lagged dependent variable could bias coefficients, artificially suppressing the coefficients of the independent variables (Achen, 2000; Keele & Kelly, 2006). One synthesis between these two approaches is to include an autoregressive parameter in which the dependent variable is predicted from prior values of itself (Box et al., 1970).

There were two ways to account for the autocorrelation structure of my data: 1) a within-person autocorrelation in which an individuals' probability of experiencing a SITB a *t* is dependent on the probability of experiencing a SITB at *t-1* regardless of whether that difference is overnight; or 2) a within-person, within-day autoregressive structure in which sleep represents a "re-set" period and inertia is maintained only on the same day. Results from model comparisons are presented in **Table 12**. For both NSSI and suicidal thoughts, PSIS-LOO (PSIS-LOO) and WAIC suggested there were minimal differences between the two models with a slight preference for the within person autoregressive parameter. However, the within person autoregressive parameter also had slightly more convergence issues than a within-day, within-person autoregressive structure. Due to the minimal differences between the two and the slightly more efficient processing speed of the within-day, within-person effect, I chose to use a within-day, within-person autoregressive parameter.

3.11 Power Analysis

Power was estimated to detect effects at Level 2 (i.e., daily) by computing a "corrected sample size", which adjusts the number of observations for the amount of clustering. This can be calculated by the following formula:

$$\text{Eq 2. CSS} = \frac{Num\ of\ Observations}{((1 + ICC) *\ Num\ of\ Level\ 2\ obs * Expected\ missing\ rate)}$$

CSS = Corrected Sample Size

Assuming an ICC of .40 (based on Nock et al. [2009] and 20% missing data (based on previous SITB EMA studies [Nock et al., 2009; Houben et al., 2017]), the effective sample size to detect Level 2 effects with 60 participants was $n = 146$. With this sample size, the current study had the sensitivity at 80% power to detect effects as small as $f^2 = .09$, which would be considered a small to medium effect size. Even with a high ICC (.80), the sample size of the current study (adjusted n = 74) would be able to detect daily effects as small as $f^2 = .16$, a medium effect size. Thus, the present study was sufficiently powered to test most hypothesized effects at Level 2.

3.12 MCMC Chains

For confirmatory analyses, I specified two MCMC chains of 6,000 iterations per chain for each of the 15 imputed datasets (for a total of 150,000 iterations per model). This number of iterations was chosen due to the complexity of the zero-inflated multi-level models and the within-day, within-person autoregressive parameter. Increasing the number of iterations was one strategy to help with model convergence. Two chains ran at the same time and both of them converged in about an hour per dataset. Each model therefore cycled through all 15 datasets in approximately 15 hours.

Chapter 4: Results

4.1 Descriptive Baseline and EMA Data

See **Table 2** for demographic and descriptive data. **Tables 3 and 4** include means and standard deviations from baseline data, while **Table 5** presents frequencies and descriptive data from EMA responses. Correlations from the baseline data are presented in **Table 7** and **Figure 3.** RSQ primary coping and secondary coping strategies were modestly correlated to each other (r = .37) and primary coping was inversely correlated with maladaptive forms of coping (r = -.61). The two forms of involuntary coping were weakly (and non-significantly) correlated, indicating the items were measuring distinct processes.

Baseline subscales of the CERQ and RSQ were moderately correlated to each other (e.g., CERQ self-blame and RSQ involuntary engagement r = .36, CERQ positive reappraisal and RSQ secondary coping r = .48). Anxiety and depression symptoms of the PROMIS were also highly correlated with each other (r = .74). These all suggest convergent validity of the baseline measures.

At baseline, participants reported they used involuntary strategies most often to cope with peer stress (involuntary engagement M = 0.29; SD = .04; involuntary disengagement mean = 0.21; SD = .04), suggesting that participants primarily relied on these non-effortful forms of coping (**Figure 13**). These involuntary engagement strategies included rumination, intrusive thoughts, physiological and emotional arousal and involuntary actions, while involuntary disengagement coping included emotional numbing, cognitive interference (i.e., mind going blank), inaction, and escape. Regarding impulsivity, negative urgency was the most prominent facet (M = 2.92; SD = 0.67) and the distribution of urgency was negatively skewed such that the majority of participants reported elevated levels (**Figure 14**). Self-blame (M = 3.92; SD = 0.96) and rumination (M = 3.71; SD = 0.84) were the most endorsed general emotion regulation strategies at baseline (**Figure 15**).

For lifetime history of SITBs, the average participant started self-harming around 13-years old (mean = 13.76, SD = 2.08). Participants reported they attempted suicide at least twice in their lifetimes on average (M = 2.25; SD = 3.35; range = 0 – 21) and engaged in about 294 episodes of NSSI (SD = 613.07; range = 0 – 4,393). The majority (68%) of the suicidal behaviors described at baseline fit criteria for "actual" suicide attempts according to CDC definitions (Posner et al., 2014), in which an individual initiated a behavior with the intent to die as a result (e.g., an individual ingesting medication with the intention for a fatal outcome). "Aborted" suicide attempts, or when an individual started to engage in a behavior with an intent to die but stopped *themselves* prior to acting (e.g., someone going to the roof of a tall building, standing on the edge and contemplating jumping, but ultimately deciding against it), accounted for the second highest category (28%). Interrupted suicide attempts, or when *another* person stopped the participant prior to initiating suicidal behavior (e.g., a parent finding a child with pills in hand and preventing them from ingesting), were infrequently reported. Overall, 82% of the sample reported a lifetime history of suicidal behavior (using a loose definition which included actual, interrupted, and aborted attempts). When using a strict definition that included only actual suicide attempts, 65% of the sample reported a lifetime history of suicidal behavior.

Only 30% of the sample reported they received some form of dialectical behavior therapy, an evidence-based treatment for youth at high-risk for suicide (McCauley et al., 2018). About 58% of the sample received crisis services in their lifetime (e.g., psychiatric hospitalization, partial hospitalization), while 65% of the sample reported they were currently prescribed a psychotropic mediation (mean # of medications = 1.37, SD = 1.44; range = 0 – 6).

At baseline, the average participant reported a 45 on the SIQ-JR, which was one-standard deviation above the clinical cut-off of 31.

In terms of mental health diagnoses (**Table 4**). The majority of participants (78%) met criteria for a current anxiety disorder (nearly 100% of the sample reported symptoms that met criteria for either a current or lifetime anxiety disorder). A significant proportion (43%) also met threshold for Major Depressive Disorder (MDD) in the past 12-months. However, there was considerable heterogeneity for other disorders, with 20% of the sample meeting criteria for an eating disorder and 20% meeting threshold for at least one substance use disorder.

Over the 14-day observational period, there were 23 instances of self-injurious behavior (**Table 6**). Scratching/cutting were the most common methods, with 65% of the behaviors reportedly fitting in this category. Pinching, hitting, harming wounds, hair pulling, and pulling nails/skin were also observed, although they were much less common (one or two instances of each). The most commonly endorsed function of self-injurious behavior was to get rid of a thought/feeling (i.e., automatic negative reinforcement). 65% of the behaviors fulfilled this function. None of these behaviors were severe enough to require medical attention. Participants reportedly used crisis services (e.g., suicide prevention hotlines) in only two of these instances.

Additionally, there were 203 instances of suicidal thoughts over the two-week follow-up (**Table 6**; **Figure 16**). As previously mentioned, suicidal thoughts were more likely to occur in the evening as compared to the morning, and the likelihood of someone experiencing a suicidal thought decreased over the study. The majority of suicidal thoughts (95.57%) were of low severity with no plan or intention of acting. Less than 5% of the observations (9/203) included at least some uncertainty of acting. Notably, participants used crisis services in only four of these instances. Contemporaneously, suicidal thoughts were correlated with sadness (r = .33), shame (r

= .23), guilt (*r* = .19), fear (*r* = .19), rumination (*r* = .21) suppression (*r* = .16), self-invalidation (*r* = .15) distraction (*r* = .14), and momentary urgency (*r* = .25; global self-report urgency *r* = .01). Trajectories of suicidal thoughts over time for each participant are plotted in **Figure 16**. **Figure 17** includes both negative emotions plotted over time as well as suicidal thoughts. In both figures, there was notable between-person heterogeneity such that participants differed substantiality in the likelihood of experiencing suicidal thoughts over the study.

4.2 Hypothesis Testing

Hypothesis 1: Higher within-person negative emotions would prospectively predict self-injurious thoughts and behaviors.

To examine whether negative emotions prospectively predicted NSSI thoughts and suicidal thoughts, I tested whether a model that predicted SITBs from negative emotions (both time-lagged (*t-1)*, centered within-person as well as grand mean centered) produced a better fitting model than one that only included an intercept and an autoregressive parameter. Models were compared using Pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO), widely applicable information criteria (WAIC; Alston et al., 2005; Vehtari et al., 2017), and Pseudo-Bayesian Model Averaging with bootstrapping (Yao et al., 2018). Model comparisons are reported in **Table 13**. See **Table 14** for the results from all univariate models.

For NSSI thoughts, the negative emotion model did not significantly contribute to model fit, suggesting that neither within- nor between-person negative emotions predicted NSSI thoughts better than an empty model (Δ ELPD = 0.2, SE ELPD = 2.4; Δ WAIC = 0.2; SE = 2.4). Pseudo-BMA also suggested that the two models were equivalent (empty model weights = 46.4%; emotion model = 53.6%). Although model fit comparisons suggested that negative emotions provided limited information in predicting NSSI thoughts, individuals who were one standard deviation above the mean in negative emotions over the course of the study were between 23 and 97% more likely to experience an NSSI thought than individuals who experienced mean levels of negative emotions. This indicated that individuals who experienced higher levels of distress over the study were slightly more likely to experience thoughts of NSSI as compared to those who experienced low levels of distress.

For suicidal thoughts, a model that included within- and between-person negative emotions was a bitter fit than an empty model (PSIS-LOO: Δ ELPD = 9.3, SE ELPD = 4.2; Δ WAIC = 8.8; SE = 4.2). Pseudo-BMA weighted the negative emotion model by 97.9% as compared to 2.1% for an empty model. This suggests that both within- and between-person negative emotions were predictive of suicidal thoughts (**Figure 18**). Individuals who reported one standard deviation above the mean in negative emotions were between 22 and 120 percent more likely to experience a suicidal thought than individuals who reported mean levels. When individuals reported a one standard deviation increase relative to their own average levels of negative emotions, they were between 13 and 38 percent more likely to report a suicidal thought at the next time point.

Hypothesis 2. When individuals used more disengagement coping strategies, or acted more on impulse, they would be at an increased risk for SITBs.

4.2.1 Disengagement coping

For NSSI thoughts, the model with disengagement was not superior to an empty model (PSIS-LOO: Δ ELPD = 0.4, SE ELPD = 2.2; WAIC: Δ WAIC = 0.8; SE = 2.2). Pseudo-BMA with bootstrapping also suggested that the two models were comparable (empty model = 44.5%; coping model = 55.5%). In other words, there were no linear associations between either within-nor between-person disengagement strategies with the probability of someone experiencing a thought about self-harm.

As for suicidal thoughts, a model with disengagement coping was superior to an empty model (PSIS-LOO: Δ ELPD = 11.9, SE ELPD = 4.7; WAIC: Δ WAIC = 11.9; SE = 4.7). Pseudo-BMA weights also determined the model with disengagement coping was favored (98.7% for coping model as compared to 1.3% for the empty model). See **Table 13** and **Figure 18**. This was driven mostly by the within-person disengagement variable. When individuals used one standard deviation more disengagement coping strategies, relative to their own average, they were about 31% more likely to experience a suicidal thought at the same time point (95% CI = 1.15 – 1.49). When someone used about four standard deviations more disengagement coping strategies, relative to their own average, the probability they reported a suicidal thought was approximately .075. Alternatively, participants had a .025 probability of reporting a suicidal thought when they used two standard deviations fewer disengagement strategies relative to adaptive behaviors. Although the credible interval for the between-person coping variable included 1.00 (suggesting the lack of a linear association), individuals who were one standard deviation above the mean in their use of disengagement coping over time were an estimated 31% more likely to experience suicidal thoughts during the follow-up period (95% CI = 0.93 – 1.84). As suggested by **Figure 18**, individuals who used as much as many as four standard deviations more disengagement strategies than the sample average still only had about a one in ten chance of thinking about suicide at some point over the 14 days.

4.2.2 Momentary Urgency

In a model predicting NSSI thoughts, urgency did not provide more predictive information than a random intercept model (PSIS-LOO: Δ ELPD = 0.1, SE ELPD = 1.9; WAIC:

Δ WAIC = 0.1; SE = 1.9). Pseudo-BMA analysis similarly suggested that an empty model was weighted 52.50% compared to 47.5% for urgency. The credible intervals for both within- and between-person urgency included 1.00 suggesting the lack of a linear association.

For suicidal thoughts, the urgency model was a slightly worse than an empty model (PSIS-LOO: Δ ELPD = -1.7; SE ELPD = 1.3; WAIC: Δ WAIC = -1.8; SE = 1.3). Urgency was not a significant predictor of suicidal thoughts. Pseudo-BMA weights also favored the empty model (78.2% for the empty model compared to 21.8% for urgency). Additionally, the credible interval for both within-person nor between-person urgency included 1.00, suggesting that neither or these factors were significantly associated with suicidal thoughts. See **Figure 20** for the conditional effects from these models.

Exploratory Hypothesis 3:

4.2.3 Specific Emotions and NSSI Thoughts

Results from the exploratory tests of specific emotions are presented in **Table 14**. For both NSSI thoughts and suicidal thoughts, individual models were compared against an empty model and to the other specific emotion models to see if any of the particular states produced a better fitting model.

For NSSI thoughts, models with shame, fear, guilt and sadness were comparable to each other. All four emotions were superior to anger. Pseudo-BMA with bootstrapping suggested that weights were nearly evenly distributed between these four specific emotion models (~25%), while anger accounted for only 2% of the weights. Coefficients from individual models are presented in **Table 14**. Notably, there no within person effects present for models predicting NSSI thoughts. Between-person, sadness (OR = 1.31; 95% CI = 1.02 – 1.70), guilt (OR = 1.32; CI = 1.03 – 1.67), fear (OR = 1.38; CI = 1.08 – 1.75), and shame (OR = 1.34; CI = 1.05 – 1.68), all suggested that a one standard deviation increase in average levels of these specific emotions was associated with a 31 to 38 percent increase in the likelihood of someone thinking about self-harm over the course of the study. Although some of these specific models produced slightly better model fit than others based on PSIS-LOO and WAIC (e.g., shame and sadness > anger), Pseudo-BMA favored empty and composite negative affect models in comparison to any of these individual models.

4.2.4 Specific Emotions and Suicidal Thoughts

In examining associations between specific emotions and suicidal thoughts, a similar pattern emerged. Results from these models are also presented in **Table 14**. Model comparisons suggested that shame, sadness and fear contributed most to predictive performance, with guilt and anger contributing relatively little information. Between-person, fear, shame and sadness were associated with an increased probability of someone thinking about suicide over the course of the study, in which a one standard deviation increase in the average levels of these emotions was associated with a 62 to 77% increase in the likelihood of someone thinking about suicide. Within-person shame (OR = 1.17; CI = 1.05 – 1.32), guilt (OR = 1.15; CI = 1.01 – 1.30) and sadness (OR = 1.26; CI = 1.09 – 1.43) were all associated with an increased likelihood of someone experiencing a suicidal thought at the next timepoint.

Aim 2: Does state and/or trait levels of disengagement behaviors, or negative urgency, moderate the association between negative emotions and SITBs?

Aim 2 Hypothesis 1. Individuals who report more trait disengaged coping or negative urgency would exhibit stronger within-person associations between momentary negative emotions and SITBs

4.2.5 Disengagement Coping

For the prediction of NSSI thoughts, the interaction between within-person negative emotions and within-person disengagement coping did not produce a superior model as compared to a model with negative emotions alone (PSIS-LOO: Δ ELPD = -1.6; SE ELPD = 2.1; WAIC: Δ WAIC = -1.6; SE = 2.1). See **Figure 21** for the conditional probability of this interaction term. Visual inspection of the conditional effects also did not suggest the presence of an interaction between disengagement coping and negative emotions.

As for suicidal thoughts, an interaction between within-person negative emotion and within-person disengagement coping (i.e., momentary strategies) was superior to the model with just negative emotions (PSIS-LOO: Δ ELPD = 11.9, SE ELPD = 4.7; WAIC: Δ WAIC = 11.9; SE = 4.7). Pseudo-BMA weights also favored the interaction model with 97.4% of the weights leaning to this model and only 2.6% to the negative emotion one. **Figure 22** includes the conditional probabilities of this interaction. Visual inspection suggested that within-person disengagement coping did slightly attenuate the association between within-person negative emotions and suicidal thoughts, although the credible intervals were wide and overlapping. When individuals reported one standard deviation *below* their average level of disengagement strategies and experienced up to a six standard deviation increase in negative emotions, the probability they thought about suicide was close to zero. However, when people reported up to one standard deviation *more* disengagement coping strategies, and also felt up to a six standard deviation increase in negative emotions, they had a one in five (i.e., 20 percent) chance of thinking about suicide.

4.2.6 Momentary Urgency

Next, models were compared with an interaction between within-person urgency and within-person negative emotions in predicting NSSI thoughts. According to model fit indices, the interaction between urgency and emotions was a worse model than emotions alone (PSIS-LOO: Δ ELPD = -4.9, SE ELPD = 1.9; WAIC: Δ WAIC = -4.9; SE = 1.9). Pseudo-BMA weighted the emotions model 97.4% as compared to 2.6% for the interaction model. Visual inspection of the conditional effects (**Figure 21**) did not suggest an interaction.

For suicidal thoughts, the interaction model also did not produce a superior fitting model (PSIS-LOO: Δ ELPD = -2.3, SE ELPD = 1.6; WAIC: Δ WAIC = -2.3; SE = 1.6). Pseudo-BMA also weighted the univariate model more favorably (84.0% compared to 16.0% for the interaction model). The conditional effects, displayed in **Figure 22** did not suggest an effect was present.

Aim 2 Hypothesis 2. The relation between momentary associations of negative emotions and SITBs would be stronger when individuals also report higher levels of disengagement coping or more acting on impulse.

4.2.7 Baseline Disengagement Coping

In analyses testing the interaction between baseline disengagement coping strategies and within-person negative emotion predicting NSSI thoughts, the interaction model was not a better fitting model than one with negative emotions only (PSIS-LOO: Δ ELPD = -2.1, SE ELPD = 0.9; WAIC: Δ WAIC = -2.1; SE = 0.9). Pseudo-BMA agreed, as the emotion model was weighted to 85.8% compared to 14.2% for the interaction model. See **Figure 21** for the conditional effects. Visual inspection of this plot did not suggest the presence of an interaction.

For suicidal thoughts, the interaction between disengagement coping strategies and within-person negative emotion also produced an inferior model to univariate negative emotions (PSIS-LOO: Δ ELPD = -1.9, SE ELPD = 0.7; WAIC: Δ WAIC = -1.7; SE = 0.7). Similarly, Pseudo-BMA weighted the emotion model to 84.6% compared to 15.4% for the interaction model. The conditional effects plot (**Figure 22**) did not suggest an interaction was present.

4.2.8 Baseline Negative Urgency

Finally, models were compared between an interaction with baseline negative urgency and within-person negative emotion in predicting NSSI thoughts. The interaction model did not produce a better fitting model (PSIS-LOO: Δ ELPD = 0.8, SE ELPD = 1.2; WAIC: Δ WAIC = -0.9, SE = 1.2), suggesting this interaction did not help predict self-injurious thoughts. Pseudo-BMA was in agreement with this assessment, weighting the interaction model to 65.4% as compared to 34.6% for the negative emotion model. Visualization inspection of the conditional effects (**Figure 21**) did appear to suggest an interaction, although the Credible Intervals were very wide. Based on the minimal predictive performance of the interaction and the wide credible intervals, an interaction was determined to be absent.

In model comparisons between the interaction of baseline urgency and within-person negative emotions predicting suicidal thoughts, PSIS-LOO and WAIC implied the negative emotion univariate model produced a better fitting model than one with an interaction (PSIS-LOO: Δ ELPD = -2.6, SE ELPD = 0.5; WAIC: Δ WAIC = -2.5; SE = 0.5). Pseudo-BMA was in alignment as the emotion model was weighted by 92.5% in comparison to the interaction model (7.5%). Visual inspection of the conditional effects (**Figure 22**) also suggested an interaction was absent.

4.3 Results Summary

Both within- and between-person negative emotions were predictive of suicidal thoughts, but not thoughts of self-harm. There was also some evidence that disengagement strategies, both within- and between-person, also predicted suicidal thoughts. These coping strategies attenuated the association between negative emotions and suicidal thoughts (but not NSSI thoughts). There was no evidence that urgency moderated the within-person association between negative emotions and SITBs. There was, however, some evidence that specific emotions were more related to SITBs than others (i.e., guilt, shame, sadness, and fear), in that internalizing negative emotions were more strongly associated with SITBs than externalizing emotions (e.g., anger).

Additionally, examinations of the bi-variate correlations hinted at some notable patterns between suicidal thoughts and specific coping strategies. Rumination, suppression, self-invalidation, and distraction were weakly correlated with contemporaneous reports of suicidal thoughts. Finally, the way urgency was assessed was associated with divergent effects as suicidal thoughts were correlated with momentary urgency at $r = .25$ but were not correlated with global self-report urgency ($r = .01$).

Chapter 5: Discussion

The present study aimed to explore momentary affect, coping, and impulsivity as near-term risk-factors of SITBs in youth. Overall, results from this study point to the strong association between emotions and suicidal thoughts, the divergent relations between specific emotions and SITBs, and the proximal dynamics between disengagement strategies and SITBs. Moreover, these disengagement strategies attenuated the association between negative emotions and SITBs. Evidence for the relation between urgency and SITBs was more limited.

5.1 Negative Affect is Robustly Associated with SITBs

These results are compatible with prior research documenting the strong link between negative affect and SITBs (Kuehn, Harned, Foster, Song, Smith, & King, 2020; Kleiman et al., 2018; Mou et al., 2018; Kiekens et al., 2020). Negative emotions appear to be a robust proximal predictor of suicidal thoughts, although due to the low base rate of suicidal thoughts, negative affect alone is not likely to be a very sensitive nor specific predictor. Indeed, examination of the conditional effects suggests that even when someone was one standard deviation above their own average level of negative emotions, they still had only about a one in 20 (5%) chance of experiencing a suicidal thought. This means a clinician would be wrong on many occasions if using elevations in distress as the only predictor of suicidal thoughts. Although negative affect appears to be proximally related to suicidal thinking, the identification of other variables that attenuate this association is crucial for both improving prediction models and developing more efficacious interventions.

These findings also align with prior studies of specific negative emotions which found that internalizing affect (i.e., fear, guilt, shame, and sadness) were more closely related to SITBs than externalizing affect (Victor et al., 2019). Although not tested in the present study, other research theorizes that some of these internalizing negative emotions (e.g., guilt, shame) are likely to remain increased following SITBs (Bresin, 2020). This hypothesis proposes that, while SITBs may decrease negative emotion overall, there may be conflicting effects based on specific emotional states, with sadness potentially decreasing post-SITB but shame increasing. Rather than treating negative affect as a uniform construct, more specificity is needed to tease apart these unique patterns. In addition to a positive/negative valence of emotion, other researchers argue that arousal is a key dimension (Barrett, 1998). In the present study, sadness, a low arousal emotion (Kessler & Staudinger, 2009), was most strongly associated with suicidal thoughts in bivariate correlations. Future research teasing apart these specific affective experiences, as well as emotional arousal is warranted. Nonetheless, these findings suggest that treatments for SITBs should continue to focus on increasing an individuals' ability to cope with specific negative emotions. Dialectical behavior therapy (DBT; Linehan, 1993), a cognitive-behavioral intervention which teaches individuals how to identify and manage specific negative emotions, appears particularly promising for youth at high-risk for suicide (McCauley et al., 2018).

5.2 Coping Strategies Moderate the Association Between Emotion and Suicidal Thoughts

There were also some notable patterns between coping strategies and SITBs. At baseline, the youth in this sample reported they relied on more involuntary forms of coping to manage stressful peer relationships, suggesting a possible skills deficit in these effortful forms of coping. Additionally, participants in this study reportedly used higher levels of self-blame and rumination emotion regulation strategies at the initial assessment. This result matched previous findings in which youth with more general internalizing problems were also elevated on these specific subscales (Garnefski et al., 2005). Furthermore, baseline interviews of lifetime SITBs revealed that youth in this study started self-harming around 13-years old. As the development of self-regulation skills is crucial for later adjustment (Eisenberg et al., 2010), and the lack of such skills are related to suicide risk (Zlotnick et al., 1997), these findings suggest that youth may benefit from cognitive-behavioral based interventions, which teach alternative coping strategies (Wenzel et al., 2016). Youth showing signs of suicide risk should be directed to these interventions ideally in middle school, prior to the onset of SITBs.

In the follow-up data, rumination, self-invalidation, suppression, and distraction were all weakly correlated with thoughts of suicide. Likewise, within-person changes in disengagement coping were associated with a higher likelihood of thinking about suicide. Disengagement forms of coping attenuated the association between negative emotions and SITBs, signifying these coping strategies increased participants' suicide risk when they felt higher levels of emotion. Continuing to teach youth alternative, more effective, coping strategies may be particularly promising. Strategies for managing particularly high levels of negative emotions, such as distress tolerance skills appear especially relevant (Denckla et al., 2015). The replacement of disengagement forms of coping with more adaptive forms of coping is already the focus of many cognitive-behavioral interventions (Neacsiu et al., 2014), and technology-based solutions are currently being developed to teach these strategies in-vivo (Schroeder et al., 2018). The present study indicates this is a promising direction, although one should interpret these results cautiously findings need to be replicated in a larger sample size. This is the particularly important given the low base rate of SITBs observed in the present analysis.

5.3 Relation between SITBs and Impulsivity is Complicated

There was some, albeit contradictory, evidence for an association between impulsivity and SITBs. On the one hand, there was indication that within-person urgency was associated with suicidal thoughts. Bivariate correlations revealed a correlation of r = .25 between momentary urgency and suicidal thoughts. Notably, this matches meta-analytic findings of the effect size between urgency and SITBs (Berg et al., 2015). However, due to a researcher error, half of the participants received items that examined trait-based impulsivity instead of how impulsive they felt in the moment. The correlation between trait-based items and suicidal thoughts was approximately zero. There was some hint that the question type moderated the association between urgency and suicidal thoughts, signifying there may be an association between momentary urgency and suicidal thoughts. Future research with a larger sample size, and with only momentary items of urgency, is needed to confirm this association.

Predictive analyses did not find an association between urgency and SITBs. A possible explanation for the lack of between-person differences may be due to the lack of a control group in the present study. Klonsky & May (2010) found that negative urgency was able to distinguish between individuals who thought about suicide from those who never did, however, levels of urgency were unable to differentiate between people who attempted suicide from those who only thought about suicide. The negative skewness of the urgency distribution in the current study may indicate that the entire sample was elevated on this facet of impulsivity, meaning there may not have been enough variance to differentiate between individuals who thought about suicide during the study from those who did not. However, a meta-analysis reported that the association between trait impulsivity and suicidal behavior was small (Anestis et al., 2014). It is therefore questionable whether the association would be present even if this study did have a control group.

5.4 Sexual Minority Youth Are Particularly Vulnerable

It was surprising that this sample was composed of mostly non-heterosexual youth (70% of the sample). Although this may represent a biased sample, previous studies have found elevated rates among sexual minority youth (Kuper et al., 2018; Mustanski & Liu, 2013; Silva et al., 2015), and estimates suggest that sexual minority youth are three times more likely to attempt suicide (rate is 4% for general population; 11-12% for sexual minority; Hottes et al., 2016; Kessler et al., 1999). Additionally, Cha et al. (2018) found that studies of SITBs often did not ask about, or publish, demographic information regarding sexual minority status. This may mean that sample compositions similar to the present study could actually be quite common in SITB research.

Within sexual minority subgroups, bisexual and lesbian females accounted for the largest group (50% of the overall sample). This matches with previous research which also found bisexual and mostly gay participants to be at an increased risk (Horwitz et al., 2020; Kuehn et al., 2019). In the present sample, there were only four participants identifying as gender minority (e.g., trans gender). This number was still over-representative relative to the general population (Collin et al., 2016), however represents too few to analyze in much detail. More research regarding mechanisms that account for an increased risk of suicide among sexual and gender minority youth is needed, and it is imperative that sexual and gender minority youth receive treatment services that is affirming of their identities (Herek & Garnets, 2007; van der Miesen et al., 2020).

5.5 Idiographic Methods are a Promising Direction

There was considerable heterogeneity in the current sample. For example, a little more than half the sample did not experience a single suicidal thought over the current study. Two participants, however, reported that suicidal thoughts were present in more than half of their surveys, meaning these two participants accounted for a large percentage of the 203 observations of suicidal thoughts. Therefore, the overall probability of someone experiencing a suicidal thought, was not uniform, suggesting that the odds ratios and conditional effects reported in the current study were a bit misleading. For example, the present study found that within-person negative emotions increased the odds of someone experiencing a suicidal thought by .25. This suggests that someone's risk of thinking about suicide increases 25% for each one standard deviation increase in negative emotions. While this may be true for the half of the sample that experienced a suicidal thought, this was driven mostly by the two participants who experienced the most suicidal thoughts and was certainly not true for the half of the sample that did not think about suicide at all over the two-week period.

This all implies that the present data violated both the "homogeneity of the population" and stationary conditions of ergodicity (Molenaar & Campbell, 2009). Violation of ergodicity makes it impossible to generalize a nomothetic-based within-person process to the individual level (Molenaar, 2004). Prior work has also found considerable heterogeneity in individuals at-risk of suicide (Allan et al., 2019; King et al., 2020; Kleiman, Turner, Fedor, et al., 2018). Due to the large of heterogeneity, and because psychologists are mostly interested on predicting risk at the individual level (i.e., "what is the probability that this particular client is going to think about suicide before the next session?"), idiographic methods (n = 1) are needed to examine person-specific risk factors of SITBs.

One recent study provided an example of how idiographic methods could be used in SITB research (Kuehn, Foster, Czyz, & King, *Under Review*). This study used intensive longitudinal data of youth recently discharged from psychiatric hospitalization and examined bi-directional links between coping and SITBs. Of the three individual models examined, there was considerable heterogeneity across participants such that some individuals exhibited strong associations between different coping strategies and suicidal thoughts, while one participant had no such link. These idiographic models have the potential to inform clinical care by providing a clinician with data-derived, person-specific treatment targets (Piccirillo et al., 2019), perhaps leading to more precision in the prediction of SITBs at the *individual-level.*

5.6 Limitations of the Current Study

There were a few limitations to the present study. First, as previously mentioned, there was a researcher error in the EMA assessment of impulsivity. Results suggested that the assessment of impulsivity affected the association between urgency and suicidal thoughts. It therefore remains unknown whether findings would have differed significantly if all participants received the same EMA items of impulsivity. Second, the data used for these nomothetic analyses were non-ergodic, limiting the ability to generalize within-person processes. Future idiographic research is needed to replicate findings.

Third, although the sample size of 60 was aligned with other intensive longitudinal studies of SITBs (Kuehn et al., 2020), it was still small. While this study was powered to test effects at the within-person level, a larger sample size would have been desirable for between-person analyses. Given the low base rate of SITBs, the small sample size also contributed to the low number of SITBs observed in the study. Both a larger sample size and a longer observations period could have led to more observations. Fourth, although the inclusion and exclusion criteria helped to obtain a relatively acute population, it is possible that the inclusion criteria were not stringent enough for ensuring a large number of SITB positive reports. For example, there were only 23 instances of self-injurious behavior and no reported suicide attempts. This limitation was somewhat offset by the specification of a zero-inflated distribution and focus on cognitions instead of behaviors, but it did preclude any analysis of behavior. It is likely that the inclusion criteria of a suicide attempt within the past year meant that participants were enrolled who were no longer at imminent risk. Recruitment from a psychiatric hospital or another facility handling a more acute population could have helped increase the number of SITB observations.

Fifth, all EMA data in this study were self-reported. It is possible that participants did not feel comfortable reporting on their SITBs as they were informed at the baseline session about limitations to confidentiality in case of imminent risk. Future studies incorporating passive forms of data collection are warranted, although this type of collection is largely still reliant on people self-reporting their thoughts of suicide and self-harm. Finally, other intensive longitudinal studies of suicidal thoughts have examined interpersonal variables such as connectedness, burdensomeness, and belongingness. Although the present study measured interpersonal stressors and coping responses to peer stress, the hypotheses of this study centered on intrapersonal variables. This was mainly driven in an attempt to explain the seemingly robust association between negative affect and SITBs, however, important predictors of SITBs could have been missed by the present study.

5.7 Implications for Theory

Theories of NSSI hypothesize that self-harm is maintained through negative reinforcement of distressing emotions (Nock & Prinstein, 2004), while theories of suicide emphasize interpersonal processes in the development of suicidal thoughts (Joiner, 2005; Klonsky & May, 2015). The present study found that both negative affect and disengagement coping strategies proximally predicted suicidal thoughts. Meta-analytic findings of intensive longitudinal studies also provides strong evidence for the affect regulation hypothesis in NSSI thoughts, NSSI behaviors, and suicidal thoughts (Kuehn et al., 2020), suggesting this negative reinforcement pathway may explain how SITBs are maintained.

It is important to mention that insights regarding the etiology of SITBs are largely absent from intensive longitudinal studies – the short observation window and recruitment strategies employed by these studies means that participants have mostly started to think about suicide or self-harm prior the initiation of data collection. Within an "ideation-to-action" framework, more work is needed to obtain a sample that experiences frequent self-harm and suicidal *behavior* during these observation periods to better understand what differentiates thoughts of suicide from instances in which someone actually attempts. Nonetheless, the present study does suggest that negative affect and disengagement coping strategies are critical proximal risk factors of suicidal thoughts, although the specificity of both of these factors as univariate predictors is questionable.

Although the present analysis is unable to add to the understanding in the etiology of SITBs, the heterogeneity present in the current study, as well as the lack of evidence for moderation, may suggest that equifinality (i.e., that a single outcome is determined by multiple risk factors that vary from person to person) and multi-finality (i.e., the same risk factor may result in many outcomes) are key principles relevant to SITB research (*see* Cicchetti & Rogosch [1996] for a primer on these concepts). Prior research does suggest some evidence for equifinality in the development of NSSI (Keenan et al., 2014), while other research highlights multiple pathways to suicide attempts (Flynn et al., 2016; Huang et al., 2020; Kuehn et al., 2019). Although still preliminary, concepts such as equifinality and multi-finality call into question the utility of universal and nomothetic-based theories as to the development of SITBs (*see* Klonsky [2019] for a counter-argument).

5.8 Future Directions

More intensive longitudinal studies with larger sample sizes and longer follow-up periods are warranted to obtain more observations of NSSI and suicidal behaviors. This type of data could shed light on “ideation-to-action” theories or provide stronger evidence for multiple pathways in the transition from ideation to behavior. Even for idiographic-based analysis, larger sample sizes could help in identifying subgroups of individuals who share common pathways. The use of burst designs, or multiple periods of intensive longitudinal windows separated by months and years,, could increase power while balancing participant response fatigue (Sliwinski, 2008).

As for the continued search for highly specific and sensitive predictive models, the current study suggests that highly accurate prediction of imminent risk will be very challenging. Emerging research suggests that a computerized-adaptive screening tool in emergency departments can be useful in discriminating between those likely to attempt suicide in the next three-months from those who will not attempt (King et al., 2021). It seems unlikely, however, that prediction as to the precise moment within those three months when someone is at imminent risk would be accurate.

The present study found that increases in within-person negative emotions predicted whether someone would think about suicide in the next few hours. In addition, there were specific coping strategies associated with SITBs, and these coping strategies strengthened the association between emotions and suicidal thoughts. Negative urgency was also correlated with suicidal thoughts at the same time-point, although more EMA research is needed to confirm this association due to the measurement error of the urgency variable. Internalizing emotions, such as guilt, shame, fear, and sadness, were correlated with SITBs, while anger was not. The utility of negative emotions as a univariate predictor is questionable, however, given the low base rate of suicidal thoughts and the low probability of someone experiencing a SITB even at high levels of negative emotions. Predictive models incorporating many more variables are likely to be more sensitive and specific (Walsh et al., 2017).

Future research should test whether Group Iterative Multiple Model Estimation (GIMME: Beltz & Gates [2017]), which simultaneously models group, sub-group, and individual-level patterns, is useful in highlighting person-specific associations between negative emotions and SITBs. Additionally, more studies of intensive longitudinal studies should take advantage of Bayesian estimation techniques to accurately convey uncertainty and incorporate previous research findings. The coefficients from the present analysis would be helpful in specifying the prior for those studies. Due to the apparent skills deficit these youth have in effortful forms of coping, and due to the association between specific disengagement coping strategies and SITBs, treatments should broaden and build effective behavioral skills for managing distressing emotions. Cognitive-behavioral based mobile health interventions appear promising in this front (Schroeder et al., 2018), particularly in teaching youth in-vivo coping strategies during periods of high negative emotions.

References

Achen, C. H. (2000). Why lagged dependent variables can suppress the explanatory power of other independent variables. *Annual Meeting of the Political Methodology Section of the American Political Science Association, UCLA*, *20*(22), 7–2000.

Allan, N. P., Gros, D. F., Lancaster, C. L., Saulnier, K. G., & Stecker, T. (2019). Heterogeneity in short-term suicidal ideation trajectories: Predictors of and projections to suicidal behavior. *Suicide and Life-Threatening Behavior*, *49*(3), 826–837.

Alston, C., Kuhnert, P., Choy, S. L., Mcvinish, R., & Mengersen, K. (2005). Bayesian Model Comparison : Review and Discussion. *International Statistical Insitute*, *55th session*.

Andrewes, H. E., Hulbert, C., Cotton, S. M., Betts, J., & Chanen, A. M. (2017). Ecological momentary assessment of nonsuicidal self-injury in youth with borderline personality disorder. *Personality Disorders: Theory, Research, and Treatment*, *8*(4), 357.

Anestis, M. D., Soberay, K. A., Gutierrez, P. M., Hernández, T. D., & Joiner, T. E. (2014). Reconsidering the Link Between Impulsivity and Suicidal Behavior. *Personality and Social Psychology Review*, *18*(4), 366–386. https://doi.org/10.1177/1088868314535988

Barrett, L. F. (1998). Discrete emotions or dimensions? The role of valence focus and arousal focus. *Cognition & Emotion*, *12*(4), 579–599.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software; Vol 1, Issue 1 (2015)* . https://www.jstatsoft.org/v067/i01

Bayarri, M. J., & Berger, J. O. (2004). The interplay of Bayesian and frequentist analysis. *Statistical Science*, 58–80.

Beavers, W. R., & Hampson, R. B. (1990). *Successful families: Assessment and intervention*.

WW Norton & Co.

Bell, B. A., Kromrey, J. D., & Ferron, J. M. (2009). Missing data and complex samples: The impact of listwise deletion vs. subpopulation analysis on statistical bias and hypothesis test results when data are MCAR and MAR. *Proceedings of the Joint Statistical Meetings, Survey Research Methods Section*, *26*, 759–4770.

Beltz, A. M., & Gates, K. M. (2017). Network Mapping with GIMME. *Multivariate Behavioral Research*, *52*(6), 789–804.

Berg, J. M., Latzman, R. D., Bliwise, N. G., & Lilienfeld, S. O. (2015). Parsing the heterogeneity of impulsivity: A meta-analytic review of the behavioral implications of the UPPS for psychopathology. *Psychological Assessment*, *27*(4), 1129.

Box, G. E. P., Jenkins, G. M., & Reinsel, G. (1970). Time series analysis: forecasting and control Holden-day San Francisco. *Box Time Series Analysis: Forecasting and Control*, Holden Day.

Bresin, K. (2020). Toward a unifying theory of dysregulated behaviors. *Clinical Psychology Review*, 101885.

Bresin, K., Carter, D. L., & Gordon, K. H. (2013). The relationship between trait impulsivity, negative affective states, and urge for nonsuicidal self-injury: A daily diary study. *Psychiatry Research*, *205*(3), 227–231.

Broderick, J. E., DeWitt, E. M., Rothrock, N., Crane, P. K., & Forrest, C. B. (2013). Advances in Patient-Reported Outcomes: The NIH PROMIS(®) Measures. *EGEMS (Washington, DC)*, *1*(1), 1015. https://doi.org/10.13063/2327-9214.1015

Bürkner, P.C. (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software; Vol 1, Issue 1 (2017)* . https://www.jstatsoft.org/v080/i01

Carpenter, B., Gelman, A., Hoffman, M. D., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M. A., Guo, J., Li, P., & Riddell, A. (2017). Stan: a probabilistic programming language. *Grantee Submission*, *76*(1), 1–32.

CDC (2020). *Web-based Injury Statistics Query and Reporting System (WISQARS)*. https://www.cdc.gov/injury/wisqars/index.html

Cha, C. B., Tezanos, K. M., Peros, O. M., Ng, M. Y., Ribeiro, J. D., Nock, M. K., & Franklin, J. C. (2018). Accounting for diversity in suicide research: Sampling and sample reporting practices in the United States. *Suicide and Life-Threatening Behavior*, *48*(2), 131–139.

Cicchetti, D., & Rogosch, F. A. (1996). Equifinality and multifinality in developmental psychopathology. *Development and Psychopathology*, *8*(4), 597–600.

Collin, L., Reisner, S. L., Tangpricha, V., & Goodman, M. (2016). Prevalence of transgender depends on the "case" definition: a systematic review. *The Journal of Sexual Medicine*, *13*(4), 613–626.

Compas, B. E., Jaser, S. S., Bettis, A. H., Watson, K. H., Gruhn, M., Dunbar, J. P., Williams, E., & Thigpen, J. C. (2017). Coping, Emotion Regulation, and Psychopathology in Childhood and Adolescence: A Meta-Analysis and Narrative Review. *Psychological Bulletin*.

Connor-Smith, J. K., Compas, B. E., Wadsworth, M. E., Thomsen, A. H., & Saltzman, H. (2000). Responses to stress in adolescence: measurement of coping and involuntary stress responses. *Journal of Consulting and Clinical Psychology*, *68*(6), 976.

Cyders, M. A., & Smith, G. T. (2008). Emotion-Based Dispositions to Rash Action: Positive and Negative Urgency. *Psychological Bulletin*, *134*(6), 807–828. https://doi.org/10.1037/a0013341

Czyz, E. K., Glenn, C. R., Busby, D., & King, C. A. (2019). Daily patterns in nonsuicidal self-injury and coping among recently hospitalized youth at risk for suicide. *Psychiatry Research*, *281*, 112588. https://doi.org/10.1016/j.psychres.2019.112588

Czyz, E.K., King, C. A., & Nahum-Shani, I. (2018). Ecological assessment of daily suicidal thoughts and attempts among suicidal teens after psychiatric hospitalization: Lessons about feasibility and acceptability. *Psychiatry Research*, *267*, 566–574.

Czyz, E.K., Horwitz, A. G., Arango, A., & King, C. A. (2019). Short-term change and prediction of suicidal ideation among adolescents: a daily diary study following psychiatric hospitalization. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *60*(7), 732–741. https://doi.org/10.1111/jcpp.12974

Davidson, C. L., Anestis, M. D., & Gutierrez, P. M. (2017). Ecological Momentary Assessment is a Neglected Methodology in Suicidolog*y, Archives of Suicide Research, 1118*. https://doi.org/10.1080/13811118.2015.1004482

Denckla, C. A., Bailey, R., Jackson, C., Tatarakis, J., & Chen, C. K. (2015). A novel adaptation of distress tolerance skills training among military veterans: Outcomes in suicide-related events. *Cognitive and Behavioral Practice*, *22*(4), 450–457.

Diop, A., Diop, A., & Dupuy, J.-F. (2016). c *Communications in Statistics - Simulation and Computation*, *45*(10), 3597–3614. https://doi.org/10.1080/03610918.2014.950743

Eisenberg, N., Spinrad, T. L., & Eggum, N. D. (2010). Emotion-related self-regulation and its relation to children’s maladjustment. *Annual Review of Clinical Psychology, 6*, 495–525.

Enders, C. K. (2010). *Applied missing data analysis*. Guilford press.

Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: a new look at an old issue. *Psychological Methods*, *12*(2), 121–138. https://doi.org/10.1037/1082-989X.12.2.121

First, M. B. (2014). Structured clinical interview for the DSM (SCID). *The Encyclopedia of Clinical Psychology*, 1–6.

Flynn, A. B., Johnson, R. M., Bolton, S.-L., & Mojtabai, R. (2016). Victimization of Lesbian, Gay, and Bisexual People in Childhood: Associations with Attempted Suicide. *Suicide and Life-Threatening Behavior*, *46*(4), 457–470. https://doi.org/10.1111/sltb.12228

Forkmann, T., Spangenberg, L., Rath, D., Hallensleben, N., Hegerl, U., Kersting, A., & Glaesmer, H. (2018). Assessing suicidality in real time: A psychometric evaluation of self-report items for the assessment of suicidal ideation and its proximal risk factors using ecological momentary assessments. *Journal of Abnormal Psychology*, *127*(8), 758–769. https://doi.org/10.1037/abn0000381

Franklin, J. C., Ribeiro, J. D., Fox, K. R., Bentley, K. H., Kleiman, E. M., Huang, X., Musacchio, K. M., Jaroszewski, A. C., Chang, B. P., & Nock, M. K. (2017). Risk factors for suicidal thoughts and behaviors: A meta-analysis of 50 years of research. *Psychological Bulletin*, *143*(2), 187–232. https://doi.org/10.1037/bul0000084

Garnefski, N., Kraaij, V., & Spinhoven, P. (2001). Negative life events, cognitive emotion regulation and emotional problems. *Personality and Individual Differences*, *30*(8), 1311–1327. https://doi.org/10.1017/S0003356100012952

Garnefski, N., Kraaij, V., & van Etten, M. (2005). Specificity of relations between adolescents' cognitive emotion regulation strategies and internalizing and externalizing psychopathology. *Journal of Adolescence*, *28*(5), 619–631.

Gelman, A., Simpson, D., & Betancourt, M. (2017). The Prior Can Often Only Be Understood in the Context of the Likelihood. In *Entropy* (Vol. 19, Issue 10). https://doi.org/10.3390/e19100555

Gross, J. J., & Thompson, R. A. (2007). *Emotion regulation: Conceptual foundations.*

Hallensleben, N., Glaesmer, H., Forkmann, T., Rath, D., Strauss, M., Kersting, A., & Spangenberg, L. (2019). Predicting suicidal ideation by interpersonal variables, hopelessness and depression in real-time. An ecological momentary assessment study in psychiatric inpatients with depression. *European Psychiatry*, *56*(2019), 43–50. https://doi.org/10.1016/j.eurpsy.2018.11.003

Hallensleben, N., Spangenberg, L., Forkmann, T., Rath, D., Hegerl, U., Kersting, A., Kallert, T. W., & Glaesmer, H. (2017). Investigating the dynamics of suicidal ideation. *Crisis*.

Hamaker, E. L., & Klugkist, I. (2011). Bayesian estimation of multilevel models. *Handbook of Advanced Multilevel Analysis*, 137–162.

Hamaker, E. L., & Wichers, M. (2017). No time like the present: Discovering the hidden dynamics in intensive longitudinal data. *Current Directions in Psychological Science*, *26*(1), 10–15.

Hamza, C. A., & Willoughby, T. (2015). Nonsuicidal self-injury and affect regulation: Recent findings from experimental and ecological momentary assessment studies and future directions. *Journal of Clinical Psychology*, *71*(6), 561–574.

Hastings, W. K. (1970). *Monte Carlo sampling methods using Markov chains and their applications*.

Hays, R. D., Martin, S. A., Sesti, A. M., & Spritzer, K. L. (2005). Psychometric properties of the Medical Outcomes Study Sleep measure. *Sleep Medicine*, *6*(1), 41–44. https://doi.org/https://doi.org/10.1016/j.sleep.2004.07.006

Hedegaard, H., Curtin, S. C., & Warner, M. (2020). *Increase in suicide mortality in the United States, 1999–2018*.

Hedegaard, H., & Warner, M. (2021). *Suicide mortality in the United States, 1999-2019* (N. C. for H. S. (U.S.) (ed.); Issue 398). http://dx.doi.org/10.15620/cdc:101761. https://stacks.cdc.gov/view/cdc/101761

Hepp, J., Carpenter, R. W., Störkel, L. M., Schmitz, S. E., Schmahl, C., & Niedtfeld, I. (2020). A systematic review of daily life studies on non-suicidal self-injury based on the four-function model. *Clinical Psychology Review*, 101888.

Herek, G. M., & Garnets, L. D. (2007). Sexual orientation and mental health. *Annu. Rev. Clin. Psychol.*, *3*, 353–375.

Hochard, K. D., Heym, N., & Townsend, E. (2015). The unidirectional relationship of nightmares on self-harmful thoughts and behaviors. *Dreaming*, *25*(1), 44.

Hoffman, M. D., & Gelman, A. (2014). The No-U-Turn sampler: adaptively setting path lengths in Hamiltonian Monte Carlo. *J. Mach. Learn. Res.*, *15*(1), 1593–1623.

Hofmann, W., & Patel, P. V. (2015). SurveySignal: A convenient solution for experience sampling research using participants' own smartphones. *Social Science Computer Review*, *33*(2), 235–253.

Honaker, J., King, G., & Blackwell, M. (2011). Amelia II: A Program for Missing Data. *Journal of Statistical Software; Vol 1, Issue 7 (2011)* . https://www.jstatsoft.org/v045/i07

Hong, R. Y. (2007). Worry and rumination: Differential associations with anxious and depressive symptoms and coping behavior. *Behaviour Research and Therapy*, *45*(2), 277–290.

Horwitz, A. G., Berona, J., Busby, D. R., Eisenberg, D., Zheng, K., Pistorello, J., Albucher, R., Coryell, W., Favorite, T., & Walloch, J. C. (2020). Variation in suicide risk among subgroups of sexual and gender minority college students. *Suicide and Life-Threatening*

Behavior, *50*(5), 1041–1053.

Horwitz, A. G., Hill, R. M., & King, C. A. (2011). Specific coping behaviors in relation to adolescent depression and suicidal ideation. *Journal of Adolescence*, *34*(5), 1077–1085.

Hottes, T. S., Bogaert, L., Rhodes, A. E., Brennan, D. J., & Gesink, D. (2016). Lifetime prevalence of suicide attempts among sexual minority adults by study sampling strategies: a systematic review and meta-analysis. *American Journal of Public Health*, *106*(5), e1–e12.

Huang, X., Ribeiro, J. D., & Franklin, J. C. (2020). The differences between suicide ideators and suicide attempters: Simple, complicated, or complex? In *Journal of Consulting and Clinical Psychology* (Vol. 88, Issue 6, pp. 554–569). American Psychological Association. https://doi.org/10.1037/ccp0000498

Husky, M., Swendsen, J., Ionita, A., Jaussent, I., Genty, C., & Courtet, P. (2017). Predictors of daily life suicidal ideation in adults recently discharged after a serious suicide attempt: A pilot study. *Psychiatry Research*, *256*, 79–84.

Ivey-Stephenson, A. Z., Demissie, Z., Crosby, A. E., Stone, D. M., Gaylor, E., Wilkins, N., Lowry, R., & Brown, M. (2020). Suicidal Ideation and Behaviors Among High School Students - Youth Risk Behavior Survey, United States, 2019. *MMWR Supplements*, *69*(1), 47–55. https://doi.org/10.15585/mmwr.su6901a6

Joiner, T. E. (2005). *Why people die by suicide.* Harvard University Press.

Kaurin, A., Dombrovski, A., Hallquist, M., & Wright, A. G. C. (2020). *Daily Suicidal Surge and Attempted Suicide in Borderline Personality Disorder*.

Keele, L., & Kelly, N. J. (2006). Dynamic models for dynamic theories: The ins and outs of lagged dependent variables. *Political Analysis*, 186–205.

Keenan, K., Hipwell, A. E., Stepp, S. D., & Wroblewski, K. (2014). Testing an equifinality model of nonsuicidal self-injury among early adolescent girls. *Development and Psychopathology*, *26*(3), 851.

Kessler, E.-M., & Staudinger, U. M. (2009). Affective experience in adulthood and old age: The role of affective arousal and perceived affect regulation. *Psychology and Aging*, *24*(2), 349.

Kessler, R. C., Borges, G., & Walters, E. E. (1999). Prevalence of and risk factors for lifetime suicide attempts in the National Comorbidity Survey. *Archives of General Psychiatry*, *56*(7), 617–626.

Kiekens, G., Hasking, P., Nock, M. K., & Boyes, M. (2020). Fluctuations in affective states and self-efficacy to resist non-suicidal self- injury as real-time predictors of non-suicidal self-injurious thoughts and behaviors. *Frontiers in Psychiatry*, *11*. https://doi.org/10.31234/osf.io/yjmc2

King, C. A., Brent, D., Grupp-Phelan, J., Casper, T. C., Dean, J. M., Chernick, L. S., Fein, J. A., Mahabee-Gittens, E. M., Patel, S. J., & Mistry, R. D. (2021). Prospective development and validation of the computerized adaptive screen for suicidal youth. *JAMA Psychiatry*.

King, C. A., Brent, D., Grupp-Phelan, J., Shenoi, R., Page, K., Mahabee-Gittens, E. M., Chernick, L. S., Melzer-Lange, M., Rea, M., & McGuire, T. C. (2020). Five profiles of adolescents at elevated risk for suicide attempts: Differences in mental health service use. *Journal of the American Academy of Child & Adolescent Psychiatry*, *59*(9), 1058–1068.

Kleiman, E. M., Coppersmith, D. D. L., Millner, A. J., Franz, P. J., Fox, K. R., & Nock, M. K. (2018). Are suicidal thoughts reinforcing? A preliminary real-time monitoring study on the potential affect regulation function of suicidal thinking. *Journal of Affective Disorders*, *232*(September 2017), 122–126. https://doi.org/10.1016/j.jad.2018.02.033

Kleiman, E. M., & Nock, M. K. (2018). Real-time assessment of suicidal thoughts and behaviors. *Current Opinion in Psychology*, *22*, 33–37. https://doi.org/10.1016/j.copsyc.2017.07.026

Kleiman, E. M., Turner, B. J., Chapman, A. L., & Nock, M. K. (2018). Fatigue Moderates the Relationship Between Perceived Stress and Suicidal Ideation: Evidence From Two High-Resolution Studies. *Journal of Clinical Child and Adolescent Psychology*, *47*(1), 116–130. https://doi.org/10.1080/15374416.2017.1342543

Kleiman, E. M., Turner, B. J., Fedor, S., Beale, E. E., Huffman, J. C., & Nock, M. K. (2017). Examination of real-time fluctuations in suicidal ideation and its risk factors: Results from two ecological momentary assessment studies. *Journal of Abnormal Psychology*, *126*(6), 726.

Kleiman, E. M., Turner, B. J., Fedor, S., Beale, E. E., Picard, R. W., Huffman, J. C., & Nock, M. K. (2018). Digital phenotyping of suicidal thoughts. *Depression and Anxiety*, *35*(7), 601–608.

Klonsky, E. D. (2019). The role of theory for understanding and preventing suicide (but not predicting it): A commentary on Hjelmeland and Knizek. *Death Studies*.

Klonsky, E. D., & May, A. (2010). Rethinking Impulsivity in Suicide. *Suicide and Life-Threatening Behavior*, *40*(6), 612–619. https://doi.org/10.1521/suli.2010.40.6.612

Klonsky, E. D., & May, A. M. (2015). The Three-Step Theory (3ST): A New Theory of Suicide Rooted in the “Ideation-to-Action” Framework. *International Journal of Cognitive Therapy*, *8*(2), 114–129. https://doi.org/10.1007/s10509-007-9498-4

Kuehn, K. S., Wagner, A., & Velloza, J. (2019). Estimating the Magnitude of the Relation between Bullying, E-Bullying, and Suicidal Behaviors among United States Youth, 2015. *Crisis*, *40*(3), 157–165. https://doi.org/10.1027/0227-5910/a000544

Kuper, L. E., Adams, N., & Mustanski, B. S. (2018). Exploring cross-sectional predictors of suicide ideation, attempt, and risk in a large online sample of transgender and gender nonconforming youth and young adults. *LGBT Health*, *5*(7), 391–400.

Lear, M. K., Wilkowski, B. M., & Pepper, C. M. (2019). A daily diary investigation of the defective self model among college students with recent self-injury. *Behavior Therapy*, *50*(5), 1002–1012.

Linehan, M.M., & Heard, H. . (1987). Treatment history interview (THI). *Unpublished Manuscript, University of Washington*.

Linehan, M.M., Comtois, K. A., Brown, M. Z., Heard, H. L., & Wagner, A. (2006). Suicide Attempt Self-Injury Interview (SASII): development, reliability, and validity of a scale to assess suicide attempts and intentional self-injury. *Psychological Assessment*, *18*(3), 303.

Mahtani, S., Melvin, G. A., & Hasking, P. (2018). Shame Proneness, shame coping, and functions of nonsuicidal self-injury (NSSI) among emerging adults: A developmental analysis. *Emerging Adulthood*, *6*(3), 159–171.

McCauley, E., Berk, M. S., Asarnow, J. R., Adrian, M., Cohen, J., Korslund, K., Avina, C., Hughes, J., Harned, M., & Gallop, R. (2018). Efficacy of dialectical behavior therapy for adolescents at high risk for suicide: A randomized clinical trial. *JAMA Psychiatry*, *75*(8), 777–785.

McCulloch, C. E., & Neuhaus, J. M. (2005). Generalized linear mixed models. *Encyclopedia of Biostatistics*, *4*.

Millner, A. J., Lee, M. D., Nock, M. K., Nock, M., Wang, P., Kessler, R., & Jenkins, R. (2015). Single-Item Measurement of Suicidal Behaviors: Validity and Consequences of Misclassification. *PLOS ONE*, *10*(10), e0141606.

https://doi.org/10.1371/journal.pone.0141606

Molenaar, P.C.M. (2004). A Manifesto on Psychology as Idiographic Science: Bringing the Person Back ...: EBSCOhost. *Measurement: Interdisciplinary Research and Perspectives, 2*(4), 201–218. https://web-a-ebscohost-com.ep.fjernadgang.kb.dk/ehost/pdfviewer/pdfviewer?vid=1&sid=257bbb8e-f698-4c63-8a11-d87feb3bbf63%40sessionmgr4010

Molenaar, P.C.M., & Campbell, C. G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science*, *18*(2), 112–117. https://doi.org/10.1111/j.1467-8721.2009.01619.x

Mou, D., Kleiman, E. M., Fedor, S., Beck, S., Huffman, J. C., & Nock, M. K. (2018). Negative affect is more strongly associated with suicidal thinking among suicidal patients with borderline personality disorder than those without. *Journal of Psychiatric Research*, *104,* 198–201. https://doi.org/10.1016/j.jpsychires.2018.08.006

Mustanski, B., & Liu, R. T. (2013). A Longitudinal Study of Predictors of Suicide Attempts Among Lesbian, Gay, Bisexual, and Transgender Youth. *Archives of Sexual Behavior, 42*(3), 437–448. https://doi.org/10.1007/s10508-012-0013-9

Neacsiu, A. D., Bohus, M., & Linehan, M. M. (2014). *Dialectical behavior therapy: An intervention for emotion dysregulation.*

Neacsiu, A. D., Fang, C. M., Rodriguez, M., & Rosenthal, M. Z. (2018). Suicidal Behavior and Problems with Emotion Regulation. *Suicide and Life-Threatening Behavior*, *48*(1), 52–74. https://doi.org/10.1111/sltb.12335

Neelon, B., Ghosh, P., & Loebs, P. F. (2013). A spatial Poisson hurdle model for exploring geographic variation in emergency department visits. *Journal of the Royal Statistical*

Society: Series A (Statistics in Society), *176*(2), 389–413. https://doi.org/https://doi.org/10.1111/j.1467-985X.2012.01039.x

Nock, M. K., & Favazza, A. R. (2009). Nonsuicidal self-injury: Definition and classification. In M. K. Nock (Ed.), *Understanding nonsuicidal self-injury: Origines, assessment, and treatment* (pp. 9–18). American Psychological Association.

Nock, M. K., & Prinstein, M. J. (2004). A functional approach to the assessment of self-mutilative behavior. *Journal of Consulting and Clinical Psychology, 72*(5), 885–890. https://doi.org/10.1037/0022-006X.72.5.885

O'Connor, R. C., O'Carroll, R. E., Ryan, C., & Smyth, R. (2012). Self-regulation of unattainable goals in suicide attempters: a two year prospective study. *Journal of Affective Disorders, 142*(1–3), 248–255.

Peters, E. M., Dong, L. Y., Thomas, T., Khalaj, S., Balbuena, L., Baetz, M., Osgood, N., & Bowen, R. (2020). Instability of suicidal ideation in patients hospitalized for depression: an exploratory study using smartphone ecological momentary assessment. *Archives of Suicide Research*, 1–14.

Piccirillo, M. L., Beck, E. D., & Rodebaugh, T. L. (2019). A clinician's primer for idiographic research: considerations and recommendations. *Behavior Therapy*, *50*(5), 938–951.

Posner, K., Brodsky, B., Yershova, K., Buchanan, J., & Mann, J. (2014). The Classification of Suicidal Behavior. In M. K. Nock (Ed.), *The Oxford Handbook of Suicide and Self-Injury* (pp. 7–22). Oxford University Press.

R Core Team. (2013). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing. http://www.r-project.org/.

Rabasco, A., & Sheehan, K. (2021). The use of intensive longitudinal methods in research on suicidal thoughts and behaviors: a systematic review. *Archives of Suicide Research*, 1–15.

Rath, D., De Beurs, D., Hallensleben, N., Spangenberg, L., Glaesmer, H., & Forkmann, T. (2019). Modelling suicide ideation from beep to beep: Application of network analysis to ecological momentary assessment data. *Internet Interventions*, *18*, 100292. https://doi.org/10.1016/J.INVENT.2019.100292

Rodríguez-Blanco, L., Carballo, J. J., & Baca-García, E. (2018). Use of Ecological Momentary Assessment (EMA) in Non-Suicidal Self-Injury (NSSI): A systematic review. *Psychiatry Research*, *263*, 212–219. https://doi.org/10.1016/j.psychres.2018.02.051

Salim, S., Robinson, M., & Flanders, C. E. (2019). Bisexual women's experiences of microaggressions and microaffirmations and their relation to mental health. *Psychology of Sexual Orientation and Gender Diversity*, *6*(3), 336.

Schafer, J. L., & Graham, J. W. (2002). Missing data: our view of the state of the art. *Psychological Methods*, *7*(2), 147.

Schroeder, J., Wilkes, C., Rowan, K., Toledo, A., Paradiso, A., Czerwinski, M., Mark, G., & Linehan, M. M. (2018). Pocket skills: A conversational mobile web app to support dialectical behavioral therapy. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–15.

Schwarzer, G. (2007). meta: An R package for meta-analysis. *R News*, *7*(3), 40–45.

Selby, E. A., Kranzler, A., Lindqvist, J., Fehling, K. B., Brillante, J., Yuan, F., Gao, X., & Miller, A. L. (2019). The Dynamics of Pain During Nonsuicidal Self-Injury. *Clinical Psychological Science*, *7*(2), 302–320. https://doi.org/10.1177/2167702618807147

Shankman, S. A., Funkhouser, C. J., Klein, D. N., Davila, J., Lerner, D., & Hee, D. (2018). Reliability and validity of severity dimensions of psychopathology assessed using the

Structured Clinical Interview for DSM-5 (SCID). *International Journal of Methods in Psychiatric Research*, *27*(1), e1590.

Sheppes, G., Suri, G., & Gross, J. J. (2015). Emotion regulation and psychopathology. *Annual Review of Clinical Psychology*, *11*, 379–405.

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological Momentary Assessment. *Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Silva, C., Chu, C., Monahan, K. R., & Joiner, T. E. (2015). Suicide risk among sexual minority college students: A mediated moderation model of sex and perceived burdensomeness. *Psychology of Sexual Orientation and Gender Diversity*, *2*(1), 22.

Sliwinski, M. J. (2008). Measurement-burst designs for social health research. *Social and Personality Psychology Compass*, *2*(1), 245–261.

Stegmueller, D. (2013). How many countries for multilevel modeling? A comparison of frequentist and Bayesian approaches. *American Journal of Political Science*, *57*(3), 748–761.

Taylor, P. J., Jomar, K., Dhingra, K., Forrester, R., Shahmalak, U., & Dickson, J. M. (2017). A meta-analysis of the prevalence of different functions of non-suicidal self-injury. *Journal of Affective Disorders*, *227*, 759–769. https://doi.org/10.1016/j.jad.2017.11.073

van der Miesen, A. I. R., Steensma, T. D., de Vries, A. L. C., Bos, H., & Popma, A. (2020). Psychological functioning in transgender adolescents before and after gender-affirmative care compared with cisgender general population peers. *Journal of Adolescent Health*, *66*(6), 699–704.

Vansteelandt, K., Houben, M., Claes, L., Berens, A., Sleuwaegen, E., Sienaert, P., & Kuppens, P.

(2017). The affect stabilization function of nonsuicidal self injury in Borderline Personality Disorder: An Ecological Momentary Assessment study. *Behaviour Research and Therapy*, *92*, 41–50. https://doi.org/10.1016/j.brat.2017.02.003

Vasishth, S., Nicenboim, B., Beckmna, M. E., Li, F., & Jong Kong, E. (2018). Baysian data analysis in the phonetic sciences: A tutorial introduction. *Journal of Phonetics*, *71*, 147–161.

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, *27*(5), 1413–1432.

Victor, S.E., Scott, L. N., Stepp, S. D., & Goldstein, T. R. (2019). I Want You to Want Me: Interpersonal Stress and Affective Experiences as Within-Person Predictors of Nonsuicidal Self-Injury and Suicide Urges in Daily Life. *Suicide and Life-Threatening Behavior*, *49*(4), 1157–1177. https://doi.org/10.1111/sltb.12513

Victor, S.E., & Klonsky, E. D. (2014). Daily emotion in non-suicidal self-injury. *Journal of Clinical Psychology*, *70*(4), 364–375. https://doi.org/10.1002/jclp.22037

Vine, V., Victor, S. E., Mohr, H., Byrd, A. L., & Stepp, S. D. (2020). Adolescent suicide risk and experiences of dissociation in daily life. *Psychiatry Research*, *287*, 112870. https://doi.org/10.1016/j.psychres.2020.112870

Walsh, C. G., Ribeiro, J. D., & Franklin, J. C. (2017). Predicting Risk of Suicide Attempts Over Time Through Machine Learning. *Clinical Psychological Science*, *5*(3), 457–469. https://doi.org/10.1177/2167702617691560

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063.

Wenzel, A., Dobson, K. S., & Hays, P. A. (2016). *Cognitive behavioral therapy techniques and strategies.* American Psychological Association.

Whiteside, S. P., & Lynam, D. R. (2001). The Five Factor Model and impulsivirty: Using a structural model of personality to understand impulsivity. *Personality and Individual Differences*, *30*, 669–689.

Wolford-Clevenger, C., Hugley, M. J., McNulty, J., Elledge, L. C., Cropsey, K., & Stuart, G. L. (2019). The risk-benefit ratio of studying psychiatric symptoms via daily diary methods. *Accountability in Research*, *26*(8), 498–511.

Zhang, Z. (2016). Multiple imputation for time series data with Amelia package. *Annals of Translational Medicine*, *4*(3), 56. https://doi.org/10.3978/j.issn.2305-5839.2015.12.60

Zlotnick, C., Donaldson, D., Spirito, A., & Pearlstein, T. (1997). Affect regulation and suicide attempts in adolescent inpatients. *Journal of the American Academy of Child & Adolescent Psychiatry*, *36*(6), 793–798.

Table 1

Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
1. Age 16-20	1. Unable to read.
2. One incident of SIB (suicide attempt in the past year OR NSSI in the past two weeks) AND current SI (SIQ-JR ≥ 31)	
3. Willing to come to office for consent, identity/age verification, and baseline[1].	
4. English speaking	
5. Parent/primary caregiver consent (for those 16-17) OR adult (18-20) participant consent	
6. Adolescent assent to study (16-17)	
7. Has internet and smart phone access	

Note. [1]This criterion was relaxed when shifting to virtual baselines in the midst of the COVID-19 global pandemic.

Table 2

Participant Demographic and Descriptive Data

Baseline Characteristic	Mean	SD
Age	18.58	1.25

Baseline Characteristic	*n*	%
Male Sex	14	23.33
Heterosexual Males	6	10
Gay or bisexual Males	6	10
Other orientation	2	3.33
Female Sex	46	76.67
Heterosexual Females	12	20
Lesbian or bisexual females	30	50
Other Females	4	6.67
Ethnicity		
White	32	53.33
Asian	13	23.67
Black	2	3.33
Native American	0	0
More than one race	5	8.33
Hispanic	7	11.67
Middle Eastern	1	1.67

Table 3

Means and Standard Deviations from Baseline Self-Report Measures

Scale	M	SD
RSQ Primary Coping	0.16	0.03
RSQ Secondary Coping	0.19	0.04
RSQ Disengagement Coping	0.16	0.02
RSQ Involuntary Engagement	0.29	0.04
RSQ Involuntary Disengagement	0.21	0.04
CERQ Self-Blame	3.92	0.96
CERQ Acceptance	3.35	0.82
CERQ Rumination	3.71	0.84
CERQ Positive Refocusing	2.02	0.98
CERQ Positive Reappraisal	2.63	1.13
CERQ Perspective Taking	2.83	1.04
CERQ Catastrophizing	2.70	0.90
CERQ Blaming Others	2.25	0.91
UPPS Negative Urgency	2.92	0.67
UPPS Premeditation	2.87	0.58
UPPS Sensation Seeking	2.64	0.62
UPPS Perseverance	2.71	0.55
UPPS Positive Urgency	2.32	0.83
PROMIS Anxiety	66.22	7.56
PROMIS Depression	66.74	6.44
PROMIS Anger	60.89	9.80
Sleep Disturbance	62.10	23.91
Sleep Adequacy	32.67	25.90
Sleep Problems Index	63.05	18.85
SFI Health Competence	3.12	0.94
SFI Conflict	2.82	0.90
SFI Cohesion	3.30	0.68
SFI Leadership	2.78	0.79
SFI Expressiveness	2.99	0.80
SIQ-JR Screen	51.08	14.52
SIQ-JR Baseline	45.25	14.57

Note. RSQ = Responses to Stress Questionnaire; CERQ = Cognitive Emotion Regulation Questionnaire; UPPS = Urgency, Premeditation, Perseverance, Sensation Seeking, and Positive Urgency Impulsive Behavior Scale; SFI = Self-Report Family Interview; SIQ-JR = Suicide Ideation Questionnaire (SIQ-JR); Administered during both the screening survey and the baseline session.

Table 4

Frequencies and Descriptive Data from Semi-Structured Assessments

THI/SASII	M	SD
Number of lifetime crisis services	1.50	1.90
Lifetime outpatient services	3.55	3.28
Proportion receiving any form of DBT	30%	--
Number of lifetime SIB	294.72	613.07
Number of lifetime SAs[a]	2.25	3.35
Age of first lifetime SIB	13.76	2.58

SASII	Total Number Reported	% of total
Lifetime Actual Suicide Attempts	93	68.38%
Lifetime Aborted Suicide Attempts	38	27.94%
Lifetime Interrupted Suicide Attempts	5	3.68%
	136	

SCID-5	Current		Lifetime	
	n	%	*n*	%
MDD	26	43.33	21	35.00
Bipolar Disorder (I or II)	8	13.33	5	8.33
Any Substance Abuse	12	20.00	19	31.67
Any Anxiety Disorder	47	78.33	13	21.67
Any Eating Disorder	12	20.00	7	11.67

Note. THI = Treatment History Interview; SASII = Suicide Attempt Self-Injury Interview; SCID-5 = Structured Clinical Interview for DSM-5; SIB = Self-injurious behavior; SA = Suicide attempts.

[a.] 81.67% of sample reported lifetime history of behavior meeting definition of any suicidal behavior (i.e., aborted, interrupted and actual suicide attempt); 65.00% for actual suicide attempt

Table 5

Frequencies and Descriptive Data from Ecological Momentary Assessments

Variable	M	SD	*n*	%
Anger	10.38	21.44		
Shame	14.56	25.35		
Sadness	21.43	28.31		
Fear	13.26	23.31		
Guilt	15.94	26.75		
Joy	44.71	25.51		
Love	46.90	27.60		
Calm	53.58	28.26		
Attentive	47.68	27.57		
Confident	45.61	26.52		
Rumination			622	14.74
Problem Solving			668	15.83
Self-Invalidation			533	12.63
Suppression			484	11.47
Distraction			611	14.48
Avoidance			757	17.94
Acceptance			875	20.74
Reappraisal			441	10.45
Social Support			99	2.35
Disengagement	0.66	1.07		
Adaptive	0.68	0.85		
Interpersonal Stress			241	5.71
Discrimination			15	0.36
Other Stress			774	18.35
Work/School Stress			441	10.45
Peer/Relative Stress			171	4.05
Urgency GSR	2.82	0.80		
Momentary Urgency	28.94	25.72		
SIT			463	10.97
NSSI behaviors			23	<.01
Suicidal thoughts	0.08	0.36	203	4.81

Note. GSR = global self-report; SIT = self-injurious thoughts; NSSI = non-suicidal self-injurious behavior; SI = suicidal intent

Table 6

Descriptive Data of Non-Suicidal Self-Injurious Behavior and Suicidal Intent

SITB variable	*n*	%
NSSI Behavior		
Method		N = 23
Hair Pulling	1	4.35%
Harming of Wound	1	4.35%
Hitting Body	1	4.35%
Pinching	1	4.35%
Pulling of nails/skin	2	8.70%
Scratching/cutting	15	65.22%
Function		
To feel something (APR)	6	26.09%
To get rid of a thought/feeling (ANR)	15	65.22%
Self-punishment	2	8.70%
SI		
Current Intention to Kill Self		N = 4219
0 = None; not planning to die by suicide	3229	76.53
1 = Thought about it but no plan	132	3.13
2 = Thought about it but no intention of acting	62	1.47
3 = Thought about it, started to plan, but unsure of acting	9	0.21
4 = Thought about specific plan and am thinking of acting	0	0%

Note. NSSI = Non-suicidal self-injury; SI = suicidal intent

Table 7

Correlation Table of Baseline Data

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Primary Coping												
2. Secondary Coping	.37**											
3. Disengagement Coping	-.46**	-.39**										
4. Invol. Engagement	-.46**	-.64***	-.01									
5. Invol. Disengagement	-.61***	-.59***	.27*	.12								
6. Self-Blame	-.18	-.55***	.09	.36**	.37**							
7. Acceptance	-.07	.22	-.19	.13	-.21	.11						
8. Rumination	-.25	-.23	-.05	.36**	.17	.37**	.29*					
9. Positive Refocusing	-.19	.34**	-.01	-.27	.09	-.11	.23	.10				
10. Positive Reappraisal	.17	.48***	-.40**	-.21	-.23	-.25	.29*	.25	.45**			
11. Perspective Taking	-.05	.22	.14	-.17	-.11	.03	.31*	.11	.48***	.52***		
12. Catastrophizing	-.31*	-.33*	.24	.26*	.25	.23	.10	.34**	-.03	.02	-.08	
13. Blaming Others	-.31*	-.08	.16	-.05	.34**	-.12	-.13	.10	.12	.17	.13	.52***
14. Negative Urgency	-.24	-.22	-.13	.29*	.28*	.14	.03	.29*	0	.20	.23	.11
15. Premeditation	.25	.30*	.07	-.34**	-.28*	-.22	.22	-.11	.27*	.20	.19	.01
16. Sensation Seeking	-.20	.16	-.16	.07	.05	-.09	.25	.24	.17	.44***	.27*	.03
17. Perseverance	.05	.19	-.02	0	-.27*	-.13	.34**	-.05	.10	.24	.05	.02
18. Positive Urgency	-.20	.02	-.24	.06	.28*	-.01	.21	.18	.29*	.40**	.15	.07
19. PROMIS Anxiety	-.39**	-.44***	.25	.41**	.30*	.37**	.13	.51***	-.07	.04	.14	.41**
20. PROMIS Depression	-.34**	-.50***	.36**	.41**	.25	.45***	.12	.51***	-.10	-.04	.18	.32*
21. PROMIS Anger	-.48***	-.20	.21	.29*	.25	.12	.11	.32*	.01	.11	.27*	.19
22. Sleep Disturbance	-.34*	-.22	.21	.24	.20	.13	-.07	.10	.04	-.13	-.07	.02
23. Sleep Adequacy	.17	.28*	-.19	-.20	-.15	-.20	-.04	-.14	.04	.10	-.05	.11
24. Sleep Problems Index	-.36**	-.35**	.22	.37**	.21	.27*	.04	.23	0	-.10	.02	.01
25. SFI Health Competence	-.21	-.18	.28*	.06	.21	.01	-.18	-.06	-.08	-.20	.21	-.20
26. SFI Conflict	-.25	-.25	.22	.24	.16	.07	-.06	.13	-.04	-.12	.20	-.02
27. SFI Cohesion	-.04	.08	.07	-.21	.13	-.01	-.12	-.17	.05	.01	.21	-.36**
28. SFI Leadership	-.04	-.15	.02	.05	.15	.11	-.08	0	.08	-.11	.05	-.29*

29. SFI Expressiveness	-.20	-.05	.18	0	.13	0	-.05	-.18	.05	-.23	.02	-.22

Note. * p < .05; ** p < .01; *** p < .001

Variable	13	14	15	16	17	18	19	20	21	22	23	24
13. Blaming Others												
14. Negative Urgency	.24											
15. Premeditation	-.09	-.54***										
16. Sensation Seeking	.31	.60***	-.32*									
17. Perseverance	-.23	-.26*	.36**	.08								
18. Positive Urgency	.15	.54***	-.23	.54***	-.12							
19. PROMIS Anxiety	.25	.36**	-.14	.27*	-.05	.33**						
20. PROMIS Depression	.12	.30*	-.14	.18	-.07	.09	.74***					
21. PROMIS Anger	.30*	.54***	-.44***	.48***	-.27*	.44***	.56***	.50***				
22. Sleep Disturbance	.02	.34**	-.28*	.28*	.03	.33*	.37**	.30*	.32*			
23. Sleep Adequacy	-.03	-.11	-.03	0	-.09	-.07	-.30*	-.28*	-.10	-.31*		
24. Sleep Problems Index	.02	.36**	-.27*	.29*	.03	.34**	.52***	.48***	.38**	.86***	-.67***	
25. SFI Health Competence	.09	.02	0	-.06	-.06	-.16	.14	.16	.16	.30*	-.20	.30*
26. SFI Conflict	.08	.14	-.02	.04	-.10	-.08	.24	.29*	.27*	.40**	-.2	.43***
27. SFI Cohesion	-.01	-.02	-.02	-.05	-.08	-.08	-.19	-.03	.01	-.07	.17	-.13
28. SFI Leadership	-.25	.07	-.06	-.07	-.02	.06	.04	.16	.01	.12	-.12	.15
29. SFI Expressiveness	-.13	-.25	.09	-.14	.14	-.16	-.10	0	-.05	.14	-.09	.11

Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Variable	25	26	27	28	29
25. SFI Health Competence					
26. SFI Conflict	.87***				
27. SFI Cohesion	.62***	.35**			
28. SFI Leadership	.39**	.33**	.41**		
29. SFI Expressiveness	.71***	.56***	.52***	.53***	

Note. * $p < .05$; ** $p < .01$; *** $p < .001$

Table 8

Correlation Tables for Ecological Momentary Assessment Data

Variable	1	2	3	4	5	6	7	8	9	10
1. Anger										
2. Shame	.31***									
3. Sadness	.39***	.52***								
4. Fear	.31***	.47***	.48***							
5. Guilt	.27***	.72***	.49***	.47***						
6. Joy	-.08***	-.20***	-.20***	-.13***	-.21***					
7. Love	-.02	.11***	-.11***	-.09***	-.13***	.68***				
8. Calm	-.17***	-.14***	-.18***	-.25***	-.15***	.50***	.43***			
9. Attentive	-.01	-.16***	-.11***	-.09***	-.13***	.53***	.48***	.54***		
10. Confident	0	-.13***	-.21***	-.14***	-.14***	.62***	.57***	.53***	.57***	
11. Rumination	.23***	.31***	.38***	.37***	.29***	-.20***	-.16***	-.22***	-.11***	-.16***
12. Problem Solving	.03	.04*	0	.11***	.06***	0	-.01	-.08***	-.01	-.01
13. Self-Invalidation	.14***	.43***	.29***	.23***	.46***	-.25***	-.21***	-.15***	-.14***	-.12***
14. Suppression	.11***	.29***	.27***	.15***	.32***	-.22***	-.17***	-.13***	-.12***	-.11***
15. Distraction	.07***	.24***	.20***	.14***	.27***	-.21***	-.18***	-.14***	-.14***	-.16***
16. Acceptance	.05**	.02	.07***	.07***	.03*	0	.03	-.04	-.01	.03
17. Reappraisal	.03	.06**	.08***	.12***	.10***	-.06**	-.01	-.09***	-.05*	.04
18. Social Support	.05**	.08***	.07***	.06***	.08***	-.01	.07**	-.03	-.04*	.02
19. Disengagement	.19***	.43***	.40***	.31***	.46***	-.29***	-.24***	-.22***	-.17***	-.20***
20. Adaptive	.05**	.05*	.07***	.13***	.09***	-.03	.01	-.09***	-.03	.03
21. Interpersonal Stress	.33***	.10***	.16***	.07***	.11***	-.02	-.07**	-.04*	.04	-.03
22. Discrimination	0	0	-.01	.02	0	0	-.02	-.02	.01	0
23. Other Stress	.14***	.04*	.13***	.22***	.05***	-.02	.01	-.12***	-.02	-.05
24. Work/School Stress	.07***	-.01	.02	.03	.01	-.12***	-.10***	-.09***	-.01	-.16***
25. Peer/Relative Stress	.08***	.07***	.15***	.11***	.07***	-.05*	-.04	-.05*	.01	-.04
26. Urgency GSR	.16***	.06*	.15***	.08***	.05**	.12***	.16***	.04*	.11***	.14***
27. Momentary Urgency	.41***	.23***	.36***	.20***	.18***	.18***	.26***	.11***	.21***	.15***

Variable	1	2	3	4	5	6	7	8	9	10
28. SITB	.13***	.31***	.33***	.24***	.25***	-.17***	-.12***	-.13***	-.11***	-.09***
29. SIB	.03	.12***	.12***	.05**	.09***	-.01	-.01	.01	0	-.01
30. SI	.14***	.27***	.33***	.19***	.19***	-.11***	-.05*	-.05*	-.06**	-.09***

Note. * $p < .05$; ** $p < .01$; *** $p < .005$

Variable	11	12	13	14	15	16	17	18	19	20	21
11. Rumination											
12. Problem Solving	.10***										
13. Self-Invalidation	.37***	.05**									
14. Suppression	.30***	.07***	.53***								
15. Distraction	.26***	.05**	.36***	.43***							
16. Acceptance	.05**	.25***	.04**	.06***	.06***						
17. Reappraisal	.19***	.33***	.15***	.15***	.19***	.32***					
18. Social Support	.06***	.05**	.09***	.06***	.03	.05**	.05*				
19. Disengagement	.67***	.09***	.77***	.76***	.71***	.07***	.24***	.08***			
20. Adaptive	.15***	.72***	.10***	.12***	.13***	.75***	.71***	.07***	.18***		
21. Interpersonal Stress	.13***	.02	.08***	.06**	.03	.06***	.01	.01	.11***	.05**	
22. Discrimination	.01	-.01	.03	.04*	-.02	0	-.01	.01	.02	-.01	.03*
23. Other Stress	.15***	.02	.05**	.03	.06***	.04*	.06***	.09***	.10***	.05**	-.06***
24. Work/School Stress	.03	.14***	.04**	.07***	.07***	.07***	.01	0	.07***	.11***	-.03
25. Peer/Relative Stress	.17***	0	.13***	.13***	.12***	.08***	.08***	.05*	.19***	.07***	.04*
26. Urgency GSR	-.01	-.11***	-.02	-.09***	-.09***	-.05**	-.02	0	-.07***	-.08***	.08***
27. Momentary Urgency	.17***	-.06*	.09**	.04	.06*	.12***	.05	.10***	.12***	.05	.31***
28. SITB	.31***	.11***	.26***	.26***	.22***	.07***	.12***	.08***	.36***	.13***	.08***
29. SIB	.10***	.01	.10***	.07***	.07***	-.02	.02	.07***	.12***	-.01	.05**
30. SI	.21***	.01	.15***	.16***	.14***	.03	.02	.08***	.23***	.03	.10***

Note. * $p < .05$; ** $p < .01$; *** $p < .005$

Variable	22	23	24	25	26	27	28	29
22. Discrimination								
23. Other Stress	-.03							
24. Work/School Stress	0	-.03***						
25. Peer/Relative Stress	.01	0	.01					
26. Urgency GSR	.01	.01	-.15***	.03				
27. Momentary Urgency	-.02	.01	-.07*	.21***	.54***			
28. SITB	.03	-.02	.02	.09***	-.01	.26***		
29. SIB	-.01	.03	.04*	0	.01	.11***	.21***	
30. SI	.05**	-.01	.03	.06***	.01	.25***	.58***	.20***

Note. * $p < .05$; ** $p < .01$; *** $p < .005$

Table 9

Response Rates of EMA Signal- and Event- Contingent Surveys Over the Follow-Up Period

Daily assessment period	Number delivered	Number received	% Complete
Morning	840	552	65.71
Mid-day	840	700	83.33
Afternoon	840	707	84.17
Evening	840	730	86.90
Night	840	725	86.31
Event-contingent	--	19	--
Total signal-contingent	4200	3414	81.29
Total surveys received	--	3433	--

Note. Response rates significantly differed based on daily assessment period (F [df = 1, 4198] = 113.60, $p < .001$). Largest percentage of missing surveys occurred in the morning.

Table 10

Comparisons Between Imputed and Observed Data

Variable	Observed Data Only		Average of Imputed Datasets	
	M/*n*	SD/%	M/*n*	SD/%
NSSI thoughts	133	3.88	205	4.85
Suicidal thoughts	203	5.91	300	6.96
Within-person negative emotion	0	1	0	1
Within-person disengagement	0	1	0	1
Within-person urgency	0	1	0	1

Table 11

Sensitivity Analysis for Weakly-Informative Prior in Predicting Suicidal Thoughts

	Weakly Informative Prior			Informed Prior		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.62	0.00	0.00 – 0.00	-11.61	0.00	0.00 – 0.00
Between Effects						
Between person predictor	**0.47**	**1.60**	**1.16 – 2.20**	**0.49**	**1.63**	**1.22 – 2.20**
Within Effects						
Within person predictor	**0.20**	**1.22**	**1.08 – 1.38**	**0.22**	**1.25**	**1.13 – 1.38**

Notes: Informed prior adjusted the lower bound of the credible interval

Table 12

Comparisons of the Autoregressive Parameter

AR structure	PSIS-LOO	WAIC	Preferred Model
NSSI thoughts			
Within-person, within-day	-496.1 (33.50)	-495.60 (36.50)	No difference (< 4)
Within-person	-495.30 (33.40)	-494.80 (38.00	
Suicidal thoughts			
Within-person, within-day	-574.00 (32.00)	-573.40 (31.90)	No difference (< 4)
Within-person	-573.30 (32.00)	-572.50 (32.00)	

Note. AR = auto-regressive parameter. Models tested differences between a within-person, within-day auto-regressive structure versus a within-person parameter.

Table 13

Model Comparisons of A-Priori Hypotheses

Model	PSIS-LOO	Difference	WAIC	Difference	Pseudo-BMA	Preferred Model
NSSI thoughts						
1. Empty model	-804.4 (42.6)	--	-803.9 (42.6)	--	--	--
2. Negative emotions	-804.2 (42.8)	0.2 (2.4)	-803.7 (42.7)	0.2 (2.4)	Mod 1 = .464 Mod 2= .536	1 vs. 2: **No difference**
3. Coping	-804.0 (43.0)	0.4 (2.2)	-808.6 (42.9)	0.8 (2.2)	Mod 1 = .445 Mod 3 = .555	1 vs. 3: **No difference**
4. Urgency	-804.6 (42.8)	0.1 (1.9)	-804.0 (42.7)	0.1 (1.9)	Mod 1 = .525 Mod 4 = .475	1 vs. 4: **No difference**
5. NE X ER	-805.8 (43.2)	-1.6 (2.1)	-805.3 (43.1)	-1.6 (2.1)	Mod 2 = .745 Mod 5 = .255	2 vs. 5: **No difference**
6. NE X NU	-809.10 (43.2)	-4.9 (1.9)	-808.60 (42.2)	-4.9 (1.9)	Mod 2 = .974 Mod 6 = .026	2 vs. 6: **Model 2**
7. NE X Base ER	-806.3 (42.9)	-2.1 (0.9)	-805.8 (42.9)	-2.1 (0.9)	Mod 2 = .858 Mod 7 = .142	2 vs. 7: **No difference**
8. NE X Base NU	-803.3 (42.8)	0.8 (1.2)	-802.9 (42.7)	0.9 (1.2)	Mod 2 = .346 Mod 8 = .654	2 vs. 8: **No difference**
Suicidal thoughts						
1. Empty model	-1009.4 (45.0)	--	-1007.8 (44.9)	--	--	--
2. Negative emotions	-1000.1 (44.8)	9.3 (4.2)	-998.9 (44.7)	8.8 (4.2)	Mod 1 = .021 Mod 2= .979	1 vs. 2: **Model 2**
3. Coping	-997.5 (44.3)	11.9 (4.7)	-995.9 (44.1)	11.9 (4.7)	Mod 1 = .013 Mod 3 = .987	1 vs. 3: **Model 3**
4. Urgency	-1011.1 (45.2)	-1.7 (1.3)	-1009.5 (45.0)	-1.8 (1.3)	Mod 1 = .782 Mod 4 = .218	1 vs. 4: **No difference**
5. NE X ER	-990.5 (44.0)	9.6 (4.6)	-989.1 (43.9)	9.8 (4.6)	Mod 2 = .026 Mod 5 = .974	2 vs. 5: **Model 5**
6. NE X NU	-1002.4 (44.9)	-2.3 (1.6)	-1001.3 (44.8)	-2.3 (1.6)	Mod 2 = .840 Mod 6 = .160	2 vs. 6: **No difference**
7. NE X Base ER	-1002.0 (44.9)	-1.9 (0.7)	-1000.7 (44.8)	-1.7 (0.7)	Mod 2 = .846 Mod 7 = .154	2 vs. 7: **No difference**
8. NE X Base NU	-1002.7 (45.0)	-2.6 (0.5)	-1001.5 (44.9)	-2.5 (0.5)	Mod 2 = .925 Mod 8 = .075	2 vs. 8: **Model 2**

Note. Generally, a difference less than 4 in ELPD and/or WAIC is considered a small difference. Some suggest a difference of ELPD or WAIC < 2 times the standard errors is trivial. Standard errors are in parentheses.

Table 14

GLMM Models of Specific Negative Emotions Predicting Self-Injurious Thoughts

NSSI Thoughts															
	Anger$_{(t-1)}$			Sadness$_{(t-1)}$			Guilt$_{(t-1)}$			Fear$_{(t-1)}$			Shame$_{(t-1)}$		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.60	0.00	0.00 – 0.00	-11.60	0.00	0.00 – 0.00	-11.59	0.00	0.00 – 0.00	-11.59	0.00	0.00 – 0.00	-11.59	0.00	0.00 – 0.00
Between Effects															
Between person predictor	0.06	1.06	.78 – 1.40	**0.27**	**1.31**	**1.02 – 1.70**	**0.28**	**1.32**	**1.03 – 1.67**	**0.32**	**1.38**	**1.08 – 1.75**	**0.29**	**1.34**	**1.05 – 1.68**
Within Effects															
Within person predictor	-0.01	0.99	0.84 – 1.15	0.04	1.04	0.89 – 1.21	0.01	1.01	0.84 – 1.13	-0.00	1.00	0.84 – 1.17	-0.01	0.99	0.83 – 1.16
Suicidal Thoughts															
	Anger$_{(t-1)}$			Sadness$_{(t-1)}$			Guilt $_{(t-1)}$			Fear$_{(t-1)}$			Shame$_{(t-1)}$		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.63	0.00	0.00 – 0.00	-11.64	0.00	0.00 – 0.00	-11.64	0.00	0.00 – 0.00	-11.63	0.00	0.00 – 0.00	-11.63	0.00	0.00 – 0.00
Between Effects															
Between person predictor	0.09	1.09	0.77 – 1.57	**0.57**	**1.77**	**1.31– 2.44**	0.31	1.36	0.97 – 1.93	**0.53**	**1.70**	**1.23 – 2.34**	**0.48**	**1.62**	**1.19 – 2.23**
Within Effects															
Within person predictor	0.06	1.06	0.93 – 1.20	**0.23**	**1.26**	**1.09 – 1.43**	**0.14**	**1.15**	**1.01 – 1.30**	0.07	1.07	0.93 – 1.13	**0.17**	**1.19**	**1.05 – 1.32**

Table 15

Lagged Zero-Inflated Binomial Bayesian GLMM Models Predicting Self-Injurious Thoughts

	NSSI Thoughts								
	Negative Emotions$_{(t-1)}$			Emotion Regulation$_{(t)}$			Negative Urgency$_{(t)}$		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.63	0.00	0.00 – 0.00	-11.63	0.00	0.00 – 0.00	-11.64	0.00	0.00 – 0.00
Between Effects									
Between person predictor	**0.43**	**1.53**	**1.23 – 1.97**	0.20	1.22	0.96 – 1.55	0.14	1.15	0.88 – 1.52
Within Effects									
Within person predictor	0.07	1.07	0.93 – 1.23	0.16	1.17	1.00 – 1.37	0.12	1.12	0.97 – 1.32
	Suicidal Thoughts								
	Negative Emotions$_{(t-1)}$			Emotion Regulation$_{(t)}$			Negative Urgency$_{(t)}$		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.61	0.00	0.00 – 0.00	-11.66	0.00	0.00 – 0.00	-11.65	0.00	0.00 – 0.00
Between Effects									
Between person predictor	**0.49**	**1.63**	**1.22 – 2.20**	0.27	1.31	0.93 – 1.84	0.29	1.34	0.82 – 2.23
Within Effects									
Within person predictor	**0.22**	**1.25**	**1.13 – 1.38**	**0.27**	**1.31**	**1.15 – 1.49**	-0.02	0.98	0.80 – 1.19

Note. GLMM = generalized linear mixed model

Table 16

Lagged Zero-Inflated Binomial GLMM Models Testing EMA Moderation of NE with NSSI Thoughts

	NSSI Thoughts					
	Negative Emotions$_{(t-1)}$ X Emotion Regulation$_{(t)}$			Negative Emotions$_{(t-1)}$ X Negative Urgency$_{(t}$		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.66	0.00	0.00 – 0.00	-11.64	0.00	0.00 – 0.00
Between Effects						
Between person NE	**0.41**	**1.51**	**1.17 – 1.95**	**0.38**	**1.46**	**1.16 – 1.88**
Between person ER/NU	0.04	1.04	0.78 – 1.35	0.08	1.00	0.83 – 1.42
Within Effects						
Within person NE	0.09	1.09	0.93 – 1.27	0.05	1.05	0.91 – 1.21
Within person ER/NU	0.16	1.17	1.00 – 1.37	0.11	1.12	0.93 – 1.32
Within person interaction	-0.00	1.00	0.85 – 1.15[d]	0.02	1.02	0.89 – 1.15
	Negative Emotions$_{(t-1)}$ X Disengagement			Negative Emotions$_{(t-1)}$ X Negative Urgency		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.64	0.00	0.00 – 0.00	-11.65	0.00	0.00 – 0.00
Between Effects						
Between person NE	**0.46**	**1.58**	**1.26 – 2.01**	**0.43**	**1.54**	**1.23 – 1.95**
Between person ER/NU	-0.14	0.87	0.67 – 1.13	0.05	1.05	0.82 – 1.36
Within Effects						
Within person NE	0.06	1.06	0.92 – 1.23	0.04	1.04	0.89 – 1.21
Interaction	0.02	1.02	0.88 – 1.19	0.08 z	1.08	0.95 – 1.26

Note. GLMM = generalized linear mixed model

Table 17

Lagged Zero-Inflated Binomial GLMM Models Testing EMA Moderation of NE with Suicidal Thoughts

	Suicidal Thoughts					
	Negative Emotions$_{(t-1)}$ X Emotion Regulation$_{(t)}$			Negative Emotions$_{(t-1)}$ X Negative Urgency$_{(t)}$		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.67	0.00	0.00 – 0.00	-11.89	0.00	0.00 – 0.00
Between Effects						
Between person NE	**0.48**	**1.60**	**1.17 – 2.20**	**0.49**	**1.63**	**1.21 – 2.18**
Between person ER/NU	0.09	1.06	0.76 – 1.48	0.07	1.07	0.67– 1.73
Within Effects						
Within person NE	**0.21**	**1.23**	**1.12 – 1.36**	**0.22**	**1.25**	**1.12 – 1.38**
Within person ER/NU	**0.18**	**1.19**	**1.04 – 1.34**	-0.03	0.97	0.84 – 1.11
Within person interaction	0.07	0.98	0.90 – 1.07 [d]	0.02	1.02	0.87– 1.19
	Negative Emotions$_{(t-1)}$ X Emotion Regulation			Negative Emotions$_{(t0)}$ X Negative Urgency		
	ß	OR	95% CI (OR)	ß	OR	95% CI (OR)
Intercept	-11.62	0.00	0.00 – 0.00	-11.63	0.00	0.00 – 0.00
Between Effects						
Between person NE	**0.50**	**1.65**	**1.23 – 2.25**	**0.50**	**1.65**	**1.22 – 2.23**
Between person ER/NU	-0.07	0.93	0.67 – 1.30	-0.04	0.96	0.69 – 1.34
Within Effects						
Within person NE	**0.22**	**1.25**	**1.13 – 1.38**	**0.22**	**1.25**	**1.13 – 1.38**
Within person interaction	-0.04	0.96	0.86 – 1.08 [d]	-0.02	0.98	0.87 – 1.09

**Note.* GLMM = generalized linear mixed model

Figure 1

Theoretical Model

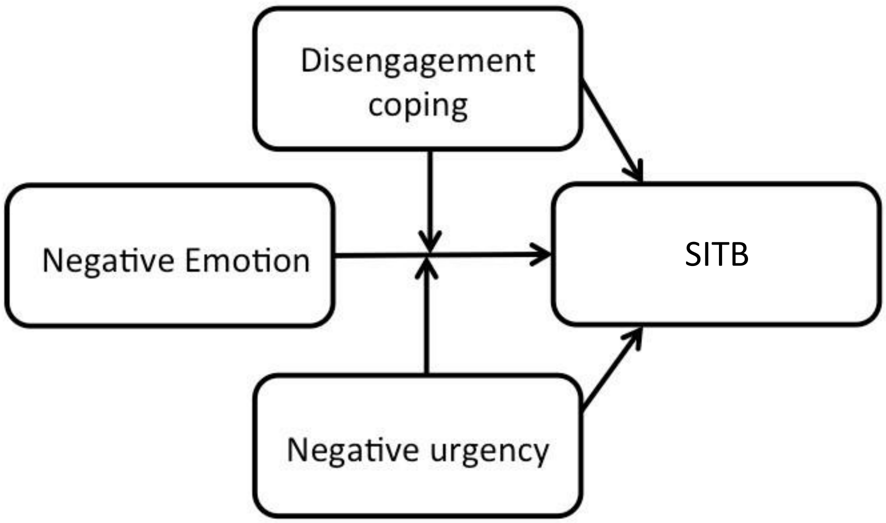


Figure 2

CONSORT Flow Diagram of Subject Enrollment

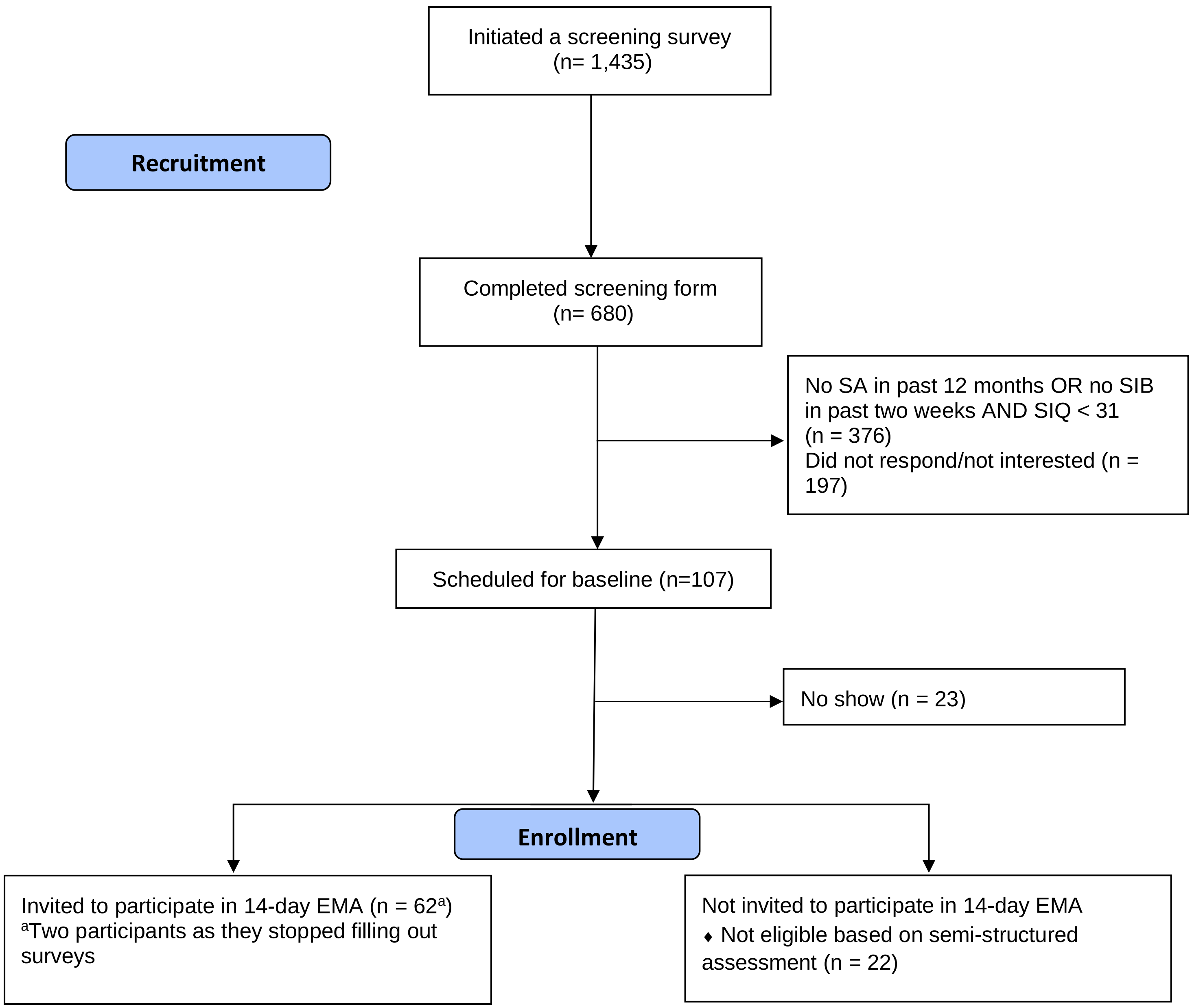


Figure 3

Correlation Plots of Baseline Self-Report Data

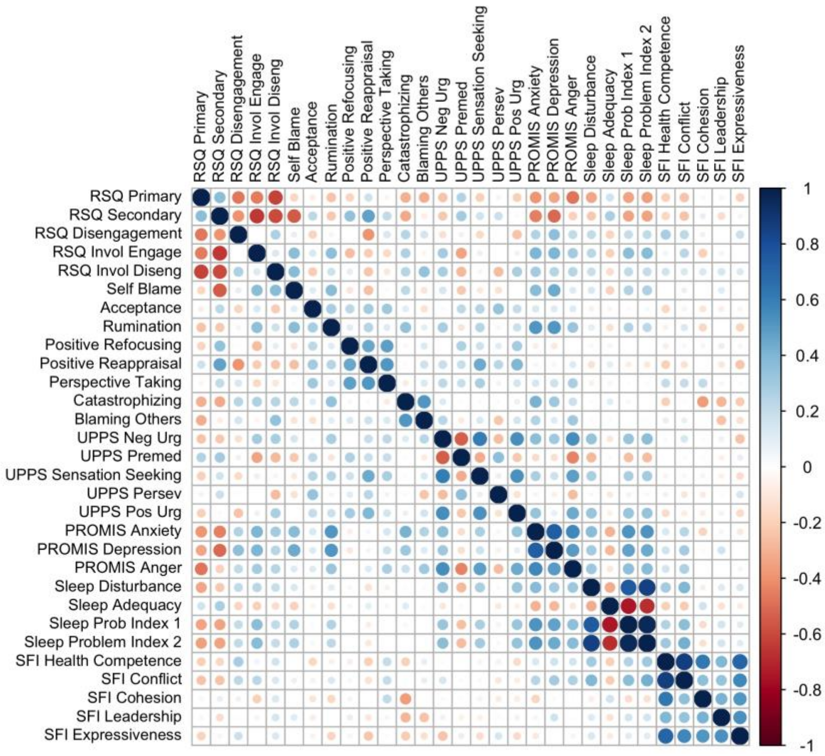


Figure 4

Correlation Plots of EMA Data

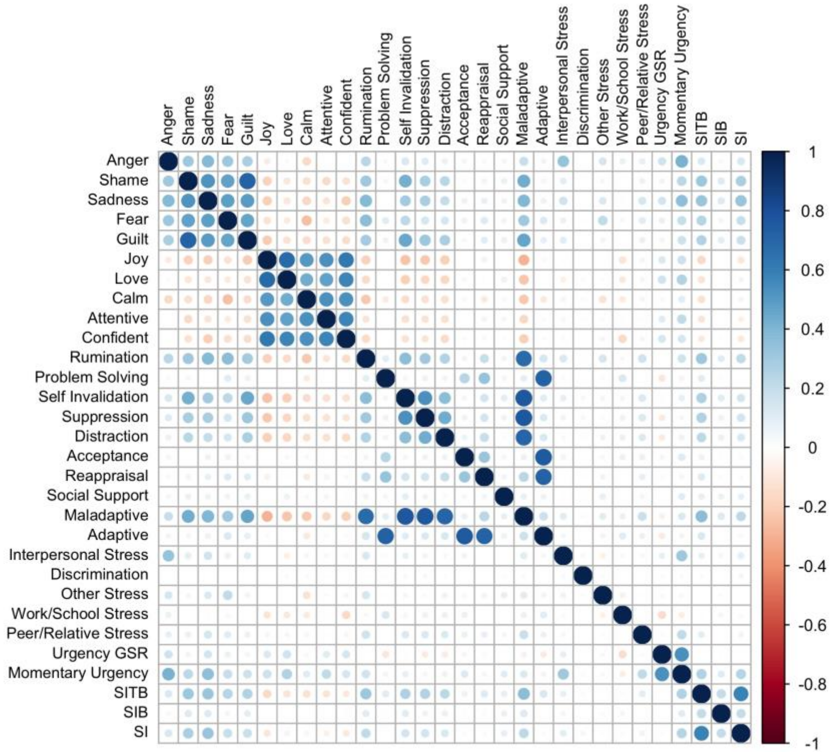
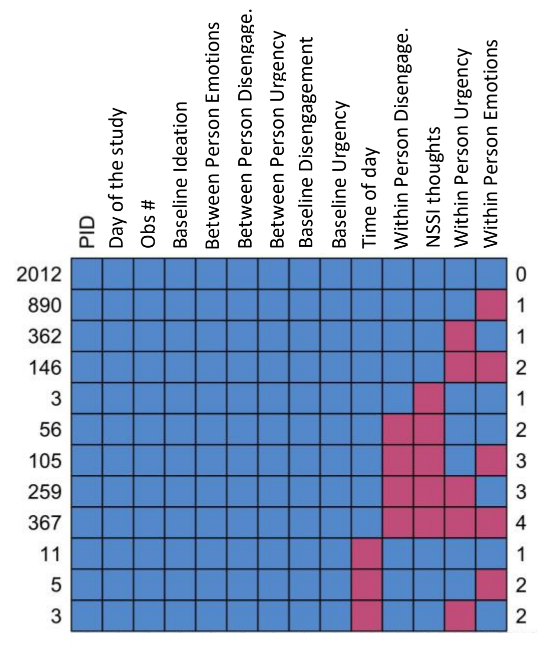


Figure 5

Missing Data Patterns of NSSI Thoughts (top) and Suicidal Thoughts (bottom)



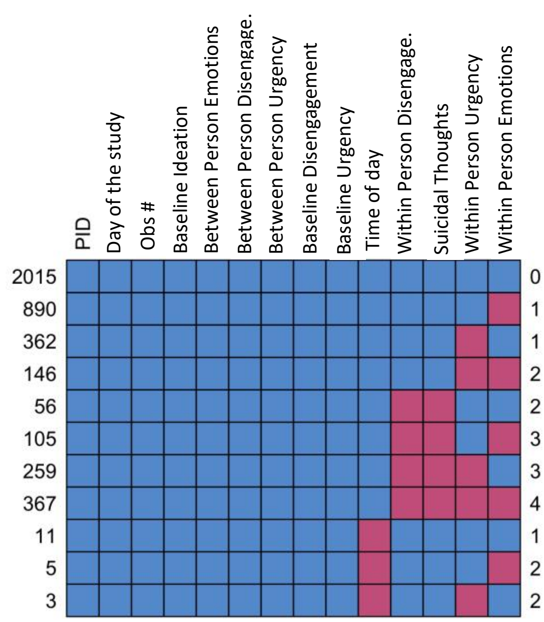
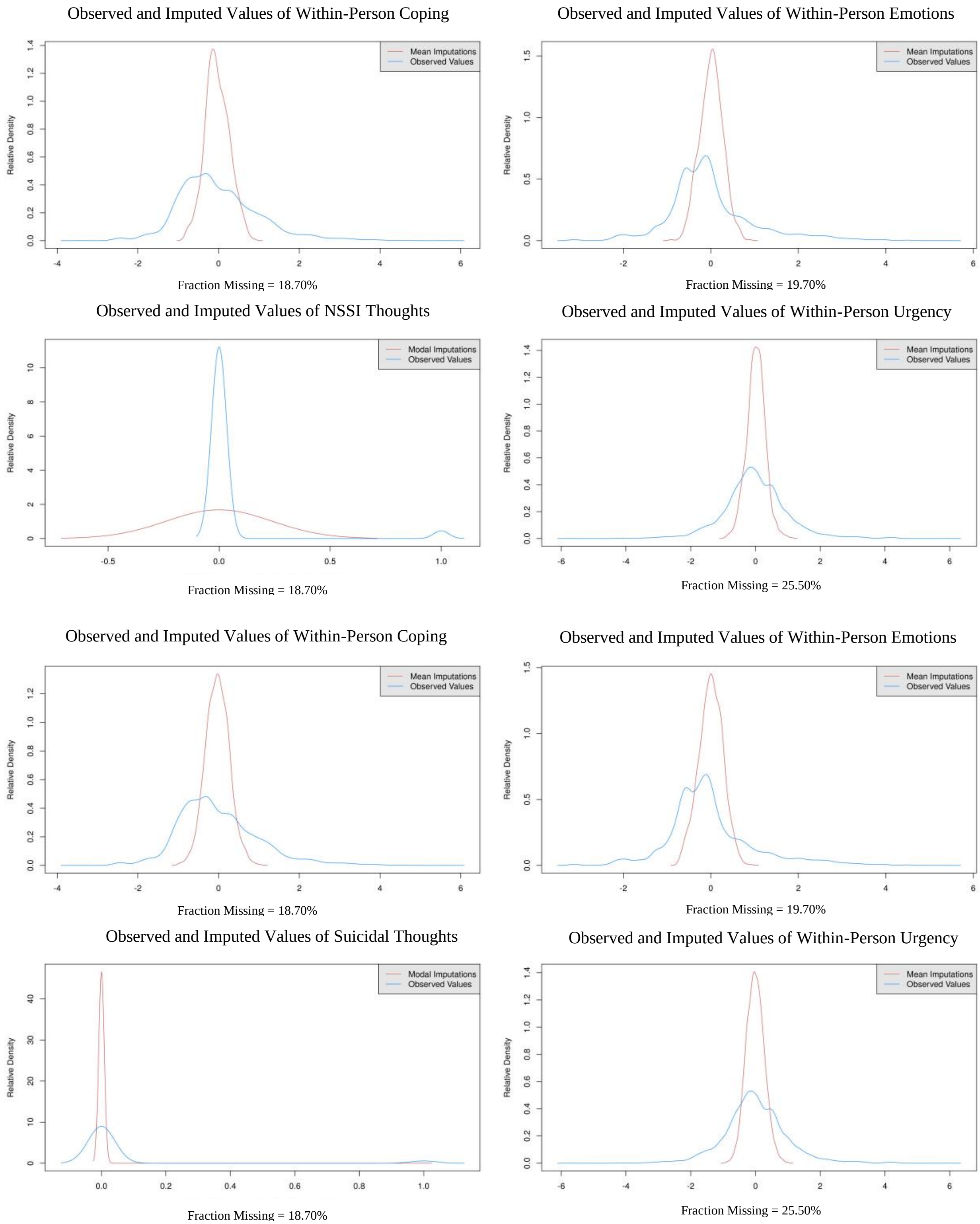


Figure 6

Observed (blue) versus Imputed (red) Data.



Note. Imputed Values are Centered around 0 with a Comparatively Smaller Variance.

Figure 7

Trace Plots and Posterior Distributions for Negative Emotions in Predicting NSSI Thoughts (top) Suicidal Thoughts (bottom)

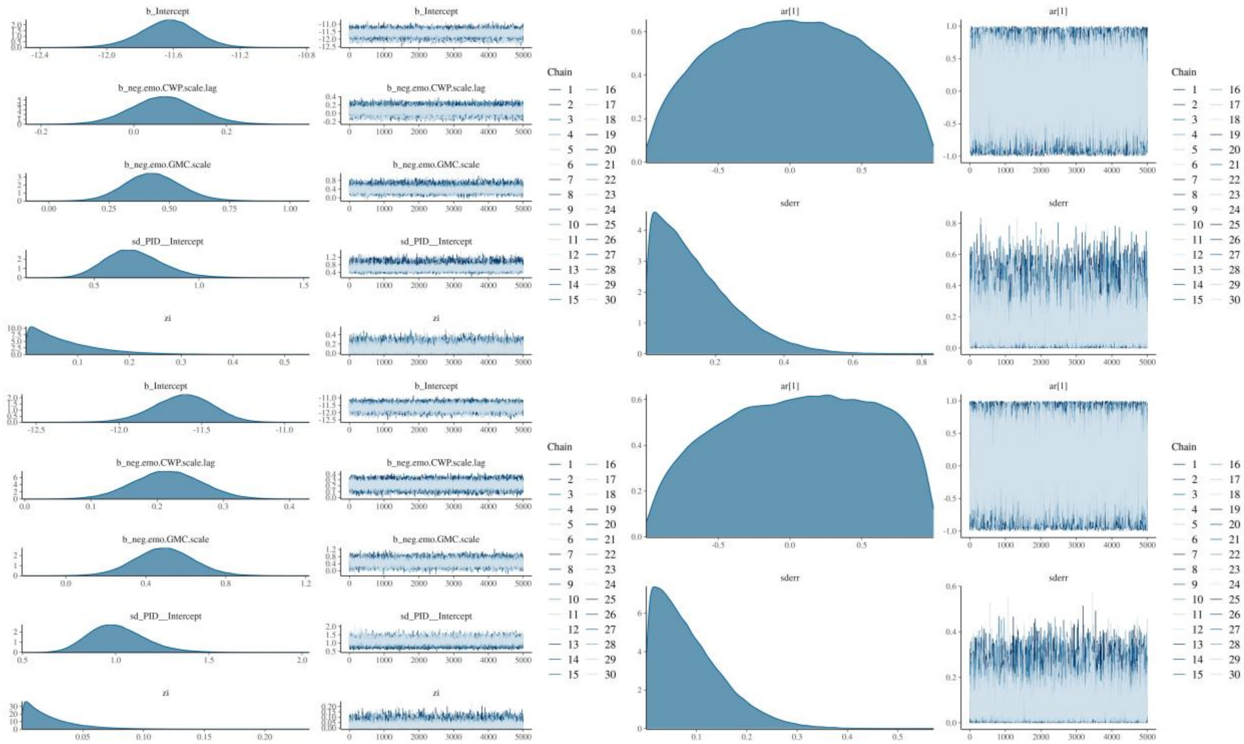


Figure 8

Trace Plots and Posterior Distributions for Disengagement Coping in Predicting NSSI Thoughts (top) and Suicidal Thoughts (bottom)

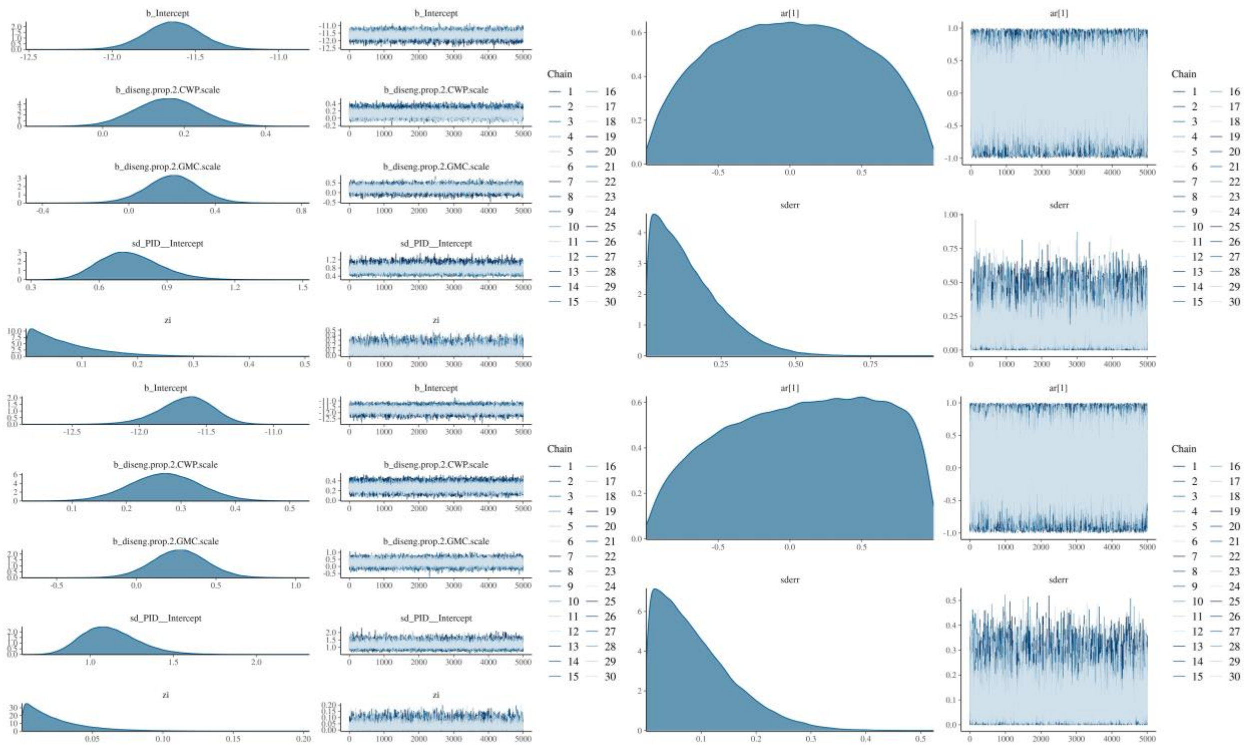


Figure 9

Trace Plots and Posterior Distributions for Negative Urgency in Predicting NSSI Thoughts (top) and Suicidal Thoughts (bottom)

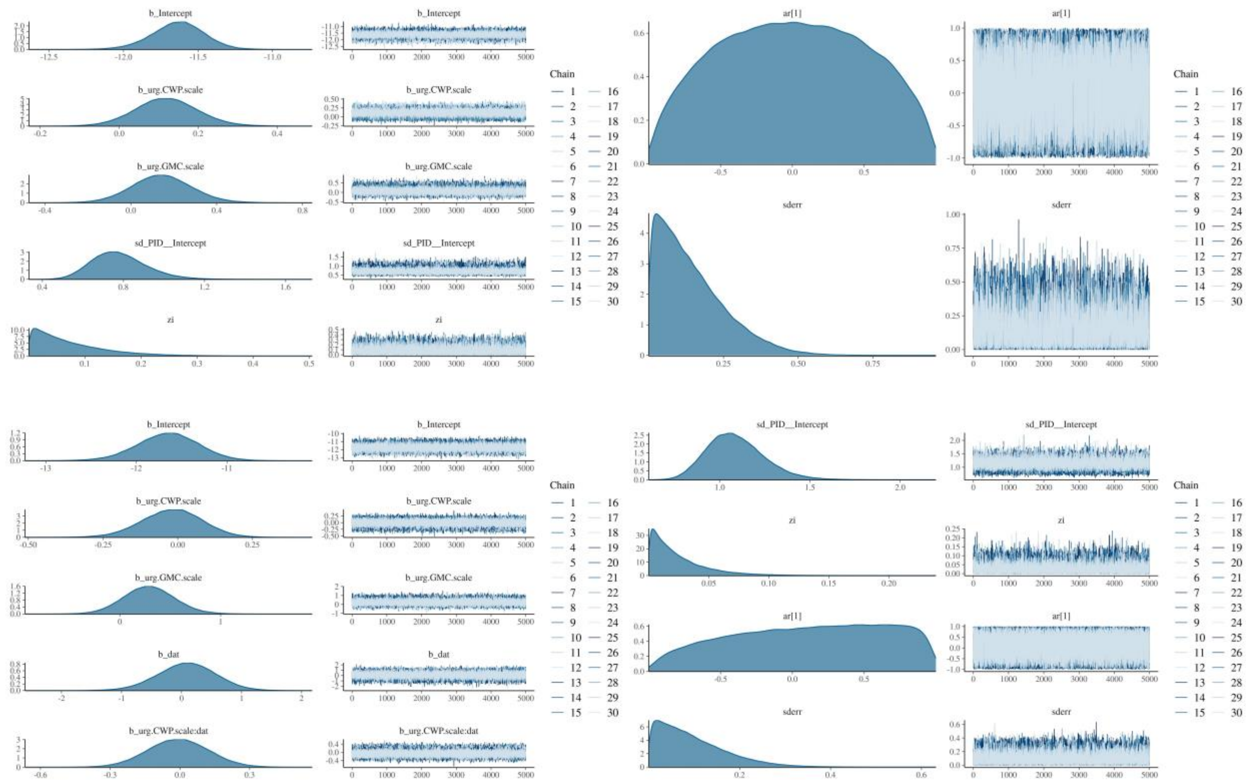
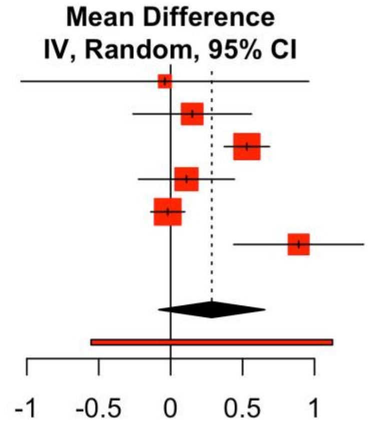


Figure 10

Results from the Meta-Analysis of the Within- (top) and Between-Person (bottom) Coefficients from Multi-Level Models Predicting NSSI Thoughts

Study	TE	SE	Weight	Mean Difference IV, Random, 95% CI
Bresin et al., 2013	-0.04	0.5100	5.4%	-0.04 [-1.04; 0.96]
Hochard et al., 2015	0.15	0.2100	15.5%	0.15 [-0.26; 0.56]
Kiekens et al., 2020	0.53	0.0800	23.0%	0.53 [0.37; 0.69]
Lear et al., 2019	0.11	0.1700	17.8%	0.11 [-0.22; 0.44]
Selby et al., 2018	-0.02	0.0600	23.9%	-0.02 [-0.14; 0.10]
Vansteelandt et al., 2017	0.89	0.2300	14.4%	0.89 [0.44; 1.34]
Total (95% CI)			**100.0%**	**0.29 [-0.08; 0.65]**
Prediction interval				**[-0.55; 1.12]**

Heterogeneity: $Tau^2 = 0.0708$; $Chi^2 = 40.01$, df = 5 ($P < 0.01$); $I^2 = 88\%$



Study	TE	SE	Weight	Mean Difference IV, Random, 95% CI
Bresin et al., 2013	0.81	1.4400	2.6%	0.81 [-2.01; 3.63]
Hochard et al., 2015	1.69	0.5700	13.0%	1.69 [0.57; 2.81]
Kiekens et al., 2020	1.59	0.5200	14.8%	1.59 [0.57; 2.61]
Lear et al., 2019	1.39	0.4600	17.6%	1.39 [0.49; 2.29]
Selby et al., 2018	0.53	0.2400	34.0%	0.53 [0.06; 1.00]
Vansteelandt et al., 2017	1.34	0.4500	18.1%	1.34 [0.46; 2.22]
Total (95% CI)			**100.0%**	**1.14 [0.61; 1.68]**
Prediction interval				**[0.07; 2.22]**

Heterogeneity: $Tau^2 = 0.1072$; $Chi^2 = 7.89$, df = 5 ($P = 0.16$); $I^2 = 37\%$

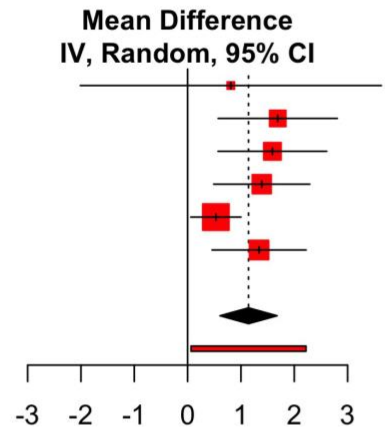
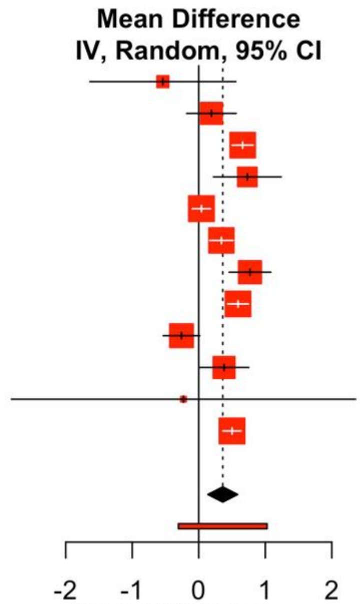


Figure 11

Results from Meta-Analyses of the Within- (top) and Between-Person (bottom) Coefficients from Multi-Level Models Predicting Suicidal Thoughts

Study	TE	SE	Weight	Mean Difference IV, Random, 95% CI
Bresin et al., 2013	-0.54	0.5600	2.4%	-0.54 [-1.64; 0.56]
Czyz et al., 2017	0.19	0.1900	8.2%	0.19 [-0.18; 0.56]
Forkmann et al., 2018	0.66	0.0800	11.1%	0.66 [0.50; 0.82]
Husky et al., 2017	0.73	0.2600	6.5%	0.73 [0.22; 1.24]
Kaurin et al., 2020	0.04	0.0700	11.3%	0.04 [-0.10; 0.18]
Kaurin et al., Under Review	0.34	0.0900	10.9%	0.34 [0.16; 0.52]
Kiekens et al., 2020	0.77	0.1600	9.0%	0.77 [0.46; 1.08]
Kleiman et al., 2017	0.59	0.0800	11.1%	0.59 [0.43; 0.75]
Kleiman et al., 2018	-0.26	0.1400	9.6%	-0.26 [-0.53; 0.01]
Peters et al., 2020	0.38	0.1900	8.2%	0.38 [0.01; 0.75]
Salim et al., 2019	-0.23	1.3200	0.5%	-0.23 [-2.82; 2.36]
Wolford-Clevenger et al., 2019	0.50	0.0700	11.3%	0.50 [0.36; 0.64]
Total (95% CI)			**100.0%**	**0.36 [0.14; 0.58]**
Prediction interval				**[-0.31; 1.03]**

Heterogeneity: $Tau^2 = 0.0791$; $Chi^2 = 78.40$, df = 11 (P < 0.01); $I^2 = 86\%$



Study	TE	SE	Weight	Mean Difference IV, Random, 95% CI
Bresin et al., 2013	1.54	1.6400	3.4%	1.54 [-1.67; 4.75]
Czyz et al., 2017	1.93	0.5600	9.4%	1.93 [0.83; 3.03]
Forkmann et al., 2018	3.20	0.5500	9.5%	3.20 [2.12; 4.28]
Husky et al., 2017	-0.63	1.2400	4.9%	-0.63 [-3.06; 1.80]
Kaurin et al., 2020	2.01	0.2900	11.4%	2.01 [1.44; 2.58]
Kaurin et al., Under Review	1.38	0.2300	11.7%	1.38 [0.93; 1.83]
Kiekens et al., 2020	2.54	1.0500	5.9%	2.54 [0.48; 4.60]
Kleiman et al., 2017	-0.53	0.1200	12.1%	-0.53 [-0.77; -0.29]
Kleiman et al., 2018	0.76	0.2700	11.5%	0.76 [0.23; 1.29]
Peters et al., 2020	3.15	1.0000	6.2%	3.15 [1.19; 5.11]
Salim et al., 2019	1.11	1.9700	2.5%	1.11 [-2.75; 4.97]
Wolford-Clevenger et al., 2019	1.76	0.2400	11.6%	1.76 [1.29; 2.23]
Total (95% CI)			**100.0%**	**1.50 [0.72; 2.27]**
Prediction interval				**[-0.88; 3.87]**

Heterogeneity: $Tau^2 = 1.0154$; $Chi^2 = 186.38$, df = 11 (P < 0.01); $I^2 = 94\%$

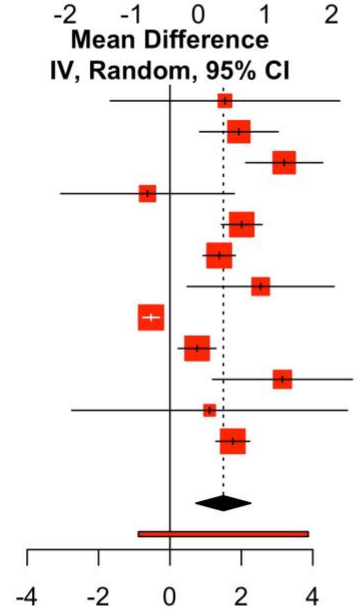


Figure 12

Density Plot of the Suicidal Thought Variable

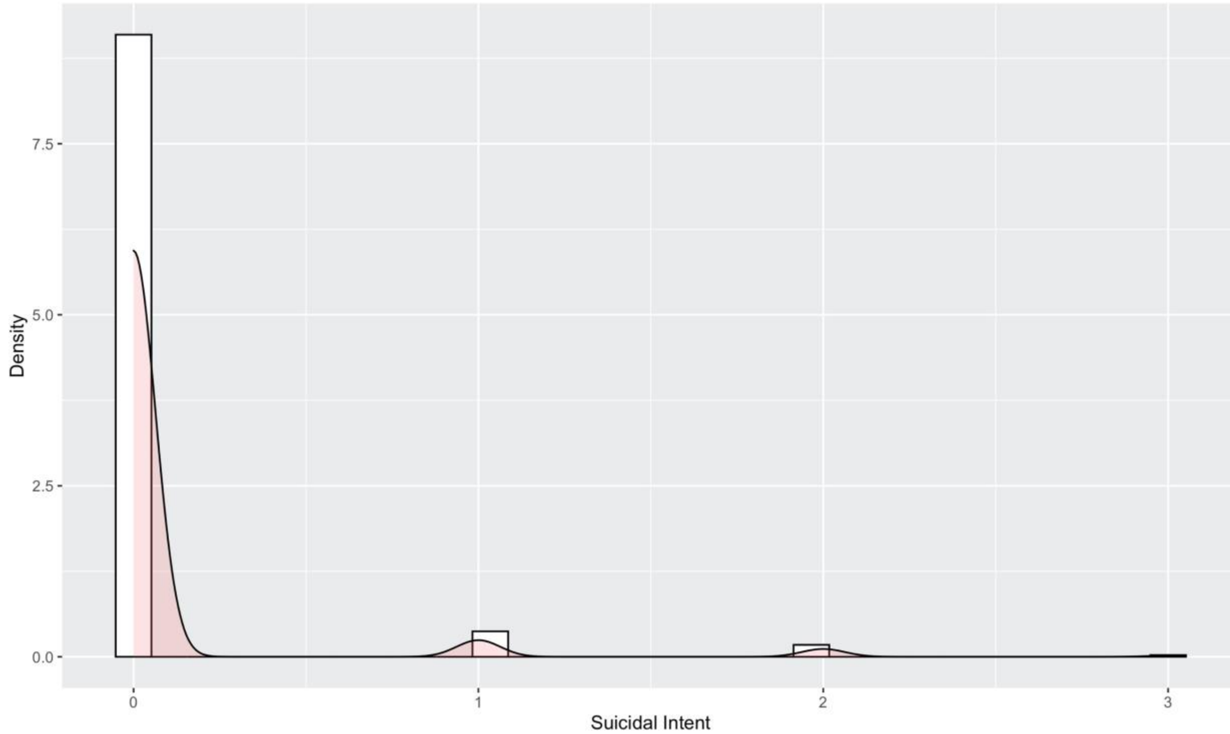
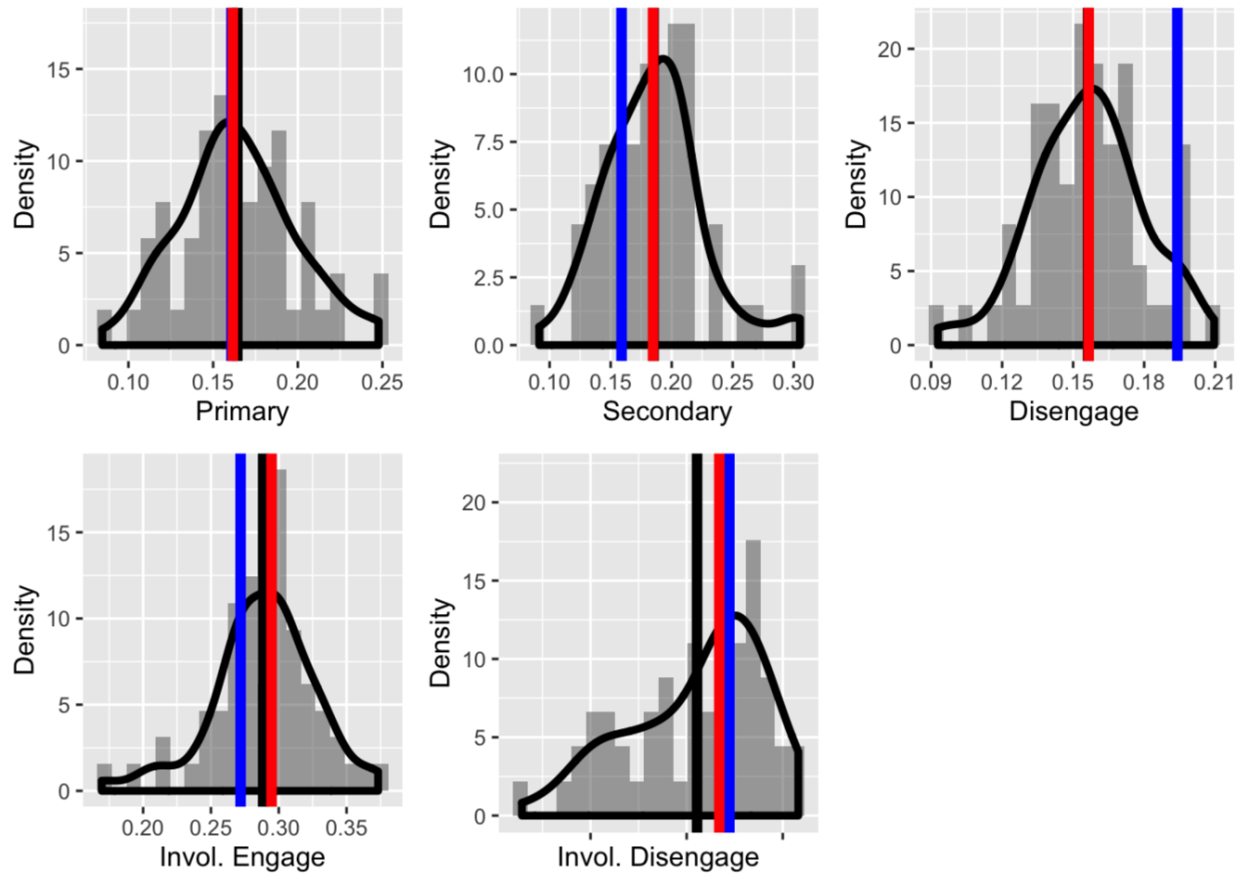


Figure 13

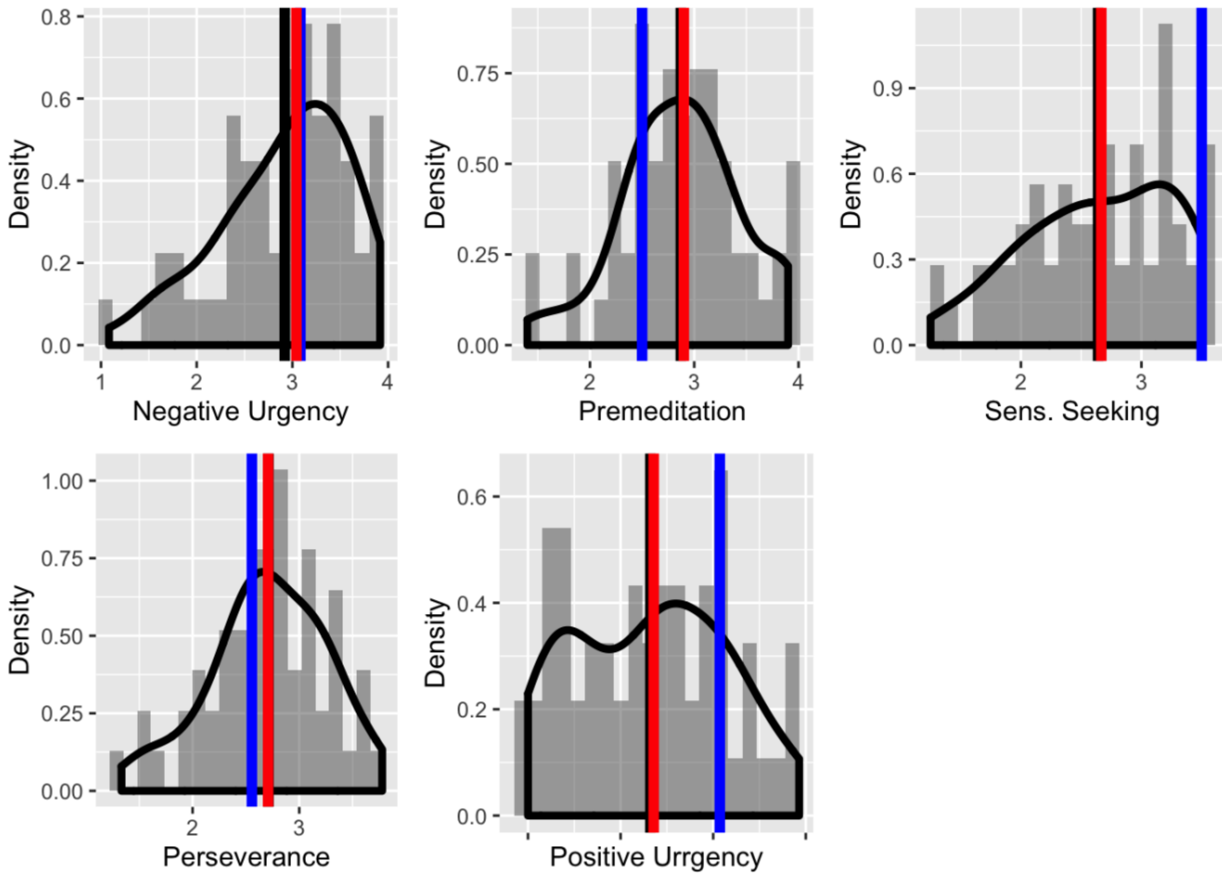
Histograms and Density Plots of the Responses to Stress Questionnaire (RSQ)



Note. Red bar = median; blue bar = mode; black bar = mean

Figure 14

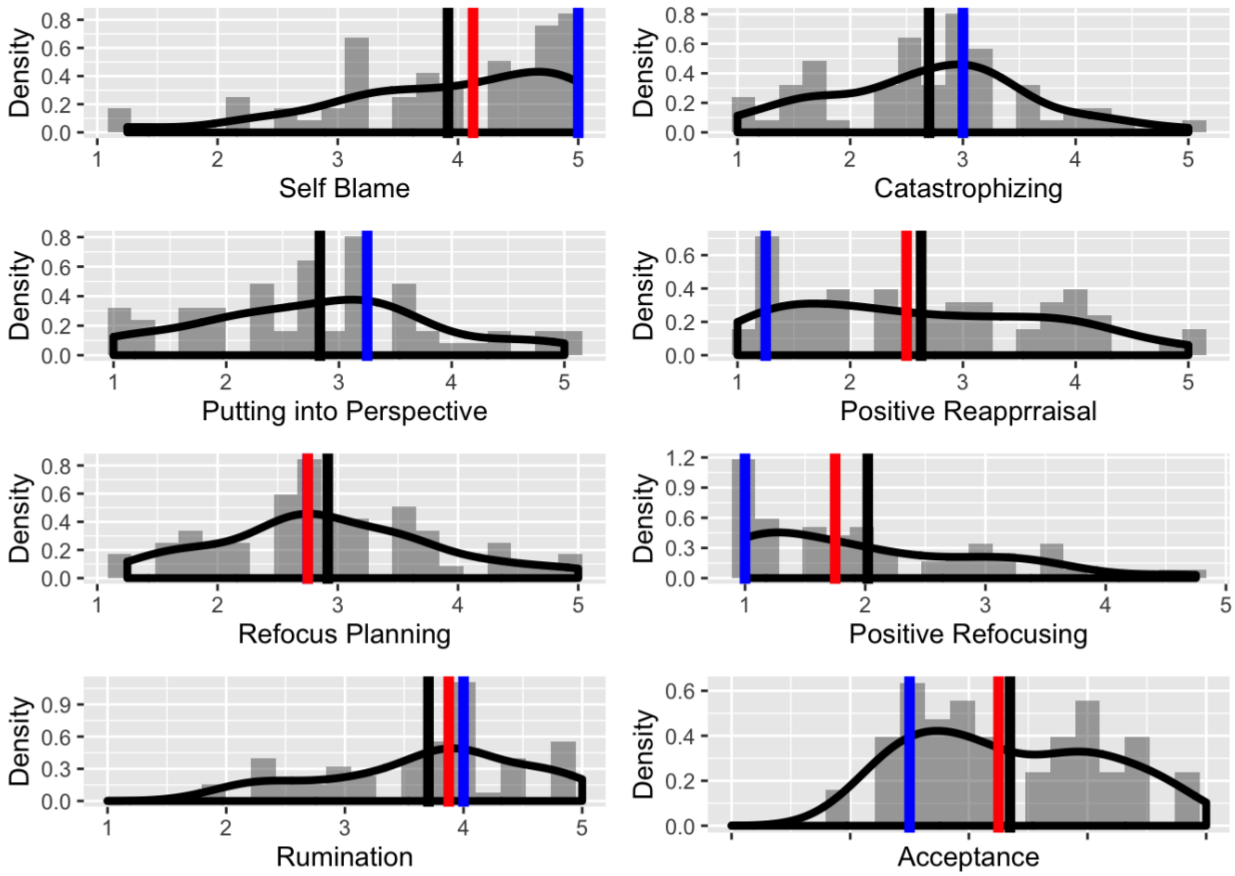
Histograms and Density Plots of the Urgency Premeditation Planning Sensation Seeking - Positive Urgency (UPPS-P) Scale



Note. Red bar = median; blue bar = mode; black bar = mean

Figure 15

Histograms and Density Plots of the Cognitive Emotion Regulation Questionnaire (CERQ)



Note. Red bar = median; blue bar = mode; black bar = mean

Figure 16

Suicidal Thoughts Plotted Over Time for Each Participant

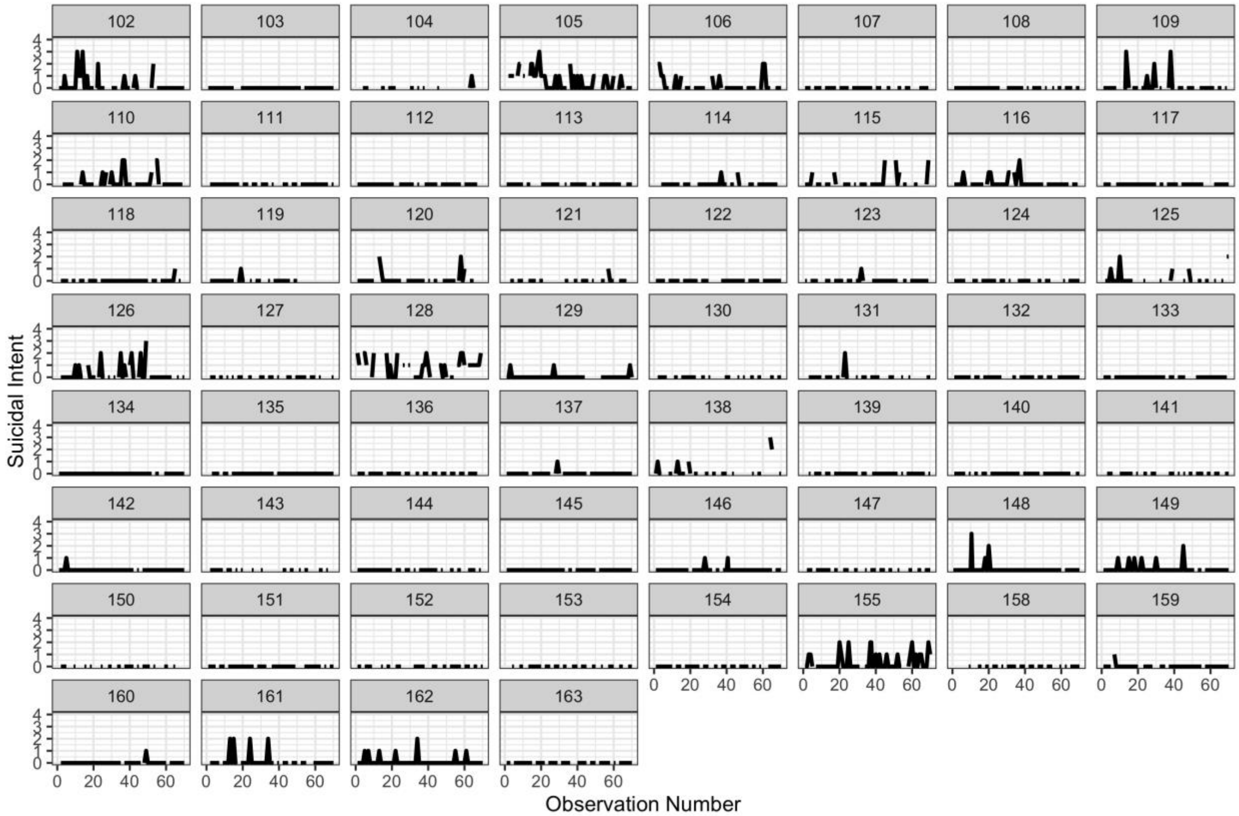


Figure 17

Mean Negative Emotions and Suicidal Intent Plotted Over Time Per Person

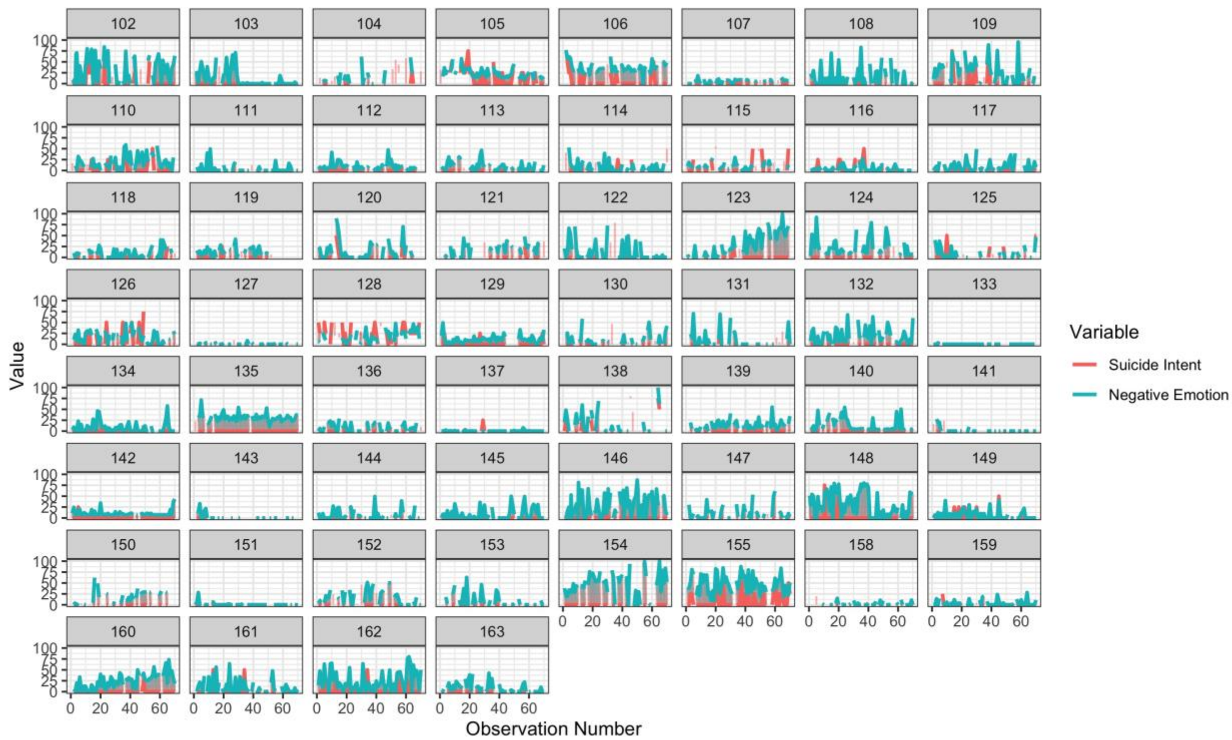


Figure 18

Conditional Effects of Within- and Between-Person Negative Emotions on NSSI thoughts (top) and Suicidal Thoughts (bottom)

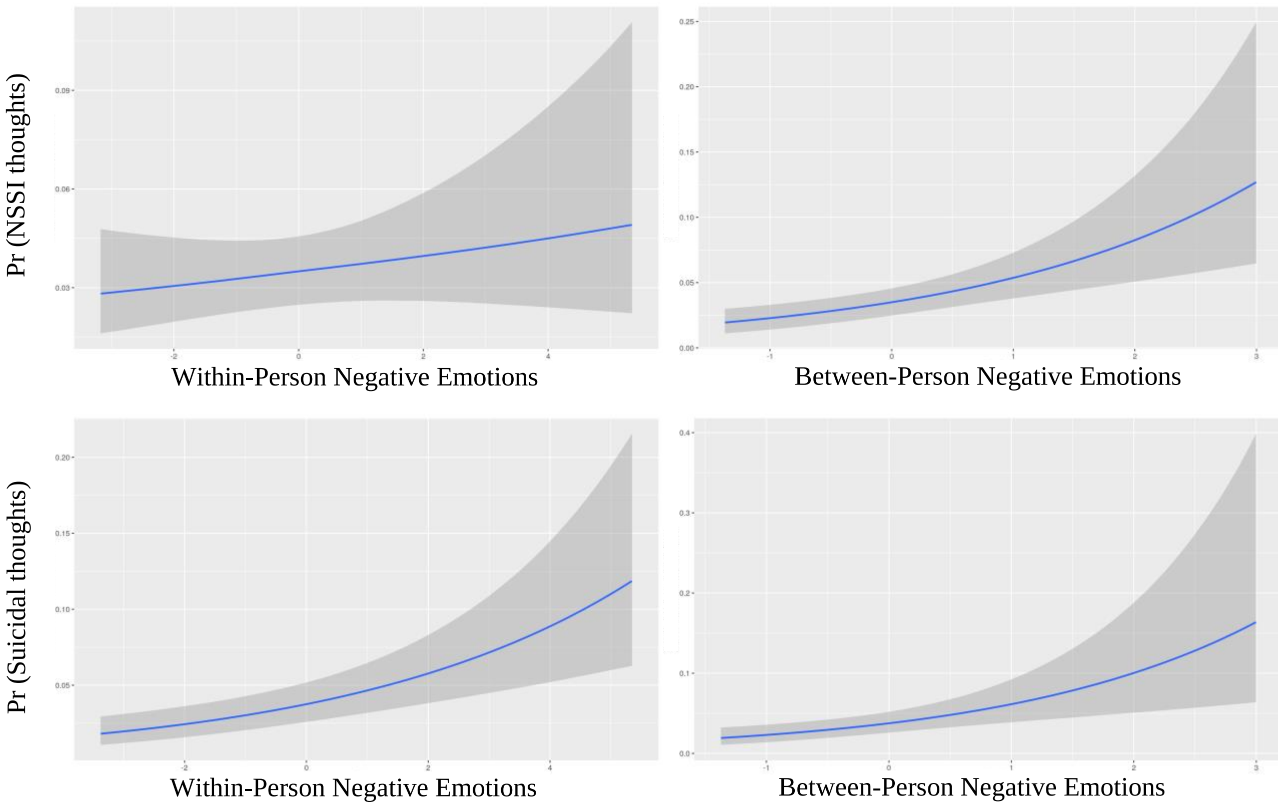


Figure 19

Conditional Effects of Within- and Between-Person Disengagement Coping in Predicting NSSI Thoughts (top) and Suicidal Thoughts (bottom)

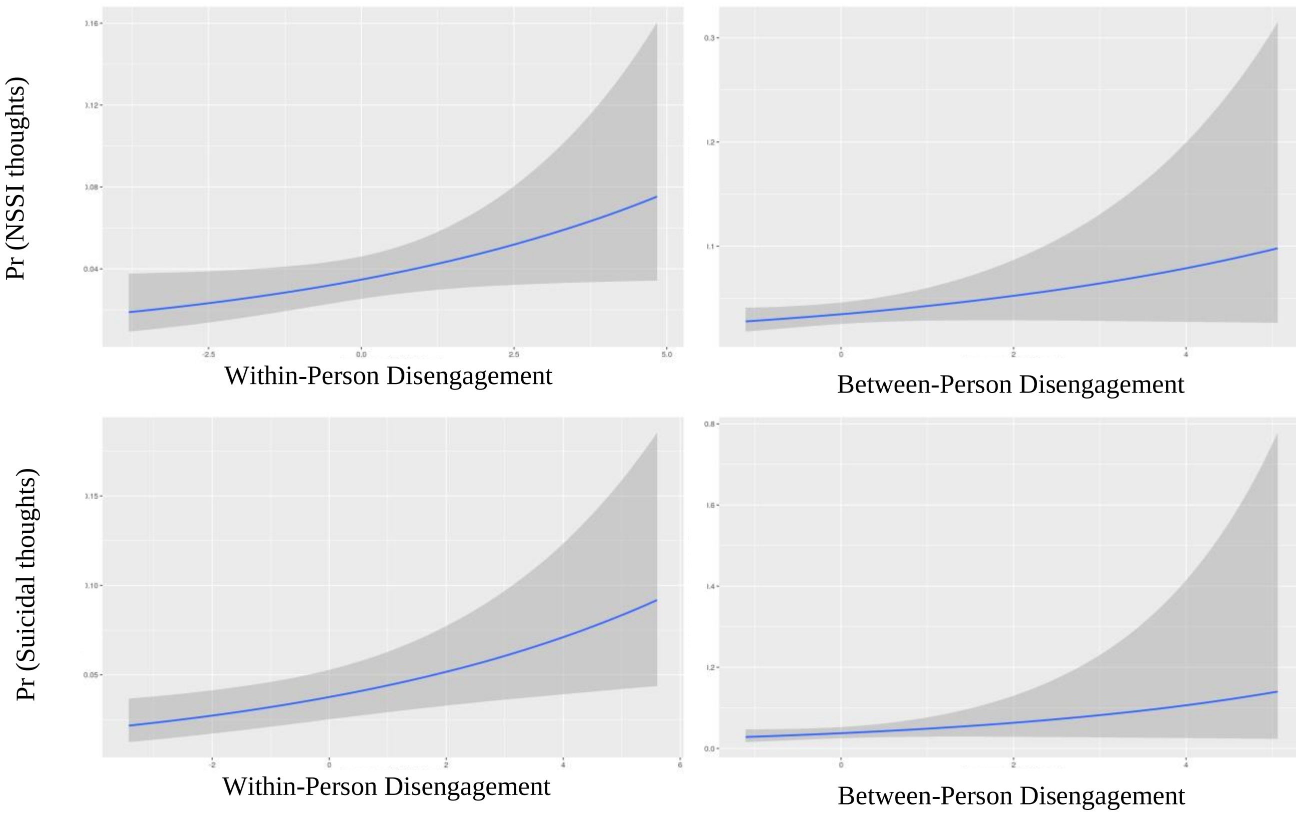


Figure 20

Conditional Effects of Within- and Between-Person Urgency in Predicting NSSI Thoughts (top) and Suicidal Thoughts (bottom)

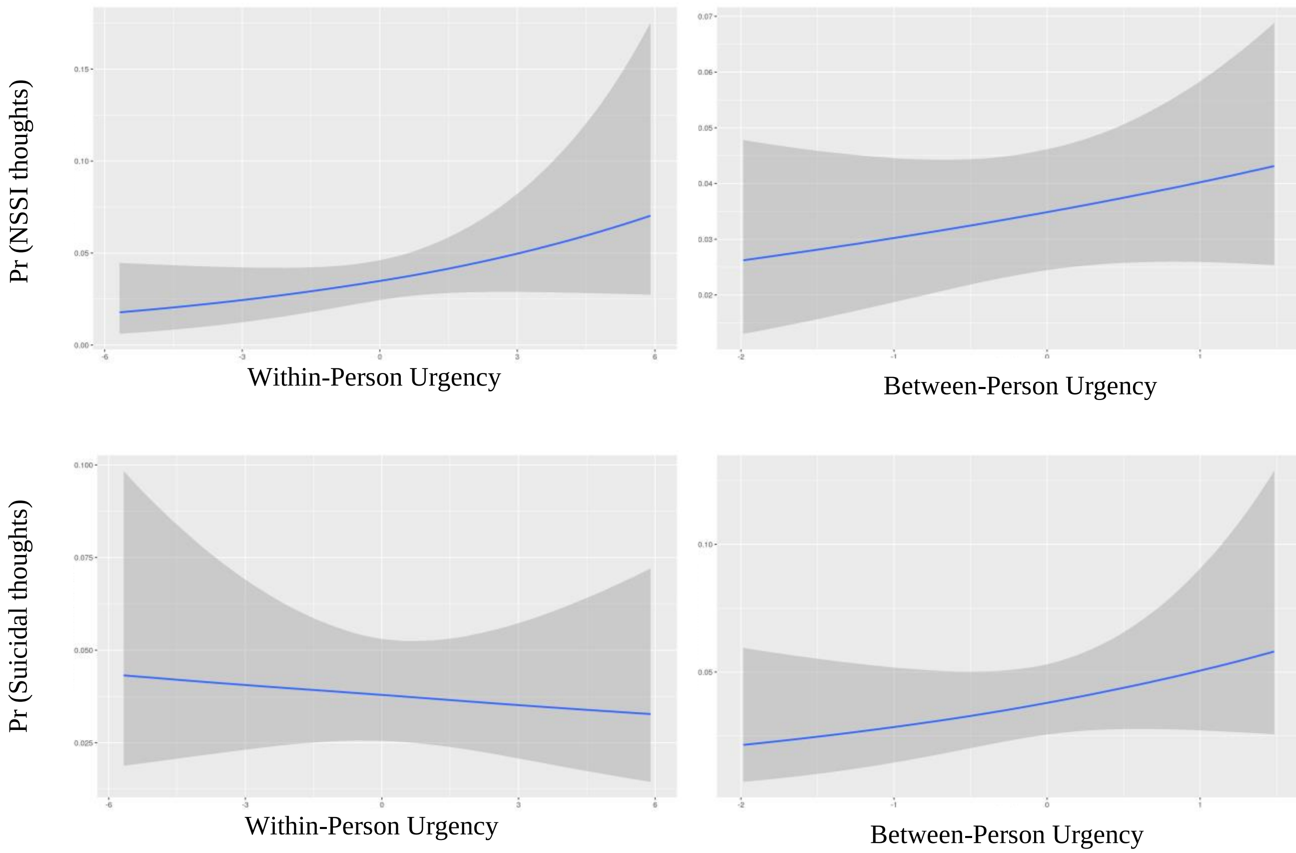


Figure 21

Conditional Effects of Moderation Analyses for NSSI Thoughts

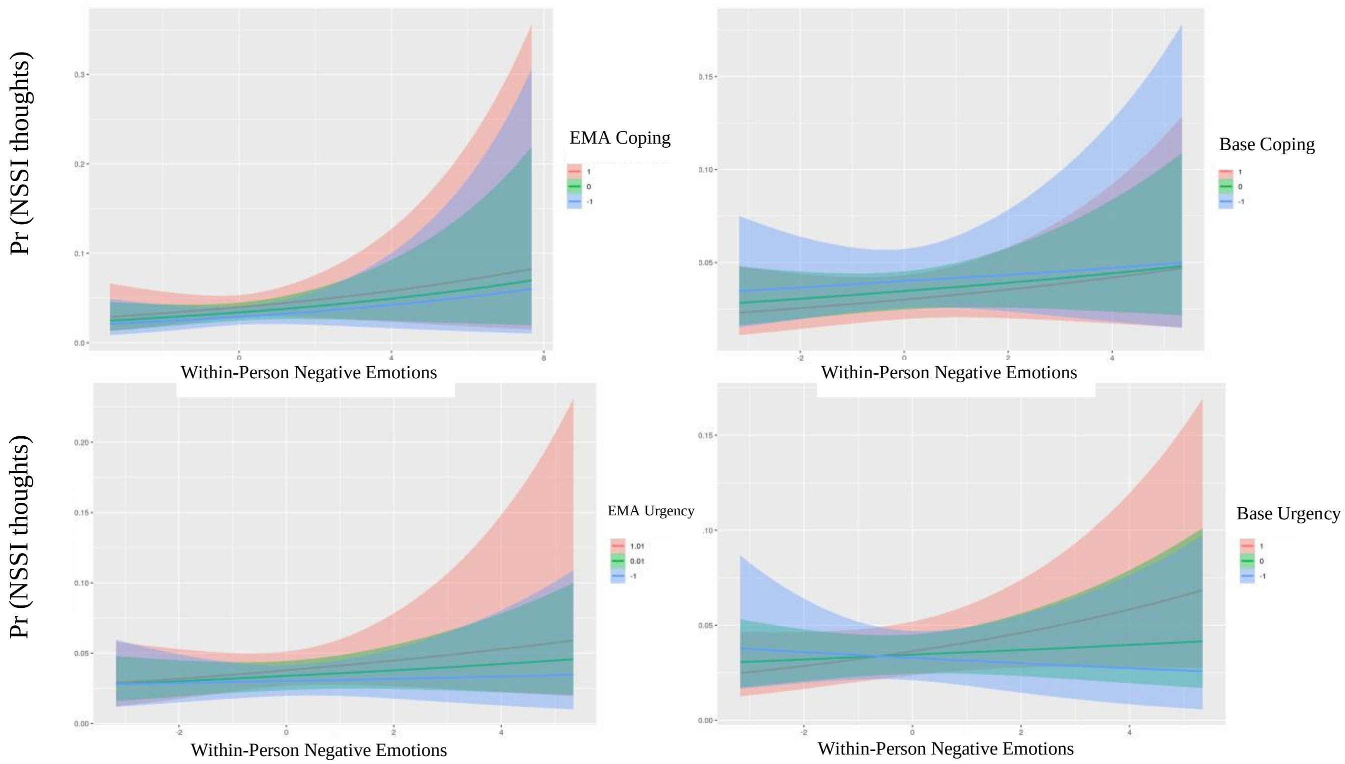


Figure 22

Conditional Effects of Moderation Analyses for Suicidal Thoughts