Regulatory Flexibility and Psychological Adjustment:

A Three-Study Multi-Method Investigation

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General Abstract

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This dissertation filled critical gaps in the regulatory flexibility literature via three empirical studies. Study 1 integrated flexibility components—context sensitivity, repertoire, and feedback responsiveness—by measuring them concurrently and applying rigorous, double-cross validation latent profile analysis to link profiles of flexibility components to depression and anxiety. Study 2 investigated the predictive ability of flexibility for longitudinal trajectories of depression, anxiety, and PTSD while examining over 50 other important factors. Specifically, this study used a machine learning approach to predict trajectories of resilience and psychopathology. Study 3 incorporated situational characteristics and flexibility in an intensive longitudinal design (i.e., ecological momentary assessment) to understand how flexibility was associated with depressed mood, anxious mood, and perceived stress across daily situations. Together, this dissertation found that greater regulatory flexibility was associated with decreased depression and anxiety (Study 1), lower likelihood of chronic depression and anxiety in the aftermath of potentially traumatic events (Study 2), and lower levels of momentary depressed mood, anxious mood, and perceived stress (Study 3).

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Chapter 1: GENERAL INTRODUCTION

The field of emotion regulation (ER) has flourished in the past decade given the central role that ER plays in various forms of psychopathology (Aldao et al., 2010, 2016; Webb et al., 2012). Theories behind emotion regulation, coping, and behaviors in general have a long history of emphasizing the dynamic interplay between situations and persons (Gross, 1999; Lazarus & Folkman, 1984; Lewin, 1935; Mischel, 1973), yet much research on ER has traditionally employed a relatively static approach that classifies a strategy as either uniformly adaptive (e.g., cognitive reappraisal) or maladaptive (e.g., rumination, expressive suppression) (Aldao et al., 2010; Aldao & Nolen-Hoeksema, 2012; D'Avanzato et al., 2013; Joormann & Stanton, 2016; Webb et al., 2012). While the traditional classification of emotion regulation strategies as adaptive versus maladaptive provides an initial understanding of their role in psychopathology, it may oversimplify the process of emotion regulation and psychological adjustment by overlooking individual and contextual differences.

In contrast to this static approach, a growing number of investigators have revisited the long-standing interactionist approach in psychological science, demonstrating that the efficacy of specific emotion regulation strategies varies markedly across situations and individuals (Birk & Bonanno, 2016; Bonanno et al., 2004, 2011; Sheppes et al., 2014; Tamir & Ford, 2012; Troy et al., 2013, 2017; Westphal et al., 2010). According to the flexibility literature, individuals need to flexibly regulate their emotions in order to navigate and manage the diverse demands across varying contexts (Aldao et al., 2015; Bonanno & Burton, 2013; Cheng et al., 2014; Kashdan & Rottenberg, 2010). Emerging empirical evidence has documented the benefit of regulatory flexibility for various aspects of psychological adjustment (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Battaglini, Rnic, Jameson, Jopling, & LeMoult, 2022; Birk & Bonanno, 2016; Blanke et al., 2020; Burton & Bonanno, 2016; Cheng, 2001; Cheng et al., 2014; Goodman et al., 2021; Rodin et al., 2017; Southward & Cheavens, 2017; Y. Wang & Hawk, 2019; Westphal et al., 2010).

Multi-componential Perspective on Emotion Regulation Flexibility

From a theoretical perspective, regulatory flexibility has been conceptualized, not as a unitary phenomenon, but as a broad multi-componential process that involves a sequence of componential abilities (Bonanno & Burton, 2013; Cheng et al., 2014). In a heuristic review by Bonanno and Burton (2013), for example, they elaborated three interrelated yet functionally independent components of flexibility. These components included: 1) the ability to evaluate contextual demands, or context sensitivity, 2) the access to a wide range of strategies that may be implemented to meet those demands, or repertoire, and 3) the capacity to monitor the efficacy of chosen strategies and modify as needed, or feedback responsiveness. Each component was not only considered essential for successful regulatory process but also likely to vary measurably across individuals. Similarly, a meta-analytic review proposed a model based on their synthesis of more than 100 empirical studies (Cheng et al., 2014). In their model, flexibility was conceptualized as abilities displayed at three unique yet closely interacted regulatory stages, respectively assessing situational characteristics, adopting regulatory strategies, and monitoring outcomes. Together, evidence from the top-down, heuristic approach (Bonanno & Burton, 2013) and bottom-up, systematic approach (Cheng et al., 2014) seems to converge and support the likely multi-componential process of regulatory flexibility, such as context-sensitivity, repertoire, and feedback responsiveness.

A growing body of work suggests that the first and arguably the most crucial component in flexible self-regulation involves the ability to read, decode, and evaluate contextual cues that signal the impinging demands and opportunities inherent in the situation, commonly referred to as context sensitivity (Aldao, 2013; Bonanno et al., 2018; Bonanno & Burton, 2013). Notably, this construct refers to the perception of context rather than the response to context. Research has shown that greater context sensitivity, in particular the ability to identify the absence of threatening cues, is associated with fewer psychopathology symptoms (Bonanno et al., 2018). Individual differences in context sensitivity move forward and exert an important impact on subsequent steps of flexible self-regulation, because errors in initial evaluation or less sensitive appraisals made when decoding the contexts make it more difficult and unlikely for one to select appropriate strategies and monitor feedback.

A subsequent component in flexible self-regulation recruits the ability to utilize a wide range of strategies to meet situational demands, commonly referred to as repertoire (Bonanno & Burton, 2013; Burton & Bonanno, 2016; Dixon-Gordon, Aldao, & Reyes, 2015). Whether or not one can successfully enact the chosen strategy depends on the repertoire of regulatory strategies available. Accumulating empirical findings have shown that, better adjustment following stressful and potentially traumatic events is associated with a greater number of strategies (Orcutt et al., 2014), increased temporal variability (Cheng, 2001), and higher categorical variability (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020; Burton et al., 2012; Chen et al., 2018).). However, evidence has also been mixed. For example, some studies found no support for temporal variability (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020). Further, the type and number of strategies examined in studies vary greatly, which may likely contribute to the mixed findings (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020; Burton & Bonanno, 2016; Goodman et al., 2021). Conceptually, using a higher number of strategies or exhibiting variability in strategy use does not guarantee greater effectiveness in meeting situational demands. For example, if one experiences similar situations over time, there may not be a need to exhibit high strategy variability across contexts. Despite the difficulty in capturing repertoire, it will be important for researchers to use prior knowledge to guide the identification of most accessible proxy measures (Bonanno et al., 2023). As one example, given that better repertoire implies that the strategies used were effective at meeting the situational demands, strategy effectiveness may be one of the many possible proxies for repertoire.

Finally, after a strategy has been implemented, a third sequential component of regulatory flexibility involves the post-implementation ability to monitor the effectiveness of the chosen strategy and either maintain or modify the strategy as needed (Bonanno & Burton, 2013; Kato, 2012; Sheppes et al., 2014). This will be referred to as feedback responsiveness in this dissertation. Research has shown that the self-reported ability to discontinue maladaptive strategies and switch to adaptive strategies is associated with fewer depressive symptoms (Kato, 2015, 2017). Although experimental research on this component is relatively sparse, a few studies have demonstrated that more frequent switching from reappraisal to distraction when confronted with high-intensity negative images was associated with a larger modulation in neural activity associated with emotional processing (Ilan et al., 2019). Further, greater frequency of switching from reappraisal to distraction at higher physiological reactivity predicted better psychological adjustment (Birk & Bonanno, 2016). Conceptual framework has highlighted the importance of maintaining effective strategies and switching from ineffective to effective strategies (Pruessner et al., 2020).

Models of flexibility have suggested that flexibility is a multi-component construct (Bonanno & Burton, 2013; Cheng et al., 2014; Sheppes et al., 2014). Despite that these models support context sensitivity, repertoire, and feedback responsiveness as important components, they inevitably overlook other processes implicated in regulatory flexibility, such as emotion regulation goals (Millgram et al., 2015) and situation selection (Gross, 2015; Urry & Gross, 2010). The possibility is tremendous; and the list can be, indeed, endless. Nevertheless, given that these three components have been relatively established theoretically and empirically in the flexibility literature (Bonanno & Burton, 2013; Cheng et al., 2014), this dissertation project will focus on one or more of these three components in each proposed study.

Extend Our Understanding of Regulatory Flexibility and Psychological Adjustment

Theoretical and empirical evidence provide important insights into the construct and function of regulatory flexibility. Yet, several important questions remain unclear. To begin with, despite the increasing number of studies on individual flexibility component, few studies have examined how different flexibility components function together. Additionally, though studies have shown the benefits of flexibility in the context of stressful and potentially traumatic life events (for a review, see Cheng et al., 2014), how robustly flexibility can predict longitudinal adjustment controlling for other important factors is unknown. This limitation results from research that often rely on cross-sectional designs and examine few predictors (for reviews, see Bonanno et al., 2010; Chen & Bonanno, 2020; Galatzer-Levy et al., 2018). Last but not least, flexibility entails adjusting regulatory strategies across contexts by definition, but there has been a curious neglect of assessing the highly diverse situations where regulation takes place. The recognition of the importance of context has appeared primary in the theoretical space, with empirical research lagging relatively behind (Aldao, 2013). Even when sensitivity to context was assessed (Bonanno et al., 2018), it was based on constructed scenarios rather than situations unique to each individual.

Toward an Integration of Flexibility Components

Although each of the flexibility components—context sensitivity, repertoire, and feedback responsiveness—is considered essential for successful self-regulation (Bonanno & Burton, 2013), these components have been studied separately rather than collectively. Multi-componential models of regulatory flexibility suggest that people who display high ability across all sequential flexibility components will exhibit the best mental health outcomes (Bonanno & Burton, 2013). However, to date, empirical research has focused almost exclusively on individual components. One noteworthy exception (Southward & Cheavens, 2017), for example, examined the interplay of these componential abilities. These authors found that deficits in repertoire predicted greater depression and anxiety only among participants who were low in context sensitivity. These findings were consistent with theories of flexibility that underscored the primacy of context sensitivity and viewed deficits in this component as especially predictive of poor clinical outcomes (Bonanno et al., 2018; Bonanno & Burton, 2013). There has been almost no empirical work to date that directly compares psychopathology symptoms between participants with different flexibility deficits. Adopting a person-centered approach holds the potential of not only identifying patterns of flexibility deficits but also examining how these patterns are related to psychopathology symptoms. Although this is relatively unexplored in the flexibility literature, previous studies on ER strategy have adopted a person-centered approach and linked patterns of ER to psychopathology symptoms such as depression and anxiety (Dixon-Gordon, Aldao, & Reyes, 2015).

Additionally, it is worth considering whether one flexibility component is more important than the others. Given that context sensitivity plays a crucial role in emotional experience and regulation (Aldao, 2013; Rottenberg et al., 2005) and that it is sequentially the first step of self-regulation (Bonanno et al., 2018), it may be the case that deficit in this component presents greater harm for psychological health than the others. However, it is also likely that strong abilities in one or two components suffice to accommodate deficits in other components, or that deficit in any flexibility component is universally associated with similar level of psychological distress. In order to better understand the nature of flexibility deficits across individuals and how different patterns of flexibility components are associated with depressive and anxious symptoms, studies integrating all the three components of regulatory flexibility are warranted.

Flexibility as a Robust Predictor for Longitudinal Adjustment

Longitudinal studies of psychological adjustment following stressful and potentially traumatic life events have consistently identified a small set of prototypical outcome trajectories (Bonanno et al., 2004; Galatzer-Levy et al., 2018). These trajectories include low distress or symptoms over time, or resilience, high onset but gradual waning distress or symptoms, or recovery, and elevated distress or symptoms over time, or chronicity. Trajectory models offer a robust methodology to reveal clinically relevant patterns of response to potential trauma and enhance the identification of predictors (Galatzer-Levy & Bonanno, 2014). Although previous research has identified predictors of chronic psychopathology and resilience following stressful and potentially traumatic events, the number of factors examined were typically small. Though these studies elucidate the heterogenous psychological response in response to adverse events and identify some predictors, the relatively small number of examined factors precluded researchers from identifying robust predictors and conducting accurate classification of long-term adjustment.

Keeping this limitation in mind, though flexibility was found predictive of longitudinal adjustment (Bonanno et al., 2004; Westphal et al., 2010), examining flexibility alongside a large set of potential predictors can further elucidate whether flexibility can robustly predict longitudinal adjustment controlling for other potentially important factors.

As one of the many possible potentially traumatic events, the global outbreak of the novel coronavirus disease 2019 (COVID-19) affords a unique historical context to study this question. During the early stage of the COVID-19 epidemic, there have been increased psychological challenges resulting from a combination of stressors, characterized by great uncertainty, life-threatening conditions, fear of COVID-19, prolonged exposure to anxiety provoking information, and loss of loved ones, financial security, perceived control, social connection, and daily activities (Gruber et al., 2021). As pandemics are dynamic events, Taylor (2019) suggested that the psychological difficulties resulted from pandemics are likely to vary across time. The initial distress-related responses to COVID-19 are a multi-faceted network of interconnected symptoms, with COVID-19 danger and contamination fears as its cores (Taylor et al., 2020). Over time, other potential deleterious practical consequences, such as economic loss and unemployment, have emerged and taken a toll on mental health (Achdut & Refaeli, 2020; Lei et al., 2020). The changing contexts inevitably pose demands on being flexible as the situation unfolds (Chen & Bonanno, 2020). Examining flexibility alongside other predictors for longitudinal adjustment in the aftermath of strict lockdowns may further our understanding as how robust flexibility is as a predictor for longitudinal psychological adjustment following stressful and potentially traumatic life events.

Incorporating Context in the Real-Time Assessment of Flexibility

Research on regulatory flexibility and psychological adjustment has relied on experimental and self-report measures. By definition, flexibility entails adjusting regulatory choices to meet the demands of changing situations. It is therefore suboptimal to assess flexibility without assessing the situations in which regulation occurs. In practice, however, there has been a lack of situation assessment in emotion regulation research. Indeed, some studies compared emotion regulation across different contexts (Dixon-Gordon, Aldao, & De Los Reyes, 2015), such as instructing participants to describe distinct situations that elicited four different emotions (i.e., anxiety, anger, sadness) in three types of intensity (i.e., moderate, high). Other studies have used emotional stimuli to expose participants to high- and low-intensity emotion (Sheppes et al., 2014). However, few studies on emotion regulation to date have assessed situations as they spontaneously occur and examined whether and how these situations may covariate with emotion regulation strategy use. In few recent studies using ecological momentary assessment to understand emotion regulation flexibility and contextual factors (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Battaglini, Rnic, Jameson, Jopling, & LeMoult, 2022), researchers often assessed a limited number of situational characteristics, such as controllability and pleasantness. A lack of systematic assessment of situations has therefore limited our understand of how situations impacted emotion regulation, and how various components of flexibility unfolded over time.

Both social and clinical literature have provided insight into important contextual factors to consider in emotion regulation research. Reappraisal, an emotion regulation strategy often considered as adaptive (Aldao et al., 2010; Webb et al., 2012), can be detrimental to mental health in the context of uncontrollable stressors (Troy et al., 2013, 2017). Additionally, when emotional intensity was high, researchers found distraction a more effective strategy than reappraisal (Ilan et al., 2019; Sheppes et al., 2014). Suppression, another emotion regulation strategy often considered as maladaptive (Aldao et al., 2010; Joormann & Stanton, 2016), was a neural or even beneficial process for East Asian population (Chen et al., 2020; Soto et al., 2011).

Social and personality psychologists have further developed tools to assess situational characteristics (Rauthmann et al., 2014; Rauthmann & Sherman, 2016), identifying eight fundamental characteristics of situations: Duty, Intellect, Adversity, Mating, pOsitivity, Negativity, Deception, and Sociality (DIAMONDS). These eight fundamental characteristics have been replicated across the globe (Guillaume et al., 2016; Lee et al., 2020). Several investigators have developed ultra-brief assessment of situations for experience sampling research (Rauthmann & Sherman, 2016), which has been used in intensive longitudinal design that aims to predict behaviors, emotions, and interpersonal dynamics (Hong et al., 2020, 2021; Horstmann et al., 2021; Sherman et al., 2015). Tools of situation assessment combined with intensive longitudinal measures of emotion regulation may provide opportunities to better understand how situations and regulatory strategy use covariate, thereby shedding light on personalized assessment of flexibility.

The Three-Study Investigation

This dissertation project aims to bridge existing gaps in the flexibility literature with three empirical papers. The goal of this dissertation project is to extend our understanding of regulatory flexibility and psychological adjustment by integrating different flexibility components (Study 1), examining whether flexibility robustly predict longitudinal trajectories of psychological adjustment controlling for a large set of potentially important factors (Study 2), and incorporating dynamic assessment of situational characteristics and emotion regulation using an intensive longitudinal design (Study 3).

The first study sought to identify predominant patterns of all three regulatory flexibility components—context-sensitivity, repertoire, feedback responsiveness—and link these patterns to symptoms of depression and anxiety. Although individuals with greater abilities in each of these components have shown better psychological adjustment (for a review, see Bonanno & Burton, 2013), these components' patterns and collective functions remain unknown. To fill this gap, the first study applied double cross-validation latent profile analysis to three flexibility components with depressive and anxious symptoms as distal outcomes. This approach enabled the identification of potential regulator subtypes and afforded a better understanding of how different components of regulatory flexibility function together to shape mental health outcomes. In this study, we capitalized on recently validated measures matching the three components of Bonanno and Burton's (2013) flexibility model, respectively context sensitivity, repertoire, and feedback responsiveness. Additionally, to understand the nature of flexibility deficits and how different flexibility profiles are linked to depression and anxiety, we conducted latent profile analysis on these three components, and then linked the constructed latent profiles to depressive and anxious symptoms.

The second paper aimed to directly examine regulatory flexibility, as measured by the Coping Flexibility Questionnaire (CFS; Kato, 2017), in combination with another 58 person- and context-level factors, in predicting psychopathology and resilience trajectories of depression, anxiety, and PTSD symptoms in the aftermath of strict COVID-19 lockdowns in Hubei, China, where COVID-19 was first reported. This study could shed light on the potential relationship between flexibility and psychological adjustment to stressful life events. Furthermore, as most studies have only controlled for few covariates when examining the predictive ability of flexibility (Rodin et al., 2017; Westphal et al., 2010), this study sought to identify whether flexibility would be a robust predictor for long-term adjustment among a large set of potentially important factors selected based on previous research and theoretical importance.

COVID-19 is a highly contagious respiratory illness first reported in Hubei Province, People's Republic of China, toward the end of 2019. As the place where COVID-19 was first reported and then contained, what happened in Hubei exemplified the influence of lockdowns that could potentially offer vital insights into ways the world may better prepare for the return to normal as well as future outbreaks. Starting with its capital, Wuhan, Hubei has witnessed the interruptions of daily life and unique stressors in this crisis. Moreover, without any predecessor from which experience or sufficient scientific knowledge of COVID-19 such as vaccination and fatality rates could be learned, Hubei residents were faced with enormous uncertainty as COVID-19 led to unprecedented quarantine and isolation policies in an attempt to contain the virus. For example, government and community officials enforced stringent lockdown measures that prohibited residents from leaving their districts, restricted each family to send only one person to purchase groceries twice a week, and banned the private use of cars; the local government even took steps to reward individuals who reported neighbors breaking social distancing rules in order to eliminate group gatherings (Feng & Cheng, 2020). As an inevitable consequence of mandatory quarantine, Hubei residents were faced with fear, economical loss, and lack of access to food supplies and routine healthcare. Forced social isolation also reduced social and physical contacts with others and likely elevated psychological distress (Brooks et al., 2020).

The third study used an EMA design to capture emotion regulation, situational characteristics, and psychological distress four times a day across 21 days. Each EMA survey also captured the effectiveness of emotion regulation repertoire initially adopted in response to the emotional situation and whether one chose to switch from the initial repertoire. Before and after the EMA phase of the study, participants completed self-report measures of context sensitivity (Bonanno et al., 2018), repertoire (Burton & Bonanno, 2016), feedback responsiveness (Kato, 2012), habitual use of emotion regulation strategies (Garnefski et al., 2001; Gross & John, 2003; Hofmann, Curtiss, et al., 2016; Meyer et al., 1990; Treynor et al., 2003), and psychopathology (Watson et al., 1995).

The goal of the third study was to test the flexibility hypothesis (Bonanno & Burton, 2013) in an intensive longitudinal design. We examined whether context sensitivity, initial effectiveness of emotion regulation repertoire, and feedback responsiveness would be associated with momentary psychological distress, depressed mood, anxious mood, and perceived stress. We developed a proxy for momentary context sensitivity and tested its validity. Although we did not have direct momentary measure for repertoire, participants reported the momentary effectiveness of their initial repertoire in three dimensions: enhancing positive affect, decreasing negative affect, and facilitating problem-solving. We conceptualized feedback responsiveness as maintaining effective repertoire and switching from the initial ineffective repertoire, which was operationalized by the interaction between change in emotion regulation and initial effectiveness.

Method

Study 1

Study 1 (Chen & Bonanno, 2021) was a cross-sectional conducted using Amazon Mechanical Turk (MTurk). We recruited a total of 802 participants (361 males, 436 females, two others, and three prefer not to answer) on average 36.41 years of age (SD = 10.79) completed the measures and were paid two dollars for their participation. The sample was racially diverse, with 75.9% of Caucasian, 10.3% of Black or African American, 9.0% of Asian American, 2.5% of American Indian, 0.5% of Native Hawaiian, and 1.7% of participants that preferred not to answer. In the sample, 10.2% of the participants self-identified as Hispanic or Latino, 88.7% of the participants considered themselves as non-Hispanic, and 1.1% preferred not to answer. Participants provided informed consent prior to participating in the study.

In the first study (Chen & Bonanno, 2021), we assessed **context sensitivity** using the Context Sensitivity Index (Bonanno et al., 2018), measured **repertoire** using the Flexible Regulation of Emotional Expressions Scale (Burton & Bonanno, 2016), evaluated **feedback responsiveness** using the Coping Flexibility Scale (Kato, 2012). These componential scores were used in latent profile analysis and linked to outcomes of **depression** and **anxiety**, measured by the Mood and Anxiety Symptom Questionnaire-Short Form (Watson et al., 1995). We expected to identify individuals who would exhibit moderate and high levels of flexibility as well as individuals may showed some patterns of flexibility. We predicted that individuals exhibiting increased flexibility would have reduced symptoms of depression and anxiety.

Study 2

Study 2 (Chen et al., 2022) aimed to identify protective and risk factors, including flexibility, that may predict longitudinal psychopathology and resilience following strict COVID-19 lockdowns. In specific, this study identified half-year longitudinal trajectories (April, June, August, and October, 2020) of three mental health outcomes (depression, anxiety, and PTSD) among a sample of Hubei resident, used a broad range of person- and context-level predictors in Least Absolute Shrinkage and Selection Operator (LASSO) logistic regression to select best predictors for trajectory memberships of resilience and chronic psychopathology. In doing so, we could determine if flexibility could "survive" an important predictor even when keeping into consideration such a large number of alternative factors.

In order to recruit participants, this study employed a snowball sampling strategy, with research assistants spreading e-posters on Chinese social media platforms (Weibo, WeChat, Zhihu, and Blog) and asking their online contacts from Hubei to do the same in a manner similar to retweeting. We included multiple social media platforms of different age groups to diversify our participant composition. Following our distribution of e-posters on social media, we received 396 signups that met our inclusion criteria (i.e., living in Hubei during the time of the lockdown). Of those, 18 provided invalid contact information (e.g., incorrect or incomplete email or phone or WeChat number), six signed up twice, leaving 372 valid signups. The research team reached out to these potential participants via their preferred contact method (text, WeChat, or email). Of these participants, 19 did not respond and 9 declined to participate because they were no longer available or interested. This left us with 344 participants at baseline and a response rate of 92.5%.

After removing 18 participants who only completed the first wave, we adopted full-information maximum likelihood, an estimation strategy that allow us to obtain parameter estimates even in the presence of some missing outcome values. We adopted this approach because there were no longitudinal outcome data on those completing only one wave and including them in LGMM would lead to model non-convergence. In addition, we handled the missing data of the baseline predictor values (0.94%) using K-nearest neighbor (KNN) imputation. In terms of attrition, among the 326 participants included in the final analysis, 8, 33, and 35 participants missed wave 2, wave 3, and wave 4, respectively, with the possibility that some participants who missed a certain wave completed the following ones upon recontact. A total of 265 completed all four waves, and 311 completed at least three waves. The attrition rate was relatively low, possibly because we contacted participants one on one instead of sending generic emails to a large list of participants and provided them with a personalized mental health report, a gift, and a thank-you letter. We included instructions on the approximate time range that each survey may take and the importance of attentive participation is to the scientific understanding of the psychological impact of the pandemic and the accuracy of personalized mental health report.

Participants ranged in age from 16 to 70 (M = 30.05, SD = 10.84) and 75.1% were female; the majority of them (77.6%) obtained a bachelor's degree or higher and 44.2% are either married or divorced. The results of t-tests and chi-squared tests showed that participants who dropped out did not differ from those who remained in demographics including age, gender, education level, marital status, number of children, quarantine location, and baseline psychopathology symptoms, $ps > .05$. Participants provided informed consent prior to participating in the study.

Outcome Measures

Depression was measured using the 20-item Center for Epidemiological Studies-Depression (CES-D; Radloff, 1977; Chinese version by Wang et al., 1999). Participants rated depression-related thoughts and behaviors during the past week on a 4-point scale from 0 (*less than 1 day a week*) to 3 (*5-7 days a week*). CES-D totals range from 0 to 60, with higher scores indicating greater depression. Cronbach's alpha coefficients were good (.91 to .93) across all four time points.

Anxiety was assessed using the 20-item State Anxiety Inventory (SAI; Spielberger, 1989; Chinese version by Wang et al., 1999). Participants reported how they feel in relation to anxiety *right now* as opposed to how they feel *usually* on a 4-point scale from 1 (*almost never*) to 4 (*almost always*). SAI totals range from 20 to 80, with higher scores indicating greater state anxiety. Cronbach's alpha coefficients for SAI were good (.93 to .95) at all four time points.

PTSD symptoms were measured by the Posttraumatic Diagnostic Scale-Chinese (PDS-C; Shen et al., 2014), which assesses PTSD symptoms on 4-point scale from 0 (*not at all*) to 3 (*almost always*). Items were tailored in wording to capture COVID-19 related traumatic experiences (e.g., the original item "Bad dreams or nightmares related to the trauma" was replaced by "Bad dreams or nightmares related to the pandemic"). Cronbach's alpha coefficients were good (.90 to .92) for PDS-C across four time points.

Person-Level Predictors

COVID-19 fear was measured using the Fear of COVID-19 Scale, (FCV-19S; Ahorsu et al., 2020; Chinese version by Chi et al., 2021). **Optimism** and **pessimism** were measured via the Life Orientation Test—Revised, (LOT-R; Scheier et al., 1994). Following a previous validation of the scale in a mainland Chinese sample (Lai & Yue, 2000), we summed the three positively worded items to reflect optimism ($\alpha = .63$) and the three negatively worded items to reflect pessimism ($\alpha = .71$).

Physical health-related measures. Participants reported information regarding their health including subjective health from 1 (*very unhealthy*) to 5 (*very healthy*), health change from -1 (*declined*) to 0 (*no change*) to 1 (*improved*), and weekly exercise frequency and hours prior to COVID-19. Body mass index (BMI) was calculated from the participants' height and weight. Participants also reported whether they have had been infected with COVID-19, whether they have had doctor visits during the pandemic, had been hospitalized during or prior to COVID-19, and whether they had any of preexisting health conditions. We included self-rated health and health change, infection and hospitalization, BMI, and a sum of health conditions as predictors.

Prosocial behaviors were measured by averaging three items: "I participate in or advocate donation", "I help government or charity raise resources", and "I show concerns and offer comfort to others" ($\alpha = .74$). **Perceived social support** was measured by averaging ten items adapted from the MOS Social Support Survey (MOS-SSS; Sherbourne & Stewart, 1991), which assesses perceived emotional/informational, tangible, and affectionate support as well as positive social interaction in times of need on a 5-point scale from 1 (*almost never*) to 5 (*always*). Items included, for example, “someone to help you if you were confined to bed” and “someone who shows you love and affection” (α = .92).

We measured habitual use of common **Emotion Regulation** strategies including reappraisal, suppression, brooding and reflection (two subtypes of rumination), distraction, worry, refocus on planning, and positive re-focusing. **Reappraisal (**α = .85**)** and **suppression** (α = .73) were measured by the 10-item Emotion Regulation Questionnaire (ERQ; Gross & John, 2003; Chinese version by Wang et al., 2007). **Brooding rumination** and **reflective rumination** were measured by the Ruminative Response Scale (RRS; Treynor et al., 2003; Chinese version by Yang et al., 2009) on a 4-point scale from 1 (*almost never*) to 4 (*almost always*). We excluded the depression-related factor given its great overlap with depressive symptoms, leaving five items (e.g., “What am I doing to deserve this?”) measuring the **brooding** aspect of rumination (α =.77) and five items (e.g., “Analyze recent events to try to understand why you are depressed” assessing the **reflective** aspect of rumination (α =.86). **Distraction** was assessed by the distraction subscale from the Response Style Questionnaire (RSQ; Nolen-Hoeksema, 1991). In the present study, we excluded items not adequate in the context of strict lockdowns (e.g., “Decide to go out and have some fun”). The internal consistency of the selected five items was good (α = .82). **Worry** was measured via five selected items from the Penn State Worry Questionnaire (PSWQ; (eyer et al., 1990) which captures an individual’s dispositional proneness to worry (e.g., “Many situations make me worry.”) on a 5-point scale from 1 (*not at all typical of me*) to 5 (*very typical of me*). The five items selected in this study from the instrument were internally consistent (α = .95). **Refocus on planning** (α = .83) and **positive refocusing** (α =.87) were measured by their corresponding subscales from the Cognitive Emotion Regulation

Questionnaire (CERQ; Garnefski et al., 2001; Chinese version by Wang et al., 2018) that measures various feelings and reflections following a threatening or stressful life event on a 5-point scale from 1 (*almost never*) to 5 (*almost always*). Specifically, the four-item **refocus on planning** subscale captures thinking that involves coming up with steps one needs to take following a negative event; the four-item **positive refocusing** subscale assesses disengaging in thinking about the negative event and instead refocusing on more joyful and pleasant events

We also measured a few **Coping** strategies a 5-point scale from 1 (*almost never*) to 5 (*always)*. **Alcohol use** was measured with the item "I alleviate stress by drinking alcohol". **Tobacco use** was assessed with the item "I alleviate stress by smoking cigarettes". **Leisure activities** frequency was assessed by four items (e.g., I participate in leisure activities such as watching movies and TV; α = .67). **Productivity maintenance** was assessed with two items including "I continue to work towards my goals by studying or working hard." Internal consistency was good (α = .72). **Regularity maintenance** was assessed with four items related to regular physical activities, sleep, and eating (α = .84). **COVID-19 related information accessing** was measured with three items like "I keep myself posted on the spread of the pandemic (such as new cases)." Internal consistency was good (α = .83). **COVID-19 related information overconsumption** was assessed by "even though I am anxious, I would still repeatedly check news about the pandemic." **Preventive measures** were assessed by five items (e.g., "I wash my hands carefully"; "I keep a distance from others"; α = .74).

In addition to coping strategies, we assessed **Coping Flexibility** (α = .84) with the 10-item Coping Flexibility Scale (CFS; Kato, 2012, 2015), which measures ability to discontinue ineffective strategies and implement alternative coping strategies and is one of the flexibility components outlined in Bonanno and Burton (2013). Participants rated the extent to which they agreed with the items (e.g., "When a stressful situation has not improved, I try to think of other ways to cope with it") on a 4-point scale from 1 (*not applicable*) to 4 (*very applicable*).

Context-Level Predictors

In addition to person-level predictors, we measured context-level predictors across domains of stress exposure, family feature, and community characteristics.

Stress Exposure: As a crucial aspect of the COVID-19 lockdowns was economic recession, we measured participants' **personal income level prior to the pandemic**, and **employment before and during COVID-19**. Our measure of **stressful life events** during the COVID-19 lockdown was adapted from two existing measures that assess the impact of various stressful life events (Life Experience Survey; Sarason et al., 1978; Chinese version by Wang et al., 1999). Participants reported whether common life events have occurred and the perceived impact of these experiences on a 4-point scale from 0 (*had no impact*) to 3 (*severe impact*). To reflect stressors specific to COVID-19, we included items such as "I was infected with COVID-19", "My family members were infected with COVID-19", and "I was forced to work /study from home". Similar to the existing measures, participants had the option to list at most five additional stressful events. Three features were derived from the LES: **Number of stressful life events** is the total number of stressors participants endorsed regardless of their perceived impact; perceived impact of each endorsed event was summed up to indicate **stress severity**, which was then divided up by the total number of stressful life events to obtain an individual's **mean appraisal of stressful events** during the COVID-19 lockdowns. A dichotomous measure of **discrimination due to COVID-19** was derived from participants' text responses to an open-ended question inquiring about what was stressful about the pandemic. Discrimination was the only noticeable theme (i.e., percentage > 5%) that emerged. Two psychology undergraduate students then independently coded whether a response described experience of discrimination due to COVID-19 (e.g., “My boss fired me because I am from Wuhan.”) The percent of agreement was high (95%), and a third graduate-level coder was included to resolve conflicts.

Family Features: Participants reported **family structures**, including marital status, number of children as well as number of underaged children. **Family relationship** was measured using 10 items adapted from the China Family Panel Studies, a longitudinal project that provides an overview of citizen health, psychological wellbeing, parental practice, and so on (Institute of Social Science Survey, 2021), on a 5-point scale ranging from 1 (*very bad*) to 5 (*very good*). Of the 10 items, five items measured **family support**, such as whether family members share a communicative, supportive, and positive relationship and support each other during life crisis ($\alpha = .92$). The other five items measured **family conflict** such as whether family members experience conflicts in daily communication and refuse to help when a family member encounters setbacks ($\alpha = .79$).

Community Characteristics*:* Participants reported information of their living environment such as the number of years they spent in the lockdown city, location and residency information (e.g., whether one possesses residency in the lockdown city, comes from rural regions, and quarantines in Wuhan). We also included **objective measures** derived from the characteristics of the cities where the participants lived during the lockdown, recorded by Chinese authorities, including neighborhood socioeconomic status (i.e., per capita disposal income) in 2018, total COVID-19 cases till April 2020, number of hospitals with fever clinics receiving COVID-19 patients (weighted by city-level population density), 2020 average housing price, 2017 population density, 2018 GDP, and 2018 weighted city-level public expenditures (i.e., how much a city spends on welfare, education, health care, and infrastructure weighted by population density). **Subjective satisfaction** with the community was measured via six items adapted from the China Family Panel Studies (CFPS; Institute of Social Science Survey, 2021), on a 5-point scale ranging from 1 (*very bad*) to 5 (*very good*). Participants reported satisfaction with community infrastructure, environment, quality of relationship with neighbors, and general feelings about the community. Scores were averaged to reflect community satisfaction, with higher scores indicating greater satisfaction with one's community (α = .88).

Study 3

A total of 173 participants were enrolled in the study. Fifteen participants left the study during the EMA phase of study, leaving 158 participants in our final analyses. Participants were compensated $40 if they completed 80% of the daily surveys and $60 if they completed 95% of the daily surveys. Those who stayed in the study completed 77 out of 84 (92.05%) daily surveys on average. Most of the participants identified as woman (36 men, 116 woman, and 6 non-binary or non-conforming individuals). Participants ranged from 18 to 72 in age (M = 35.97, SD = 12.45) and were racially diverse, with 49.37% of Caucasian American, 18.35% Black or African American, 27.22% Asian American, and 2.53% American Indian, Alaska Native, or Native Hawaiian. In the sample, 10.76% identified as Hispanic or Latinx. The institutional review broad at Teachers College, Columbia University has approved this study (IRB#22-218).

Baseline and Exit Survey

Participants completed a baseline and an exit survey before and after the EMA phase of study. Both surveys were distributed through the Qualtrics platform. Measures of the baseline and exit surveys were identical, including demographics, components of flexibility, habitual use of emotion regulation, and symptoms of depression and anxiety. Only components of flexibility and habitual emotion regulation were used in this paper and the remaining measures were reported elsewhere.

Context Sensitivity was measured by the Context Sensitivity Index (CSI; Bonanno et al., 2018). CSI is a scenario-based inventory that captures one's sensitivity to the relative presence of contextual cues (Cue Presence Index, CPI) and to the relative absence of cues (Cue Absence Index, CAI). The CPI is composed of ten appraisal items normed as relatively present in the scenarios; the CAI is composed of ten appraisal items normed as relatively absent in the scenarios. The CAI items were reverse-coded so that higher scores reflected greater sensitivity to the absence of a contextual cue. After reading each daily situation (e.g., You take a medicine and it makes your nauseous. Your doctor tells you that it is not serious and that you just have to "wait it out"), participants were asked to rate their perception of cues including threat, self-control, other-control, urgency, and cooperation on a 7-point scale from 1 (*not at all*) to 7 (*very much*). The CSI has been associated with flexible coping, emotion regulation, and psychopathology symptoms, and has been validated against behavioral measures of cue sensitivity such as the Picture Arrangement Test from the Wechsler Adult Intelligence Scale- Third Edition (Bonanno et al., 2018). In this study, we calculated the sum of CPI and CAI to reflect the context sensitivity component of emotion regulation flexibility.

Repertoire was measured at baseline using a proxy scale, the Flexible Regulation of Emotional Expression Scale (FREE, Burton & Bonanno, 2016). FREE is a scenario-based questionnaire that measures participants' ability to up- and down-regulate their emotional expressions to meet situational demands—commonly referred to as ***expressive flexibility***—which is an important aspect of repertoire. The FREE includes two subscales that measure the ability to enhance and suppress emotional expressions. A total score can be calculated by summing the enhancement and suppression scores. Higher scores indicate that participants are better able to up- and down-regulate their emotional expressions to meet divergent contextual commands. Participants indicated how well they would be able to be even more expressive (e.g., Your boss is complaining about a project you know little about and have no involvement with.) or conceal how they were feeling (e.g., You are at a social event and the person you're talking to frequently spits while they speak.) following each scenario on a 6-point scale from 1 (*unable*) to 6 (*very able*). Studies have found an association between the FREE and measures of emotion regulation, psychopathology symptoms, and well-being (Burton & Bonanno, 2016; Chen et al., 2018). Keeping in mind the limitation of FREE that it only captured repertoire in up- and down-regulating emotional expressions, we used the total score of the FREE scale to reflect the repertoire component of ER flexibility.

Feedback Responsiveness was measured by the Coping Flexibility Scale (CFS, Kato, 2012). CFS is a ten-item self-report questionnaire that captures the ability to discontinue an ineffective strategy (e.g., If I feel that I have failed to cope with stress, I change the way in which I deal with stress.) and produce and implement an alternative strategy (e.g., When a stressful situation has not improved, I try to think of other ways to cope with it). Participants were asked to indicate how the statements apply to them on a 4-point scale from 1 (*not applicable*) to 4 (*very applicable*). Higher CFS scores were associated with more adaptive outcomes (Kato, 2012). In this study, we calculated a sum score to reflect feedback responsiveness.

The baseline survey also included habitual use of common emotion regulation strategies, including cognitive reappraisal, expressive suppression, brooding and reflection (two forms of rumination), worry, planning, positive refocusing, perspective taking, soothing, and seeking others' perspective. We selected these strategies in order to cover a wide range of cognitive, expressive, and interpersonal emotion regulation strategies.

Cognitive reappraisal and **expressive suppression** were measured by the 10-item Emotion Regulation Questionnaire (ERQ; Gross & John, 2003) on a seven-point scale from 1 (*strongly disagree*) to 7 (*strongly agree*). There are six items (e.g., When I want to feel more positive emotion [such as joy or amusement], I change what I'm thinking about) measuring reappraisal ($\alpha = .83$) and four items (e.g., When I am feeling positive emotions, I am careful not to express them) measuring suppression ($\alpha = .72$).

Brooding and **reflection** were measured by the Ruminative Response Scale (RRS; Treynor et al., 2003) on a four-point scale from 1 (*almost never*) to 4 (*almost always*). We excluded the depression-related factor given its great overlap with depressive symptoms, leaving five items (e.g., "What am I doing to deserve this?") measuring the brooding aspect of rumination ($\alpha = .77$) and five items (e.g., "Analyze recent events to try to understand why you are depressed" assessing the reflective aspect of rumination ($\alpha = .86$).

Worry was measured via three selected items from the Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990) which captures an individual's dispositional proneness to worry (e.g., "Many situations make me worry.") on a 5-point scale from 1 (*not at all typical of me*) to 5 (*very typical of me*). The three items selected in this study from the instrument were internally consistent ($\alpha = .80$).

Planning and **positive refocusing** were measured by their corresponding subscales from the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2001) that measures various feelings and reflections following a stressful life event on a 5-point scale from 1 (*almost never*) to 5 (*almost always*). Specifically, the four-item planning subscale (e.g., I think about how

I can best cope with the situation) captures thinking that involves coming up with steps one needs to take following a negative event (α = .83); the four-item positive refocusing subscale (e.g., I think of something nice instead of what has happened) assesses disengaging in thinking about the negative event and instead refocusing on more joyful and pleasant events (α =.87).

Soothing and **perspective seeking** were measured by the soothing and perspective taking subscales from the Interpersonal Emotion Regulation Questionnaire (IERQ; Hofmann et al., 2016) that measures interpersonal emotion regulation on a 5-point scale from 1 (*not true for me at all*) to 5 (*extremely true for me*). The five-item **soothing** subscale (e.g., I look for other people to offer me compassion when I am upset) captures behaviors of seeking compassion, comforting, and emotional support from others when feeling upset (α = .81). The five-item **perspective seeking** subscale (e.g., Having people telling me not to worry can calm me down when I am anxious) assesses how much one relies on others' perspectives to regulate emotions (α = .91).

EMA Measures

Each participant completed an orientation meeting with one of ten trained graduate research assistants the day before their first EMA survey. During the orientation meeting, the research assistant explained the EMA procedure and instructed the participant to complete a practice survey that was identical to the EMA survey. This allowed participants an opportunity to ask questions about the EMA procedure. During the EMA phase of the study, participants were prompted by Metricwire, a mobile app designed for experience sampling, to complete EMA surveys four times per day at approximately 12 PM, 3 PM, 6 PM, and 9 PM over the course of 21 days (i.e., 84 EMA surveys in total). Once they received the prompt, they had 90 minutes to respond; after that, the EMA survey expired and was marked as missing. All 84 EMA surveys were identical, assessing the most emotional situation in the past three hours, followed by measures of perceived situational characteristics, emotion regulation strategies, effectiveness of emotion regulation strategies, whether participant changed their initial emotion regulation strategies, and level of momentary psychological distress following the regulation attempt. All questions were detailed below in the order of how they present in each EMA survey.

The Emotional Situation. Each EMA survey started with asking the participant to recall the most emotionally salient situation in the past three hours. Similar to previous studies (Horstmann et al., 2021; Rauthmann & Sherman, 2016; Sherman et al., 2015), participants were asked to write a response covering the following information: Where were you? Who was with you? What were you (and others) doing? What was happening? Unlike previous studies, however, we did not ask participant to indicate when the situation occurred to avoid redundancy since the prompt already required the participant to recall the most emotional situation in the past three hours.

Perceived Situational Characteristics. We used ultra-brief measures for the situational eight DIAMONDS (i.e., **D**uty, **I**ntellect, **A**dversity, **M**ating, p**O**sitivity, **N**egativity, **D**eception, and **S**ociality) domains (Rauthmann & Sherman, 2016) to assess perceived situational characteristics. Additionally, we included an item on controllability, given recent studies highlighting its important role in the effectiveness of emotion regulation strategies (Troy et al., 2013, 2017). Participants rated how much each of these nine characteristics applied to the most emotional situation they wrote on 7-point scale from 1 (*not at all*) to 7 (*totally*). Duty was measured by "Work has to be done." Intellect was measured by "Deep thinking is required." Adversity was measured by "Someone is being threatened, blamed, or criticized." Mating was measured by "The situation is romantically or sexually charged." Positivity was measured by "Situation is enjoyable." Negativity was measured by "Situation includes negative feelings (e.g., stress, anxiety, guilt)." Deception was measured by "Someone is being deceived." Sociality was measured by "Social interaction is possible or required." Controllability was measured by "I have control over the situation."

Initial Momentary Emotion Regulation Strategies. Participants rated whether they used a series of emotion regulation strategies as 0 (*no*) or 1 (*yes*) based on their initial, knee-jerk response to the situation. Participants were instructed to **select all strategies they utilized in the situation**. These strategies included reappraisal (i.e., I changed how I thought about the event), suppression (i.e., I made sure to hide how I feel), rumination (i.e., I repeatedly thought about the event and could not stop), worry (i.e., I worried about what may happen), distraction (i.e., I did something else to take my mind off it), problem solving (i.e., I tried to solve problems or resolve the events), savoring (i.e., I took time to savor or enjoy what happened), planning (i.e., I made plans for the next steps), positive refocusing (i.e., I focused on the positive aspect of the event), soothing (i.e., I looked to others for comfort), and perspective seeking (i.e., I tried to find out what others would do if they were in my situation).

Effectiveness of Initial ER strategies. After indicating their initial emotion regulation strategies, participants were asked to rate the effectiveness of the ER strategies they used on a 5-point scale from 1 (*not at all*) to 5 (*extremely*). Specifically, they were asked three questions: Did your initial response decrease distress, sadness, or anxiety? Did your initial response enhance pleasure, happiness, or calmness? Did your initial response facilitate problem solving? These three items were summed to reflect the effectiveness of initial repertoire ($\alpha = .71$).

Emotion Regulation Change. After rating the effectiveness of their initial ER strategies, participants were asked to indicate whether they change their initial response to the situation, on a binary scale of either 0 (*no*) or 1 (*yes*).

Updated/Hypothetical Momentary ER Strategies and **Their Effectiveness**. Depending on whether the participant changed or maintained their initial emotion regulation strategies, they were asked to indicate either their updated emotion regulation strategies (if they changed) or hypothetical emotion regulation strategies they would have used next (if they maintained). We included the hypothetical questions for participants who maintained their initial ER strategies in order to balance the length of EMA surveys and to reduce the likelihood that participants might indicate no strategy change so that they could end the EMA session more quickly. After indicating their updated or hypothetical momentary emotion regulation strategies, participants rated the effectiveness of these strategies. Items assessing updated/hypothetical momentary emotion regulation strategies and their effectiveness were identical to those for initial momentary emotion regulation strategy and the effectiveness of initial repertoire.

Total Momentary Distress. The EMA survey ended with questions regarding momentary psychological distress in the past three hours. Similar to previous studies (e.g., Fried et al., 2022), total momentary distress was assessed by six items selected from the Depression, Anxiety, and Stress Scale (Lovibond & Lovibond, 1995) and the Generalized Anxiety Disorder Scale (Spitzer et al., 2006). Participants rated these on a 5-point scale from 1 (*not at all*) to 5 (*extremely*). Two items captured momentary **perceived stress** ($\alpha = .81$): “I found it difficult to relax” and “I felt irritable.” Two items assessed momentary **anxious mood** ($\alpha = .89$): “I was worried about different things” and “I felt nervous, anxious, or on edge.” Two items assessed momentary **depressed mood** ($\alpha = .89$): “I felt that I had nothing to look forward” and “I couldn’t seem to experience any positive feeling at all.” In addition to calculating scores of momentary perceived stress, anxious mood, and depressed mood by summing up their corresponding items, we summed all six items to reflect total momentary **distress** ($\alpha = .91$).

Data Analysis

Study 1

All data were analyzed with MPlus Version 7.4 (Muthén & Muthén, 1998). A three-step analysis approach to latent variable modeling was utilized (Asparouhov & Muthén, 2013). This approach allows researchers to use the input variables to create latent profiles, and then link constructed profiles to distal outcomes taking into account of classification uncertainty (Asparouhov & Muthén, 2013; Wisco et al., 2018).

In the first step, LPA was performed and the optimal number of profiles was identified. We did an LPA using the standardized scores of context sensitivity, repertoire, and feedback responsiveness to ease interpretation. To determine the most appropriate number of latent profiles, we used fit indices including Akaike Information Criterion (AIC), Sample-Size Adjusted Bayesian Information Criterion (BIC), Entropy, Adjusted Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT), and Bootstrap Likelihood Ratio Test (BLRT). Lower BIC or ABIC values suggest better fit, and significant LMR-LRT or BLRT for n profiles ($p < .05$) demonstrates that *n* profiles fit better than *n-1* profiles. According to Nylund et al. (2007), when these two likelihood ratio tests yield different results, BLRT outperforms other information-theoretic and likelihood-ratio statistical test methods. In addition, it has been shown through simulation studies (Morovati, 2004) that rare classes (lower than 5%) are generally difficult to replicate. Therefore, we opted not to include classes with a prevalence of less than 5% to avoid potentially unstable solutions (Nylund-Gibson & Choi, 2018). Last but not least, we took into consideration the interpretability of classes when making the final decision. **In the second step,** the most likely profile memberships were obtained along with the classification uncertainty. In other words, not only were individuals assigned to the profile that best fitted their abilities on three ER flexibility components, but the uncertainty of this assignment was also considered and modeled. **In the third step,** the most likely profile membership variables were analyzed as concurrent predictors of the distal outcome variables (i.e., depression and anxiety) when taking into consideration the classification uncertainty. Chi-square tests were provided which examine whether profiles differ significantly from each other on each distal outcome. In this process, we estimated overall chi-square likelihood ratio tests for each outcome, in which all means of outcomes were constrained to be equal (i.e., the means in outcomes are the same), compared to a freely estimated model (i.e., the means in outcomes are different). Then, for each pairwise comparison of latent profiles, two models were estimated and compared: one in which the means for each outcome were freely estimated for each latent profile (i.e., the means in outcomes are different), and one in which the means were constrained to be equal between the two profiles (i.e., the means in outcomes are the same). We planned two separate models for anxiety and depression. The equality tests of means across latent profiles used posterior probability-based multiple imputations with three degrees of freedom for the overall test and one degree of freedom for the pairwise tests.

In addition to the three-step approach (Nylund et al., 2007), we used a double cross-validation approach to assess the replicability of the latent profiles (Masyn, 2013). In specific, we randomly halved the sample, performed **exploratory LPAs** on each half separately, selected the best fitting models in each half, and then conducted **confirmatory LPAs** to validate them in the other half of the sample. Since the two halves have different means and standard deviations, we used original scores instead of standardized scores to perform all LPAs. However, when visualizing the results, to ease interpretation, we standardized the item thresholds based on the means and standard deviations of the three componential scores of the joint sample. After deciding on a few candidate models, we performed double cross-validation to select solutions that could reliably replicate in the other halves of the sample. When more than one candidate model successfully replicates, we choose the one that has higher interpretability. In terms of relationships between constructed latent profiles and outcomes, we set latent profile means and item thresholds to the values that resulted from the exploratory analyses. This ensured that the outcome variables (i.e., anhedonic depression and anxious arousal) were compared across latent profiles that were decided in previous steps of analysis, again enhancing replicability (Masyn, 2013).

To correct for the increased likelihood of type I error due to multiple comparison, we adopted the Benjamini-Hochberg (B-H) procedure to adjust the critical value and decrease false discovery rate (Benjamini & Hochberg, 1995). In order to obtain variances accounted for (omega-squared, or ω^2) and effect sizes (Hedges' *g*; Hedges, 1981), one-way ANOVAs were performed using most likely class membership from the LPAs as the independent variable and the two outcomes (i.e., depression and anxiety) as dependent variables. This approach is recommended and adopted in previous studies (Merians et al., 2019), given that the three-step method does not allow estimation of variances accounted for by profile memberships. It is important to keep in mind, however, that treating most likely class membership as an independent variable without considering the classification uncertainty will slightly underestimate the relation. Hedges' *g* is a better and less biased estimate of effect size than Cohen's *d* (Cohen, 1988) when samples are not equal in size. Rules of thumb for interpreting ω^2 are .01 (small), 06 (medium) and .14 (large; Albers & Lakens, 2018). Hedges' *g* values are considered large, medium, and small at 0.80, 0.50, and 0.20 (Hedges, 1981).

Study 2

Statistical analyses were performed in Mplus Version 7.4 and R Version 4.0.4 via *caret, glmnet, fbroc* packages (Muthén & Muthén, 1998; R Core Team, 2022). First, latent growth mixture modeling (LGMM) was performed to identify trajectories of depression, anxiety and PTSD. We explored intercept, slope, and quadratic parameters as either random or fixed effects. In the final models, both slope and intercept variances were allowed to be freely estimated and quadratic parameters were nonsignificant and thus removed to facilitate model convergence. Model solutions from 1 to 5 classes were compared by model fit indices, including Akaike (AIC), sample-size adjusted Bayesian Information Criteria (SSABIC), Entropy, and Bootstrap Likelihood Ratio Test (BLRT). In addition, we excluded solutions with infrequent classes (< 5%) because these tend to be unstable, and difficult to replicate (Nylund-Gibson & Choi, 2018). Choice of best-fitting solutions was based on these indices, theoretical coherence, and explanatory relevance.

Second, least absolute shrinkage and selection operator (LASSO) logistic regression, a form of supervised machine learning suited for high-dimensional data (i.e., where sample size does not substantially exceed the number of predictors), was built to predict 1) resilience against all other trajectories, and 2) chronicity against all other trajectories. In other words, we dichotomized participants into two groups by combining the chronicity and recovery trajectories when predicting resilience, and similarly, combining resilience and recovery trajectories when predicting chronicity. Although multinomial classification is most ideal when more than two trajectories are identified, we adopted binary LASSO given our interest in factors setting resilient individuals (and individuals exhibiting psychopathology over time) apart from everyone else. Predicting one against all other trajectories is also an approach adopted by other researchers when using machine learning method (Schultebraucks et al., 2021), and is appropriate given that our relatively small group size (e.g., only 5% of the participants were in the recovery trajectory for anxiety) could not support reliable multinomial classification. Moreover, LASSO logistic regression is particularly useful because of the large number of predictors we examined as it applies a penalization that reduces coefficients of less important predictors to zero, addresses the issues of multicollinearity and model overfitting, and improves interpretability (McNeish, 2015). To select the optimal shrinkage parameters (i.e., lambda) for the LASSO models and obtain mean cross-validation estimates of model performance, 10-fold cross-validation with three repetitions was performed when building each model using the *caret* package following previous recommendation (Kuhn & Johnson, 2013). While splitting the dataset into a single training and test data set makes it difficult to accurately characterize uncertainty in prediction, especially when the sample size is small, the use of repeated k-fold cross-validation can provide more reasonable estimates of how accurate the resultant model's prediction would be in predicting unseen future data sets (Kuhn & Johnson, 2013). For models with class imbalance where more than 70% of observations belong to one class, upsampling, a type of subsampling technique that randomly samples (with replacement) the class of smaller size to improve class balance, was used. The performance metric of the models is Area under the Receiver Operating Characteristic Curve (AUC), which can be classified into five categories, respectively fail (.50–.59), poor (.60–.69), fair (.70–.79), good (.80–.89), and excellent (.90–1.00). In order to capture the variability of each model's performance across the 30 cross-validations, we calculated and reported a 95% bias-corrected and accelerated confidence interval of the AUCs using 5,000 bootstrapped resamples in order to reduce the risk of overfitting and to provide a more complete picture of model performance, in addition to also reporting sensitivity, specificity, NPV, PPV and their respective confidence interval. The resultant optimal lambda parameters were used to refit the models to obtain the predictor coefficients needed to rank relative importance of predictors in each model. Specifically, variable importance was estimated by reordering the coefficients of predictors whose values are not shrunken to zero on a scale from 0 to 100 with the predictor of the greatest magnitude scoring 100 using the VarImp() function of the *caret* package.

Study 3

R Version 4.2.1 (R Core Team, 2022) and the *nlme* (Pinheiro et al., 2022), *lme4* (Bates et al., 2015), *reghelper* (Beiner & Hughes, 2022), *glmnet* (Friedman et al., 2010), and *caret* (Kuhn, 2022) packages were used for our analyses.

First, we reported intraclass correlation coefficients (ICCs) for each momentary emotion regulation strategies to illustrate how much variances were within-person. Then, we built multilevel models (MLMs) to predict momentary reappraisal, suppression, rumination, worry, planning, positive refocusing, soothing, and perspective seeking with their respective habitual measure. We did not have habitual measures for distraction, problem solving, and savoring, given the lack of well-validated measures for these strategies. Therefore, these three strategies were not included in this analysis. This analysis allowed us to assess how much momentary emotion regulation was associated with their habitual counterparts.

Second, we tested the flexibility model by examining whether momentary measures of context sensitivity, use of repertoire, and feedback responsiveness would be associated with total momentary distress and its three subdimensions (i.e., depressed mood, anxious mood, and perceived stress) measured after the regulation attempt.

We estimated a proxy for **momentary context sensitivity** by obtaining the coefficient of variation of the nine situational characteristics (i.e., DIAMONDS and controllability) for each situation to reflect how much individuals could differentiate between different situational characteristics in that given situation (see formula below). To further validate whether this score can serve as a proxy measure that reflects momentary context sensitivity, we built a MLM with momentary context sensitivity as the dependent variable, and baseline measures of context sensitivity, repertoire, and feedback responsiveness as predictors. Analyses were conducted with random intercepts.

$$Momentary\ Context\ Sensitivity = \frac{SD(Nine\ Situational\ Characteristics)}{Mean(Nine\ Situational\ Charateristics)}$$

We estimated two repertoire variables: **overall repertoire**, a between-person variable, and **momentary use of repertoire,** an within-person variable. We estimated the **overall repertoire** score for each participant by summing the number of effective ER strategies a participant used over the course of the entire EMA study. An ER strategy was considered effective for a participant, when across all EMA situations, the correlation between using this strategy and strategy effectiveness (i.e., the sum of increasing positive affect, decreasing negative affect, and facilitating problem-solving) was positive and at least small in size (i.e., $r > .10$; Cohen, 1988). To estimate the validity of the overall repertoire score, we examined its correlation with baseline context sensitivity, expressive flexibility, and feedback responsiveness. We estimated the **momentary use of repertoire** as each participant's use of strategies from their overall repertoire in each situation For example, if a participant had four effective ER strategies across EMA situations (e.g., reappraisal, distraction, problem solving, savoring), their overall repertoire would be 4. If they had used two out of these four effective ER strategies (e.g., reappraisal, problem solving) in a situation, their momentary use of repertoire in that situation would be 2.

We used the interaction between ER change and initial effectiveness to assess the adaptiveness of **momentary feedback responsiveness**. In specific, we hypothesized that individuals would report lower levels of momentary psychological distress in situations where they maintained effective strategies (i.e., ER Change = 0 when initial effectiveness was high) or switched from ineffective strategies (i.e., ER Change = 1 when initial effectiveness was low).

Finally, we built a MLM predicting momentary measures of total distress and as well as three component measures (i.e., depressed mood, anxious mood, and perceived stress) by momentary measures of context sensitivity, use of repertoire, effectiveness of initial ER strategies, ER change, and the interaction between ER change and initial effectiveness. At Level 1, momentary context sensitivity, use of repertoire, initial effectiveness, and ER change were person-centered to assess within-person deviations from the participant's mean. At Level 2, they were grand-mean centered to evaluate and control for between-person effects (Bolger & Laurenceau, 2013; Yaremych et al., 2021).

Chapter 2: THREE PAPERS

Paper 1

Components of Emotion Regulation Flexibility:

Linking Latent Profiles to Depressive and Anxious Symptoms

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Abstract

Emotion regulation flexibility has been conceptualized as a multi-componential construct that consists of ***context sensitivity***, ***repertoire***, and ***feedback responsiveness***. Although individuals with greater abilities in each component show better psychological adjustment, the patterns of these components remain unknown. In two cross-sectional Mturk studies (N = 200 and 802), we identified four or five predominant latent profiles, respectively *High Flexible Regulators* (*HFR*), *Medium Flexible Regulators* (*MFR*), *Context Insensitive Regulators* (*CIR*), *Feedback Irresponsive Regulators* (*FIR*), and *Low Repertoire Regulators* (*LRR*, Study 2 only). Inflexible regulators (*CIR*, *FIR*, and *LRR*) exhibited greater depressive and anxious symptoms than *MFR* and then *HFR.* Though inflexible regulators did not differ from each other on depressive symptoms, *CIR* showed more anxious symptoms than *FIR* and *LRR*. These findings support the importance of all three flexibility components with a highlight on context sensitivity, and moreover, suggest one potential way in which future studies can integrate various flexibility components.

Keywords: Emotion Regulation Flexibility; Context Sensitivity; Repertoire; Depression; Anxiety

Introduction

The field of emotion regulation (ER) has flourished in the past decade given the central role that ER plays in many forms of psychopathology (Aldao, Nolen-Hoeksema, & Schweizer, 2010; Webb, Miles, & Sheeran, 2012). Although traditionally, the theories behind coping and emotion regulation highlighted the dynamic interplay between persons and situations (e.g., Gross, 1999; Lazarus & Folkman, 1984; Mischel, 1973), much of the research on ER has adopted a relatively static approach that emphasized the adaptiveness or maladaptiveness of specific strategies such as reappraisal, suppression, and rumination (e.g., Aldao et al., 2010; Webb et al., 2012). Recently, however, a growing number of investigators have revisited the interactionist approach and demonstrated that the efficacy of specific ER strategies varies markedly across situations and individuals (Birk & Bonanno, 2016; Bonanno, Papa, Lalande, Westphal, & Coifman, 2004; Bonanno, Pat-Horenczyk, & Noll, 2011; Sheppes et al., 2014; Tamir & Ford, 2012; Troy, Shallcross, & Mauss, 2013; Troy, Ford, McRae, Zrolia, & Mauss, 2017; Westphal, Seivert, & Bonanno, 2010). According to the flexibility literature, in order to manage the diverse demands across varying situations, one needs to flexibly regulate their emotions (Aldao, Sheppes, & Gross, 2015; Bonanno & Burton, 2013; Cheng, 2001; Cheng, Lau, & Chan, 2014; Kashdan & Rottenberg, 2010).

Multi-Componential Perspective on ER Flexibility

From a theoretical perspective, ER flexibility has been conceptualized, not as a unitary phenomenon, but as a broad multi-componential process involving a sequence of componential abilities (e.g., Bonanno & Burton, 2013; Cheng et al., 2014). For example, in their review of the literature on flexibility in coping and emotion regulation, Bonanno and Burton (2013) articulated three interrelated yet functionally distinct components. These components included: 1) the ability to evaluate contextual demands, or **context sensitivity**, 2) the availability of a range of strategy that may be implemented to meet those demands, or **repertoire**, and 3) the capacity to monitor the efficacy of a chosen strategy and modify as needed, or **feedback responsiveness**. Each of these components was considered essential for successful self-regulation but also likely to vary measurably across individuals. Similarly, Cheng and colleagues (2014) proposed a flexibility model based on their review of more than one hundred empirical studies. In their model, flexibility was conceptualized as ability displayed at three unique and interacted regulatory stages, respectively assessing situational characteristics, adopting regulatory strategies, and monitoring outcomes, which resonates with the model suggested by Bonanno and Burton (2013). We acknowledge that these models may likely still overlook the fact that flexibility may involve other processes, such as emotion regulation goals (Millgram et al., 2015), and situation selection (Gross, 2015). Nevertheless, given that these components are relatively established both theoretically and empirically in the flexibility literature, they were the focus of the current investigation.

Multi-componential models of ER flexibility have proposed that people who are able to display high flexibility across all three components would exhibit the best outcomes. However, to date, empirical research has focused almost exclusively on individual components (e.g., repertoire). One noteworthy exception (Southward & Cheavens, 2017), for example, examined the interplay of these componential abilities. Specifically, deficits in repertoire of expressive regulation predicted depression and anxiety only among participants who were low in context sensitivity. These findings were consistent with theories of flexibility that have underscored the primacy of context sensitivity and viewed deficits in this component as especially predictive of poor clinical outcomes (Aldao, 2013; Bonanno & Burton, 2013; Cheng et al., 2014). According to our knowledge, there is no empirical work to date that directly compares psychopathology symptoms between participants with different flexibility deficits. Adopting a person-centered approach has the potential of not only identifying patterns of flexibility deficits but also examining how these patterns are related to psychopathology symptoms. Although this is relatively unexplored in the flexibility literature, previous studies on ER strategy have adopted a person-centered approach and linked patterns of ER to psychopathology symptoms such as depression and anxiety (e.g., Dixon-Gordon, Aldao, & De Los Reyes, 2015).

In this study, we capitalized on recently validated measures matching the three components of Bonanno and Burton's (2013) flexibility model, respectively context sensitivity, repertoire, and feedback responsiveness. Additionally, to understand the nature of flexibility deficits and how different flexibility profiles are linked to depression and anxiety, we conducted latent profile analysis on these three components, and then linked the constructed latent profiles to depressive and anxious symptoms.

Context Sensitivity, Repertoire, and Response to Feedback

A growing body of work have suggested that the first and arguably the most crucial step in flexible self-regulation involves the ability to read, decode, and evaluate contextual cues that signal the impinging demands and opportunities inherent in the situation, commonly referred to as **context sensitivity** (Aldao, 2013; Bonanno et al., 2018; Bonanno & Burton, 2013). Notably, this construct refers to the perception of context rather than the response to context. Research has shown that greater context sensitivity, in particular the ability to identify the absence of threatening cues, is associated with fewer psychopathology symptoms (Bonanno et al., 2018). Individual differences in context sensitivity move forward and exert an important impact on subsequent steps of flexible self-regulation, because errors in initial evaluation or less sensitive appraisals made when decoding the contexts will make it more difficult and unlikely for one to select appropriate strategies and monitor feedback.

A subsequent step in flexible self-regulation recruits the ability to utilize a wide range of strategies, commonly referred to as **repertoire** (Bonanno & Burton, 2013; Dixon-Gordon et al., 2015). Whether or not one can successfully enact the chosen strategy depends on the repertoire of regulatory strategies available. Accumulating empirical findings have shown that, better adjustment following stressful and potentially traumatic events is associated with a greater number of strategies (Orcutt, Bonanno, Hannan, & Miron, 2014), increased temporal variability (Cheng, 2001), and higher categorical variability (Bonanno et al., 2004; Burton et al., 2012). One particularly important indicator of repertoire is the ability to both up and down-regulate emotions, which has been consistently linked to greater psychological distress and better psychological adjustment (Bonanno et al., 2004; Rodin et al., 2017; Westphal et al., 2010).

Finally, after a strategy has been implemented, a third step in regulatory flexibility involves the post-implementation ability to monitor the effectiveness of the chosen strategy and either maintain or modify the strategy as needed, commonly referred to **feedback responsiveness** (Bonanno & Burton, 2013; Kato, 2012; Sheppes et al., 2014). Research has shown that the self-reported ability to discontinue maladaptive strategies and switch to adaptive strategies is associated with fewer depressive symptoms (Kato, 2015, 2017). Although experimental research on this component is relatively sparse, a few recent studies demonstrated that switching from reappraisal to distraction in the face of high-intensity negative images was associated with larger modulation in neural activity associated with emotional processing (Ilan, Shafir, Birk, Bonanno, & Sheppes, 2019), and that the switching frequency predicted better adjustment when it was in accord with internal physiological response (Birk & Bonanno, 2016).

These findings provided support for the importance of monitoring the efficacy of an initial strategy, and modifying or replacing ineffective strategies when necessary.

Towards an Integration of Flexibility Components

Although each of these components- context sensitivity, repertoire, and feedback responsiveness- has been hypothesized to be essential for successful self-regulation (Bonanno & Burton, 2013), they have been studied separately rather than jointly. Thus, it remains unknown as to whether and how these components work together in shaping one's overall adjustment. It has been hypothesized that strong abilities in all three components yield the most desirable outcomes (Bonanno & Burton, 2013). However, it is worth considering whether one component is more important than the others. For example, given that context sensitivity plays a crucial role in emotional experience and regulation (e.g., Aldao, 2013; Rottenberg, Gross, & Gotlib, 2005) and that it is sequentially the first step of self-regulation (Bonanno et al., 2018; Bonanno & Burton, 2013), it may be that deficit in this component is more detrimental for psychological health than the others. However, it is also likely that strong abilities in one or two components suffice to accommodate deficits in other components, or that deficit in any flexibility component is universally associated with similar level of psychological distress. In order to develop a better understanding of the nature of flexibility deficits across individuals as well as how different patterns of flexibility components are associated with depressive and anxious symptoms, studies incorporating all the three components of emotion regulation flexibility seem particularly beneficial and important.

The Current Investigation

To address these questions in the current investigation, we measured individual differences on each flexibility component using recently developed and well-validated measures.

Two of the three measures have been validated against experimental paradigms (Bonanno et al., 2018; Burton & Bonanno, 2016). In addition, measures of all three flexibility components had low or no correlation with social desirability (Bonanno et al., 2018; Kato, 2012), which lowers the interference of social desirability bias with the interpretation of individual differences in flexibility (Crowne & Marlowe, 1960). We conducted latent profile analysis (LPA) to determine the predominant patterns of abilities across these flexibility components and compared concurrently measured levels of depression and anxiety across the constructed latent profiles.

The current investigation was consisted of two studies. In Study 1, we used a relatively small sample to preliminarily evaluate the feasibility of applying LPA to identify predominant patterns of flexibility components. In specific, we examined if the model provides interpretable latent profiles that were associated with clinical outcomes (i.e., depression and anxiety). Then, in Study 2, we recruited a considerably larger sample and adopted a more rigorous, double cross-validation LPA to replicate and further our findings.

Pilot Study

From a multi-componential point of view, emotion regulation flexibility can be viewed as **context sensitivity** at the evaluation stage, **repertoire** at the implementation stage, and **feedback responsiveness** at the modification stage (Bonanno & Burton, 2013). Questions then arise as to whether there are individuals who are highly flexible across all regulatory components or alternatively deficient in at least some of flexibility components. If we are able to identify different flexible and inflexible profiles, a further question is whether and how these profiles are clinically relevant and meaningful. In other words, we are interested in learning whether highly flexible people are the least depressed and anxious, and what inflexible profiles are most elevated in depression and anxiety. To answer these questions, we conducted Study 1 in which we used LPA to first classify potential subgroups and then relate outcomes with group memberships.

Method

Data and Participants

Study 1 was conducted using Amazon's Mechanical Turk (Mturk) Service. Mturk facilitates high-quality data collection from a large pool of diverse participants. Recent studies have found that Mturk participants performed similarly to participants recruited offline (e.g., Paolacci, Chandler, & Ipeirotis, 2010) and showed high test–retest reliability (Casler et al., 2013). The questionnaire session was advertised on Mturk as a "Life Events Survey" and consisted of demographic items, measures of different components of ER flexibility, and two attention check items that directed participants to select certain items to ensure that they were paying attention to questions when responding.

Two hundred participants (115 males, 85 females) on average 34.19 years of age (*SD* = 9.54) completed the measures and were paid two dollars for their participation. The sample was racially diverse, with 83.6% of Caucasian, 9.0% of Black or African American, 6.5% of Asian American, 2.0% of American Indian, 0.5% of Native Hawaiian, and 0.5% of participants that preferred not to answer. In the sample, 9.5% of the participants self-identified as Hispanic or Latino, 88.0% of the participants considered themselves as non-Hispanic, and 2.5% preferred not to answer. The institutional review broad has approved this study.

Measures

In order to establish latent profiles of the three flexibility components mentioned earlier as well as examine potential relationships between profile memberships and symptoms of depression and anxiety, we measured components of flexibility (i.e., context sensitivity, repertoire, and feedback responsiveness) and symptoms of depression and anxiety.

Context Sensitivity was measured by the Context Sensitivity Index (CSI, Bonanno et al., 2018). CSI is a scenario-based inventory that captures one's sensitivity to the relative presence of contextual cues (Cue Presence Index, CPI) and to the relative absence of cues (Cue Absence Index, CAI). The CPI is composed of ten appraisal ratings that are normed as relatively highly present in the scenarios; the CAI is composed of ten items that are normed as relatively absent from the scenarios. The CAI items were reverse-coded so that high scores reflected sensitivity to the absence of a contextual cue. After reading each daily situation (e.g., You take a medicine and it makes your nauseous. Your doctor tells you that it is not serious and that you just have to "wait it out".), participants were asked to rate their perception of cues including threat, self-control, other-control, urgency, and cooperation by circling the number that best corresponds with their response (1 = *not at all*, 7 = *very much*). The CSI is associated with flexible coping, emotion regulation, and psychopathology symptoms, and is validated against behavioral measures of cue sensitivity such as the Picture Arrangement Test from the Wechsler Adult Intelligence Scale-Third Edition (Bonanno et al., 2018). In this study, we calculated the sum of CPI and CAI to reflect the context sensitivity component of ER flexibility.

Repertoire was measured by the Flexible Regulation of Emotional Expression Scale (FREE, Burton & Bonanno, 2016). FREE is a scenario-based questionnaire that measures participants' perceived ability to enhance and suppress their emotional expressions to meet situational demands. The FREE includes two subscales that measure the ability to enhance and suppress emotional expression, based on which a total score can be calculated by summing the enhancement and suppression scores. The higher score that the participants had, the more able they would be to utilize an adequate range of regulatory strategies that might accommodate divergent contextual commands and opportunities. Participants indicated how well they would be able to *be even more expressive* (e.g., Your boss is complaining about a project you know little about and have no involvement with.) or *conceal how they were feeling* (e.g., You are at a social event and the person you're talking to frequently spits while they speak.) following each scenario (1 = *unable*, 6 = *very able*). The FREE is associated with measures of emotion regulation, psychopathology symptoms, and well-being (Burton & Bonanno, 2016; Chen et al., 2018). Moreover, enhancement ability and suppression ability were previously found associated with participants' corresponding regulatory abilities in the lab setting, which provides support for its validity (Burton & Bonanno, 2016). In this study, we used the total score of the FREE scale to reflect the repertoire component of ER flexibility.

Feedback Responsiveness was measured by the Coping Flexibility Scale (CFS, Kato, 2012). CFS is a ten-item self-report questionnaire that captures the ability to discontinue an ineffective strategy (e.g., If I feel that I have failed to cope with stress, I change the way in which I deal with stress.) and produce and implement an alternative strategy (e.g., When a stressful situation has not improved, I try to think of other ways to cope with it.). Participants were asked to indicate how the statements apply to them (1 = *not applicable*, 4 = *very applicable*). Higher CFS scores were associated with more adaptive outcomes (Kato, 2012). In this study, we calculated a sum score to reflect the feedback responsiveness component of ER flexibility.

Depressive and Anxious Symptoms were measured by the depression and anxiety subscales from the 21-item version of Depression, Anxiety, Stress Scale (DASS, Lovibond & Lovibond, 1995). The DASS is a self-report instrument designed to measure the three related negative emotional states of depression, anxiety, and stress. After reading each statement (e.g., I felt that life was meaningless), participants were asked to rate how much the statement applied to them over the past week (0 = *did not apply to me at all*, 3 = *applied to me very much or most of the time*). In this study, depression and anxiety scores were calculated by summing items within each of these two subscales. The α for anxiety and depression subscales were .83 and .91, respectively. Scores of 9, 13, and 20 on the depression scale are considered cutoffs for mild, moderate, and severe depression, and scores of 7, 9, 14 on the anxiety scale are considered cutoffs for mild, moderate, and severe anxiety.

Data Analytic Plan

All data were analyzed with MPlus Version 7.4 (Muthén & Muthén, 1998). A three-step analysis approach to latent variable modeling was utilized (Asparouhov & Muthen, 2013). This approach allows researchers to use the input variables to create latent profiles, and then link constructed profiles to distal outcomes taking into account of classification uncertainty (Asparouhov & Muthen, 2013; Wisco et al., 2018).

In the first step, LPA was performed and the optimal number of profiles was identified. We did an LPA using the standardized scores of context sensitivity, repertoire, and feedback responsiveness to ease interpretation. To determine the most appropriate number of latent profiles, we used fit indices including Akaike Information Criterion (AIC), Sample-Size Adjusted Bayesian Information Criterion (BIC), Entropy, Adjusted Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT), and Bootstrap Likelihood Ratio Test (BLRT). Lower BIC or ABIC values suggest better fit, and significant LMR-LRT or BLRT for n profiles ($p < .05$) demonstrates that n profiles fit better than n-1 profiles. According to Nylund, Asparouhov, and Muthén (2007), when these two likelihood ratio tests yield different results, BLRT outperforms other information-theoretic and likelihood-ratio statistical test methods. In addition, it has been shown through simulation studies (e.g., Morovati, 2014) that rare classes (lower than 5%) are generally difficult to replicate. Therefore, we opted not to include classes with a prevalence of less than 5% to avoid potentially unstable solutions (Nylund-Gibson & Choi, 2018). Last but not least, we took into consideration the interpretability of classes when making the final decision. **In the second step**, the most likely profile memberships were obtained along with the classification uncertainty. In other words, not only were individuals assigned to the profile that best fitted their abilities on three ER flexibility components, but the uncertainty of this assignment was also considered and modeled. **In the third step**, the most likely profile membership variables were analyzed as concurrent predictors of the distal outcome variables (i.e., depression and anxiety) when taking into consideration the classification uncertainty. Chi-square tests were provided which examine whether profiles differ significantly from each other on each distal outcome. In this process, we estimated overall chi-square likelihood ratio tests for each outcome, in which all means of outcomes were constrained to be equal (i.e., the means in outcomes are the same), compared to a freely estimated model (i.e., the means in outcomes are different). Then, for each pairwise comparison of latent profiles, two models were estimated and compared: one in which the means for each outcome were freely estimated for each latent profile (i.e., the means in outcomes are different), and one in which the means were constrained to be equal between the two profiles (i.e., the means in outcomes are the same). We planned two separate models for anxiety and depression. The equality tests of means across latent profiles used posterior probability-based multiple imputations with three degrees of freedom for the overall test and one degree of freedom for the pairwise tests.

To correct for the increased likelihood of type I error due to multiple comparison, we adopted the Benjamini-Hochberg (B-H) procedure to adjust the critical value and decrease false discovery rate (Benjamini & Hochberg, 1995). In specific, we set the false discovery rate (FDR) at .05, and calculated the B-H critical value for each pairwise comparison by first multiplying the individual *p* value's rank (from low to high) by the false discovery rate and then dividing the product by the total number of tests. Next, we identified the highest *p* value that was still smaller than the B-H critical value. Finally, all *p* values smaller than this identified highest *p* value identified were considered significant.

$$\text{B} - \text{H Critical Value} = \frac{\text{rank of } p \text{ value} \times FDR}{\text{total number of tests}},$$

In order to obtain variances accounted for (omega-squared, or ω^2) and effect sizes (Hedges' *g*; Hedges, 1981), one-way ANOVAs were performed using most likely class membership from the LPAs as the independent variable and the two outcomes (i.e., depression and anxiety) as dependent variables. This approach is recommended and adopted in previous studies (e.g., Merian, Baker, Frazier, & Lust, 2019), given that the three-step method does not allow estimation of variances accounted for by profile memberships. It is important to keep in mind, however, that treating most likely class membership as an independent variable without considering the classification uncertainty will slightly underestimate the relation. Hedges' *g* is a better and less biased estimate of effect size than Cohen's *d* (Cohen, 1988) when samples are not equal in size. Rules of thumb for interpreting ω^2 are .01 (small), 06 (medium) and .14 (large; Albers & Lakens, 2018). Hedges' *g* values are considered large, medium, and small at 0.80, 0.50, and 0.20 (Hedges, 1981).

Results

Latent Profile Analysis

We reported all fit indices in Table 1. The BLRTs were significant for the two-, three-, four-profile solutions (*p.s.* < .001), but not for the five-profile solution (*p* = .60), suggesting that the four-profile solution provided the best possible fit. Though LMR-LRTs were significant for the two- and three- profile solutions (*p*.s. < .01) but not four-profile solution (*p* =.14), we did not choose the three-profile solution given that BLRT proved to be a consistent indicator of classes that outperformed LMR-LRT (Nylund et al., 2007). The fourth-profile solution had lower AIC and BIC values than the two- and three profile solutions, suggesting that it fitted better. Though the five-profile solution had the highest entropy (.84) among all profile solutions, we did not choose it for the reason that it included a profile with few participants (2.2%, four participants) and that rare classes (lower than 5%) were potentially unstable and limited in replicability (Nylund-Gibson & Choi, 2018). In terms of interpretability, compared with the three-profile solution, the four-profile solution included a clearly interpretable profile that was low in feedback responsiveness and medium in context sensitivity and repertoire.

Figure 1a shows the standardized group means for the four-profile solution. Participants were assigned to one of the following profiles with classification uncertainty: (1) high ability across three components (*High Flexible Regulators, HFR,* 13.6%), (2) average ability across three components (*Medium Flexible Regulators, MFR*, 55.7%), (3) average levels of context sensitivity and repertoire but low levels of feedback responsiveness (*Feedback Irresponsive Regulators, FIR*, 19.5%), or (4) average levels of feedback responsiveness and repertoire but low levels of context sensitivity (*Context Insensitive Regulators, CIR*, 11.2%). Classification probabilities were high across the four profiles, with probabilities of .77 in the *HFR*, .91 in the *MFR*, .77 in the *FIR*, and .82 in the *CIR*.

Associations with Depression and Anxiety

We examined potential differences among these four latent profiles on depressive and anxious symptoms, using each of the distal outcomes as auxiliary variable in the model. Figure

1b shows the means and standard errors of depression and anxiety scores in each profile. The p values and effect sizes are presented in Table 2. To adjust for multiple comparison and control false discovery rate at .05, the Benjamini-Hochberg procedure was adopted (Benjamini & Hochberg, 1995). A total of 12 pairwise comparison tests were conducted. The first eleven p values in rank were lower than their respective B-H critical values and were thus all considered significant. The only insignificant pairwise comparison was between *FIR* and *CIR* on depressive symptoms. We reported detailed results of symptom comparison in the following two paragraphs.

For depression, both inflexible profiles (*CIR* and *FIR*) exhibited greater levels of symptoms than the flexible profiles (*MFR* and *HFR*), though they did not differ from each other on symptom severity. The *CIR* showed higher symptom level than *HFR* (g = 1.84) and *MFR* (g = 1.01), χ^2s > 11, *p.s.* < .01, but did not differ from that of *FIR* (g = -0.04), χ^2 = .016, p = .90. The *FIR* exhibited more depressive symptoms than the *HFR* (g = 1.81) and *MFR* (g = 1.06), χ^2 > 24, *p.s.* < .001. Between the two flexible profiles, the *MFR* showed higher symptom level than that of *HFR* (g = 0.72), χ^2 = 44, p < .001. The variances of depression explained by the latent profile memberships were large, ω^2 = .15.

For anxiety, similarly, both profiles with deficit in one flexibility component (*CIR* and *FIR*) showed greater symptom severity than medium and high flexible regulators (*MFR* and *HFR*). The *CIR* showed higher symptom level than the *FIR* (g = 0.96), *MFR* (g = 1.68), and *HFR* (g = 2.06), χ^2s > 7, *p.s.* < .01. The *FIR* exhibited higher symptom level than the *MFR* (g = 0.62) and *HFR* (g = 1.10), χ^2s > 10, *p.s.* < .01. *MFR* had more symptoms than *HFR* (g = 0.36), χ^2 = 7.83, p = .005. The variances of anxiety explained by the latent profile memberships were large, ω^2 = .20.

Discussion

In this study, we were able to subtype four different groups of individuals that clearly demonstrated unique patterns of flexibility components. Although more than half the sample were average across these components (i.e., *MFR*), there were clear subgroups that appeared either highly flexible (i.e., *HFR*) or deficient in one flexibility component (i.e., *FIR* and *CIR*). We did not see a profile characterized by low repertoire, but this may be attributed to both our relatively small sample size and sample characteristics. In fact, though a five-profile solution was not optimal based on the fit indices, a close scrutiny of this solution revealed that it did include a small profile that was low in repertoire (*Low Repertoire Regulators, LRR*, 2.2%). This would add theoretical interpretability since in the four-profile solution there was no profile showing deficits in repertoire. Given that a five-profile solution exhibited the highest entropy (.84) and included an interpretable profile, recruiting a larger sample may help us further determine whether retaining this solution (i.e., including *LRR*) is reasonable.

When linking latent profiles to depression and anxiety, we found that *HFR* exhibited the lowest depressive and anxious symptoms, and that participants with deficits in one flexibility components (i.e., *FIR* and *CIR*) showed greater symptom severity than participants who were relatively flexible (i.e., *HFR* and *MFR*). These findings were consistent with the flexibility literature that has emphasized the adaptive functions of these components (Aldao, 2013; Aldao et al., 2015; Bonanno et al., 2018; Bonanno & Burton, 2013; Burton & Bonanno, 2016; Cheng et al., 2014; Kato, 2015). Individuals with deficit in one flexibility component (i.e., *CIR* and *FIR*) showed relatively comparable elevation in depression, but participants with deficit in context sensitivity (i.e., *CIR*) reported more anxious symptoms than those with deficit in feedback responsiveness (i.e., *FIR*). For one thing, this is partially in line with literature suggesting that context sensitivity is the most crucial and first step in regulatory process (Bonanno et al., 2018; Bonanno & Burton, 2013). For another, our findings seem to suggest that despite the role of flexibility deficits play in both depression and anxiety, the **type** of flexibility deficit matters more for anxiety than for depression. Given that there is a high degree of overlap in the depression and anxiety measures in our study, to better understand whether there are unique and shared flexibility deficits in relation to depression and anxiety, it may be helpful to replicate the current findings with measures that better differentiate depression and anxiety.

Formal Study

In the pilot study, we successfully identified four predominant patterns of the three flexibility components. Two of the latent profiles were characterized by deficit in one flexibility component (i.e., *CIR* and *FIR*), while the remaining two showed moderate to high ability across components (i.e., *HFR* and *MFR*). Moreover, the constructed latent profiles derived from three ER flexibility components were associated with depressive and anxious symptoms.

In this study, we aimed to further our findings from the following several aspects. First, we recruited a new and considerably larger sample, which may potentially help us determine whether or not to include a fifth profile of low repertoire. Second, unlike most prior LPA studies, this study attempted to **double cross-validate** the profiles across two random halves of the sample so as to ensure replicability of the profile solutions. By constraining the parameters in one sample to the parameters obtained from the other sample, we can examine the replicability of a few candidate latent profile solutions and select one that can reliably cross-validate. Third, in order to gain a more nuanced understanding of the association between latent profiles and symptoms of depression and anxiety, we adopted a measure known to differentiate unique and shared aspects of depression and anxiety.

Method

Data and Participants

This study was conducted using Mturk. We recruited a total of 802 participants (361 males, 436 females, two others, and three prefer not to answer) on average 36.41 years of age (*SD* = 10.79) completed the measures and were paid two dollars for their participation. The sample was racially diverse, with 75.9% of Caucasian, 10.3% of Black or African American, 9.0% of Asian American, 2.5% of American Indian, 0.5% of Native Hawaiian, and 1.7% of participants that preferred not to answer. In the sample, 10.2% of the participants self-identified as Hispanic or Latino, 88.7% of the participants considered themselves as non-Hispanic, and 1.1% preferred not to answer. The institutional review broad has approved this study.

Measures

Similar to Study 1, we aimed to establish latent profiles that exhibit different patterns across the three flexibility components as well as investigate their potential relationships with depressive and anxious symptoms.

Context Sensitivity, **Repertoire**, and **Feedback Responsiveness** were measured using the same instruments reported in the measure section of Study 1.

Depressive and Anxious Symptoms were measured by the 62-item Mood and Anxiety Symptom Questionnaire- Short Form (MASQ-SF; Watson et al., 1995). MASQ-SF assesses symptoms that commonly occur in anxiety and mood disorders. Items were rated on a five-point scale (1 = *not at all*, 5 = *extremely*), with higher scores indicating greater levels of depression and anxiety. MASQ-SF consists of four subscales: General Distress- Anxiety Symptoms (GDA) subscale, which includes 11 items that reflect non-specific symptoms of anxiety (e.g., “was unable to relax”), General Distress- Depressive Symptoms (GDD) subscale, which includes 12 items reflecting non-specific depressive symptoms (e.g., “felt sluggish or tired”), Anxious Arousal subscale, which includes 17 items assessing anxiety-specific symptoms (e.g., “startled easily”), and Anhedonic Depression (AD) subscale, which includes 22 items that assess symptoms specific to depression (e.g., “felt withdrawn from other people”). In the present investigation, we only utilized the AA and AD subscales, since they have lower overlap and are therefore likely to produce stronger empirical differentiation between the highly overlapping constructs of anxiety and depression (in this sample, for AA and AD, $r = .39$, $p <.01$, whereas for GDA and GDA, $r =.82$, $p <.01$). It should be noted, however, that the AA subscale tends to capture physiological arousal of anxiety disorders (e.g., panic) but provides less information about anxious distress (e.g., social anxiety). Watson et al. (1995) reported high levels of internal consistency in multiple samples. In this study, the α for AA and AD subscales were .90 and .92, respectively.

Data Analytic Plan

All latent profile analyses were analyzed with MPlus Version 7.4 (Muthén & Muthén, 1998). In addition to the three-step approach mentioned in Study 1 (Asparouhov & Muthen, 2013; Wisco et al., 2018), we used a double cross-validation approach to assess the replicability of the latent profiles (Masyn, 2013). In specific, we randomly halved the sample, performed **exploratory LPAs** on each half separately, selected the best fitting models in each half, and then conducted **confirmatory LPAs** to validate them in the other half of the sample. Since the two halves have different means and standard deviations, we used original scores instead of standardized scores to perform all LPAs. However, when visualizing the results, to ease interpretation, we standardized the item thresholds based on the means and standard deviations of the three componential scores of the joint sample.

In each exploratory LPA, we used fit indices including AIC, BIC, entropy, LMR-LRT, and BLRT to identify a few candidate models. To begin with, we looked at LMR-LRT and BLRT, and when those two yielded different results, we preferred BLRT because it proved more consistent than other criteria (Nylund et al., 2007). In addition, we avoided solutions that include rare classes because they were usually unstable and difficult to replicate (Morovati, 2014; Nylund-Gibson & Choi, 2018). After deciding on a few candidate models, we performed double cross-validation to select solutions that could reliably replicate in the other halves of the sample. When more than one candidate model successfully replicates, we choose the one that has higher interpretability. In terms of relationships between constructed latent profiles and outcomes, we set latent profile means and item thresholds to the values that resulted from the exploratory analyses. This ensured that the outcome variables (i.e., anhedonic depression and anxious arousal) were compared across latent profiles that were decided in previous steps of analysis, again enhancing replicability (Masyn, 2013).

Finally, to obtain variances accounted for (omega-squared, or ω^2) and effect sizes (Hedges'*g*), two one-way ANOVAs were performed separately in each half and then in the combined sample using most likely class membership from the LPAs as the independent variable and the two outcomes (i.e., anhedonic depression and anxious arousal) as dependent variables. This will slightly underestimate the relationship, but it is recommended given that the three-step approach does not allow estimation of variances accounted for by profile memberships. Rules of thumb for interpreting ω^2 are .01 (small), 06 (medium) and .14 (large; Albers & Lakens, 2018). Hegdes' *g* values are considered large, medium, and small at 0.80, 0.50, and 0.20 (Hedges, 1981).

Results

Exploratory Latent Profile Analysis

We reported all fit indices in Table 1. In the first half of the sample, the BLRTs were significant for the two-, three-, four-, and five-profile solutions (*p.s.* $< .05$), but not for the six-profile solution ($p = .08$), suggesting that the five-profile solution provided the best possible fit. The LMR-LRTs for the two-, three-, four-, and five-profile solutions (*p.s.* $< .05$), but not for the six-profile solution ($p = .06$), again supporting the five-profile solution. In addition, the six-profile solution yielded a low-frequency profile (2.31%), which suggested that six-profile solution was not ideal. The AIC and BIC of the five-profile solution was lower than those of the four-, three-, two-profile solutions, supporting the five-profile solution.

In the second half of the sample, the BLRTs were significant for the two-, three-, four-, five-, and six-profile solutions, supporting the six-profile solution. The LMR-LRTs were significant for the two-, three-, and four-profile solutions (*p.s.* $< .001$), but not for the five-profile solution ($p = .07$), supporting the four-profile solution. The six-profile solution had low-frequency profile (4.74%), and was thus not considered. Between the four and five- and four-profile solution, the BIC and AIC values was lower for the five-profile solution, suggesting that it provided better fit.

Double Cross Validation

The results of exploratory LPA in two random halves were mixed regarding whether a four- or five-profile solution should be adopted. Additionally, based on the BLRT statistics, the six-profile solution fitted better than either the four- or five-profile solution for the second half of the sample. Therefore, we further performed double cross validation for the four-, five-, and six-profile solutions to evaluate their respective replicability. Specifically, we examined whether the parameters for the four-, five-, and six-profile solutions estimated in one half of the sample (i.e., item thresholds and latent profile means) displayed good fit when applied to the other half of the sample, and vice versa.

For both the four- and five-profile solutions, the likelihood ratio tests did not find significant differences in both halves between the freely estimated models and the models constrained by parameters estimated in the other half of the sample, χ^2s < 19.70, *p.s.* > .50, indicating that these constraints did not reduce fit and that the models successfully cross-validated across samples. For the six-profile solution, however, the likelihood ratio tests revealed significant differences between the freely estimated and the constrained models, χ^2s > 49, *p.s.* < .01, suggesting that the six-profile solution did not cross-validate for either half of the sample. In other words, the six-profile solution was not reliable across random halves and thus should not be adopted. Given that both the four- and five- profile solutions cross-validated successfully, we chose the five-profile solution as the optimal solution because it included a new profile that was clearly interpretable. The fifth profile was low in repertoire but medium in context sensitivity and feedback responsiveness.

Since the patterns of the five-profile solution were similar in both halves, we reported the standardized group means and symptom comparison using the full sample for brevity (Figure 2). Figure 2a presented the standardized group means for the five-profile solution. Participants were assigned to one of the following profiles: (1) high ability across three components (*High Flexible Regulators, HFR,* 9.8%), (2) average ability across three components (*Medium Flexible Regulators, MFR*, 47.5%), (3) average levels of context sensitivity and repertoire but low levels of feedback responsiveness (*Feedback Irresponsive Regulators, FIR*, 15.3%), (4) average levels of feedback responsiveness and repertoire but low levels of context sensitivity (*Context Insensitive Regulators, CIR*, 14.0%), or (5) average levels of feedback responsiveness and context sensitivity but low levels of repertoire (*Low Repertoire Regulators, LRR*, 13.3%). Classification probabilities were high across the five profiles, with probabilities of .92 in the *HFR*, .85 in the *MFR*, .89 in the *FIR*, and .90 in the *CIR*, and .81 in the *LRR*.

Associations with Depression and Anxiety

We examined potential differences between the five profiles on anhedonic depression and anxious arousal, using each of the distal outcomes as auxiliary variable in the model. Since results were similar in both halves, we reported results using the full sample for brevity (Figure 2b). The p values for each pairwise comparison and corresponding effect size are presented in Table 2. To adjust for multiple comparison and control false discovery rate at .05, the Benjamini-Hochberg procedure was adopted (Benjamini & Hochberg, 1995). A total of 20 pairwise comparison tests were conducted. We ranked the p values for pairwise tests and compared them to their respective B-H critical value. All p values below .02 were lower than their respective B-H critical values and thus considered significant. We reported detailed results of symptom comparison in the following two paragraphs.

For anhedonic depression, the inflexible profiles (*CIR*, *LRR*, and *FIR*) showed higher symptom level than that of the flexible profiles (*HFR and MFR*), χ^2s > 3.6, *p.s.* < .01. The *HFR* had the lowest symptom level, χ^2s > 12, *p.s.* < .001. The *CIR* did not differ from *LRR* (g = 0.14) or *FIR* (g = -0.10) in symptom severity, χ^2s < 1.1, *p.s.* > .10, but exhibited greater symptom severity than the *MFR* (g = 0.49) and *HFR* (g = 1.57). The *FIR* and *LRR* did not differ in symptom severity (g = 0.25), χ^2 = 3.34, p = .07, which was consistent with the findings from

Study 1 that the type of deficit was not associated with different elevation in depressive symptoms. The variances explained by the latent profile memberships were medium, $\omega^2 = .09$.

For anxious arousal, consistent with findings on anhedonic depression, the inflexible profiles (*CIR*, *LRR*, and *FIR*) exhibited greater symptom severity than the flexible profiles (*HFR and MFR*), χ^2s > 15, *p.s.* < .01. The *CIR* exhibited higher symptom level than any of the other groups (*g.s.* > 0.85), χ^2s > 40, *p.s.* < .001. The *FIR* showed higher symptom level than the *MFR* ($g = 0.64$) and *HFR* ($g = 0.76$), χ^2s > 23, *p.s.* < .001, but did not differ from that of the *LRR* ($g = 0.26$), $\chi^2 = 3.68$, $p = .06$. *LRR* had more symptoms than *MFR* ($g = 0.35$), $\chi^2 = 7.16$, $p = .007$, and showed greater symptom severity than *HFR* ($g = 0.58$), $\chi^2 = 15.73$, $p < .001$. In sum, those that showed high ability across three ER flexibility components exhibited the least anxious symptoms, whereas those showing one deficit, especially context insensitivity, exhibited greater symptom severity. The variances explained by the latent profile memberships were large, $\omega^2 = .21$.

Discussion

In this study, we used a rigorous double cross validation approach to identify subtypes of regulators that differ in components of ER flexibility. We adopted the five-profile solution based on fit indices, replicability across samples, and interpretability. This profile solution suggests that there were clearly distinguishable subpopulations that are highly flexible (i.e., *HFR*), moderately flexible (i.e., *MFR*), or inflexible in one of three regulatory components (i.e., *CIR*, *LRR*, and *FIR*). These findings appeared inconsistent with the results of Study 1, where the four-profile solution fitted the best. However, this could be partially attributed to the inability to always identify rare profile with small samples. Moreover, in this study, we found that both the four- and five-profile solutions could reliably cross-validate, which suggests that both the four- and five-profile solutions could fit the data relatively well. We preferred the inclusion of a fifth profile when identifiable given that it clearly added theoretical interpretability and allowed comparison of symptoms between groups with different flexibility deficits.

Furthermore, these groups differed in depressive and anxious symptoms. Those who were highly flexible across regulatory components exhibited the least depressive and anxious symptoms. On the contrary, participants with flexibility deficits showed worse outcomes, but results were divergent for anxious and depressive symptoms. The *Context Insensitive Regulators* (*CIR*) exhibited the highest level of anxiety, followed by the *Feedback Irresponsive Regulators* (*FIR*) and the *Low Repertoire Regulators* (*LRR*). For depressive symptoms, the three inflexible profiles with deficits in one regulatory component did not differ with each other. These findings were consistent with those from Study 1, which suggest that flexibility deficits, regardless of which component, are associated with elevated depressive symptoms, whereas impairment in context sensitivity is clearly related to increased anxious symptoms beyond other flexibility deficits.

Sequential, multi-componential models of flexibility have been proposed in review and meta-analyses (Bonanno & Burton, 2013; Cheng et al., 2014), and individual components of ER flexibility have consistently shown links to health and psychopathology. However, no empirical study has yet examined all components of the flexibility model within the same study and examined their hypothesized combined benefits to mental health. In two studies, we addressed this gap by applying LPA to the three components of ER flexibility proposed by Bonanno and Burton (2013), and connecting profile memberships with the severity of depressive and anxious symptoms.

Our findings demonstrated unique profiles of ER flexibility. Specifically, the most common profile included around half of the participants who showed an average ability across all three flexibility components (i.e., *Medium Flexible Regulators*, *MFR*). By contrast, superior flexibility, manifesting as high scores across all three regulatory components, was evident in only about one tenth of the sample (i.e., *High Flexible Regulators*, *HFR*). Approximately thirty percent of the participants belonged to any of the three relatively inflexible profiles, manifesting as impairment in one regulatory component: some exhibited difficulty accurately perceiving the cues in stressful situations (i.e., *Context Insensitive Regulators*, *CIR*), some experienced challenges in enhancing and suppressing emotions (i.e., *Low Repertoire Regulators*, *LRR*), others could effectively monitor and adjust strategy use via feedback (i.e., *Feedback Irresponsive Regulators*, *FIR*). Notably, inflexible regulators with deficit in one component generally did not show high abilities in the other two domains comparably to *HFR*, suggesting that failure at one flexibility component may make it unlikely to succeed at the others (Bonanno & Burton, 2013).

The number of profiles emerged was similar but not identical across the two studies. In Study 1, we did not observe a latent profile that captured a deficit in repertoire (i.e., *LRR*). In Study 2, however, we were able to identify *LRR* in both halves of the sample ($N = 401$ in each half). Whereas Study 1 supported a four-profile solution, Study 2 showed that both the four- and five-profile solutions successfully cross-validated across random halves. That the first study did not support the five-profile solution may result from both the small sample size and sample variability. This occurs frequently for small classes as previously demonstrated in simulation studies (Morovati, 2014). In other words, given the relatively low frequency of *LRR* and sample variability, it could not always be identified in studies with small sample size, such as Study 1 ($N = 200$). As mentioned in Study 2, the inclusion of a fifth profile increases theoretical interpretability by capturing deficits in all components of flexibility. Moreover, the inclusion of *LRR* allows comparison of symptoms among participants with different types of flexibility deficits (*CIR*, *FIR*, and *LRR*).

Despite the apparent inconsistency, however, profile solutions in both studies shared great similarity. First, the order in which the latent profiles emerged was consistent in both studies, respectively *MFR*, *HFR*, *CIR*, and *FIR*. Second, although the fit indices reported in Study 1 failed to support the five-profile solution, we did observe a fifth profile characterized by low repertoire (*LRR*, 2.2%) when setting the number of profiles to five. Although likely unstable due to its small size, this profile was consistent with the fifth profile identified in Study 2. Third, the pattern of relations between profile memberships and psychopathology symptoms were similar across the two studies. For instance, inflexible profiles (*CIR*, *LRR*, and *FIR*) had greater level of depressive and anxious symptoms than the two flexible profiles (*MFR* and *HFR*). Additionally, inflexible groups did not differ in symptoms of depression, but *CIR* exhibited significantly greater severity of anxiety than groups with other deficits.

From a clinical science perspective, our studies contribute to a growing body of literature that emphasize the effect of flexibility on psychological health. Crucially and consistent with prevailing assumptions in the flexibility literature, the latent profiles were associated with depressive and anxious symptoms. As previously hypothesized (e.g., Bonanno & Burton, 2013), *HFR* had the lowest levels of symptoms, which again highlights the importance of all three flexibility components. However, varied combinations of the three components also showed differential relations to adjustment. Also as previously hypothesized (Bonanno et al., 2018; Bonanno & Burton, 2013), *CIR* had the poorest overall adjustment. *CIR* showed greater elevation of depression and anxiety than that of the *HRF* and *MFR,* and more anxiety symptoms than all other profiles. These findings suggest that context insensitivity may confer particular risk for anxiety, or anxiety may make people less sensitive to context. Although there has been relatively little research on the feedback component of ER flexibility, *FIR* also showed poor adjustment as evidenced by high levels of anxiety and depression. In fact, *FIR* did not differ statistically from *CIR* on depression in both studies. These findings suggest that anxiety is particularly high for those with deficits in context sensitivity, whereas elevation of depression seems similar across individuals with different types of flexibility impairments. Future studies adopting longitudinal designs and recruiting clinical population with depression, anxiety, and comorbid condition may elucidate shared and unique flexibility impairments in depression and anxiety and establish temporal priority of flexibility and psychopathology, which could potentially improve our understanding of the highly comorbid nature of these two forms of disorders.

The advances suggested by our findings should be understood in the context of several noteworthy methodological limitations. First of all, the cross-sectional nature of our study precludes us from establishing causal relationships or evaluating the stability of latent profiles over time. Though previous studies have demonstrated the longitudinal predictability of flexibility (e.g., Bonanno et al., 2004; Westphal et al., 2010), no study to date has examined if deficits in flexibility components precede depression and anxiety or if the onset of these conditions decrease flexibility over time. Though our measures were previously found to have very low social desirability, it is still likely that the presence of depression and anxiety may lead participants to downrate their perceived ability in these flexibility components. Longitudinal studies could potentially further our findings by establishing temporal order of flexibility and psychopathology. This may help shed light on the etiology of depression and anxiety as well as differential diagnosis. Additionally, our assessment of the ER flexibility components was limited to self-report measures. Though two of the three measures were validated against experimental and behavioral indexes, it is necessary for future research to adopt other flexibility assessments, including self-report as well as experimental measures. Moreover, our measure of repertoire was limited in that it only assessed up- and down-regulation of emotional expression, which prohibits the understanding of repertoire in emotion regulation flexibility. Though this was frequently examined in the flexibility literature (e.g., Bonanno et al., 2004; Westphal et al., 2010; Burton & Bonanno, 2016), other studies have conceptualized repertoire as the use of a wider range of strategies (e.g., Dixon-Gordon et al., 2015; Southward, Altenburger, Moss, Cregg, & Cheavens, 2018). This limitation also precluded us from examining whether individuals with high ability across flexibility components are overlapping or populated by individuals who use putatively adaptive strategies. One study, for example, showed that those relying heavily on adaptive strategies exhibited fewer depressive and anxious symptoms (Dixon-Gordon et al., 2015). To examine additive and unique effects of flexibility, comparing flexibility and trait emotion regulation in the same study could be potentially informative and beneficial. Future studies may benefit from considering various operationalizations of regulatory repertoire and their potential impact on findings. Finally, our analyses were bound to one theoretical perspective on ER flexibility. It may be worth examining other models (Aldao et al., 2015; Pruessner, Barnow, Holt, Joormann, & Schulze, 2020), as well as alternative flexibility components, such as pre-existing goals (e.g., Millgram, Joormann, Huppert, & Tamir, 2015).

In conclusion, five subtypes of regulators were identified based on the flexibility model proposed by Bonanno and Burton (2013). Those with great abilities in all regulatory components exhibited the least depressive and anxious symptoms. On the contrary, inflexibility, as demonstrated by deficits in context sensitivity, repertoire, or feedback responsiveness, was associated with depressive and anxious symptoms. Individuals who were relatively insensitive to context exhibited the highest level of anxiety. These findings are consistent with theory highlighting the importance of flexibility (Aldao et al., 2015; Bonanno & Burton, 2013; Cheng et al., 2014; Kashdan & Rottenberg, 2010). Future research may extend these findings by incorporating longitudinal designs, adopting multi-method measures of different flexibility components, and examining the relationship between flexibility and psychopathology in various samples.

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Table 1. Model fit indices for exploratory latent profile analyses and double cross-validation

	Exploratory Latent Profile Analyses							Double Cross-Validation			
No. of Classes	max LL	AIC	BIC	Entropy	LMR-LRT *p*	PB-LRT *p*	Per. Small	max LL	BIC	LRTS (*df*), *p*	Entropy
Study 1- Full Sample (N = 200)											
1	-847.02	1706.04	1706.82	-	-	-	-	-	-	-	-
2	-832.85	1685.69	1686.99	.71	.004	< .001	17.20%	-	-	-	-
3	-819.76	1667.52	1669.35	.74	.002	< .001	10.80%	-	-	-	-
4	**-812.49**	**1660.98**	**1663.36**	**.73**	**.46**	**< .001**	**11.20%**	**-**	**-**	**-**	**-**
5	-808.43	1660.86	1663.73	.84	.14	.60	2.20%	-	-	-	-
6	-804.26	1660.51	1663.89	.74	.68	.43	2.10%	-	-	-	-
Study 2- Sample 1 (N = 401)											
1	-4308.32	8628.64	8633.56	-	-	-	-	-	-	-	-
2	-4267.57	8555.13	8563.34	.84	< .001	< .001	11.00%	-	-	-	-
3	-4244.46	8516.92	8528.42	.82	< .001	< .001	10.70%	-	-	-	-
4	-4214.80	8465.60	8480.37	.81	.03	< .001	11.80%	-4222.75	8453.97	15.9 (18), .60	.81
5	**-4204.73**	**8453.45**	**8471.51**	**.77**	**.04**	**.01**	**9.00%**	**-4211.38**	**8431.23**	**13.30 (22), .92**	**.78**
6	-4197.89	8447.76	8469.11	.79	.06	.08	2.31%	-4230.37	8469.21	64.96 (26), <.001	.74
Study 2- Sample 2 (N = 401)											
1	-4308.51	8629.01	8633.94	-	-	-	-	-	-	-	-
2	-4256.70	8533.40	8541.61	.84	< .001	< .001	12.98%	-	-	-	-
3	-4224.33	8476.66	8488.15	.83	<.001	<.001	13.26%	-	-	-	-
4	-4196.47	8428.95	8443.72	.85	<.001	<.001	13.38%	-4206.27	8421.01	19.60 (18), .36	.81
5	**-4184.77**	**8413.55**	**8431.61**	**.78**	**.07**	**<.001**	**10.47%**	**-4192.93**	**8394.33**	**16.32 (22), .80**	**.78**
6	-4166.20	8384.41	8405.75	.81	<.001	<.001	4.74%	-4191.14	8390.73	49.88 (26), =.003	.79

Note. No. = Number. max LL = maximized log likelihood value. AIC=Akaike Information Criterion. BIC=Sample-size adjusted Bayesian Information Criterion. LMR-LRT=Adjusted Lo-Mendell-Rubin likelihood ratio test. PB-LRT = Parametric Bootstrapped likelihood ratio test. Per. Small = Percentage of participants in the smallest group. LRTS=loglikelihood ratio test statistic. - = not available. Bolded lines indicate the best profile solution based on AIC, BIC, LMR-LRT, PB-LRT, Per. Small, and interpretability of that solution.

Table 2. Differences in depressive and anxious symptoms among ER flexibility profiles

		Study 1 (DASS; $N = 200$)				Study 2 (MASQ; $N = 802$)			
		Depression		Anxiety		Anhedonic Depression		Anxious Arousal	
	Range	[0 21]		[0 21]		[22 110]		[17 85]	
M (*SD*)	Full Sample	8.84 (10.68)		6.37 (7.83)		60.88 (18.69)		25.97 (11.02)	
	CIR	15.71 (11.82)		17.01 (10.22)		66.62 (15.66)		39.39 (15.87)	
	FIR	16.11 (10.86)		8.79 (7.50)		68.12 (14.76)		27.88 (10.66)	
	LRR	-		-		64.47 (14.16)		25.32 (8.63)	
	MFR	6.42 (8.62)		4.46 (6.87)		58.70 (16.17)		22.75 (7.07)	
	HFR	0.75 (1.57)		2.14 (2.65)		44.13 (12.21)		21.11 (5.02)	
		Hedges' *g*	*p*	Hedges' *g*	*p*	Hedges' *g*	*p*	Hedges' *g*	*p*
Symptom Comparison	CIR>FIR	-0.04	.90	0.96	**.001**	-0.10	.46	0.86	**<.001**
	CIR>LRR	-	-	-	-	0.14	.30	1.08	**<.001**
	CIR>MFR	1.01	**.001**	1.68	**<.001**	0.49	**<.001**	1.73	**<.001**
	CIR>HFR	1.84	**<.001**	2.06	**<.001**	1.57	**<.001**	1.45	**<.001**
	FIR>LRR	-	-	-	-	0.25	.07	0.26	.06
	FIR>MFR	1.06	**<.001**	0.62	**.001**	0.59	**<.001**	0.64	**<.001**
	FIR>HFR	1.81	**<.001**	1.10	**<.001**	1.74	**<.001**	0.76	**<.001**
	LRR>MFR	-	-	-	-	0.36	**.001**	0.35	**0.007**
	LRR>HFR	-	-	-	-	1.53	**<.001**	0.58	**<.001**
	MFR>HFR	0.72	**<.001**	0.36	**.005**	0.93	**<.001**	0.24	**.02**

Note. 1) **DASS**= Depression Anxiety Stress Scale. **MASQ**= Mood and Anxiety Symptom Questionnaire. **CIR**= Context Insensitive Regulators. **FIR**= Feedback Irresponsive Regulators. **LRR**= Low Repertoire Regulators. **MFR**= Medium Flexible Regulators. **HFR**= High Flexible Regulators. 2) Hedges' values are considered large, medium, and small at 0.80, 0.50, and 0.20. 3) **Bolded** *p* values are considered significant after Benjamini-Hochberg Procedure with false discovery rate set to be .05.

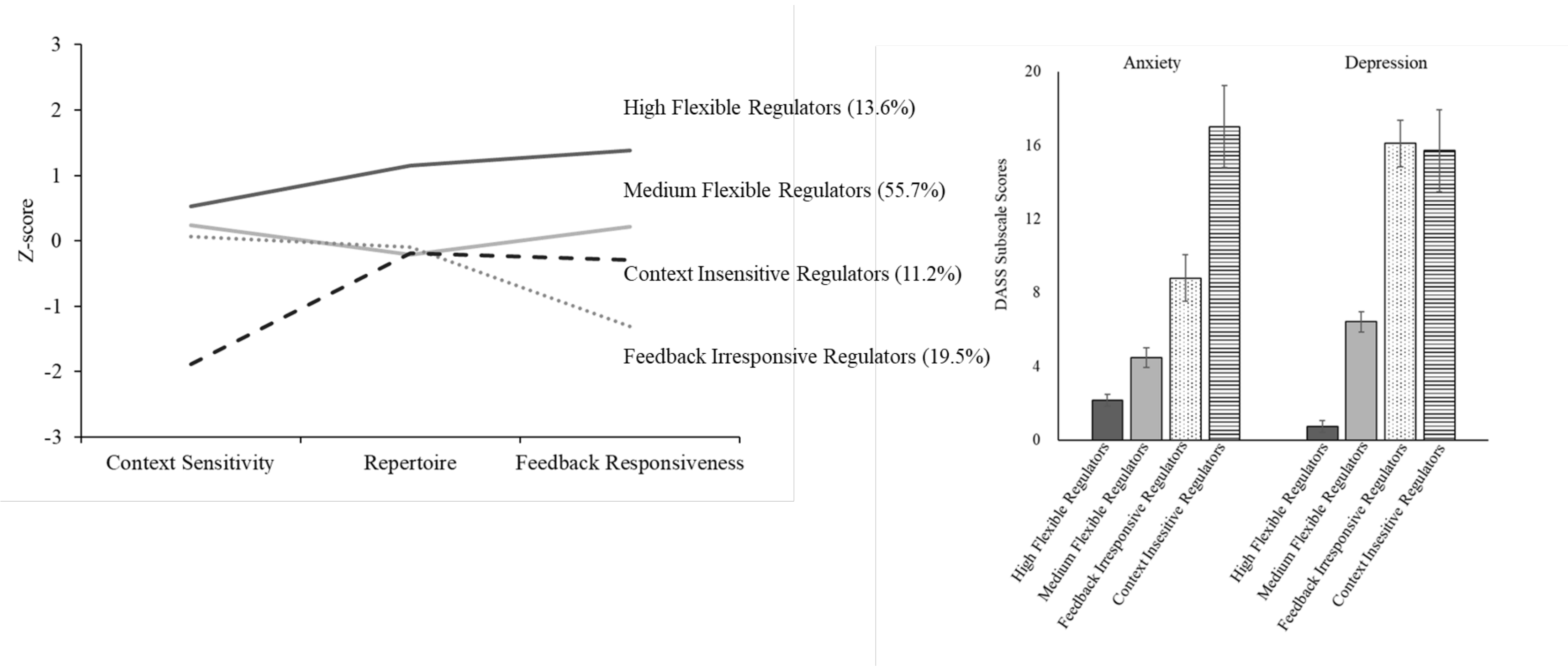

Figure 1. Sample item means for the four latent profiles of ER flexibility (Figure 1a) and comparisons of depressive and anxious symptoms among these profiles (Figure 1b) in Study 1. *Note*. DASS = Depression Anxiety Stress Scales.

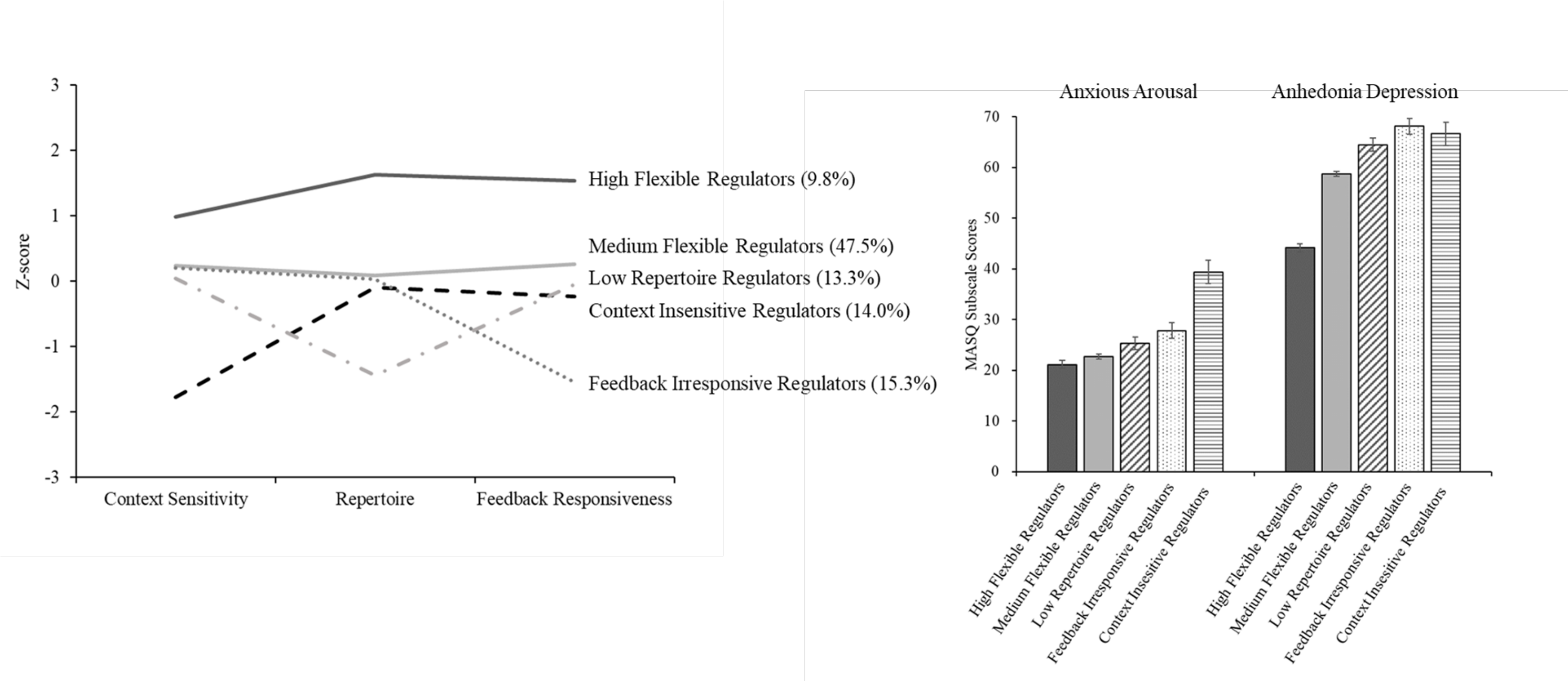

Figure 2. Sample item means for the five latent profiles of ER flexibility (Figure 2a) and comparisons of depressive and anxious symptoms among these profiles (Figure 2b) in Study 2. *Note*. MASQ = Mood and Anxiety Symptom Questionnaire. Here we only showed findings of full sample for brevity.

Paper 2

Psychopathology and Resilience Following Strict COVID-19 Lockdowns in Hubei, China: Examining Person- and Context-Level Predictors for Longitudinal Trajectories

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Abstract

In Hubei, China, where the COVID-19 epidemic first emerged, the government has enforced strict quarantine and lockdown measures. Longitudinal studies suggest that the impact of adverse events on psychological adjustment is highly heterogenous. To better understand protective and risk factors that predict longitudinal psychopathology and resilience following strict COVID-19 lockdowns, this study used unsupervised machine learning to identify half-year longitudinal trajectories (April, June, August, and October, 2020) of three mental health outcomes (depression, anxiety, and PTSD) among a sample of Hubei residents (*N* = 326), assessed a broad range of person- and context-level predictors, and applied LASSO logistic regression, a supervised machine learning approach, to select best predictors for trajectory memberships of resilience and chronic psychopathology. Across outcomes, most individuals remained resilient. Models with both person- and context-level predictors showed excellent predictive accuracy, except for models predicting chronic anxiety. The person-level models showed either good or excellent predictive accuracy. The context-level models showed good predictive accuracy for depression trajectories but were only fair in predicting trajectories of anxiety and PTSD. Overall, the most critical person-level predictors were worry, optimism, fear of COVID, and coping flexibility, whereas important context-level predictors included features of stressful life events, community satisfaction, and family support. This study identified clinical patterns of response to COVID-19 lockdowns and used a combination of risk and protective factors to accurately differentiate these patterns. These findings have implications for clinical risk identifications and interventions in the context of potential trauma.

Keywords: Psychopathology, Resilience, Trajectory, Machine Learning, COVID-19

Public Significance Statements

As COVID-19 continues to impact the world, it is critical to understand protective and risk factors contributing to psychological adjustment following strict lockdowns. This article reports longitudinal patterns of mental health among residents in Hubei, China, where COVID-19 first emerged, and key individual and contextual predictors of these trajectories. This study holds the potential to inform research directions and clinical approaches in the era of pandemic and long after.

Introduction

The global outbreak of the novel coronavirus disease 2019 (COVID-19) is an unprecedented public health event. Declared a pandemic by the World Health Organization (2020), the disease has spread to almost every country, infecting hundreds of millions and causing over three million global deaths (John Hopkins University, 2021). The COVID-19 pandemic has posed a combination of unique stressors, exerted widespread and severe impacts on multiple domains of life without a specific end date, and blocked access to protective factors such as social support (Gruber et al., 2020).

COVID-19 is a highly contagious respiratory illness first reported in Hubei Province, People's Republic of China, toward the end of 2019. As the place where COVID-19 was first reported and then contained, what happened in Hubei exemplifies the influence of lockdowns that potentially offers vital insights into ways the world may better prepare for the return to normal as well as future outbreaks. Starting with its capital, Wuhan, Hubei has witnessed the interruptions of daily life and unique stressors in this crisis. Moreover, without any predecessor from which experience can be learned or sufficient scientific knowledge of COVID-19 such as fatality rates, Hubei residents endured enormous uncertainty as COVID-19 led to unprecedented quarantine policies in an attempt to contain the virus. For example, government and community officials enforced stringent lockdown measures that prohibited residents from leaving their districts, restricted each family to send only one person to purchase groceries twice a week, and banned the private use of cars; the local government even took steps to reward individuals who reported neighbors breaking social distancing rules in order to eliminate group gatherings (Feng & Cheng, 2020). As an inevitable consequence of mandatory quarantine, Hubei residents were faced with fear, economical loss, and lack of access to food supplies and routine healthcare. Forced social isolation also reduced social and physical contacts with others and likely elevated psychological distress (Brooks et al., 2020). Although the strict lockdown measures in Hubei were lifted in April 2020, residents continued to face challenges such as financial stress, health concerns, and discrimination from citizens in other provinces.

Increased psychological challenges in the context of the COVID-19 epidemic are likely to result from a combination of stressors, characterized by great uncertainty, life-threatening conditions, fear of COVID-19, prolonged exposure to anxiety provoking information, and loss of loved ones, financial security, perceived control, social connection, and daily activities (Gruber et al., 2020). As pandemics are dynamic events, Taylor (2019) suggested that the psychological difficulties resulted from pandemics are likely to vary across time. The initial distress-related responses to COVID-19 are a multi-faceted network of interconnected symptoms, with COVID-19 danger and contamination fears as its cores (Taylor, et al., 2020). Over time, other potential deleterious practical consequences, such as economic loss and unemployment, have emerged and taken a toll on mental health (Lei et al., 2020; Achdut & Refaeli, 2020). During the lockdowns, forced social isolation and lack of adequate physical space are also cited concerns that can negatively impact mental health (Pancani et al., 2021).

A number of cross-sectional studies have demonstrated elevation in psychopathology symptoms following COVID-19 lockdowns (e.g., Han et al., 2021). However, these studies say little about the course of resilience or psychopathology over time. Moreover, a recent review indicated that the impact of COVID-19 lockdowns on mental health was small in overall effect size while also exhibiting considerable heterogeneity (for a review, see Prati & Mancini, 2021). In other words, there is no direct evidence that lockdowns are universally harmful to mental health across individuals.

Longitudinal studies of psychological adjustment following stressful and potential traumatic life events have consistently identified a small set of prototypical outcome *trajectories*

(Bonanno, 2004; Galatzer-Levy et al., 2018). These trajectories include resilience (low distress or symptoms over time), gradual recovery (high onset but gradual waning distress or symptoms), and chronicity (elevated distress or symptoms over time). Trajectory models offer a robust methodology to identify clinically relevant patterns of response to potential trauma and enhance the identification of predictors (Galatzer-Levy et al., 2014). Although previous research has identified predictors of chronic psychopathology and resilience following stressful and potentially traumatic events, including disease outbreaks, the number of factors examined were typically small. In a sample of hospitalized survivors of the 2003 severe acute respiratory syndrome (SARS), for example, Bonanno and colleagues (2008) found that those who remained resilient had greater social support and less SARS-related worry and were more likely to be male. Though these studies elucidate the heterogenous psychological response in response to adverse events and identify some predictors, the relatively small number of protective and risk factors precluded the identification of robust predictors and accurate classification of long-term adjustment.

The Current Investigation

In the current study, we aimed to identify longitudinal trajectories of resilience and psychopathology among a sample of Hubei residents, and then to identify a broad range of person- and context-level variables that might differentiate these trajectories. The data from Hubei were particularly well-suited for this type of longitudinal analyses given Hubei was hard hit by the epidemic without any prior experience to consult. Although comparatively small in population and size, Hubei accounted over two thirds of the total number of inflected individuals in China. We conducted the study from April to October in 2020 given our interest in understanding mental health in the aftermath of the acute impact of the pandemic. The Hubei province lifted the strictest lockdown measures in April.

The primary measures for outcomes in this study were depression, anxiety, and posttraumatic stress disorder (PTSD) symptoms, which are commonly examined outcomes in disaster research (Bonanno et al., 2010). Based on previous findings (Chen & Bonanno, 2020; Galatzer-Levy et al., 2018), we expected to observe trajectories of resilience, recovery, and chronicity, with resilience being the modal response, but also that the number and type of trajectories might vary across outcomes.

In considering potential predictors of these trajectories, we examined a broad range of person- and context-predictors. The predictors we chose were either identified as important by previous studies on potential trauma (for reviews, see Bonanno et al., 2015; Chen et al., 2020) or highly relevant to COVID-19 (e.g., fear of COVID-19). Person-level predictors included COVID-fear, optimism, physical health, prosocial behaviors, perceived social support, coping and emotion regulation strategies, and flexibility. The context-level predictors we examined spanned across domains of stress exposure, family features, and community characteristics (Bonanno et al., 2015).

Our study advances previous COVID research in several important ways. First, rather than measure only average-level or categorical outcomes, we explored the full range of longitudinal responses to the pandemic by identifying trajectories of resilience and psychopathology over time. Second, whereas previous trajectory studies have often reported convergence issues due to multicollinearity with some predictor variables, we employed a form of supervised machine learning, LASSO regression, which controls for multicollinearity. Third, we examined a wider range of possible variables than previous COVID studies, and included both person-level and contextual factors.

As the world attempts to gradually return to normal and reflects on how to better prepare for new waves of COVID-19 or a future pandemic, our study provides important information about long-term patterns of psychological response to lockdowns. Additionally, as the first study on predictors for longitudinal resilience and chronic psychopathology among Hubei residents, our study offers critical information for risk identifications and interventions.

Method

Participants and Procedure

In order to recruit participants, this study employed a snowball sampling strategy, with research assistants spreading e-posters on Chinese social media platforms (Weibo, WeChat, Zhihu, and Blog) and asking their online contacts from Hubei to do the same in a manner similar to retweeting. We included multiple social media platforms of different age groups to diversify our participant composition. Following our distribution of e-posters on social media, we received 396 signups that met our inclusion criteria (i.e., living in Hubei during the time of the lockdown). Of those, 18 provided invalid contact information (e.g., incorrect or incomplete email or phone or WeChat number), six signed up twice, leaving 372 valid signups. The research team reached out to these potential participants via their preferred contact method (text, WeChat, or email). Of these participants, 19 did not respond and 9 declined to participate because they were no longer available or interested. This left us with 344 participants at baseline and a response rate of 92.5%.

After removing 18 participants who only completed the first wave, we adopted full-information maximum likelihood, an estimation strategy that allow us to obtain parameter estimates even in the presence of some missing outcome values. We adopted this approach because there are no longitudinal outcome data on those completing only one wave and including them in LGMM would lead to model non-convergence. In addition, we handled the missing data of the baseline predictor values (0.94%) using K-nearest neighbor (KNN) imputation. In terms of attrition, among the 326 participants included in the final analysis, 8, 33, and 35 participants missed wave 2, wave 3, and wave 4, respectively, with the possibility that some participants who missed a certain wave completed the following ones upon recontact. A total of 265 completed all four waves, and 311 completed at least three waves. The attrition rate was relatively low, possibly because we contacted participants one on one instead of sending generic emails to a large list of participants and provided them with a personalized mental health report, a gift, and a thank-you letter. We included instructions on the approximate time range that each survey may take and the importance of attentive participation is to the scientific understanding of the psychological impact of the pandemic and the accuracy of personalized mental health report.

Participants ranged in age from 16 to 70 (M = 30.05, SD = 10.84) and 75.1% were female; the majority of them (77.6%) obtained a bachelor's degree or higher and 44.2% are either married or divorced. The results of t-tests and chi-squared tests showed that participants who dropped out did not differ from those who remained in demographics including age, gender, education level, marital status, number of children, quarantine location, and baseline psychopathology symptoms, *p.s.* > .05. The Institutional Review Board of [Deidentified for Masked Review] approved the study, and participants provided informed consent prior to participating in the study.

Measures

We examined three outcome variables and a total of 59 person- and context-level predictors. Given that prior research has shown a negative association between survey length and response rate (Deutskens et al., 2004), we used three single-item measures (i.e., **alcohol use**, **tobacco use**, and **information overconsumption**) and adopted shorter versions of some scales (e.g., **worry** and **perceived social support**) to reduce participant burden and attrition in the current study. When translation from English to Chinese was required, bilingual psychology graduate students followed the standard translation and back-translation procedures (Brislin, 1970).

Specifically, the outcome measures for all waves included measures of depression (Center for Epidemiological Studies-Depression [CES-D]; Radloff, 1977; Chinese version by Wang et al., 1999), anxiety (State Anxiety Inventory [SAI]; Spielberger et al., 1983; Chinese version by Wang et al., 1999), and PTSD (Posttraumatic Diagnostic Scale-Chinese [PDS-C]; Shen et al., 2014).

Baseline person-level predictors included age, gender, education, measures of COVID-19 fear (Fear of COVID-19 Scale [FCV-19S]; Ahorsu et al., 2020; Chinese version by Chi et al., 2021), optimism and pessimism (Life Orientation Test—Revised [LOT-R]; Scheier et al., 1994), physical health-related measures regarding subjective health, health change, weekly exercise frequency and hours prior to COVID-19, body mass index (BMI), doctor visits , hospitalization, pre-existing health conditions, prosocial behaviors, perceived social support (MOS Social Support Survey [MOS-SSS]; Sherbourne & Stewart, 1991), reappraisal and suppression (Emotion Regulation Questionnaire [ERQ]; Gross & John, 2003; Chinese version by Wang et al., 2007), brooding rumination and reflective rumination (Ruminative Response Scale (RRS; Treynor et al., 2003; Chinese version by Yang et al., 2009), distraction (Response Style Questionnaire [RSQ]; Butler & Nolen-Hoeksema, 1994; Nolen-Hoeksema & Morrow, 1991), worry (Penn State Worry Questionnaire [PSWQ]; Meyer et al., 1990), refocus on planning and positive refocusing (Cognitive Emotion Regulation Questionnaire [CERQ]; Garnefski et al., 2000; Chinese version by Wang et al., 2017) , coping strategies including alcohol use, tobacco use, leisure activities, productivity maintenance, regularity maintenance, COVID-19 related information accessing and information overconsumption, preventive measures, and coping flexibility (Coping Flexibility Scale [CFS]; Kato 2012; Chinese version by Kato, 2015).

Baseline context-level predictors included personal income level prior to the pandemic, employment before and during COVID-19, number of stressful life events, perceived stress severity, mean appraisal of stressful events, discrimination due to COVID-19, marital status, number of children, number of underaged children, perceived family support, perceived family conflict, number of years in the lockdown city, location, residency information (e.g., whether one possess residency in the lockdown city, comes from rural regions), objective measures of city characteristics including neighborhood socioeconomic status (i.e., per capita disposal income) in 2018, 2020 average housing price, 2017 population density, 2018 GDP, and 2018 weighted city-level public expenditures on welfare, education, health care, infrastructure, subjective satisfaction with the community's infrastructure, environment, quality of relationship with neighbors, and general feelings about the community. We also controlled for whether one quarantined in Wuhan or other cities and severity of the outbreak (i.e., total COVID-19 cases till April 2020, number of hospitals with fever clinics receiving COVID-19 patients weighted by city-level population density) given that these factors could impact the experience of individuals during the lockdown.

More information about included measures can be found in **Supplement 1**.

Data Analytic Plan

Statistical analyses were performed in Mplus Version 7.4 and R Version 4.0.4 via *caret, glmnet, fbroc* packages (Muthén & Muthén, 2012; R Core Team, 2021).

First, latent growth mixture modeling (LGMM), a form of unsupervised machine learning, was performed to identify trajectories of depression, anxiety and PTSD (Muthén & Muthén, 2012). We explored intercept, slope, and quadratic parameters as either random or fixed effects. In the final models, both slope and intercept variances were allowed to be freely estimated and quadratic parameters were nonsignificant and thus removed to facilitate model convergence. Because recent simulation studies (Depaoli et al, 2019; Shader & Beauchaine, 2021) indicated that LGMM on non-normal data can over-identify latent groups, we also examined the levels of skewness and kurtosis of our data (**Supplement 2**). Model solutions from

1 to 5 classes were compared by model fit indices, including Akaike (AIC), sample-size adjusted Bayesian Information Criteria (SSABIC), Entropy, and Bootstrap Likelihood Ratio Test (BLRT). In addition, we excluded solutions with infrequent classes (< 5%) because these tend to be unstable, and difficult to replicate (Nylund-Gibson & Choi, 2018). Choice of best-fitting solutions was based on these indices, theoretical coherence, and explanatory relevance.

Second, least absolute shrinkage and selection operator (LASSO) logistic regression, a form of supervised machine learning suited for high-dimensional data (i.e., where sample size does not substantially exceed the number of predictors), was built to predict 1) resilience against all other trajectories, and 2) chronicity against all other trajectories. In other words, we dichotomized participants into two groups by combining the chronicity and recovery trajectories when predicting resilience, and similarly, combining resilience and recovery trajectories when predicting chronicity. Although multinomial classification is most ideal when more than two trajectories are identified, we adopted binary LASSO given our interest in factors setting resilient individuals (and individuals exhibiting psychopathology over time) apart from everyone else. Predicting one against all other trajectories is also an approach adopted by other researchers when using machine learning method (e.g., Schultebraucks et al., 2020), and is appropriate given that our relatively small group size (e.g., only 5% of the participants were in the recovery trajectory for anxiety) could not support reliable multinomial classification. Moreover, LASSO logistic regression is particularly useful because of the large number of predictors we examined as it applies a penalization that reduces coefficients of less important predictors to zero, addresses the issues of multicollinearity and model overfitting, and improves interpretability (McNeish, 2015; Tibshirani, 1996).

To select the optimal shrinkage parameters (i.e., lambda) for the LASSO models and obtain mean cross-validation estimates of model performance, 10-fold cross-validation with three repetitions was performed when building each model using the *caret* package following the recommendation of Kuhn and Johnson (2013). While splitting the dataset into a single training and test data set makes it difficult to accurately characterize uncertainty in prediction, especially when the sample size is small, the use of repeated k-fold cross-validation can provide more reasonable estimates of how accurate the resultant model's prediction would be in predicting unseen future data sets (Kuhn & Johnson, 2013). For models with class imbalance where more than 70% of observations belong to one class, upsampling, a type of subsampling technique that randomly samples (with replacement) the class of smaller size to improve class balance, was used. In order to ensure that the outcomes of test data in the cross-validation process remain unaltered, upsampling was only conducted within the resampling process (Kuhn, 2008). The performance metric of the models is Area under the Receiver Operating Characteristic Curve (AUC), which can be classified into five categories, respectively fail (.50–.59), poor (.60– .69), fair (.70–.79), good (.80–.89), and excellent (.90–1.00) (Safari et al., 2016). In order to capture the variability of each model's performance across the 30 cross-validations, we calculated and reported a 95% bias-corrected and accelerated confidence interval of the AUCs using 5,000 bootstrapped resamples in order to reduce the risk of overfitting and to provide a more complete picture of model performance, in addition to also reporting sensitivity, specificity, NPV, PPV and their respective confidence interval (**Table 2**).

The resultant optimal lambda parameters were used to refit the models to obtain the predictor coefficients needed to rank relative importance of predictors in each model. Specifically, variable importance was estimated by reordering the coefficients of predictors whose values are not shrunken to zero on a scale from 0 to 100 with the predictor of the greatest magnitude scoring 100 using the VarImp() function of the *caret* package.

Results

Latent Growth Mixture Modeling

We examined one- to five-class solutions for each outcome (**Table 1**) and reported distribution information and intercept effect sizes of selected solutions (**Supplement 2**). For depression and anxiety where there was mild skewness and kurtosis, information criteria (AIC, BIC, and SSABIC) decreased consistently, indicating improved model fit with increasing class number. BLRTs, which compared n-class solution with (n-1)-class solution, were significant up to three classes for anxiety and four classes for depression. However, the four-class depression solution included one class with low prevalence. Thus, three-class solutions were selected as optimal for both depression and anxiety (**Figure 1**), and each included similar trajectories of stable low symptoms (resilience), consistently high symptoms (chronicity), and initially high but gradually declining symptoms (recovery). For PTSD symptoms where some data were skewed and leptokurtic, the BLRT was significant up to five classes. However, we selected the two-class solution as optimal because subsequent class solutions had at least one class with low prevalence (< 5%). The two classes had reasonably large intercept effect sizes (Cohen's d = 1.55) easing concern of non-normal data driving grouping solutions according to simulation studies (Depaoli et al, 2019; Shader & Beauchaine, 2021). All of the selected models produced the best AIC and SSABIC among models without any class of low prevalence (<5%). The two-class PTSD solution included trajectories of resilience and chronicity (**Figure 1**). Across all three outcomes, most individuals were resilient and entropy for each selected solution was high (>.80).

LASSO Logistic Regression Performance

While two (depression and anxiety) of the three LGMM models produced solutions with more than two classes, we decided to build LASSO binary logistic regression models over multinomial logistic regression models for all three outcomes for the following reasons: 1) We were interested in understanding what set individuals falling under the resilience/chronicity trajectories apart from everyone else. From a theoretical perspective, this yields the potential to identify factors predictive of longitudinal stable mental health (resilience versus chronicity + recovery), and factors predictive of consistent psychopathology over observations (chronicity versus resilience + recovery). One potential implication of this practice is risk and resilience identification. 2) From a practical standpoint, our relatively small group size (e.g., only 5% of the participants were in the recovery trajectory for anxiety) made it unlikely to perform reliable multinomial classification; 3) Finally, previous studies have utilized this approach. For example, Schultebraucks et al. (2020) predicted non-remitting (i.e., chronicity) against other trajectories. Therefore, we build three different types of LASSO binary logistic regression models (i.e., one with only person-level predictors, one with only context-level predictors, and one with predictors at both levels) to differentiate resilience versus other trajectories for each symptom type (depression, anxiety, and PTSD). For depression and anxiety only, we repeated these analyses to predict chronicity against other trajectories (**Table 2**).

For depression, models using person-level or both-level predictors showed excellent predictive accuracy (.90 < AUCs < .91; .87 < CIs < .94), except when predicting chronicity using only person-level predictors (AUC = .89; CI= .85, .92), whereas models using context-level predictors showed good predictive accuracy (AUCs = .83 and .85 for resilience and chronicity trajectories, respectively). For anxiety, models using person-level or both level predictors (.81 < AUCs < .87; .78 < CIs < .89) again outperformed models with only context-level predictors (AUCs = .75 and .71 for resilience and chronicity trajectories, respectively; .67 < CIs < .78). Moreover, models predicting resilience using person-level (AUC = .86; CI = .84, .88) or context-level (AUC = .75; CI = .73, .78) or both-level (AUC = .87; CI= .86, .89) predictors were more accurate in classification than models predicting chronicity with person-level (AUC = .81; CI =

.78, .84) or context-level (AUC = .71; CI = .67, .74) or both-level (AUC = .82; CI = .80, .85) predictors. For PTSD, models with person- (AUC = .91; CI = .88, .93) and both-level predictors (AUC = .92; CI = .89, .93) were excellent in predictive accuracy and again outperformed the context-level model (AUC = .76; CI = .71, .81). Across three outcomes, models of person-level predictors outperformed models of context-level predictors. While the AUCs for the full models tend to be the highest across prediction models, the actual AUCs for the full models are marginally higher and well within the confidence interval, suggesting that the person-level models perform almost equally well as the full models. To aid more accurate interpretation of model performance, we also reported sensitivity, specificity, NPV, and PPV in **Table 2**.

Variable Importance

Plots of variables in descending order of importance are shown in **Figure 2**. It is noteworthy that highly important predictors include both person- and context-level variables across models. Unless otherwise specified, contributory variables with variable importance below 10 were omitted. However, coefficients of all included predictors are shown in **Table 3**. Variable importance plots and coefficients for models with only person-level or context-level predictors were reported in **Supplements 3** and **4**.

Predicting Trajectories of Depression

The most important predictors of the resilience trajectory included optimism, family support, BMI, and subjective health and, inversely, worry, brooding rumination, and mean appraisal of stressful events. The most important predictors of the chronicity trajectory included worry, family conflict, COVID fear and, inversely, family support and coping flexibility.

Predicting Trajectories of Anxiety

For the resilience model, the most important predictors included reappraisal, productivity maintenance, weighted public budget cost, optimism, regularity maintenance, BMI, hospitalization during COVID-19 lockdowns, and coping flexibility and, inversely, worry, pessimism, being married or from rural regions, stress severity, information overconsumption, and preventive measures. For the chronicity model, the most important predictors included worry, pessimism, being from rural regions, and stress severity and, inversely, productivity maintenance, coping flexibility, reappraisal, weighted public budget cost, BMI, and optimism,

Predicting Trajectories of PTSD

Since only two trajectories (resilience and chronicity) were identified for PTSD symptoms, we only specified one model predicting the resilience trajectory. The most important predictors of resilience included regularity maintenance, family support, exercise hours pre-COVID, and productivity maintenance and inversely, COVID fear, family conflict, number of stressful events, worry, and alcohol use.

With regards to transdiagnostic predictors, both worry and family support were predictive (i.e., coefficients not reduced to zero) in all models. Three predictors – coping flexibility, regularity maintenance, and COVID fear – were predictive in four full models, while six predictors – BMI, optimism, pessimism, productivity maintenance, stress severity, and family conflict – remained so in three out of the five full models. Among the predictors that remained contributory, worry was the most robust predictor and exhibited the highest variable importance (i.e., 100 on a scale of 0 to 100) across all five but one model, while being from rural regions, family support, family conflict, reappraisal, productivity maintenance, and COVID fear were also robust, appearing among the top five predictors in two out of five cases.

Discussion

We used unsupervised machine learning to identify heterogeneous trajectories of depression, anxiety, and PTSD symptoms in the aftermath of strict COVID-19 lockdowns in a sample of Hubei residents and then to discriminate these trajectories using person- and context-level predictors. By including three overlapping yet different mental health outcomes, we were able to compare their longitudinal trajectories and corresponding predictors in the context of COVID-19 lockdowns, which enabled us, in turn, to elucidate transdiagnostic and diagnosis specific risk and protective factors.

Across three mental health outcomes, most individuals remained resilient despite the stressful and potentially traumatic nature of the strict lockdowns in Hubei, a finding consistent with previous research (for a review, see Bonanno et al., 2010). As countries like the United States aim to return to normalcy thanks to a successful vaccination program, our findings documenting the prevalence of resilience highlight the importance of heterogeneity in psychological response and risk identifications. Of note, however, was our finding that the proportion of resilient individuals was lower for anxiety (58%) than either depression (87%) or PTSD (93%). One plausible reason is that anxiety may be a normative and perhaps temporary response during COVID-19 lockdowns and may not necessarily signal psychopathology (Bonanno et al., 2015). It is also worth considering that the measure of anxiety we used captured general distress rather than clinical-level anxiety, which may further inflate the estimation of chronic anxiety. Relatedly, our LASSO models predicting depression and PTSD were more accurate than models predicting anxiety. Taking into consideration the proportion of anxiety trajectories and the nature of our anxiety measure, it is likely that predictors included in this study excelled at classifying the absence or presence of psychopathology but were less able to differentiate individuals with varying levels of distress.

Our findings demonstrate that resilience and chronicity depend on a combination of person and context-level predictors. Importantly, although, person-level predictors outperformed context-level predictors, including context-level predictors still tended to improve the model performance, suggesting the importance of both person- and context-level predictors with a highlight on person-level predictors. We identified transdiagnostic predictors such as worry, family support, coping flexibility, and fear of COVID-19. Given that studies have identified the central role that various forms of worry play in avoidance and coping behaviors during the COVID-19 pandemic (Taylor et al, 2020), it was not a surprise that worry emerged as an important transdiagnostic predictor of chronic psychopathology. We also identified a few diagnosis-specific predictors. For example, alcohol use and exercise before COVID-19 were only predictive for the course of PTSD. These findings offer vital insight, not only for risk identifications but also targeted prevention and intervention. For example, transdiagnostic risk factors for chronic depression, anxiety, and PTSD, such as worry, lack of family support, fear of COVID-19, and coping inflexibility, appear to be particularly important targets for psychoeducation, prevention-intervention efforts.

Somewhat unexpected were a few counterintuitive predictors. For example, residing in rural China was associated with increased likelihood of chronicity and decreased likelihood of resilience trajectory of anxiety, a finding inconsistent with recent research documenting lower anxiety among rural residents during COVID-19 lockdowns (Zhang et al., 2021). One possible explanation is that individuals living in rural areas of Hubei, where COVID-19 was first reported and resources most strained, faced more challenges of drug shortage and relatively limited access to high-quality healthcare compared to rural citizens living in less impacted areas of China, again showing the importance of context. Another variable, BMI, was predictive of resilience trajectories of depression and anxiety. A closer scrutiny of data revealed that only five participants' BMI was high enough to fall under the obesity range (BMI > 30) whereas 52 participants were within the underweight range (BMI < 18.5); therefore, greater BMI in this study may indicate average weight rather than obesity. Despite these plausible explanations, we suggest caution in emphasizing predictors with relatively lower importance such as BMI. In the same vein, although we adopted 10-fold within-sample cross-validations with three repetitions to enhance the likelihood of generalizability, further validations in external samples are highly desirable.

From a clinical science perspective, our study adds to a small but growing literature demonstrating the effectiveness of using machine learning to examine a large body of diverse predictors to effectively differentiate longitudinal trajectories of psychopathology symptoms (e.g., Galatzer-Levy et al., 2018; Schultebraucks et al., 2020, 2021). Many resilience and psychopathology studies often included few predictors and adopted univariate analyses (for a review, see Bonanno et al., 2010), limiting their capacity to distinguish the most robust predictors. Future research may benefit from adopting our approach to address this critical gap. The current study also highlights the need for comparative analysis across contexts and cultures. Although perceived social support has been consistently identified as an essential resilience factor (e.g., Chen et al., 2020; Galatzer-Levy et al., 2018), our findings showed family support to be a stronger predictor, which likely resulted from the cultural backdrop where the study took place. As the first study that examined a large number, multi-domain predictors for longitudinal trajectories of mental health in an Asian sample, our study makes important contributions to psychological data that were traditionally dominated by samples from Western, educated, industrialized, rich, and democratic (WEIRD) nations (Henrich et al., 2010). From the perspective of practice and policy, our study suggests important implications for risk identification. As worry emerged as a consistent predictor of longitudinal mental health trajectories, incorporating worry as a standard assessment in the aftermath of disasters may provide useful information to clinicians providing care for exposed residents. The findings from this study also offer preliminary information regarding factors that can likely serve as targets in prevention and intervention efforts, including coping, emotion regulation, and family relationships. Further investigations to establish the efficacy of possible prevention and intervention programs are needed, but our study sheds light on factors that may play the most important roles in the psychological adjustment following the acute phase of disease outbreak.

The advances of our findings should be considered alongside several methodological limitations. First, we did not perform power analysis due to the lack of prior hypothesis, but this along with our small sample size may bias the results and negatively impact the generalizability of our findings. In the same vein, the relatively small sample size did not allow us to split the data into training and test sets. While we used 10-fold cross-validation with three repetitions to obtain more reliable estimates of model performance, the lack of external validation increases risk of overfitting and limits the generalizability of the analysis. Future studies with a larger sample size can enhance power and enable external validation. One possibility for future research may be to use information (e.g., standardized coefficient and odd ratios) from our relatively exploratory study to inform calculation of what an appropriate sample size may be. Second, there were limitations in our data collection methods. Self-selection bias is very likely given that those who saw the recruitment flyers decided entirely for themselves whether they want to participate. Moreover, our snowball sampling method recruiting participants from social media platforms (e.g., more female and young adult participants in our sample) also limits the sample representativeness and result generalizability. As another limitation in our data collection, we did not account for careless responding except for highlighting the importance attentive participation is to scientific research and accuracy of personalized mental health report. This may negatively impact our data quality. Third, the use of LGMM can identify the wrong number of groups according to the levels of skew, kurtosis, intercept effect size, and group proportions (Depaoli et al., 2019; Shader & Beauchaine, 2021). Following recommendations by Nylund-Gibson and Choi

(2018), we excluded solutions with infrequent classes (< 5%) even when some fit indices may support solutions with more classes, because small classes tend to be unstable. This, however, could have been better addressed if we had a larger sample that would allow cross-validation. As LGMM was more effective when intercept effect sizes were large, we examined the group with the least (i.e., resilience) and most symptoms (i.e., chronicity). Although the intercept effect sizes were large, which attenuates concern of identifying wrong number of groups in LGMM, the non-normal distribution for PTSD still poses risks for class misidentification. Therefore, it is critical to keep in mind this limitation when interpretating our findings. Relatedly, although longitudinal trajectories effectively capture outcome heterogeneity, the certainty of trajectory membership is nonetheless variable. Although this concern was reduced in our study as indicated by the relatively high entropies we observed, it will be important for future studies to explore the role of uncertainty in trajectory membership. One approach, for example, may be to use unsupervised machine learning to first identify robust predictors that would then be included in a conditional LGMM. Fourth, our study may overestimate the percentage of chronicity given that we did not take into consideration pre-existing mental illness or more gradual recovery occurring beyond six months after the strict lockdowns. Fifth, keeping in mind that the duration of the study is only six months, it is important to note that the term chronicity is used to stay consistent with the literature (Galtzer-Levy, Huang & Bonanno, 2018) and to distinguish this trajectory from the recovery trajectory, and does not necessarily amount to chronic psychopathology such as dysthymia and generalized anxiety disorder. Some of those who exhibit a chronicity trajectory may recover if examined over a longer period. Sixth, as mentioned earlier, the anxiety measure we used may have captured general distress rather than clinical anxiety, limiting our conclusions on anxiety and its predictors. Finally, although we included objective indices for some community features, most predictors were derived from self-report measures. In predicting anxiety specifically, a few predictors emerged as important were small in their relative importance and should thus be viewed and interpreted with caution. Future studies that include multilevel measures will likely further enhance predictive accuracy (e.g., Schultebraucks et al, 2020).

In conclusion, this study examined a large and diverse set of predictors to identify the most important risk and resilience factors that accurately differentiate longitudinal trajectories of depression, anxiety, and PTSD during the COVID-19 lockdown in China. Future studies are encouraged to take into consideration model uncertainty, validate findings in external samples, and identify and risk and resilience factors across individuals and cultural contexts.

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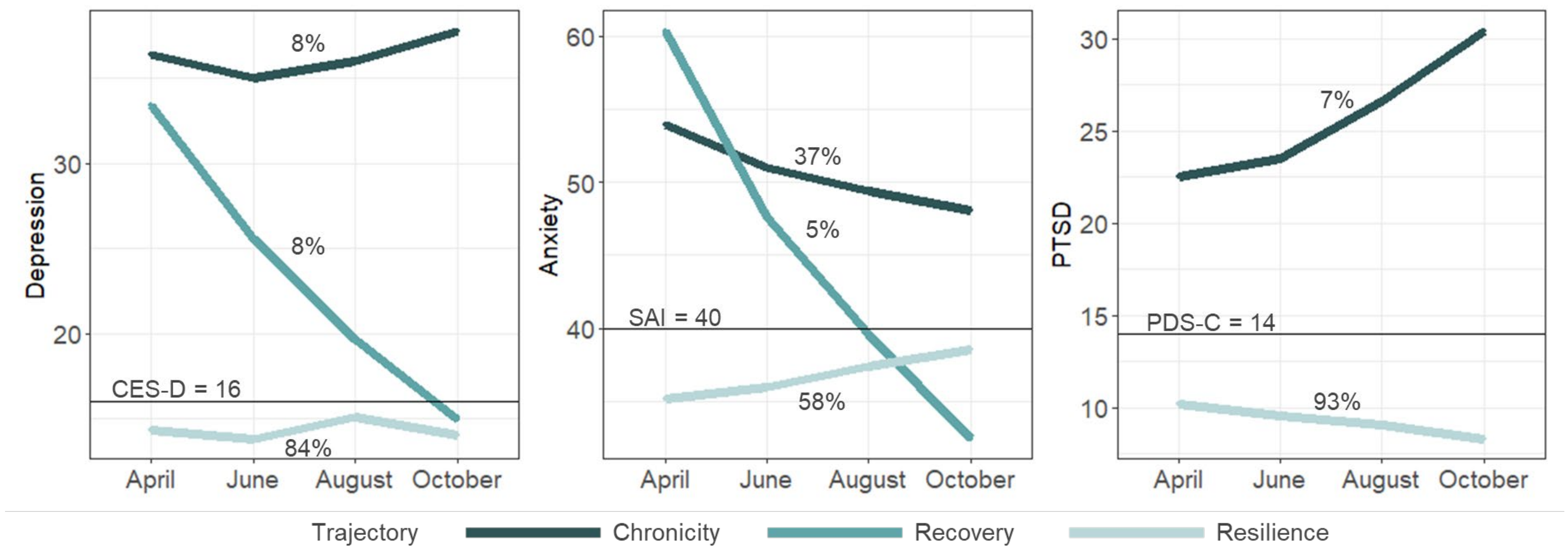

Figure 1. *Group Means for Trajectories of Three Mental Health Outcomes (Depression, Anxiety, and PTSD)*
Note. Reference lines represent cutoff scores for Center for Epidemic Survey- Depression (CES-D), State Anxiety Inventory (SAI), and Posttraumatic Diagnostic Scale-Chinese (PDS-C).

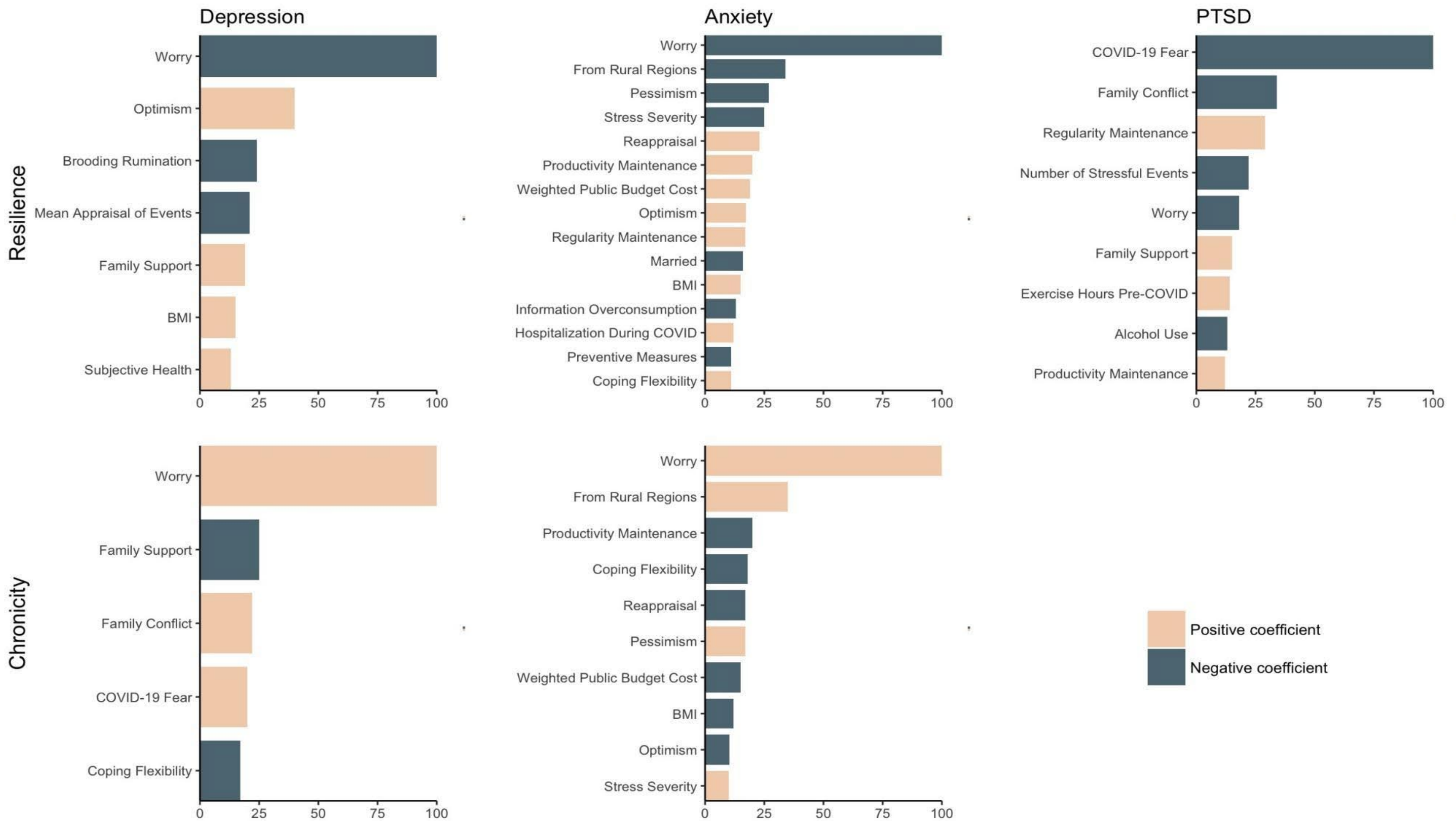

Figure 2. *Relative Importance of Variables in the LASSO Full Models Predicting Resilience or Chronicity Trajectory of Depression, Anxiety, and PTSD*

Table 1. *Fit Indices for Latent Growth Mixture Models (LGMM) for Depression, Anxiety, PTSD.*

Class Number	max LL	AIC	SSABIC	Entropy	BLRT *p*	Per. Small
Depression						
1	-4294.62	8607.25	8612.78	-	-	-
2	-4273.01	8570.01	8577.38	.84	< .001	13%
3	-4261.23	8552.45	8561.68	.83	< .001	8%
4	-4252.40	8540.80	8551.87	.84	< .001	2%
5	-4241.41	8524.28	8537.20	.85	<. 001	2%
Anxiety						
1	-4478.69	8975.38	8980.92	-	-	-
2	-4471.38	8966.76	8974.14	.84	< .001	7%
3	-4465.60	8961.21	8970.43	.84	.02	5%
4	-4462.93	8961.85	8972.92	.74	.48	2%
5	-4458.78	8959.56	8972.47	.79	.20	2%
PTSD						
1	-3999.82	8017.63	8023.17	-	-	-
2	-3977.85	7979.70	7987.08	.86	< .001	7%
3	-3963.86	7957.73	7966.95	.83	< .001	3%
4	-3949.52	7935.03	7946.10	.86	< .001	1%
5	-3939.47	7920.94	7933.85	.84	< .001	1%

Note. max LL = maximized log likelihood value. AIC=Akaike Information Criterion. SSABIC=Sample-size adjusted Bayesian Information Criterion. BLRT = Parametric Bootstrapped likelihood ratio test. Per. Small = Percentage of participants in the smallest group.

Table 2. *Model Performance of Lasso Logistic Regressions*

Outcome	Predictors	Resilience AUC [CI]	Resilience Sensitivity [CI]	Resilience Specificity [CI]	Resilience PPV [CI]	Resilience NPV [CI]	Resilience λ	Chronicity AUC [CI]	Chronicity Sensitivity [CI]	Chronicity Specificity [CI]	Chronicity PPV [CI]	Chronicity NPV [CI]	Chronicity λ
Depression	Person−Level Only	.90 [.87, .92]	.81 [.74, .86]	.84 [.82, .87]	.53 [.48, .59]	.96 [.95, .97]	0.023	.89 [.85, .92]	.83 [.81, .86]	.73 [.63, .82]	.97 [.96, .98]	.30 [.26, .39]	0.033
	Context−Level Only	.83 [.80, .85]	.73 [.66, .80]	.76 [.72, .78]	.38 [.34, .41]	.94 [.92, .95]	0.037	.85 [.80, .88]	.77 [.74, .80]	.78 [.68, .86]	.98 [.97, .99]	.25 [.22, .29]	0.08
	Both Levels	.90 [.88, .92]	.81 [.74, .86]	.84 [.82, .86]	.51 [.48, .56]	.96 [.95, .97]	0.033	.91 [.87, .94]	.84 [.81, .86]	.78 [.67, .86]	.98 [.97, .99]	.33 [.28, .41]	0.045
Anxiety	Person−Level Only	.86 [.84, .88]	.70 [.64, .75]	.85 [.82, .87]	.77 [.74, .81]	.80 [.77, .84]	0.018	.81 [.78, .84]	.86 [.84, .88]	.57 [.50, .62]	.77 [.75, .80]	.71 [.66, .76]	0.039
	Context−Level Only	.75 [.73, .78]	.53 [.48, .58]	.81 [.77, .84]	.68 [.63, .73]	.71 [.68, .74]	0.015	.71 [.67, .74]	.87 [.84, .90]	.34 [.28, .38]	.69 [.67, .71]	.62 [.53, .79]	0.026
	Both Levels	.87 [.86, .89]	.71 [.66, .75]	.85 [.83, .88]	.78 [.75, .81]	.81 [.78, .83]	0.019	.82 [.80, .85]	.87 [.84, .90]	.57 [.51, .61]	.77 [.75, .79]	.74 [.70, .78]	0.023
PTSD	Person−Level Only	.91 [.88, .93]	.76 [.67, .83]	.82 [.80, .85]	.26 [.23, .29]	.98 [.97, .99]	0.063	–	–	–	–	–	–
	Context−Level Only	.76 [.71, .81]	.60 [.49, .69]	.78 [.74, .81]	.18 [.15, .22]	.96 [.95, .97]	0.098	–	–	–	–	–	–
	Both Levels	.92 [.89, .93]	.80 [.70, .87]	.86 [.84, .88]	.33 [.29, .38]	.98 [.98, .99]	0.047	–	–	–	–	–	–

Note. AUC = area under the ROC curve. CI = confidence interval. NPV = negative predictive value. PPV = positive predictive value. Lambda parameters were identified through ten−fold cross−validation repeated three times for lasso models.

Table 3. *Standardized Coefficients for Predictor Variables in Full-Model LASSO Logistic Regressions*

Predictor	Predicting Resilience			Predicting Chronicity	
	Depression	Anxiety	PTSD	Depression	Anxiety
Person−Level Predictors					
Gender	—	—	—	−0.081	—
Age	—	−0.051	0.017	—	—
BMI	0.214	0.162	—	—	−0.105
Education Level	—	—	—	—	—
COVID−19 Fear	−0.095	—	−1.222	0.286	0.080
Optimism	0.463	0.194	—	—	−0.089
Pessimism	−0.079	−0.300	—	—	0.157
Subjective Health	0.189	—	—	—	—
Health Change	0.153	—	—	—	0.068
Exercise Frequency Pre−COVID−19	—	—	—	—	—
Exercise Hours Pre−COVID−19	—	—	0.165	—	—
COVID−19 Infection	—	—	—	—	—
Doctor Visits During COVID−19	—	—	—	—	−0.020
Hospitalization During COVID−19	—	0.130	—	—	0.033
Hospitalization 2019	—	−0.083	—	—	—
Preexisting Health Conditions	—	—	—	—	—
Prosocial Behaviors	—	—	—	—	—
Perceived Social Support	—	—	—	—	—
Reappraisal frequency	—	0.251	—	—	−0.157
Suppression frequency	—	−0.080	—	—	0.006
Brooding Rumination	−0.298	−0.020	—	—	—
Reflective Rumination	—	—	—	—	—
Distraction	—	—	—	—	—
Worry	−1.068	−1.105	−0.209	1.280	0.928
Refocus on Planning	—	—	—	—	—
Positive Refocusing	—	—	—	—	—
Alcohol Use	—	—	−0.148	—	—
Tobacco Use	—	—	—	—	—
Leisure Activities	—	—	—	—	−0.043
Productivity Maintenance	—	0.217	0.138	—	−0.187
Regularity Maintenance	—	0.194	0.352	−0.047	−0.013
COVID−19 Information Accessing	0.071	—	—	—	—
COVID−19 Information Overconsumption	—	−0.139	—	—	0.0530
Preventive Measures	—	−0.122	—	—	—
Coping Flexibility	0.088	0.118	—	−0.246	−0.169
Context−Level Predictors					
Personal Income Level Pre−COVID−19	—	—	—	—	—
Employment Pre−COVID−19	—	—	—	—	—
Employment During COVID−19	—	—	—	—	—
Number of Events	—	—	−0.264	—	0.041
Stress Severity	−0.104	−0.281	—	—	0.088
Mean Appraisal of Events	−0.268	—	—	—	—
Discrimination due to COVID−19	—	—	—	—	—
Married	—	−0.176	—	—	0.028
Number of Children	—	—	—	—	—
Number of Underaged Children	—	—	—	—	—
Family Support	0.251	0.074	0.171	−0.35	−0.033
Family Conflict	−0.126	—	−0.412	0.307	—
Years Spent in Lockdown City	—	—	—	—	−0.010
Residency Possession	—	0.012	—	0.109	−0.038
From Rural Regions	—	−0.382	—	—	0.326
From Wuhan	—	—	—	—	—
Neighborhood SES 2018	—	—	−0.005	—	—
Total COVID−19 Cases till April 2020	—	—	—	—	—
Weighted Number of COVID−19 Hospitals	—	—	—	—	—
Average Housing Price 2020	—	—	—	—	—
Population Density 2017	—	—	—	—	—
GDP 2018	—	—	—	—	—
Weighted Public Budget Cost 2018	—	0.215	—	—	−0.141
Satisfaction with Community	0.104	—	—	−0.1	—

Supplementary Materials

Supplementary Material 1

Measures

Outcome Measures

Depression was measured using the 20-item Center for Epidemiological Studies-Depression (CES-D; Radloff, 1977; Chinese version by Wang et al., 1999). Participants rated depression-related thoughts and behaviors during the past week on a 4-point scale from 0 (*less than 1 day a week*) to 3 (*5-7 days a week*). CES-D totals range from 0 to 60, with higher scores indicating greater depression. Cronbach's alpha coefficients were good (.91 to .93) across all four time points.

Anxiety was assessed using the 20-item State Anxiety Inventory (SAI; Spielberger et al., 1983; Chinese version by Wang et al., 1999). Participants reported how they feel in relation to anxiety *right now* as opposed to how they feel *usually* on a 4-point scale from 1 (*almost never*) to 4 (*almost always*). SAI totals range from 20 to 80, with higher scores indicating greater state anxiety. Cronbach's alpha coefficients for SAI were good (.93 to .95) at all four time points.

PTSD symptoms were measured by the Posttraumatic Diagnostic Scale-Chinese (PDS-C; Shen et al., 2014), which assesses PTSD symptoms on 4-point scale from 0 (*not at all*) to 3 (*almost always*). Items were tailored in wording to capture COVID-19 related traumatic experiences (e.g., the original item "Bad dreams or nightmares related to the trauma" was replaced by "Bad dreams or nightmares related to the pandemic"). Cronbach's alpha coefficients were good (.90 to .92) for PDS-C across four time points.

Person-Level Predictors

COVID-19 fear was measured using the Fear of COVID-19 Scale, (FCV-19S; Ahorsu et al., 2020; Chinese version by Chi et al., 2021), a seven-item scale that assesses fear about COVID-19 (e.g., "I am most afraid of coronavirus-19.") on a 5-point scale from 1 (*totally disagree*) to 5 (*strongly agree*). Items were averaged to reflect fear of COVID-19 (α = .92).

Optimism and **pessimism** were measured via the Life Orientation Test—Revised, (LOT-R; Scheier et al., 1994), which assesses outlook about the future on a 5-point scale from 1 (*strongly disagree*) to 4 (*strongly agree*). Following a previous validation of the scale in a mainland Chinese sample (Lai & Yue, 2000), we summed the three positively worded items to reflect optimism (α = .63) and the three negatively worded items to reflect pessimism (α = .71).

Physical health-related measures. Participants reported information regarding their health including subjective health from 1 (*very unhealthy*) to 5 (*very healthy*), health change from -1 (*declined*) to 0 (*no change*) to 1 (*improved*), and weekly exercise frequency and hours prior to COVID-19. Body mass index (BMI) was calculated from the participants' height and weight. Participants also reported whether they have had been infected with COVID-19, whether they have had doctor visits during the pandemic, had been hospitalized during or prior to COVID-19, and whether they had any of preexisting health conditions. We included self-rated health and health change, infection and hospitalization, BMI, and a sum of health conditions as predictors.

Prosocial behaviors were measured by averaging three items: "I participate in or advocate donation", "I help government or charity raise resources", and "I show concerns and offer comfort to others" (α = .74). **Perceived social support** was measured by averaging ten items adapted from the MOS Social Support Survey (MOS-SSS; Sherbourne & Stewart, 1991), which assesses perceived emotional/informational, tangible, and affectionate support as well as positive social interaction in times of need on a 5-point scale from 1 (*almost never*) to 5 (*always*). Items included, for example, “someone to help you if you were confined to bed” and “someone who shows you love and affection” (α = .92).

We measured habitual use of common **Emotion Regulation** strategies including reappraisal, suppression, brooding and reflection (two subtypes of rumination), distraction, worry, refocus on planning, and positive re-focusing. **Reappraisal (**α = .85**)** and **suppression** (α = .73) were measured by the 10-item Emotion Regulation Questionnaire (ERQ; Gross & John, 2003; Chinese version by Wang et al., 2007).

Brooding rumination and **reflective rumination** were measured by the Ruminative Response Scale (RRS; Treynor et al., 2003; Chinese version by Yang et al., 2009) on a 4-point scale from 1 (*almost never*) to 4 (*almost always*). We excluded the depression-related factor given its great overlap with depressive symptoms, leaving five items (e.g., “What am I doing to deserve this?”) measuring the **brooding** aspect of rumination (α =.77) and five items (e.g., “Analyze recent events to try to understand why you are depressed” assessing the **reflective** aspect of rumination (α =.86).

Distraction was assessed by the distraction subscale from the Response Style Questionnaire (RSQ; Butler & Nolen-Hoeksema, 1994; Nolen-Hoeksema & Morrow, 1991). In the present study, we excluded items not adequate in the context of strict lockdowns (e.g., “Decide to go out and have some fun”). The internal consistency of the selected five items was good (α = .82).

Worry was measured via five selected items from the Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990) which captures an individual’s dispositional proneness to worry (e.g., “Many situations make me worry.”) on a 5-point scale from 1 (*not at all typical of me*) to 5 (*very typical of me*). The five items selected in this study from the instrument were internally consistent (α = .95).

Refocus on planning and **positive refocusing** were measured by their corresponding subscales from the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2000; Chinese version by Wang et al., 2017) that measures various feelings and reflections following a threatening or stressful life event on a 5-point scale from 1 (*almost never*) to 5 (*almost always*). Specifically, the four-item **refocus on planning** subscale captures thinking that involves coming up with steps one needs to take following a negative event (α = .83); the four-item **positive refocusing** subscale assesses disengaging in thinking about the negative event and instead refocusing on more joyful and pleasant events (α =.87).

We also measured a few **Coping** strategies a 5-point scale from 1 (*almost never*) to 5 (*always)*. **Alcohol use** was measured with the item "I alleviate stress by drinking alcohol". **Tobacco use** was assessed with the item "I alleviate stress by smoking cigarettes". **Leisure activities** frequency was assessed by four items (e.g., I participate in leisure activities such as watching movies and TV; α = .67). **Productivity maintenance** was assessed with two items including "I continue to work towards my goals by studying or working hard." Internal consistency was good (α = .72). **Regularity maintenance** was assessed with four items related to regular physical activities, sleep, and eating (α = .84). **COVID-19 related information accessing** was measured with three items like "I keep myself posted on the spread of the pandemic (such as new cases)." Internal consistency was good (α = .83). **COVID-19 related information overconsumption** was assessed by "even though I am anxious, I would still repeatedly check news about the pandemic." **Preventive measures** were assessed by five items (e.g., "I wash my hands carefully"; "I keep a distance from others"; α = .74).

In addition to coping strategies, we assessed **coping flexibility** with the 10-item Coping Flexibility Scale (CFS; Kato 2012; Chinese version by Kato, 2015), which measures ability to discontinue ineffective strategies and implement alternative coping strategies. Participants rated the extent to which they agreed with the items (e.g., “When a stressful situation has not improved, I try to think of other ways to cope with it”) on a 4-point scale from 1 (*not applicable*) to 4 (*very applicable*). We included this scale as the constantly changing situations in the context of COVID-19 requires flexibility in adjusting coping strategies. Internal consistency of the CFS was good (α = .84).

Context-Level Predictors

In addition to person-level predictors, we measured context-level predictors across domains of stress exposure, family feature, and community characteristics.

Stress Exposure

As a crucial aspect of the COVID-19 lockdowns was economic recession, we measured participants’ **personal income level prior to the pandemic**, and **employment before and during COVID-19**.

Our measure of **stressful life events** during the COVID-19 lockdown was adapted from two existing measures that assess the impact of various stressful life events (Life Experience Survey; Sarason et al., 1978; Life Event Scale; Wang et al., 1999). Participants reported whether common life events have occurred and the perceived impact of these experiences on a 4-point scale from 0 (*had no impact*) to 3 (*severe impact*). To reflect stressors specific to COVID-19, we included items such as “I was infected with COVID-19”, “My family members were infected with COVID-19”, and “I was forced to work /study from home”. Similar to the existing measures, participants had the option to list at most five additional stressful events. Three features were derived from the LES: **Number of stressful life events** is the total number of stressors participants endorsed regardless of their perceived impact; perceived impact of each endorsed event was summed up to indicate **stress severity**, which was then divided up by the total number of stressful life events to obtain an individual's **mean appraisal of stressful events** during the COVID-19 lockdowns.

A dichotomous measure of **discrimination due to COVID-19** was derived from participants' text responses to an open-ended question inquiring about what was stressful about the pandemic. Discrimination was the only noticeable theme (i.e., percentage > 5%) that emerged. Two psychology undergraduate students then independently coded whether a response described experience of discrimination due to COVID-19 (e.g., "My boss fired me because I am from Wuhan.") The percent of agreement was high (95%), and a third graduate-level coder was included to resolve conflicts.

Family Features

Participants reported **family structures**, including marital status, number of children as well as number of underaged children.

Family relationship was measured using 10 items adapted from the China Family Panel Studies, a longitudinal project that provides an overview of citizen health, psychological wellbeing, parental practice, etc. (CFPS; Institute of Social Science Survey, 2010), on a 5-point scale ranging from 1 (*very bad*) to 5 (*very good*). Of the 10 items, five items measured **family support**, such as whether family members share a communicative, supportive, and positive relationship and support each other during life crisis (α = .92). The other five items measured **family conflict** such as whether family members experience conflicts in daily communication and refuse to help when a family member encounters setbacks (α = .79).

Community Characteristics

Participants reported information of their living environment such as the number of years they spent in the lockdown city, location and residency information (e.g., whether one possesses residency in the lockdown city, comes from rural regions, and quarantines in Wuhan).

We also included **objective measures** derived from the characteristics of the cities where the participants lived during the lockdown, recorded by Chinese authorities, including neighborhood socioeconomic status (i.e., per capita disposal income) in 2018, total COVID-19 cases till April 2020, number of hospitals with fever clinics receiving COVID-19 patients (weighted by city-level population density), 2020 average housing price, 2017 population density, 2018 GDP, and 2018 weighted city-level public expenditures (i.e., how much a city spends on welfare, education, health care, and infrastructure weighted by population density). **Subjective satisfaction** with the community was measured via six items adapted from the China Family Panel Studies (CFPS; ISSS, 2010), on a 5-point scale ranging from 1 (*very bad*) to 5 (*very good*). Participants reported satisfaction with community infrastructure, environment, quality of relationship with neighbors, and general feelings about the community. Scores were averaged to reflect community satisfaction, with higher scores indicating greater satisfaction with one's community ($\alpha = .88$).

Supplementary Material 2

Table S2-1. *Levels of Skewness and Kurtosis of Symptom Measures in Each Wave*

Outcome	Skewness	Kurtosis
T1_Depression	0.99	0.96
T2_Depression	0.90	0.54
T3_Depression	0.89	0.74
T4_Depression	0.94	0.84
T1_Anxiety	0.23	-0.41
T2_Anxiety	0.33	-0.37
T3_Anxiety	0.37	-0.08
T4_Anxiety	0.4	0.07
T1_PTSD	1.14	1.66
T2_PTSD	0.76	-0.09
T3_PTSD	1.04	1.44
T4_PTSD	1.24	1.94

Note. T1 = Time 1, T2 = Time 2, T3 = Time 3, T4 = Time 4.

Table S2-2. *Intercept Effect Sizes of LGMM Solutions*

	Trajectory Comparison	Intercept Effect Size (Cohen's *d*)
Depression	Chronicity VS Resilience	3.21
	Recovery VS Resilience	2.83
Anxiety	Chronicity VS Resilience	1.62
	Recovery VS Resilience	1.28
PTSD	Chronicity VS Resilience	1.55

Supplementary Material 3

Table S3-1. *Coefficients for Variables in Person-Level LASSO Logistic Regressions*

Predictor	Models Predicting Resilience			Models Predicting Chronicity	
	Depression	Anxiety	PTSD	Depression	Anxiety
Gender	—	—	—	-0.205	—
Age	—	-0.278	—	—	—
BMI	0.335	0.176	—	—	—
Education Level	—	—	—	—	—
COVID-19 Fear	-0.238	-0.047	-1.056	0.340	0.049
Optimism	0.601	0.195	—	-0.083	-0.009
Pessimism	-0.154	-0.291	—	—	0.072
Subjective Health	0.294	—	—	-0.119	—
Health Change	0.282	—	—	-0.010	—
Exercise Frequency Pre COVID-19	—	—	—	—	—
Exercise Hours Pre COVID-19	0.074	—	0.188	-0.118	—
COVID-19 Infection	—	—	—	—	—
Doctor Visits During COVID-19	—	—	—	—	—
Hospitalization During COVID-19	—	0.100	—	—	—
Hospitalization in 2019	—	-0.076	—	—	—
Preexisting Health Conditions	-0.120	—	—	—	—
Prosocial Behaviors	—	-0.048	—	—	—
Perceived Social Support	—	0.019	0.047	-0.004	—
Reappraisal	—	0.289	—	—	-0.130
Suppression	-0.012	-0.139	—	—	—
Brooding Rumination	-0.335	-0.070	—	—	—
Reflective Rumination	—	—	—	0.075	—
Distraction	—	—	—	—	—
Worry	-1.358	-1.131	-0.337	1.465	0.873
Refocus on Planning	—	0.040	—	—	—
Positive Refocusing	—	—	—	—	—
Alcohol Use	—	—	-0.151	—	—
Tobacco Use	—	—	—	—	—
Leisure Activities	—	—	—	—	—
Productivity Maintenance	0.039	0.238	0.065	—	-0.164
Regularity Maintenance	—	0.215	0.392	-0.188	—
COVID-19 Information Accessing	0.165	—	—	-0.002	—
COVID-19 Information Overconsumption	—	-0.201	—	—	0.011
Preventive Measures	—	-0.079	—	-0.035	—
Coping Flexibility	0.120	0.140	0.004	-0.381	-0.163

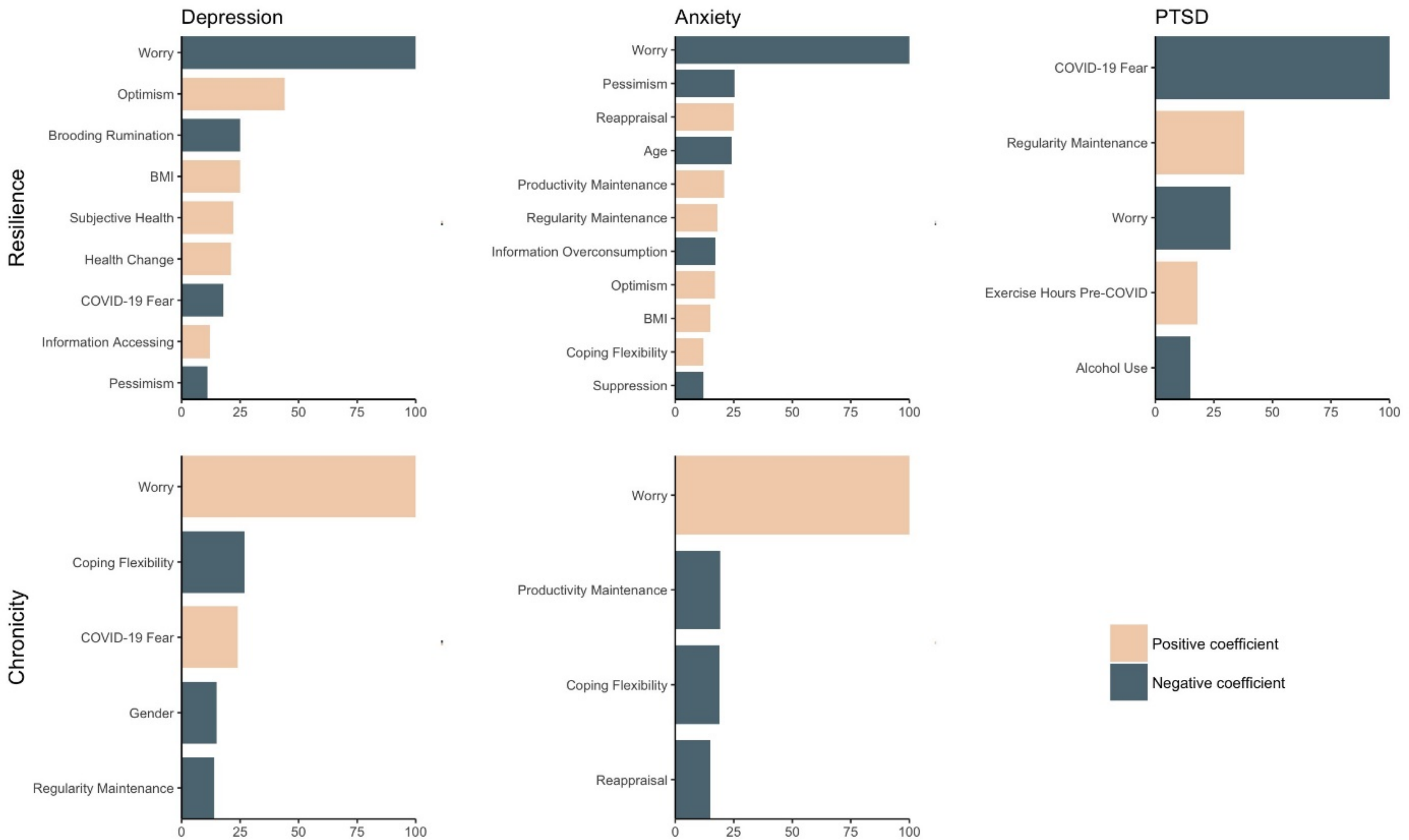

Figure S3-1. *Relative Importance of Variables in the LASSO Person-Level Models Predicting Resilience or Chronicity Trajectory of Depression, Anxiety, and PTSD*

Supplementary Material 4

Table S4-1. *Model Performance of Context-Level Lasso Logistic Regressions*

Predictor	Models Predicting Resilience			Models Predicting Chronicity	
	Depression	Anxiety	PTSD	Depression	Anxiety
Personal Income Level Pre-COVID-19	0.132	—	—	—	—
Employment Pre-COVID-19	—	—	—	—	—
Employment During COVID-19	—	0.226	—	—	-0.068
Number of Events	—	—	-0.262	0.007	—
Stress Severity	-0.064	-0.383	-0.186	—	0.297
Mean Appraisal of Events	-0.749	-0.245	—	0.391	0.08
Discrimination due to COVID-19	—	—	—	—	—
Married	—	-0.089	—	—	—
Number of Children	—	—	—	—	—
Number of Underaged Children	—	—	—	—	—
Family Support	0.539	0.555	0.089	-0.588	-0.411
Family Conflict	-0.261	-0.027	-0.337	0.286	—
Years Spent in Lockdown City	—	0.152	0.003	—	-0.161
Residency Possession	—	0.002	—	—	—
From Rural Regions	0.041	-0.247	—	—	0.188
From Wuhan	—	—	—	—	—
Neighborhood SES 2018	—	—	—	—	—
Total COVID-19 Cases till April 2020	0.024	—	—	—	—
Weighted Number of COVID-19 Hospitals	—	—	—	—	—
Average Housing Price 2020	—	—	—	—	—
Population Density 2017	—	—	—	—	—
GDP 2018	—	—	—	—	—
Weighted Public Budget Cost 2018	—	0.214	—	—	-0.128
Satisfaction with Community	0.241	0.002	—	-0.047	-0.026

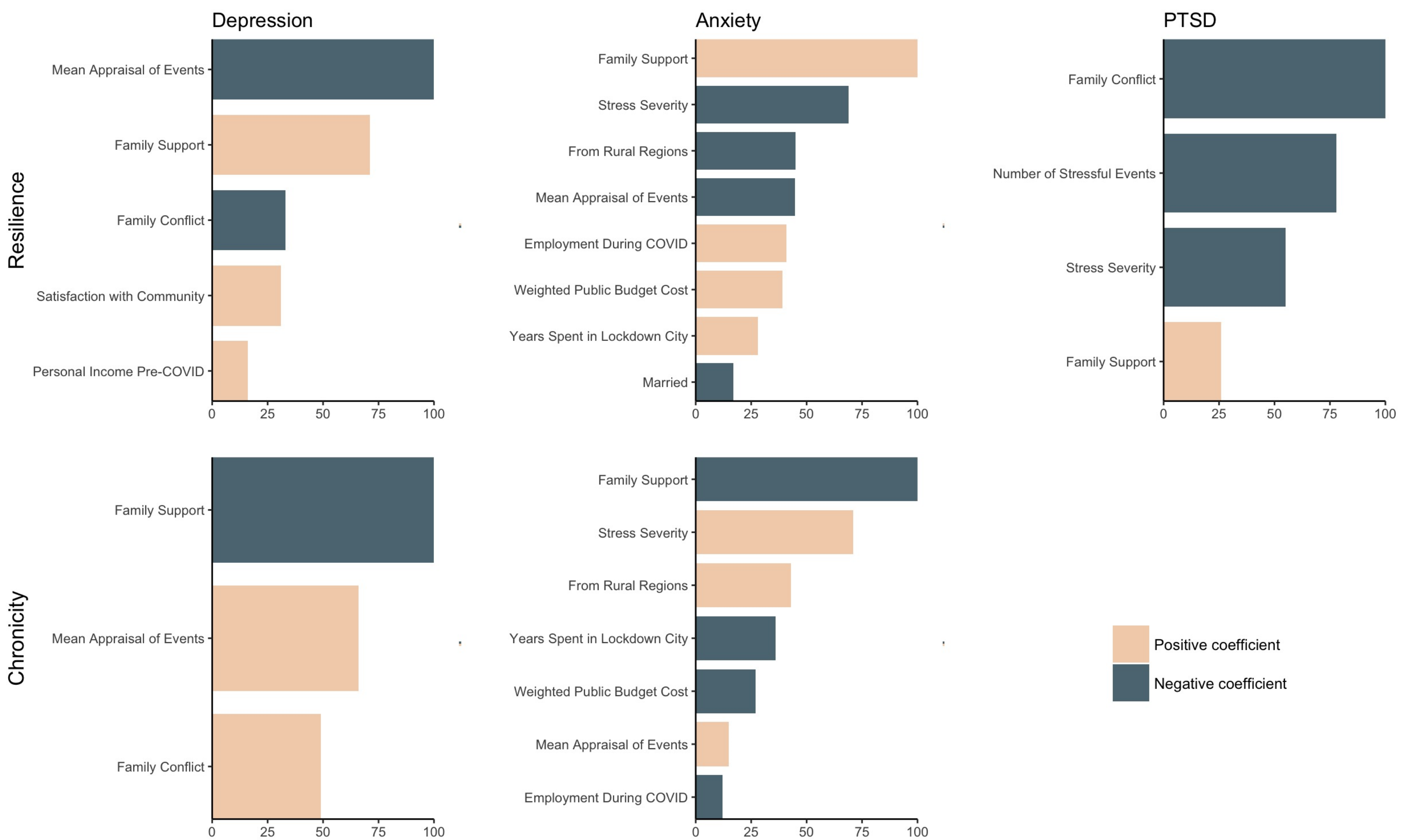

Figure S4-1. *Relative Importance of Variables in the LASSO Context-Level Models Predicting Resilience or Chronicity Trajectory of Depression, Anxiety, and PTSD*

Supplementary Material 5

Table S5-1. Logistic Regression Predicting Resilience Trajectory of Depression

Predictors	*OR*	95% CI	*p*
BMI	1.29	1.08, 1.55	<.01
Subjective Health	1.40	0.77, 2.60	.27
Health Change	2.47	0.82, 7.94	.12
Stress Severity	1.01	0.95, 1.07	.79
Mean Appraisal	0.24	0.06, 0.88	<.05
Optimism	1.50	1.14, 2.03	<.01
Pessimism	0.92	0.73, 1.16	.50
Coping Flexibility	1.40	0.56, 3.56	.47
Brooding Rumination	0.39	0.14, 1.02	.06
Worry	0.34	0.19, 0.60	<.001
COVID-19 Information Accessing	1.86	1.05, 3.44	<.05
COVID-19 Fear	0.54	0.30, 0.92	<.05
Family Support	1.30	0.58, 3.05	.53
Family Conflict	0.49	0.21, 1.10	.09
Community Satisfaction	2.38	1.11, 5.42	<.05

Note. Model exhibited excellent fit, McFadden's pseudo $R^2 = .57$. Predictors were selected based on the results of the corresponding LASSO model. Only predictors with non-zero coefficients in the full LASSO model predicting resilience trajectory of depression with both person- and context-level predictors were chosen.

Table S5-2. Logistic Regression Predicting Chronicity Trajectory of Depression

Predictors	*OR*	95% CI	*p*
Gender	1.01	0.14, 5.07	.99
Residency Possession	6.35	1.25, 45.1	<.05
Coping Flexibility	0.13	0.03, 0.43	<.01
Worry	4.00	2.08, 8.62	<.001
Regularity Maintenance	1.25	0.56, 2.92	.59
COVID-19 Fear	2.89	1.43, 6.57	<.01
Family Support	0.52	0.20, 1.48	.19
Family Conflict	3.11	1.18, 10.4	<.05
Community Satisfaction	0.57	0.22, 1.45	.25

Note. Model exhibited excellent fit, McFadden's pseudo $R^2 = .54$. Predictors were selected based on the results of the corresponding LASSO model. Only predictors with non-zero coefficients in the full LASSO model predicting chronicity trajectory of depression with both person- and context-level predictors were chosen.

Table S5-3. Logistic Regression Predicting Resilience Trajectory of Anxiety

Predictors	*OR*	95% CI	*p*
Age	0.96	0.91, 1.01	.10
BMI	1.20	1.05, 1.38	<.01
Hospitalization During COVID-19	14.10	1.34, 218	<.05
Hospitalization 2019	0.27	0.05, 1.36	.11
Residency Possession	1.83	0.79, 4.30	.16
From Rural Regions	0.24	0.10, 0.52	<.001
Married	0.71	0.26, 1.90	.49
Stress Severity	0.97	0.94, 1.00	.06
Optimism	1.27	1.02, 1.60	<.05
Pessimism	0.78	0.65, 0.92	<.01
Coping Flexing	1.51	0.66, 3.49	.33
Suppression	0.83	0.58, 1.18	.31
Reappraisal	1.59	1.00, 2.61	.06
Brooding Rumination	0.87	0.43, 1.74	.69
Worry	0.25	0.15, 0.39	<.001
Preventive Measures	0.49	0.24, 0.98	<.05
Information Overconsumption	0.81	0.61, 1.06	.13
Productivity Maintenance	1.45	0.94, 2.28	.09
Regularity Maintenance	1.49	0.95, 2.36	.09
Family Supported	1.10	0.65, 1.89	.71
Weighted Public Budget Cost 2018	1.85	1.10, 3.18	.02

Note. Model exhibited excellent fit, McFadden's pseudo $R^2 = .50$. Predictors were selected based on the results of the corresponding LASSO model. Only predictors with non-zero coefficients in the full LASSO model predicting resilience trajectory of anxiety with both person- and context-level predictors were chosen.

Table S5-4. Logistic Regression Predicting Chronicity Trajectory of Anxiety

Predictors	*OR*	95% CI	*p*
BMI	0.89	0.79, 0.99	<.05
Health Change	1.94	0.98, 3.90	.06
Hospitalization During COVID-19	0.28	0.03, 2.22	.25
Hospitalization 2019	3.25	0.70, 14.9	.13
Residency Possession	0.69	0.31, 1.55	.37
Years Spent in Lockdown City	0.98	0.95, 1.01	.25
From Rural Regions	2.76	1.38, 5.69	<.01
Married	1.61	0.75, 3.53	.23
Stress Severity	1.02	0.98, 1.06	.32
Num of Events	1.00	0.92, 1.09	.99
Optimism	0.88	0.73, 1.06	.19
Pessimism	1.15	0.99, 1.34	.06
Coping Flexibility	0.65	0.31, 1.34	.25
Suppression	1.18	0.87, 1.62	.28
Reappraisal	0.69	0.45, 1.05	.09
Worry	2.88	1.98, 4.32	<.001
Information Overconsumption	1.13	0.89, 1.45	.32
Leisure Activities	0.89	0.58, 1.36	.59
Productivity Maintenance	0.74	0.49, 1.11	.14
Regularity Maintenance	0.92	0.61, 1.40	.70
COVID-19 Fear	1.21	0.83, 1.76	.32
Family Conflict	0.98	0.61, 1.58	.94
Weighted City Budget Cost 2018	0.61	0.38, 0.97	.04

Note. Model exhibited excellent fit, McFadden's pseudo $R^2 = .37$. Predictors were selected based on the results of the corresponding LASSO model. Only predictors with non-zero coefficients in the full LASSO model predicting chronicity trajectory of anxiety with both person- and context-level predictors were chosen.

Table S5-5. Logistic Regression Predicting Resilience Trajectory of PTSD

Predictors	*OR*	95% CI	*p*
Age	1.06	0.98, 1.17	.21
Num of Events	0.92	0.80, 1.05	.23
Worry	0.83	0.40, 1.71	.61
Productivity Maintenance	1.91	0.83, 4.73	.14
Regularity Maintenance	1.10	0.44, 2.63	.83
Alcohol Use	0.49	0.27, 0.86	<.05
Exercise Hours Pre-COVID	1.27	1.01, 1.79	.10
COVID-19 Fear	0.09	0.03, 0.24	<.001
Neighborhood SES 2018	1.00	1.00, 1.00	.12
Family Support	2.94	0.84, 10.5	.09
Family Conflict	0.47	0.14, 1.26	.19

Note. Model exhibited excellent fit, McFadden's pseudo $R^2 = .57$. Predictors were selected based on the results of the corresponding LASSO model. Only predictors with non-zero coefficients in the full LASSO model predicting resilience trajectory of PTSD with both person- and context-level predictors were chosen.

Paper 3

Emotion Regulation Flexibility and Momentary Distress: An EMA Study

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Abstract

In contrast to traditional theories considering emotion regulation (ER) strategies as either maladaptive or adaptive, recent theoretical models underscore the importance of ER flexibility. This study used an Ecological Momentary Assessment (EMA) design to examine how proxy measures of flexibility components based on Bonanno and Burton (2013) were associated with momentary measures of total distress and its three subdimensions (i.e., depressed mood, anxious mood, and perceived stress). A sample of 158 adults in the United States completed four surveys per day for 21 days (N = 12,217) in which they reported an emotional situation, situational characteristics, ER use, initial ER effectiveness, ER change, and total momentary distress after the regulation attempt. We found evidence that increased momentary context sensitivity and momentary use of repertoire were associated with decreased distress and its three subdimensions. Results were less consistent for feedback responsiveness. Maintaining effective strategies seemed adaptive for momentary anxiety, perceived stress, and total distress, whereas switching from ineffective strategies seemed adaptive only for momentary depression, suggesting some disorder-specific association. This study introduces a way to study ER flexibility by incorporating situation assessments and underscores the importance of ER flexibility to psychological adjustment.

Keywords: Emotion Regulation Flexibility; Context Sensitivity; Stress; Depression; Anxiety

Introduction

Emotion regulation (ER) plays a central role in various forms of psychopathology (Aldao et al., 2010, 2016; Webb et al., 2012). Although traditional theories and research on ER have classified strategies as either uniformly adaptive or maladaptive (Aldao et al., 2010; Aldao & Nolen-Hoeksema, 2012; D'Avanzato et al., 2013; Joormann & Stanton, 2016), recent theoretical models and empirical research have revisited the person-situation interactionist approach long existed in psychology (Lazarus & Folkman, 1984; Lewin, 1935; Mischel, 1973) and demonstrated that the efficacy of specific ER strategies varies across situations and individuals (e.g., Sheppes et al., 2014; Tamir & Ford, 2012; Troy et al., 2013, 2017). The theoretical and empirical evidence have drawn attention to the importance of ER flexibility to navigating and managing diverse demands across various contexts (Aldao et al., 2015; Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Battaglini, Rnic, Jameson, Jopling, & LeMoult, 2022; Birk & Bonanno, 2016; Bonanno et al., 2004; Bonanno & Burton, 2013; Chen & Bonanno, 2021; Cheng, 2001; Cheng et al., 2014; Kashdan & Rottenberg, 2010; Westphal et al., 2010).

Context Sensitivity, Repertoire, and Feedback Responsiveness

From a theoretical perspective, flexibility has been conceptualized as a broad multi-componential process that involves a sequence of componential abilities (Bonanno & Burton, 2013; Cheng et al., 2014). In a review by Bonanno and Burton (2013), for example, they elaborated three interrelated yet functionally independent components of flexibility. These components included: 1) the ability to evaluate contextual demands, or **context sensitivity**, 2) the access to a wide range of strategies that may be implemented to meet those demands, or **repertoire**, and 3) the capacity to monitor the efficacy of chosen strategies and modify as needed, or **feedback responsiveness**. Each component was not only considered essential for successful regulatory process but also likely to vary measurably across individuals and situations. Similarly, a meta-analytic review proposed a model based on their synthesis of more than 100 empirical studies (Cheng et al., 2014). In their model, flexibility was conceptualized as abilities displayed at three unique yet closely interacted regulatory stages, respectively evaluating situational characteristics, adopting regulatory strategies, and monitoring outcomes. Together, evidence from the top-down, heuristic approach (Bonanno & Burton, 2013) and bottom-up, systematic approach (Cheng et al., 2014) have converged to support the multi-componential process of flexibility, such as context-sensitivity, repertoire, and feedback responsiveness.

A growing body of theoretical and empirical evidence suggests that the first and arguably the most crucial step in flexible self-regulation involves the ability to read, decode, and evaluate contextual cues that signal the impinging demands and opportunities inherent in the situation, commonly referred to as context sensitivity (Aldao, 2013; Bonanno et al., 2018; Bonanno & Burton, 2013). Bonanno and colleagues (2018) clarified context sensitivity as the perception of context, not the response to context. Research has shown that greater context sensitivity—in particular, the ability to identify the absence of threatening cues—was associated with lower levels of depression and anxiety symptoms (Bonanno et al., 2018). It was also hypothesized that sensitivity to context sensitivity plays an essential role in subsequent sequential components of flexibility, as mistakes in initial contextual evaluation may lead to difficulty and even inability to select effective strategies and monitor feedback in a given situation.

The next sequential component of flexibility involves the ability to utilize a wide range of strategies to meet the demands of the situation, commonly referred to as repertoire (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020; Bonanno & Burton, 2013; Burton & Bonanno, 2016; Dixon-Gordon et al., 2015). Several studies have found an association between better psychological adjustment in the context of stress or potential trauma and higher strategy number (Orcutt et al., 2014), categorical variability (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020), and temporal variability (Cheng, 2001). However, evidence has also been mixed. For example, some studies found no support for temporal variability (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020). Further, the type and number of strategies examined in studies vary drastically, which may likely contribute to the mixed findings (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020; Burton & Bonanno, 2016; Goodman et al., 2021). Conceptually, using a higher number of strategies or exhibiting variability in strategy use does not guarantee greater effectiveness. For example, if one experiences similar situations over time, there may not be a need to exhibit high strategy variability across contexts. Keeping the difficulty of capturing repertoire in mind, it will be important for researchers to use prior knowledge to guide the identification of most accessible proxy measures (Bonanno et al., 2023). As one example, given that effectiveness of strategies may differ across individuals, one potential way to conceptualize repertoire is to sum the number effective strategies for each individual based on their own intensive longitudinal data.

The third and final sequential component flexibility is the post-implementation ability to monitor the effectiveness of chosen strategies and either maintain or modify strategies as needed, commonly referred to feedback responsiveness (Birk & Bonanno, 2016; Bonanno & Burton, 2013; Ilan et al., 2019; Kato, 2012; Shafir et al., 2016). Research has shown that the self-reported ability to discontinue maladaptive strategies and switch to adaptive strategies is associated with fewer depressive symptoms (Kato, 2015, 2017). Empirical studies have demonstrated that more frequent switching from reappraisal to distraction when confronted with high-intensity negative images was associated with a larger modulation in neural activity associated with emotional processing (Ilan et al., 2019) and better psychological adjustment (Birk & Bonanno, 2016). Conceptual framework has also highlighted the importance of maintaining effective strategies and switching from ineffective to effective strategies (Pruessner et al., 2020).

Theoretical and empirical evidence provide important insights into the construct and function of flexibility. However, there are three critical gaps within the ER flexibility literature. First, few studies have examined ER flexibility in daily situations (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Battaglini, Rnic, Jameson, Jopling, & LeMoult, 2022; Blanke et al., 2020; Goodman et al., 2021) using intensive longitudinal design (e.g., ecological momentary assessment, EMA). Second, most studies have limited environmental variability to few situational characteristics such as controllability or intensity (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Goodman et al., 2021). By definition, emotion regulation flexibility requires adapting ER to situational demands, but there has been lack of comprehensive situational assessments of the varying context in which ER takes place. The recognition of the importance of context has appeared primarily in the theoretical space, with empirical research lagging relatively behind (Aldao, 2013). Even when sensitivity to context was evaluated, it was based on either constructed scenarios (Bonanno et al., 2018) or interaction of controllability and emotion-focused strategies (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022). The latter also suffered from methodological concern in that it confounded the evaluation of the context and response to the context. Third, few studies have examined all flexibility components in one model, with one exception (Chen & Bonanno, 2021) examining latent profiles of self-report measures of all three components in a cross-sectional design. Recent EMA studies have examined all three flexibility components, but each flexibility component was tested in separate model in the study (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022)

The Current Investigation

To address these gaps, we aimed to study all three components and their associations with psychological adjustment using intensive longitudinal design. In addition, we aimed to assess a diverse range of situational characteristics. Social and personality psychologists have further developed tools to assess situational characteristics (Horstmann et al., 2021; Rauthmann et al., 2014; Sherman et al., 2015), identifying eight fundamental characteristics of situations, respectively **D**uty, **I**ntellect, **A**dversity, **M**ating, p**O**sitivity, **N**egativity, **D**eception, and **S**ociality (DIAMONDS). These eight fundamental characteristics have been replicated across the globe (Guillaume et al., 2016; Lee et al., 2020). Several investigators have developed ultra-brief assessment of situations for experience sampling research (Rauthmann & Sherman, 2016) and used them in studies aiming to predict behaviors, emotions, and interpersonal dynamics (Hong et al., 2020, 2021; Horstmann et al., 2021; Sherman et al., 2015). Tools of situation assessment combined with intensive longitudinal measures of emotion regulation may provide opportunities to better understand how situations and regulatory strategy use covariate, thereby shedding light on personalized assessment of flexibility.

The current investigation used an EMA design to capture emotion regulation, situational characteristics, and psychological distress four times a day across 21 days. Each EMA survey also captured the effectiveness of emotion regulation repertoire initially adopted in response to the emotional situation and whether one chose to switch from the initial repertoire. Before and after the EMA phase of the study, participants completed self-report measures of context sensitivity (Bonanno et al., 2018), repertoire (Burton & Bonanno, 2016), feedback responsiveness (Kato, 2012), habitual use of emotion regulation strategies (Garnefski et al., 2001; Gross & John, 2003; Hofmann et al., 2016; Meyer et al., 1990; Treynor et al., 2003), and psychopathology (Watson et al., 1995).

The goal of the current investigation was to test the flexibility model (Bonanno & Burton, 2013). We examined whether momentary measures of context sensitivity, use of repertoire, and feedback responsiveness would be associated with momentary measures of total distress, depressed mood, anxious mood, and perceived stress. We developed a proxy for momentary context sensitivity and tested its validity. We developed a repertoire measure that assess how many effective strategies each participant has at their disposal across all EMA situations. Then, we identified how many strategies each participant recruited from their repertoire in each EMA situation. We conceptualized feedback responsiveness as either maintaining effective strategies or switching from ineffective strategies, which was operationalized by the interaction between change in emotion regulation and initial effectiveness.

Method

Data and Participants

A total of 173 participants were enrolled in the study. Fifteen participants left the study during the EMA phase of study, leaving 158 participants in our final analyses. Participants were compensated $40 if they completed 80% of the daily surveys and $60 if they completed 95% of the daily surveys. Those who stayed in the study completed 77 out of 84 (92.05%) daily surveys on average. Most of the participants identified as woman (36 men, 116 woman, and 6 non-binary or non-conforming individuals). Participants ranged from 18 to 72 in age (M = 35.97, SD = 12.45) and were racially diverse, with 49.37% of Caucasian American, 18.35% Black or African American, 27.22% Asian American, and 2.53% American Indian, Alaska Native, or Native

Hawaiian. In the sample, 10.76% identified as Hispanic or Latinx. The institutional review broad at Teachers College, Columbia University has approved this study (IRB#22-218).

Measures

Baseline and Exit Survey

Participants completed a baseline and an exit survey before and after the EMA phase of study. Both surveys were distributed through the Qualtrics platform. Measures of the baseline and exit surveys were identical, including demographics, components of flexibility, habitual use of emotion regulation, and symptoms of depression and anxiety. Only components of flexibility and habitual emotion regulation were used in this paper and the remaining measures were reported elsewhere.

Context Sensitivity was measured by the Context Sensitivity Index (CSI; Bonanno et al., 2018). CSI is a scenario-based inventory that captures one's sensitivity to the relative presence of contextual cues (Cue Presence Index, CPI) and to the relative absence of cues (Cue Absence Index, CAI). The CPI is composed of ten appraisal items normed as relatively present in the scenarios; the CAI is composed of ten appraisal items normed as relatively absent in the scenarios. The CAI items were reverse-coded so that higher scores reflected greater sensitivity to the absence of a contextual cue. After reading each daily situation (e.g., You take a medicine and it makes your nauseous. Your doctor tells you that it is not serious and that you just have to "wait it out"), participants were asked to rate their perception of cues including threat, self-control, other-control, urgency, and cooperation on a 7-point scale from 1 (*not at all*) to 7 (*very much*). The CSI has been associated with flexible coping, emotion regulation, and psychopathology symptoms, and has been validated against behavioral measures of cue sensitivity such as the Picture Arrangement Test from the Wechsler Adult Intelligence Scale- Third Edition (Bonanno et al., 2018). In this study, we calculated the sum of CPI and CAI to reflect the context sensitivity component of emotion regulation flexibility.

Repertoire was measured at baseline using a proxy scale, the Flexible Regulation of Emotional Expression Scale (FREE, Burton & Bonanno, 2016). FREE is a scenario-based questionnaire that measures participants' ability to up- and down-regulate their emotional expressions to meet situational demands—commonly referred to as ***expressive flexibility***—which is an important aspect of repertoire. The FREE includes two subscales that measure the ability to enhance and suppress emotional expressions. A total score can be calculated by summing the enhancement and suppression scores. Higher scores indicate that participants are better able to up- and down-regulate their emotional expressions to meet divergent contextual commands. Participants indicated how well they would be able to be even more expressive (e.g., Your boss is complaining about a project you know little about and have no involvement with.) or conceal how they were feeling (e.g., You are at a social event and the person you're talking to frequently spits while they speak.) following each scenario on a 6-point scale from 1 (*unable*) to 6 (*very able*). Studies have found an association between the FREE and measures of emotion regulation, psychopathology symptoms, and well-being (Burton & Bonanno, 2016; Chen et al., 2018). Keeping in mind the limitation of FREE that it only captured repertoire in up- and down-regulating emotional expressions, we used the total score of the FREE scale to reflect the repertoire component of ER flexibility.

Feedback Responsiveness was measured by the Coping Flexibility Scale (CFS, Kato, 2012). CFS is a ten-item self-report questionnaire that captures the ability to discontinue an ineffective strategy (e.g., If I feel that I have failed to cope with stress, I change the way in which I deal with stress.) and produce and implement an alternative strategy (e.g., When a stressful situation has not improved, I try to think of other ways to cope with it). Participants were asked to indicate how the statements apply to them on a 4-point scale from 1 (*not applicable*) to 4 (*very applicable*). Higher CFS scores were associated with more adaptive outcomes (Kato, 2012). In this study, we calculated a sum score to reflect feedback responsiveness.

The baseline survey also included habitual use of common emotion regulation strategies, including cognitive reappraisal, expressive suppression, brooding and reflection (two forms of rumination), worry, planning, positive refocusing, perspective taking, soothing, and seeking others' perspective. We selected these strategies in order to cover a wide range of cognitive, expressive, and interpersonal emotion regulation strategies.

Cognitive reappraisal and **expressive suppression** were measured by the 10-item Emotion Regulation Questionnaire (ERQ; Gross & John, 2003) on a seven-point scale from 1 (*strongly disagree*) to 7 (*strongly agree*). There are six items (e.g., When I want to feel more positive emotion [such as joy or amusement], I change what I'm thinking about) measuring reappraisal ($\alpha = .83$) and four items (e.g., When I am feeling positive emotions, I am careful not to express them) measuring suppression ($\alpha = .72$).

Brooding and **reflection** were measured by the Ruminative Response Scale (RRS; Treynor et al., 2003) on a four-point scale from 1 (*almost never*) to 4 (*almost always*). We excluded the depression-related factor given its great overlap with depressive symptoms, leaving five items (e.g., "What am I doing to deserve this?") measuring the brooding aspect of rumination ($\alpha = .77$) and five items (e.g., "Analyze recent events to try to understand why you are depressed" assessing the reflective aspect of rumination ($\alpha = .86$).

Worry was measured via three selected items from the Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990) which captures an individual's dispositional proneness to worry (e.g., “Many situations make me worry.”) on a 5-point scale from 1 (*not at all typical of me*) to 5 (*very typical of me*). The three items selected in this study from the instrument were internally consistent (α = .80).

Planning and **positive refocusing** were measured by their corresponding subscales from the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2001) that measures various feelings and reflections following a stressful life event on a 5-point scale from 1 (*almost never*) to 5 (*almost always*). Specifically, the four-item planning subscale (e.g., I think about how I can best cope with the situation) captures thinking that involves coming up with steps one needs to take following a negative event (α = .83); the four-item positive refocusing subscale (e.g., I think of something nice instead of what has happened) assesses disengaging in thinking about the negative event and instead refocusing on more joyful and pleasant events (α =.87).

Soothing and **perspective seeking** were measured by the soothing and perspective taking subscales from the Interpersonal Emotion Regulation Questionnaire (IERQ; Hofmann et al., 2016) that measures interpersonal emotion regulation on a 5-point scale from 1 (*not true for me at all*) to 5 (*extremely true for me*). The five-item **soothing** subscale (e.g., I look for other people to offer me compassion when I am upset) captures behaviors of seeking compassion, comforting, and emotional support from others when feeling upset (α = .81). The five-item **perspective seeking** subscale (e.g., Having people telling me not to worry can calm me down when I am anxious) assesses how much one relies on others’ perspectives to regulate emotions (α = .91).

EMA Measures

Each participant completed an orientation meeting with one of ten trained graduate research assistants the day before their first EMA survey. During the orientation meeting, the research assistant explained the EMA procedure and instructed the participant to complete a practice survey that was identical to the EMA survey. This allowed participants an opportunity to ask questions about the EMA procedure. During the EMA phase of the study, participants were prompted by Metricwire, a mobile app designed for experience sampling, to complete EMA surveys four times per day at approximately 12 PM, 3 PM, 6 PM, and 9 PM over the course of 21 days (i.e., 84 EMA surveys in total). Once they received the prompt, they had 90 minutes to respond; after that, the EMA survey expired and was marked as missing. All 84 EMA surveys were identical, assessing the most emotional situation in the past three hours, followed by measures of perceived situational characteristics, emotion regulation strategies, effectiveness of emotion regulation strategies, whether participant changed their initial emotion regulation strategies, and level of momentary psychological distress following the regulation attempt. All questions were detailed below in the order of how they present in each EMA survey.

The Emotional Situation. Each EMA survey started with asking the participant to recall the most emotionally salient situation in the past three hours. Similar to previous studies (Horstmann et al., 2021; Rauthmann & Sherman, 2016; Sherman et al., 2015), participants were asked to write a response covering the following information: Where were you? Who was with you? What were you (and others) doing? What was happening? Unlike previous studies, however, we did not ask participant to indicate when the situation occurred to avoid redundancy since the prompt already required the participant to recall the most emotional situation in the past three hours.

Perceived Situational Characteristics. We used ultra-brief measures for the situational eight DIAMONDS (i.e., **D**uty, **I**ntellect, **A**dversity, **M**ating, p**O**sitivity, **N**egativity, **D**eception, and **S**ociality) domains (Rauthmann & Sherman, 2016) to assess perceived situational characteristics. Additionally, we included an item on controllability, given recent studies highlighting its important role in the effectiveness of emotion regulation strategies (Troy et al., 2013, 2017). Participants rated how much each of these nine characteristics applied to the most emotional situation they wrote on 7-point scale from 1 (*not at all*) to 7 (*totally*). Duty was measured by "Work has to be done." Intellect was measured by "Deep thinking is required." Adversity was measured by "Someone is being threatened, blamed, or criticized." Mating was measured by "The situation is romantically or sexually charged." Positivity was measured by "Situation is enjoyable." Negativity was measured by "Situation includes negative feelings (e.g., stress, anxiety, guilt)." Deception was measured by "Someone is being deceived." Sociality was measured by "Social interaction is possible or required." Controllability was measured by "I have control over the situation."

Initial Momentary Emotion Regulation Strategies. Participants rated whether they used a series of emotion regulation strategies as 0 (*no*) or 1 (*yes*) based on their initial, knee-jerk response to the situation. Participants were instructed to **select all strategies they utilized in the situation**. These strategies included reappraisal (i.e., I changed how I thought about the event), suppression (i.e., I made sure to hide how I feel), rumination (i.e., I repeatedly thought about the event and could not stop), worry (i.e., I worried about what may happen), distraction (i.e., I did something else to take my mind off it), problem solving (i.e., I tried to solve problems or resolve the events), savoring (i.e., I took time to savor or enjoy what happened), planning (i.e., I made plans for the next steps), positive refocusing (i.e., I focused on the positive aspect of the event), soothing (i.e., I looked to others for comfort), and perspective seeking (i.e., I tried to find out what others would do if they were in my situation).

Effectiveness of Initial ER strategies. After indicating their initial emotion regulation strategies, participants were asked to rate the effectiveness of the ER strategies they used on a 5-

point scale from 1 (*not at all*) to 5 (*extremely*). Specifically, they were asked three questions: Did your initial response decrease distress, sadness, or anxiety? Did your initial response enhance pleasure, happiness, or calmness? Did your initial response facilitate problem solving? These three items were summed to reflect the effectiveness of initial repertoire ($\alpha = .71$).

Emotion Regulation Change. After rating the effectiveness of their initial ER strategies, participants were asked to indicate whether they change their initial response to the situation, on a binary scale of either 0 (*no*) or 1 (*yes*).

Updated/Hypothetical Momentary ER Strategies and **Their Effectiveness**. Depending on whether the participant changed or maintained their initial emotion regulation strategies, they were asked to indicate either their updated emotion regulation strategies (if they changed) or hypothetical emotion regulation strategies they would have used next (if they maintained). We included the hypothetical questions for participants who maintained their initial ER strategies in order to balance the length of EMA surveys and to reduce the likelihood that participants might indicate no strategy change so that they could end the EMA session more quickly. After indicating their updated or hypothetical momentary emotion regulation strategies, participants rated the effectiveness of these strategies. Items assessing updated/hypothetical momentary emotion regulation strategies and their effectiveness were identical to those for initial momentary emotion regulation strategy and the effectiveness of initial repertoire.

Total Momentary Distress. The EMA survey ended with questions regarding momentary psychological distress in the past three hours. Similar to previous studies (e.g., Fried et al., 2022), total momentary distress was assessed by six items selected from the Depression, Anxiety, and Stress Scale (Lovibond & Lovibond, 1995) and the Generalized Anxiety Disorder Scale (Spitzer et al., 2006). Participants rated these on a 5-point scale from 1 (*not at all*) to 5 (*extremely*). Two items captured momentary **perceived stress** (α = .81): "I found it difficult to relax" and "I felt irritable." Two items assessed momentary **anxious mood** (α = .89): "I was worried about different things" and "I felt nervous, anxious, or on edge." Two items assessed momentary **depressed mood** (α = .89): "I felt that I had nothing to look forward" and "I couldn't seem to experience any positive feeling at all." In addition to calculating scores of momentary perceived stress, anxious mood, and depressed mood by summing up their corresponding items, we summed all six items to reflect total momentary **distress** (α = .91).

Data Analytic Plan

R Version 4.2.1 (R Core Team, 2022) and the *nlme* (Pinheiro et al., 2022), *lme4* (Bates et al., 2015), *reghelper* (Beiner & Hughes, 2022), *glmnet* (Friedman et al., 2010), and *caret* (Kuhn, 2022) packages were used for our analyses.

First, we reported intraclass correlation coefficients (ICCs) for each momentary emotion regulation strategies to illustrate how much variances were within-person. Then, we built multilevel models (MLMs) to predict momentary reappraisal, suppression, rumination, worry, planning, positive refocusing, soothing, and perspective seeking with their respective habitual measure. We did not have habitual measures for distraction, problem solving, and savoring, given the lack of well-validated measures for these strategies. Therefore, these three strategies were not included in this analysis. This analysis allowed us to assess how much momentary emotion regulation was associated with their habitual counterparts.

Second, we tested the flexibility model by examining whether momentary measures of context sensitivity, use of repertoire, and feedback responsiveness would be associated with total momentary distress and its three subdimensions (i.e., depressed mood, anxious mood, and perceived stress) measured after the regulation attempt.

We estimated a proxy for **momentary context sensitivity** by obtaining the coefficient of variation of the nine situational characteristics (i.e., DIAMONDS and controllability) for each situation to reflect how much individuals could differentiate between different situational characteristics in that given situation (see formula below). To further validate whether this score can serve as a proxy measure that reflects momentary context sensitivity, we built a MLM with momentary context sensitivity as the dependent variable, and baseline measures of context sensitivity, repertoire, and feedback responsiveness as predictors. Analyses were conducted with random intercepts.

$$Momentary\ Context\ Sensitivity = \frac{SD(Nine\ Situational\ Characteristics)}{Mean(Nine\ Situational\ Charateristics)}$$

We estimated two repertoire variables: **overall repertoire**, a between-person variable, and **momentary use of repertoire,** a within-person variable. We estimated the **overall repertoire** score for each participant by summing the number of effective ER strategies a participant used over the course of the entire EMA study. An ER strategy was considered effective for a participant, when across all EMA situations, the correlation between using this strategy and strategy effectiveness (i.e., the sum of increasing positive affect, decreasing negative affect, and facilitating problem-solving) was positive and at least small in size (i.e., $r > .10$; Cohen, 1988). To estimate the validity of the overall repertoire score, we examined its correlation with baseline context sensitivity, expressive flexibility, and feedback responsiveness. We estimated the **momentary use of repertoire** as each participant's use of strategies from their overall repertoire in each situation. For example, if a participant had four effective ER strategies across EMA situations (e.g., reappraisal, distraction, problem solving, savoring), their overall repertoire would be 4. If they had used two out of these four effective ER strategies (e.g., reappraisal, problem solving) in a situation, their momentary use of repertoire in that situation would be 2.

We used the interaction between ER change and initial effectiveness to assess the adaptiveness of **momentary feedback responsiveness**. In specific, we hypothesized that individuals would report lower levels of momentary psychological distress in situations where they maintained effective strategies (i.e., ER Change = 0 when initial effectiveness was high) or switched from ineffective strategies (i.e., ER Change = 1 when initial effectiveness was low).

Finally, we built a MLM predicting momentary measures of total distress and as well as three component measures (i.e., depressed mood, anxious mood, and perceived stress) by momentary measures of context sensitivity, use of repertoire, effectiveness of initial ER strategies, ER change, and the interaction between ER change and initial effectiveness. At Level 1, momentary context sensitivity, use of repertoire, initial effectiveness, and ER change were person-centered to assess within-person deviations from the participant's mean. At Level 2, they were grand-mean centered to evaluate and control for between-person effects (Bolger & Laurenceau, 2013; Yaremych et al., 2021).

Results

Comparing Habitual ER with Momentary ER

First, we used MLMs to examine the relationship between habitual and momentary ER use. The intraclass correlation coefficients (ICCs) were all low, ranging from .24 to .36 across emotion regulation strategies (see Table 1). In summary, habitual emotion regulation use was predictive of the momentary use of the respective strategy, $ps < .05$, with the exception for reappraisal, $B = 0.2$, $SE = 0.2$, $p = .40$. However, the magnitude of associations varies across strategies, suggesting that habitual ER is not a consistent or reliable proxy for ER in real time.

Predictor Preparation/Validation

We created a proxy for momentary context sensitivity by dividing the standard deviation of the nine situational characteristics by their mean (i.e., coefficient of variation). This approach captured how much one can differentiate various situational characteristics at a given situation. We built a multilevel model predicting this index by baseline measures of context sensitivity, repertoire, and feedback. As expected, the momentary context sensitivity was associated with baseline context sensitivity, $B = 0.003$, $SE = .001$, $p = .002$, but not baseline expressive flexibility, $B = .0005$, $SE = .001$, $p = .56$, or baseline feedback responsiveness, $B = .0002$, $SE =.002$, $p =.89$. Therefore, this index was used as a proxy for momentary context sensitivity.

Additionally, we captured overall repertoire by counting the number of effective strategies for each participant across EMA situations. An effective strategy should have at least a small correlation (r => .10) with the effectiveness score. This overall repertoire measure was marginally associated with baseline expressive flexibility, $r = .13$, $p = .09$, but not associated with baseline context sensitivity, $r = -.01$, $p = .86$, or baseline feedback, $r = .03$, $p = .72$. We then obtained a momentary use of repertoire measure to reflect how many strategies one recruited from their overall repertoire in each situation. This momentary use of repertoire measure utilized used in subsequent MLMs.

Finally, we used the interaction between emotion regulation change and the effectiveness of initial strategies to test two aspects of feedback responsiveness. In specific, we examined if individuals exhibited lower levels of momentary psychological distress in situations where they maintained effective strategies (i.e., ER Change = 0 when initial effectiveness was high) or switched from ineffective strategies (i.e., ER Change = 1 when initial effectiveness was low).

Multilevel Models Predicting Total Momentary Distress

To test the flexibility model, we built a multilevel model predicting **total momentary distress** after the regulation attempt (i.e., the sum of momentary depressed mood, anxious mood, and perceived stress in each EMA situation) with momentary context sensitivity, momentary use of repertoire, and the interaction between ER change and initial effectiveness. Consistent with theory suggesting the benefit of context sensitivity (Bonanno & Burton, 2013), there was a significant inverse association between momentary context sensitivity and total momentary distress, $B = -2.94$, $SE = 0.51$, $p < .001$, and between momentary use of repertoire and total momentary distress, $B = -0.45$, $SE = 0.11$, $p < .001$. The effectiveness of the initial strategies was also inversely associated with total distress after the regulation attempt, $B = -0.28$, $SE = 0.04$, $p < .001$. Finally, there was a significant interaction between emotion regulation change and initial effectiveness, $B = 0.14$, $SE = 0.05$, $p = .002$. The simple slope analyses indicated that when the initial effectiveness was high (i.e., 1 *SD* above the mean), participants who maintained their initial strategy choice (ER Change = 0) reported lower total momentary distress after the regulation attempt, $B = 0.81$, $SE = .18$, $p < .001$. In contrast, participants who changed their strategies (ER Change = 1) when the initial effectiveness was low (i.e., 1 *SD* below the mean) did not differ in total momentary distress compared with those who maintained their initial strategies, $B = 0.11$, $SE = 0.15$, $p = .47$. This suggests that maintaining effective emotion regulation strategies was adaptive, while switching from ineffective emotion strategies was surprisingly not associated with psychological distress (Figure 1).

Multilevel Models for Predicting Momentary Depression, Anxiety, and Perceived Stress

We further built MLMs predicting each momentary outcome (i.e., depressed mood, anxious mood, and perceived stress) separately. The results for momentary anxious mood and perceived stress were similar to the results for the combined variable–total momentary distress–in that maintaining effective strategies seemed adaptive.

When predicting **momentary anxious mood**, there was an inverse association between momentary context sensitivity and momentary anxious mood, $B = -1.48$, $SE = 0.23$, $p < .001$. Momentary use of repertoire was also inversely associated with momentary anxious mood, $B = -0.13$, $SE = 0.04$, $p = .003$. Additionally, increased effectiveness of the initial strategies was associated with decreased momentary anxious mood, $B = -0.11$, $SE = 0.02$, $p < .001$. Finally, there was a significant interaction between emotion regulation change and initial effectiveness, $B = 0.04$, $SE = 0.02$, $p = .04$. The simple slope analyses indicated that when the initial effectiveness was high (i.e., 1 *SD* above the mean), participants who maintained their ER strategies (ER Change = 0) reported lower momentary anxious mood, $B = 0.38$, $SE = .08$, $p < .001$. In contrast, participants who switched their strategies (ER Change = 1) when the initial effectiveness was low (i.e., 1 *SD* below the mean) did not differ in anxious mood compared with those who maintained their strategies, $B = 0.05$, $SE = 0.06$, $p = .43$.

When predicting **momentary perceived stress**, there was an inverse association between momentary context sensitivity and momentary perceived stress, $B = -1.09$, $SE = 0.20$, $p < .001$, and between momentary use of repertoire and momentary perceived stress, $B = -0.21$, $SE = 0.04$, $p < .001$. The effectiveness of the initial ER strategies was also inversely associated with momentary perceived stress, $B = -0.11$, $SE = 0.02$, $p < .001$. Finally, there was a significant interaction between emotion regulation change and initial effectiveness, $B = 0.07$, $SE = 0.02$, $p < .001$. The simple slope analyses indicated that when the initial effectiveness was high (i.e., 1 *SD* above the mean), participants who maintained their ER strategies (ER Change = 0) reported lower momentary perceived stress, $B = 0.39$, $SE = .08$, $p < .001$. In contrast, participants who switched their strategies (ER Change = 1) when the initial effectiveness was low (i.e., 1 *SD* below the mean) did not differ in perceived stress compared with those who maintained their strategies, $B = 0.03$, $SE = 0.07$, $p = .57$.

Contrary to the aforementioned results, the results for **momentary depressed mood** suggested that switching from ineffective strategies was adaptive. There was an inverse association between momentary context sensitivity and momentary depressed mood, $B = -0.39$, $SE = 0.16$, $p = .01$, and between momentary use of repertoire and momentary depressed mood, $B = -0.09$, $SE = 0.02$, $p < .001$. The effectiveness of the initial strategies was also inversely associated with momentary depressed mood, $B = -0.06$, $SE = 0.01$, $p < .001$. Finally, there was a significant interaction between emotion regulation change and initial effectiveness, $B = 0.03$, $SE = 0.02$, $p = .04$. The simple slope analyses indicated that when the initial effectiveness was high (i.e., 1 *SD* above the mean), participants who maintained their ER strategies (ER Change = 0) did not differ in momentary depressed mood after the regulation attempt, compared with those who changed their ER strategies, $B = 0.05$, $SE = 0.06$, $p = .38$. In contrast, participants who switched their ER strategies (ER Change = 1) when the initial effectiveness was low (i.e., 1 *SD* below the mean) reported lower momentary depressed mood following the regulation attempt, $B = - 0.10$, $SE = 0.05$, $p = .04$.

Discussion

The emerging field of emotion regulation flexibility has highlighted several critical components that are enacted in sequential order, such as context sensitivity, repertoire, and feedback responsiveness (Bonanno & Burton, 2013). The present study tested this sequence using EMA to assess the association between momentary ER flexibility and momentary measures of total distress and its three sub-dimensions (i.e., depressed mood, anxious mood, and perceived stress). Consistent with theory, higher momentary measures of context sensitivity and use of repertoire were associated with better psychological adjustment (i.e., lower momentary depressed mood, anxious mood, perceived stress, and total distress). Findings were less consistent, however, for the feedback responsiveness component at the end of the sequence. On the one hand, maintaining effective strategies was adaptive for momentary measures of anxious mood, perceived stress, and total distress. On the other hand, switching from ineffective strategies was adaptive only for depressed mood.

We developed a proxy measure for momentary context sensitivity by obtaining the coefficient of variation of the nine situational characteristics. In support of the validity of this proxy measure, we found that baseline context sensitivity was associated with momentary context sensitivity (i.e., convergent validity), but not expressive flexibility, or feedback responsiveness (i.e., discriminant validity). Further, enhanced momentary context sensitivity predicted decreased momentary distress, depression, anxiety, and stress. These findings supported the adaptiveness of context sensitivity in daily emotional situations. Our findings extended investigations of controllability-ER sensitivity to the examination of broader range of situational characteristics.

We developed an overall repertoire measure by summing the number of effect strategies for a participant across EMA situations (i.e., had at least a small positive correlation with effectiveness across situations). This measure was only marginally associated with expressive flexibility measured by FREE. This may result from the differences in the scope of these two measures. FREE only captures one component of repertoire, expressive flexibility, whereas the overall repertoire score based on EMA data that captured a broad range of strategies spanning across expressive, cognitive, and interpersonal domains. We also measured momentary use of repertoire. Previous EMA studies have created proxies for repertoire using either the total number of ER strategies or variability in ER strategy (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020). However, since the use of repertoire not only involves access to a wide range of strategies but also at least some ability or skill in those strategies (Aldao & Nolen-Hoeksema, 2013; Bonanno & Burton, 2013; Cheng, 2003), we measured the momentary use of repertoire based on participant's use of strategies that they had used effectively across the entire EMA. The momentary use of repertoire measure was associated with momentary measures of total distress and sub-domains of psychopathology. Future research would benefit by directly empirical comparison of the different conceptualization of repertoire.

Lastly, we tested the adaptiveness of feedback responsiveness by examining the interaction between emotion regulation change and the effectiveness of initial ER strategies. Maintaining effective strategies was adaptive for anxiety, stress, and total distress, but not depression, whereas switching from ineffective strategies was adaptive only for depression. One possible explanation why we did not observe any benefit of switching from ineffective strategies for anxiety and stress could be that switching alone did not guarantee subsequent regulatory success. For example, one may switch from one set of ineffective strategies to another set of ineffective strategies, which may not facilitate adaptation. However, depression has been characterized by the tendency for affective states that were resistant to change (Koval et al., 2012), which may have contributed to the observed inverse association between switching and momentary depressed mood. Together, these findings suggest that both maintaining effective strategies and switching from ineffective strategies have adaptive implications but for different mood outcomes.

Our study had several strengths. First, this study expands the scope of research by using an intensive longitudinal design to capture several components of emotion regulation flexibility and examining them in one model, which is an extension to cross-sectional investigation of these components (Chen & Bonanno, 2021) and EMA studies that examine these components in separate models (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Battaglini, Rnic, Jameson, Jopling, & LeMoult, 2022). Second, the present study borrows from situation research in social psychology (Rauthmann & Sherman, 2016), which extends investigations of limited types of environmental variability—such as controllability and intensity (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Goodman et al., 2021)–to a much more comprehensive assessment of situations.

There were also several limitations to our study. First, our study was limited to a fixed schedule of EMA assessments, and may not necessarily capture real-time emotion regulation. Additional research is needed to better understand the role of timescale as well as assessment intervals when assessing the benefits of ER flexibility. Further, incorporating passive sensing may provide information as to when relatively emotional situations occur and enable ER and situation assessments on the spot. Second, our study requires participants to report whether they change their ER strategies, which may represent a process whereby the modification of ER strategies happen sequentially in the moment. However, feedback may occur immediately or over a longer time span. Future research is needed to examine various types of feedback and test their adaptiveness. Third, although we found the association between flexibility and short-term mood outcomes, future research is needed to examine long-term mental health outcomes. Finally, the observed associations reported in this study could not infer causality. The field of ER flexibility would benefit from experimental and intervention studies that directly test the affective benefits of flexibility.

In conclusion, this EMA study documented the importance of several ER flexibility components to momentary total distress and its three subdimensions. Moreover, different types of feedback responsiveness were differentially associated with depression and anxiety, which may inform theoretical models and applied work. Findings underscore the importance of ER flexibility in assessment and intervention of emotion regulation.

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Table 1. Habitual ER Strategy Predicting Momentary ER Use

ER Strategy	ICC	*B* (*SE*)
Reappraisal	0.28	0.02 (0.02)
Suppression	0.24	0.05 (0.02)*
Rumination	0.27	0.13 (0.04)***
Worry	0.25	0.14 (0.03)***
Plan	0.27	0.12 (0.03)**
Positive Refocus	0.27	0.10 (0.03)***
Soothing	0.29	0.14 (0.02)***
Perspective Seeking	0.36	0.10 (0.03)***

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

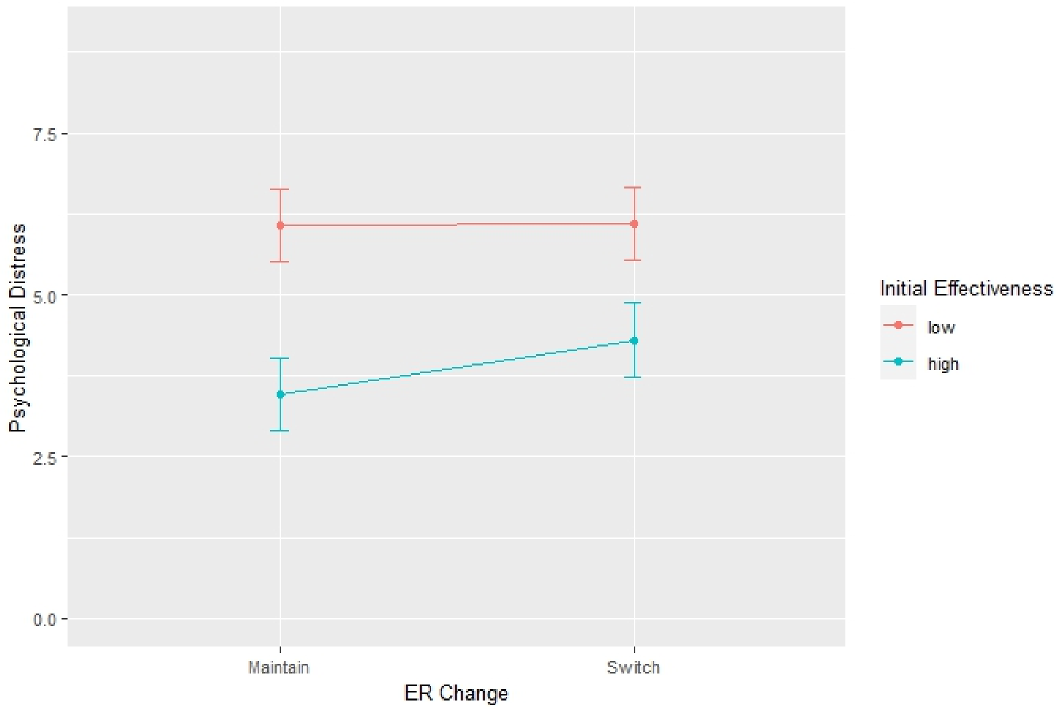

Figure 1. Association between Emotion Regulation Change and Psychological Distress at Low (-1 SD) and High (+ 1 SD) Levels of Initial Effectiveness

Chapter 3: GENERAL DISCUSSION

Regulatory flexibility has been increasingly theorized to have multiple components that may be distinct yet interdependent, including context sensitivity, repertoire, and feedback responsiveness (Bonanno & Burton, 2013). Several studies have demonstrated the association between components of flexibility and various aspects of psychological adjustment, such as psychopathology (e.g., Bonanno et al., 2018; Chen et al., 2018; Goodman et al., 2021; Kato, 2012), satisfaction with life (e.g., Birk & Bonanno, 2016), and positive and negative affect (e.g., Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Battaglini, Rnic, Jameson, Jopling, & LeMoult, 2022; Blanke et al., 2020).

However, there are several fundamental gaps in the regulatory flexibility literature. First, despite the increasing number of studies on individual flexibility components mentioned earlier, almost no study has examined how different flexibility components function as a whole. Study 1 in this dissertation addressed this gap by adopting latent profile analysis to examine patterns of regulatory flexibility and link them to psychopathology symptoms. Second, although studies have shown the benefits of flexibility in the context of stressful and potentially traumatic life events (for a review, see Cheng et al., 2014), it is unknown how robustly flexibility can predict longitudinal adjustment when simultaneously controlling for other important factors (Bonanno et al., 2010; Chen & Bonanno, 2020; Galatzer-Levy et al., 2018). This limitation results from research that often relies on cross-sectional designs, examines few predictors, and uses univariate design. Study 2 in this dissertation filled this gap by examining one component of flexibility, feedback responsiveness, in relation to trajectories of depression, anxiety, and PTSD symptoms following potentially traumatic events. Third, by definition, flexibility entails adjusting regulatory strategies across contexts, but there has been a curious neglect of assessing the highly diverse situations where regulation takes place. The recognition of the importance of situation assessments has appeared primary in the theoretical space, with empirical research lagging relatively behind (Aldao, 2013). Even when contexts were considered in previous studies, the number of situational characteristics was limited to hypothetical scenarios (Bonanno et al., 2018), controllability of stressors (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Troy et al., 2013), types of emotion (Dixon-Gordon, Aldao, & De Los Reyes, 2015), and intensity of emotion (Sheppes et al., 2014). Thus far, no study has attempted to systematically capture situational characteristics unique to each individual in the study of regulatory flexibility. Study 3 in this dissertation incorporated situational assessments from social psychology to facilitate the study of regulatory flexibility.

This dissertation aimed to fill the aforementioned gaps via three empirical studies. Study 1 integrated flexibility components by measuring them concurrently and applying rigorous, double-cross validation latent profile analysis to link profiles of flexibility components to depression and anxiety. Study 2 investigated the predictive ability of flexibility for longitudinal trajectories of depression, anxiety, and PTSD while examining over 50 other important factors. Specifically, we used a machine learning approach to predict trajectories of resilience and psychopathology. This study elucidated whether flexibility could robustly predict longitudinal trajectories of depression, anxiety, and PTSD in the aftermath of potentially traumatic events when simultaneously considering other potentially important factors. Study 3 incorporated situational characteristics (Rauthmann & Sherman, 2016) and flexibility in an intensive longitudinal design (i.e., EMA) to understand how flexibility was associated with depressed mood, anxious mood, and perceived stress across 84 daily situations. Tools of situation assessment combined with intensive longitudinal measures of emotion regulation provide opportunities for researchers to better understand how situations and regulatory strategy use covariate and shed light on personalized assessment of flexibility.

Together, this dissertation found evidence that greater regulatory flexibility was associated with decreased depression and anxiety (Study 1), higher likelihood of resilience and lower likelihood of psychopathology in the aftermath of potentially traumatic event (Study 2), and lower levels of momentary depressed mood, anxious mood, and perceived stress (Study 3).

Findings from Study 1

Theoretical models of flexibility suggest that it has multiple components that are beneficial for psychological adjustment (Bonanno & Burton, 2013; Cheng et al., 2014), and individual components of ER flexibility have consistently shown links to psychopathology, affect, and positive functioning (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Birk & Bonanno, 2016; Bonanno et al., 2018; Goodman et al., 2021; Kato, 2017). Study 1 of this dissertation was the first to examine all components of flexibility and elucidate their combined benefits to mental health within the same study. In specific, this study applied LPA to the three components of ER flexibility proposed by Bonanno and Burton (2013), and connected profile memberships with the severity of depression and anxiety.

Our findings revealed unique profiles of ER flexibility. Specifically, the most common profile was characterized by an average ability across all three flexibility components (i.e., Medium Flexible Regulators, MFR). By contrast, superior flexibility, manifesting as high scores across all three regulatory components, was evident in only about one tenth of the sample (i.e., High Flexible Regulators, HFR). Approximately thirty percent of the participants belonged to any of the three relatively inflexible profiles, manifesting as impairment in one regulatory component: some exhibited difficulty accurately perceiving the cues in stressful situations (i.e., Context Insensitive Regulators, CIR), some experienced challenges in enhancing and suppressing emotions (i.e., Low Repertoire Regulators, LRR), others could effectively monitor and adjust strategy use via feedback (i.e., Feedback Irresponsive Regulators, FIR).

Study 1 also elucidated transdiagnostic and diagnostic-specific association between flexibility profiles and psychopathology symptoms. Consistently with the flexibility theory, inflexible profiles (CIR, LRR, and FIR) exhibited greater level of depressive and anxious symptoms than the two flexible profiles (MFR and HFR). Additionally, inflexible groups did not differ in symptoms of depression, but CIR exhibited significantly greater severity of anxiety than groups with other deficits. These findings underscore the importance of context sensitivity, particularly for anxiety.

From a clinical science perspective, our studies contribute to a growing body of literature that emphasize the effect of flexibility on psychological health. Crucially and consistent with prevailing assumptions in the flexibility literature, the latent profiles were associated with depressive and anxious symptoms. As previously hypothesized (Bonanno & Burton, 2013), HFR had the lowest levels of depressive and anxious symptoms, which again highlights the importance of all three flexibility components. Notably, varied combinations of the three components also showed differential relations to depression and anxiety. CIR showed greater elevation of depression and anxiety than that of the HRF and MFR, and more anxiety symptoms than all other profiles. These findings suggest that anxiety is particularly high for those with deficits in context sensitivity, whereas elevation of depression seems similar across individuals with different types of flexibility deficits.

In summary, five subtypes of regulators were identified based on the flexibility model proposed by Bonanno and Burton (2013). Those with great abilities in all regulatory components exhibited the least depressive and anxious symptoms. On the contrary, inflexibility, as demonstrated by deficits in context sensitivity, repertoire, or feedback responsiveness, was associated with depressive and anxious symptoms. Individuals who were relatively insensitive to context exhibited the highest level of anxiety. These findings are consistent with theory highlighting the importance of flexibility (Aldao et al., 2015; Bonanno & Burton, 2013; Cheng et al., 2014; Kashdan & Rottenberg, 2010). Future research may extend these findings by incorporating longitudinal designs, adopting multi-method measures of different flexibility components, and examining the relationship between flexibility and psychopathology in various samples.

Findings from Study 2

Study 2 used unsupervised machine learning to identify heterogeneous trajectories of depression, anxiety, and PTSD symptoms in the aftermath of strict COVID-19 lockdowns in a sample of Hubei residents and then to discriminate these trajectories using person- and context-level predictors. By including three overlapping yet different mental health outcomes, we were able to compare their longitudinal trajectories and corresponding predictors in the context of COVID-19 lockdowns, which enabled us, in turn, to elucidate transdiagnostic and diagnosis specific risk and protective factors.

Of particular interest to this dissertation, we found that coping flexibility—measured by the Coping Flexibility Scale (Kato, 2012) and considered the feedback responsiveness component of flexibility—was one of most robust predictor retained in the model predicting greater likelihood of resilience and lower likelihood of psychopathology in anxiety. Additionally, lower coping flexibility was also one of the top five predictors for chronic depression trajectory. Although coping flexibility appeared lower on the relative importance plot, it should be noted that this study specifically selected factors that were important for psychological adjustment both in the aftermath of potentially traumatic events in general and in the context of the COVID-19 pandemic. This would undoubtedly shrink the importance of predictors. For example, social support was one of the most frequently examined predictor for psychological adjustment following potential trauma, but it was not retained in any of the models. Therefore, feedback responsiveness did predict some domains of flexibility, but the effect was relatively low.

Across three mental health outcomes, most individuals remained resilient despite the stressful and potentially traumatic nature of the strict lockdowns in Hubei, a finding consistent with previous research (for a review, see Bonanno et al., 2010). Of note, however, was our finding that the proportion of resilient individuals was lower for anxiety (58%) than either depression (87%) or PTSD (93%). One plausible reason is that anxiety may be a normative and perhaps temporary response during COVID-19 lockdowns and may not necessarily signal psychopathology. It is also worth considering that the measure of anxiety we used captured general distress rather than clinical-level anxiety, which may further inflate the estimation of chronic anxiety. Relatedly, our LASSO models predicting depression and PTSD were more accurate than models predicting anxiety. Taking into consideration the proportion of anxiety trajectories and the nature of our anxiety measure, it is likely that predictors included in this study excelled at classifying the absence or presence of psychopathology but were less able to differentiate individuals with varying levels of distress.

Our findings demonstrate that resilience and chronicity depend on a combination of person and context-level predictors. Other than flexibility, we identified transdiagnostic predictors such as worry, family support, and fear of COVID-19. Research has identified the central role that various forms of worry play in avoidance and coping behaviors during the

COVID-19 pandemic (Taylor et al., 2020b), which was consistent with our finding that worry emerged as the most important transdiagnostic predictor of chronic psychopathology.

From a clinical science perspective, our study adds to a small but growing literature demonstrating the effectiveness of using machine learning to examine a large body of diverse predictors to effectively differentiate longitudinal trajectories of psychopathology symptoms (e.g., Schultebraucks et al., 2021). Many resilience and psychopathology studies often included few predictors and adopted univariate analyses (for a review, see Bonanno et al., 2010), limiting their capacity to distinguish the most robust predictors. Future research may benefit from adopting our approach to address this critical gap. The current study also highlights the need for comparative analysis across contexts and cultures. Although perceived social support has been consistently identified as an essential resilience factor (Galatzer-Levy et al., 2018), our findings showed family support to be a stronger predictor, which likely resulted from the cultural backdrop where the study took place. As the first study that examined a large number, multi-domain predictors for longitudinal trajectories of mental health in an Asian sample, our study makes important contributions to psychological data that were traditionally dominated by samples from Western, educated, industrialized, rich, and democratic (WEIRD) nations (Henrich et al., 2010). From the perspective of practice and policy, our study suggests important implications for risk identification. The findings from this study also offer preliminary information regarding factors that can likely serve as targets in prevention and intervention efforts, including worry, flexibility, and family relationships.

Findings from Study 3

The first two studies have highlighted the cross-sectional and longitudinal benefits of flexibility, Study 3 used an intensive longitudinal design to increase the ecological validity of findings. The emerging field of emotion regulation flexibility has highlighted several critical components, such as context sensitivity, repertoire, and feedback responsiveness (Bonanno & Burton, 2013). Study 3 concurrently tested these theories by assessing the association between ER flexibility and psychological distress using an EMA design (i.e., four times a day over the course of 21 days). The findings provided evidence that greater context sensitivity and initial effectiveness of repertoire were associated with better psychological adjustment (i.e., lower psychological distress, depressed mood, anxious mood, and perceived stress). Additionally, interesting divergent findings emerged for feedback responsiveness. Maintaining effective strategies was adaptive for anxious mood, perceived stress, and psychological distress (i.e., associated with lower levels of these measures), whereas switching from ineffective strategies to a different set of strategies was adaptive only for depressed mood (i.e., associated with lower levels of depressed mood).

We developed a proxy measure for momentary context sensitivity by obtaining the coefficient of variation of the nine situational characteristics. We evaluated its validity and found that baseline context sensitivity (i.e., convergent validity), but not repertoire or feedback responsiveness (i.e., discriminant validity), predicted momentary context sensitivity, which supported its potential as a proxy measure for context sensitivity. Further, enhanced momentary context sensitivity predicted decreased momentary psychological distress, depression, anxiety, and stress. These findings supported the adaptiveness of context sensitivity in daily emotional situations. Our findings extended investigations of controllability-ER sensitivity to the examination of broader range of situational characteristics.

As expected, greater initial effectiveness of repertoire was associated with lower levels of psychological distress as well as its three subdimensions. This supported the benefit of employing effective strategies at the beginning. Since the definition of repertoire not only involves access to a wide range of strategies but also the correspondence of the ER strategies with situational demands, we chose not to use the number of ER strategies or variability in ER use as proxies for repertoire like previous studies (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Blanke et al., 2020). However, using effectiveness of ER strategies (i.e., enhancing positive emotions, decreasing negative emotions, and facilitating problem solving) may confound repertoire with outcomes. Keeping this in mind, this is likely an imperfect proxy. One possibility of assessing momentary repertoire in future research may be to capture how much the implemented ER strategies meet the ER goals in each situation.

Lastly, we tested the adaptiveness of feedback responsiveness by examining the interaction between emotion regulation change and initial effectiveness of repertoire. Maintaining effective strategies was adaptive for anxiety, stress, and psychological distress, but not depression, whereas switching from ineffective strategies was adaptive for depression but not anxiety, stress, or psychological distress. One possible explanation why we did not observe any benefit of switching from ineffective repertoire in anxiety, stress, and psychological stress could be that switching alone did not guarantee subsequent regulatory success. For example, individuals with greater anxiety and stress may exhibit "busy coping," switching from one set of ineffective strategies to another set of ineffective strategies, which may not necessarily facilitate adaptation. However, depression was characterized by the tendency for affective states that were resistant to change (Koval et al., 2012), which may have contributed to the observed association between difficulty in switching and depressed mood. Together, these findings suggest that the two components of feedback responsiveness—maintaining effective strategies and switching from ineffective strategies both have adaptive implications—but for different mood outcomes.

Our study has several strengths. First, this study expands the scope of research by using an intensive longitudinal design to capture several components of emotion regulation flexibility and examine them in one model, which is an extension to cross-sectional investigation of these components (Study 1) and EMA studies that examine these components in separate models (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Battaglini, Rnic, Jameson, Jopling, & LeMoult, 2022). Second, the present study borrows from situation research in social psychology (Rauthmann & Sherman, 2016), which extends investigations of limited types of emotional variability—such as controllability and intensity (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Goodman et al., 2021; Troy et al., 2013)–to a much more comprehensive assessment of situations.

Limitations and Future Directions

The dissertation presents significant advances in understanding emotion regulation (ER) flexibility and its association with psychopathology. However, there are several noteworthy limitations that need to be considered.

First, the cross-sectional nature of Study 1 limits our ability to evaluate the stability of latent profiles over time and the temporal relationship between flexibility and psychopathology. Similarly, in Study 3, although we found the association between flexibility short-term mood outcomes, it was within a relatively short time frame which provides limited information as to the long-term affective benefits of flexibility. Additionally, the observed associations reported in Study 3 could not infer causality. Future research can undertake two important directions. First, the field of ER flexibility would benefit from experimental and intervention studies that directly test the affective benefits of regulatory flexibility. Second, future studies recruiting clinical samples and adopting longitudinal design could help shed light on the transdiagnostic and diagnostic specific temporal association from flexibility components and their constructed profiles to various aspects of internalizing psychopathology.

Second, our measure of repertoire in Study 1 was limited to up- and down-regulation of emotional expressions. In Study 2, we only examined feedback responsiveness due to the unavailability of valid self-report measures of repertoire or context sensitivity for predominantly middle-aged Chinese-speaking adults in China. In Study 3, we developed a proxy measure for repertoire, but this surprisingly only correlated mildly with trait-based repertoire measure (i.e., FREE). Despite their consistency with theoretical models (Bonanno & Burton, 2013; Cheng et al., 2014) and empirical research (Bonanno et al., 2004; Burton & Bonanno, 2016; Westphal et al., 2010), the conceptualizations of trait-based repertoire in Study 1 and 3 may be limited to repertoire concerning emotional expressions. Important to note, however, other studies have conceptualized repertoire differently, as categorical and temporal variability (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022), latent profiles of strategy use (Dixon-Gordon, Aldao, & Reyes, 2015), or number of strategies (Southward et al., 2018; Southward & Cheavens, 2017). The divergent conceptualization and operationalization may have contributed to the mixed findings in this flexibility component (Blanke et al., 2020). Even within similar conceptualization (e.g., number of strategies), studies often differ in the number of strategies they examined (Battaglini, Rnic, Jameson, Jopling, Albert, et al., 2022; Southward et al., 2018), making it difficult, if not impossible, to cross-compare findings. The operationalization of repertoire itself could be an empirical investigation. Future research is needed to compare the benefits of different conceptualizations of repertoire in one study so as to expand our understanding of the adaptiveness of the number of ER, categorical and temporal variability of ER, or any other repertoire conceptualizations of ER.

Third, in Study 2, we only examined feedback responsiveness due to the unavailability of valid self-report measures of repertoire or context sensitivity for predominantly middle-aged Chinese-speaking adults in China. Although previous studies have validated or developed measures of repertoire for Chinese adolescents (Wang & Hawk, 2019) and college students (Chen et al., 2018), they proved difficult to understand during the pilot study and thereby were not measured in the study. In future research, investigating all three components of flexibility and their prediction of longitudinal trajectories of psychological adjustment across samples and cultural contexts would enhance our understanding of the adaptiveness of different conceptualizations of emotion regulation flexibility. Additionally, the relatively small sample size and the lack of external validation in Study 2 limits the robustness of these findings. While we used 10-fold cross-validation with three repetitions to obtain more reliable estimates of model performance, the lack of external validation inevitably increases risk of overfitting and limits the generalizability of the benefit of flexibility. Future studies with larger samples and external validation are required to enhance the power and reliability when examining the benefit of flexibility.

Fourth, Study 2 may overestimate the percentage of chronicity given that we did not take into consideration pre-existing mental illness or more gradual recovery occurring beyond six months after the strict lockdowns. Another possibility could be that the anxiety measure we used, State Anxiety Inventory, may have captured general distress rather than clinical anxiety, limiting our conclusions on anxiety and its predictors. Future studies, when possible, should adopt prospective design with more valid clinical measures or psychiatric interviews, to assess flexibility prior to exposure to stress or potential trauma, and examine the benefit for flexibility for prospective trajectories of psychopathology and resilience. Similarly, keeping in mind that the duration of Study 2 was only six months, it is important to note that the term chronicity is used to stay consistent with the literature (Galatzer-Levy et al., 2018) and to distinguish this trajectory from the recovery trajectory, and does not necessarily amount to chronic psychopathology such as dysthymia and generalized anxiety disorder. Some of those who exhibit a chronicity trajectory may recover if examined over a longer period. Finally, although we included a large number of predictors in Study 2, most predictors were derived from self-report measures. Future studies that include multimethod assessment of flexibility will likely further enhance predictive accuracy.

Fifth, in Study 3, our EMA design was based on a fixed schedule, which may not necessarily capture real-time emotion regulation. Additional research is needed to better understand the role of timescale as well as assessment intervals when assessing the benefits of ER flexibility. Likewise, our study requires participants to report whether they change their ER strategies, which may represent a process whereby the modification of ER strategies happen sequentially in the moment. However, feedback may occur immediately or over a longer time span. Future research is needed to examine various types of feedback at different time frames and test their adaptiveness. Further, incorporating passive sensing may provide information as to when relatively emotional situations occur and enable ER and situation assessments in the real time.

Finally, given the diverse empirical studies and theories on emotion regulation flexibility, capturing the divergence and convergence in findings seems imperative. As one example mentioned earlier, the divergence in the definition, conceptualization, and operationalization of repertoire hinders researchers from drawing consistent and reliable findings to advance the theory of flexibility. To chart a path forward, future studies can incorporate multiple levels of assessments (e.g., physiology, cross-sectional self-report, experience sampling), different time frames (e.g., cross-sectional, prospective, and intensive longitudinal designs), and various conceptualizations of flexibility components. This will allow us to compare findings in a way that can help identify the most robust and reliable findings and inform theory of emotion regulation flexibility. These findings can also be translated into time-sensitive interventions such as ecological momentary interventions.

In summary, although the dissertation makes significant contributions to our understanding of ER flexibility and its association with psychopathology, future research should overcome the limitations mentioned above to further expand our knowledge in this area.

Conclusions

This dissertation filled several fundamental gaps in the flexibility literature via three empirical studies. Study 1 measured all three flexibility components and linked latent profiles of emotion regulation flexibility to depression and anxiety. Individuals with high or moderate flexibility exhibited lower levels of depressive and anxious symptoms compared with those with deficit in one component. Notably, context-insensitive individuals exhibited higher anxiety than other inflexible profiles, indicating that context sensitivity may be particularly associated with anxiety. Study 2 used a machine learning approach to investigate the predictive ability of flexibility, conceptualized as the feedback responsiveness component of flexibility, for longitudinal trajectories of depression, anxiety, and PTSD against 50 other important factors. This study demonstrated that higher flexibility predicted a lower likelihood of chronic depression and anxiety. Study 3 incorporated situational characteristics (Rauthmann & Sherman, 2016) and flexibility in an intensive longitudinal design (i.e., EMA) to understand how flexibility was associated with depressed mood, anxious mood, and perceived stress across 84 daily situations.

This EMA study documented the importance of several ER flexibility components to depressed mood, anxious mood, and perceived stress. Moreover, types of feedback responsiveness were differentially associated with depression and anxiety, which may inform theoretical models and applied work.

In summary, this dissertation found that greater regulatory flexibility was associated with decreased depression and anxiety (Study 1), a lower likelihood of chronic depression or anxiety trajectories in the aftermath of a potentially traumatic event (Study 2), and lower levels of momentary depressed mood, anxious mood, perceived stress, and overall distress (Study 3). These findings underscore the importance of assessing and intervening in emotion regulation through the lens of flexibility.

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