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Examining underlying structures of cognitive emotion regulation strategies using exploratory structural equation modeling

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Abstract

Cognitive emotion regulation strategies (ERSs) are salient predictors of numerous mental health outcomes. Individuals rely on combinations of strategies and these are often context-dependent, so it is advantageous to evaluate several cognitive ERSs in studies on relations between emotion regulation and mental health. However, it is not always practical to examine several ERSs as separate predictors in statistical models (e.g., due to small sample size), especially when evaluating multiple factors that impact mental health. We aimed to evaluate a parsimonious underlying factor structure for overall reliance on different domains of cognitive ERSs. Using data from 2,077 young adults, we used Exploratory Structural Equation Modeling (ESEM) to evaluate underlying factor structures for nine ERSs as measured by the Cognitive Emotion Regulation Questionnaire. A three-factor solution was identified, including factors termed Positive ERSs, Internally-Oriented Negative ERSs, and Externally-Oriented Negative ERSs. The Positive ERS factor was a protective factor and the Internally-Oriented Negative ERS factor was a risk factor for several health-risk behaviors and mental health diagnoses, and effects were larger for Internally-Oriented Negative ERSs. Relations between the Externally-Oriented Negative ERSs factor and mental health outcomes were generally null. Results extend previous literature indicating that maladaptive ERSs have larger impacts on mental health concerns than adaptive strategies, and highlight that ERSs involving negative cognitions about oneself and one's internal experiences are a salient, transdiagnostic feature of psychopathology and health-risk behaviors. This parsimonious three-factor modeling approach for cognitive ERSs may be useful in etiological models for mental health concerns.

Keywords Emotion regulation strategies · Cognitive emotion regulation questionnaire · Psychopathology · Health-risk behavior · Adaptive · Maladaptive

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1 Introduction

Emotion regulation is a set of processes by which an emotional experience is modulated, either automatically without conscious control or through intentional action (Gross 2015). Emotion regulation has an inherently adaptive element in which individuals attempt to shape their emotional experience, often to reduce distress or enhance positive emotions (Beauchaine 2015). These processes involve valuation of emotional stimuli as either negative or positive, which leads to activating a goal in response to this valuation (Gross 2015). Emotion regulation is often studied in the context of emotion regulation strategies (ERSs), which include behavioral (e.g., changing a situation), affective (e.g., expressive suppression), or cognitive (e.g., re-appraising a situation) methods of attempting to regulate one's emotional experience (Gross 2015). Cognitive ERSs appear to become more important than behavioral and affective strategies in late adolescence through adulthood, possibly due to brain development and concomitant refinement of cognitive skills during this time (Steinberg 2005). Cognitive ERSs have been identified as transdiagnostic risk and resilience factors for a wide range of mental health outcomes, including psychopathology and several health-risk behaviors (Aldao et al. 2010; Berking et al. 2008; Silvers et al. 2012). Thus, cognitive ERSs are important considerations for etiological models of mental health concerns.

Several cognitive ERSs have been associated with internalizing and/or externalizing symptoms, mental disorders, and suicidal and health-risk behaviors (Aldao and Nolen-Hoeksema 2010; Gross and Jazaieri 2014). For example, self-blame, catastrophizing, rumination, suppression, positive reappraisal (inversely), and acceptance (inversely) have been significantly associated with depression and anxiety (e.g., Garnefski and Kraaij 2007; Garnefski et al. 2004; Potthoff et al. 2016; Schafer et al. 2017). In studies on health-risk behaviors, rumination has been associated with non-suicidal self-injury (NSSI), heavy episodic alcohol use, and binge eating (Nolen-Hoeksema et al. 2008). Lower utilization of cognitive ERSs in general has also been associated with higher rates of unprotected sex (Chen et al. 2018).

In addition to reported associations with numerous mental health outcomes, previous research suggests that patterns of reliance on ERSs can be complex (Naragon-Gainey et al. 2017). Individuals utilize multiple ERSs and these may synergistically influence each other when used in combination (e.g., Brans et al. 2013; Dixon-Gordon et al. 2015; Lyubomirsky et al. 1999). Individuals may also engage different ERSs when modulating responses to approach (e.g., anger) versus avoidance (e.g., fear) emotions, since these two regulatory systems may have distinct underlying mechanisms (Fox et al. 2008). Further, there appear to be individual differences in reliance on different combinations and numbers of ERSs (e.g., Dixon-Gordon et al. 2015; John and Gross 2007; Moumne et al. 2020). Therefore, there are important benefits to considering multiple ERSs in studies aiming to elucidate relations between emotion regulation and mental health (Tull and Aldao 2015).

1.1 Limitations of Traditional modeling approaches for ERSs

Conventional methods of modeling ERSs can limit the breadth of both ERSs and other risk factors that can be examined in studies predicting mental health outcomes. Different ERSs are often examined as separate variables in statistical models (e.g., Potthoff et al. 2016; Schafer et al. 2017). For example, the ERSs rumination, catastrophizing, and positive reappraisal would typically be evaluated as unique predictors in models examining mental health outcomes. However, separately examining multiple ERSs in a single model is not always practical (Naragon-Gainey et al. 2017). For example, the number of variables one can consider is sometimes limited due to factors such as small sample size. Further, mental health concerns have complex etiologies, often resulting from combinations of biopsychosocial and environmental factors (e.g., Cuthbert and Insel 2013). Several constructs in addition to emotion regulation have accounted for variance in mental health outcomes, such as personality, trauma history, social identities and demographics, normative perceptions, and genomic and physiological factors, among others (American Psychiatric Association 2013). ERSs also appear to interact with other constructs that have shown robust associations with mental health concerns (e.g., Powell 2018).

Researchers aiming to evaluate several domains of risk and protective factors for mental health concerns often encounter power constraints, in which only a limited number of predictors can be justifiably examined in a single study. Power constraints are exacerbated when researchers examine complex relations between multiple predictors, such as mediation and moderation models (e.g., Wahlsten 1991). This parsimony constraint presents a problem for emotion regulation research; given the large number of ERSs that have been associated with mental health and the tendency for individuals to employ multiple strategies, it can be difficult to comprehensively include emotion regulation in complex models. While there can certainly be value in examining and intervening on individual ERSs (e.g., Berking et al. 2008; Sheppes et al. 2015), having a more parsimonious yet comprehensive option for examining ERSs could improve the predictive power of etiological models for mental health concerns. One solution to this difficulty is to identify underlying factors for sets of ERSs that have similar implications for outcomes (Naragon-Gainey et al. 2017).

ERSs have often been categorized as putatively adaptive or maladaptive, based on whether they display negative versus positive associations with psychopathology (Aldao and Nolan-Hoeksema 2010; Naragon-Gainey et al. 2017; Moumne et al. 2020; te Brinke et al. 2020). Depending on when they occur temporally in relation to an internal or external stimulus, ERSs can be antecedent-focused, regulating an emotional experience before it has fully developed, or response-focused, in which an emotional experience is regulated after it has fully developed (Gross and John 2003). Antecedent-focused strategies are generally considered more adaptive than response-focused strategies because they can reframe a negative emotional response before it becomes distressing (Gross and John 2003; Silvers et al. 2012). Notably, cognitive ERSs that are often considered maladaptive, such as rumination, suppression of negative thoughts, and catastrophizing, generally have larger effects on psychopathology than adaptive strategies, such as re-appraisal, acceptance, and problem-solving (Aldao and Nolen-Hoeksema 2010, 2012b; Aldao et al. 2010). Lack of adaptive strategies may therefore be less harmful than the presence of maladaptive strategies (Aldao and Nolen-Hoeksema 2010; Aldao et al. 2010).

However, focus on a particular strategy as adaptive or maladaptive may be inappropriate, as the adaptiveness of a strategy can be importantly influenced by context (Aldao and Nolen-Hoeksema 2012a, b; Barrett 2013; Gross 2015). For example, a problem- or planning-focused strategy is highly adaptive if a solution exists for the stressful context, but less so for a stressful event such as loss of a loved one, which cannot be truly remediated or even avoided in the future. By identifying underlying factor structures for several strategies that are more likely to be adaptive or maladaptive and combining these into a simplified measure, as opposed to selecting one or a few ERSs through methods such as regularization, one can better account for the context-dependent nature of specific strategies (Naragon-Gainey et al. 2017; te Brinke et al. 2020). Thus, it may be advantageous to have an overall measure for multiple putatively adaptive strategies versus multiple putatively maladaptive strategies. Reliance on more maladaptive versus adaptive cognitive ERSs have previously been examined using factor analysis (e.g., Naragon-Gainey et al. 2017; Skinner et al. 2003; te Brinke et al. 2020) and cluster analysis (e.g., Moumne et al. 2020) approaches. Results from these studies have generally supported two-factor structures that distinguish between greater overall reliance on adaptive versus maladaptive strategies. However, a more complex factor structure may be needed to accurately model some sets of ERSs (Aldao and Nolen-Hoeksema 2010; Naragon-Gainey et al. 2017; Seligowski and Orcutt 2015; Skinner et al. 2003).

Importantly, it is unknown if an underlying factor structure can be derived for one of the most commonly used measures of cognitive ERSs, the Cognitive Emotion Regulation Questionnaire (CERQ) (Garnefski et al. 2001, 2004; Garnefski and Kraaij 2007). The CERQ measures nine distinct cognitive ERSs and has been widely used internationally; its psychometric properties have been tested in adolescent (Garnefski et al. 2001) and adult (Garnefski and Kraaij 2007) samples, and it has been validated in several languages (e.g., Domínguez-Sánchez et al. 2013; Jermann et al. 2006; Zhu et al. 2008). Notably, large correlations have been observed between the ERSs measured by the CERQ (e.g., Ireland et al. 2017; Tuna and Bozo 2012), indicating the possibility of underlying latent factors among these subscales. Further, some groups of CERQ ERSs have consistently demonstrated similar associations with mental health constructs.

All nine ERSs measured by the CERQ have been identified as being putatively adaptive or maladaptive in previous research: the Positive Refocusing, Positive Reappraisal, Acceptance, Refocus on Planning, and Putting into Perspective subscales have shown negative associations with psychopathology, while the Catastrophizing, Rumination, Blaming Others, and Self-Blame subscales have demonstrated positive associations with psychopathology (Garnefski et al. 2001, 2004; Garnefski and Kraaij 2007). Accordingly, previous studies have tested and found support for a two-factor structure of adaptive and maladaptive subscales in the CERQ (e.g., Domínguez-Sánchez et al. 2013; Jermann et al. 2006), although findings have been mixed (e.g., McKinnon 2020). A bi-factor analysis of the five putatively maladaptive CERQ subscales supported a two-factor structure of implicit versus explicit ERSs, suggesting a more complex factor structure may be present among all nine subscales (Flores-Kanter et al. 2019). However, to our knowledge, no previous research has evaluated the underlying structures of all nine CERQ subscales beyond a two-factor adaptive versus. maladaptive strategy model. It is unknown if a two-factor approach is the most appropriate way to simplify the CERQ, or if a different number of underlying factors more accurately represents the CERQ's nine subscales. Given the widespread use of the CERQ and the importance of cognitive ERSs in mental health research, simplifying the CERQ into a more parsimonious structure could yield a useful measurement tool by accounting for several ERSs in multivariate mental health models without sacrificing model parsimony.

1.2 Present Study

The present study aimed to discern a novel, more parsimonious interpretation of ERSs from the CERQ. Using data from a large sample of university students, we employed Exploratory Structural Equation Modeling (ESEM) to evaluate underlying factor structures for cognitive ERSs from the nine strategies measured by the CERQ (Asparouhov and Muthén 2009; Marsh et al. 2014). ESEM was selected because it can account for the context-dependent nature of ERSs by allowing individual strategies to load onto multiple factors. In addition, we evaluated the clinical utility of these constructs in predicting several health-risk behaviors and mental health diagnoses, both within the ESEM and when the ERS factors were examined as observed variables. Thus, we assessed if discerned ERS constructs consistently predicted mental health outcomes when assessed in a structural equation model versus a non-multivariate regression framework, since some studies are better suited for one analysis type over the other.

Given previous research on the distinction between putatively adaptive and maladaptive ERSs, we hypothesized that a two-factor structure would be identified as the best-fitting model from the CERQ subscales. Specifically, we hypothesized that discerned factors would align with previous research, such that the CERQ ERSs Rumination, Catastrophizing, Self-Blame, and Blaming Others would have high factor loadings on a maladaptive construct and low factor loadings on an adaptive construct, while Positive Refocusing, Positive Reappraisal, Acceptance, Refocus on Planning, and Putting into Perspective would have high factor loadings on an adaptive construct and low factor loadings on a maladaptive construct (Garnefski et al. 2001, 2004; Garnefski and Kraaij 2007; Moumne et al. 2020). We also hypothesized that the putatively adaptive (negatively) and maladaptive (positively) strategy constructs would significantly predict health-risk behaviors and mental health diagnoses and, given previous literature (Aldao and Nolen-Hoeksema 2010; Aldao et al. 2010), that maladaptive strategies would have larger effect sizes across mental health outcomes than adaptive strategies.

2 Method

2.1 Participants

Data came from 2,077 students at a university in the Mountain West of the United States who completed an online survey with self-report measures of emotion regulation, mental health diagnoses, and health-risk behaviors. Participants were sampled from psychology courses and received research credit for their participation. Self-identified characteristics of the cross-sectional sample were: 67.2% female sex, 98.5% cisgender, 85.1% heterosexual, M_{age} = 19.61 years (SD=2.15), 18.7% Hispanic or Latino ethnicity, and 3.8% American Indian or Alaska Native, 6.56% Asian, 4.07% Black or African American, 0.91% Native Hawaiian or Other Pacific Islander, and 88.22% White race (3.16% “do not wish to respond”). Informed consent was obtained from all participants and study procedures were approved by the Institutional Review Board of the participating institution.

2.2 Measures

1. **2.2.1 Cognitive Emotion Regulation Strategies.** Reliance on nine cognitive ERSs was assessed with the 36-item Cognitive Emotion Regulation Questionnaire (CERQ) (Garnefski and Kraaij 2007; Garnefski et al. 2001). CERQ items were assessed on a 5-point Likert-style scale ranging from 1 (almost never) to 5 (almost always). For each item, participants indicated how frequently the statement applied to them after or while experiencing a "stressful or threatening" event; the CERQ measures responses to anxiety situations, and may therefore provide a more accurate representation of emotion regulation tendencies for avoidance emotions than for approach emotions. Each of the nine CERQ subscales includes four items, and internal consistency values ranged from acceptable to good in the present sample. The Self-blame subscale measures the tendency to blame oneself for negative experiences (α=0.82, ω=0.82). Blaming Others refers to blaming other people and/or the environment for negative experiences (α=0.77, ω=0.79). Catastrophizing measures the tendency to emphasize the negativity of a distressing experience (α=0.71, ω=0.73). The Rumination subscale measures compulsively focusing on the feelings associated with the negative experience (α=0.71, ω=0.71). Positive Refocusing measures the propensity to think about other, positive things instead of the negative experience (α=0.82, ω=0.83). The Positive Reappraisal subscale measures participants' tendency to reframe the event in a positive light (α=0.87, ω=0.87). Acceptance gauges thoughts of resigning oneself to what they experienced (α=0.79, ω=0.80). Refocus on Planning assesses the frequency of thinking about solution-focused steps to address the negative experience (α=0.79, ω=0.80). Putting into Perspective refers to thoughts of comparing the magnitude of the event to previous experiences and the experiences of others (α=0.81, ω=0.81).
2. **2.2.2 Health-risk Behaviors.** Seven health-risk behaviors were examined as binary outcome variables: past 30-day heavy alcohol use, lifetime presence of uncommon drug use, lifetime presence of attempted suicide, lifetime presence of serious suicidal ideation, engaging in non-suicidal self-injury (NSSI) multiple times, past 6-month daily disordered eating, and past-12 month engagement in unprotected sex.

Heavy alcohol use was assessed with the item "in the past 30 days, how many times have you consumed five or more drinks (if you are male) or four or more drinks (if you are female) on one drinking occasion?" These alcohol use patterns represent criteria for binge drinking, and binge drinking five or more times within a 30-day period denotes heavy alcohol use (National Institute on Alcohol Abuse and Alcoholism 2019). Participants were coded as 0 if they reported less than five past 30-day binge drinking episodes and were coded as 1 if they reported five or more binge drinking episodes.

Uncommon drug use was measured with the items "have you ever used: ketamine/special K, heroin, pills/prescription drugs not for medical reasons but to get high, cocaine, crack, methamphetamine, inhalants or huffed anything in order to get high, or a substance not yet mentioned to get high?" Participants were coded as 1 if they endorsed lifetime use of one or more of these substances and as 0 if they did not. These drugs have relatively low use prevalence rates among university students (e.g., Johnston et al. 2016) and are often associated with poor health consequences and increased likelihood of severe substance use patterns compared to more commonly used drugs (e.g., National Institute on Drug Abuse 2020).

Lifetime presence of attempted suicide was measured with the item "have you ever attempted to take your own life?" Lifetime presence of serious suicidal ideation was assessed with the item "have you ever seriously considered taking your own life?" For both items, participants who responded "no, never" were coded as 0, while participants who responded "yes, more than a year ago" or "yes, within the last year" were coded as 1. NSSI was measured with the item "how many times in your life have you hurt yourself on purpose?" Participants were coded as 0 if they reported NSSI once or never, and coded as 1 if they reported having engaged in NSSI multiple times. While engaging in NSSI once can indicate distress, individuals who endorse multiple occasions of NSSI typically report more severe NSSI behavior and overall distress (Nock and Prinstein 2004).

Disordered eating was measured with three items from the Eating Attitudes Test (EAT-26) (Garner et al. 1982): "In the past six months have you: gone on eating binges where you feel that you may not be able to stop, ever made yourself sick (vomited) to control your weight or shape, ever used laxatives, diet pills or diuretics (water pills) to control your weight or shape?" Participants respond on a 6-point Likert-style scale ranging from 0 (never) to 6 (once a day or more). Participants were coded as 1 if they endorsed any form of daily disordered eating (i.e., responded "6" to one or more item) and 0 if they did not.

Unprotected sex was measured with the items "how many times in the last 12 months have you had unprotected vaginal and/or anal intercourse?" Participants who endorsed engagement in any past 12-month unprotected sexual intercourse were coded as 1, while those who did not were coded as 0.

2.2.1 Mental Health Diagnoses

Self-reported lifetime presence of seven mental health diagnoses was assessed with the following item: "Have you ever been diagnosed with and/or treated by a professional for any of the following conditions: Depression, Anxiety, Post-Traumatic Stress Disorder (PTSD), Obsessive Compulsive Disorder (OCD), Attention Deficit Hyperactivity Disorder (ADHD), Anorexia, Bulimia, and/or any other Eating Disorder, and Insomnia and/or any other Sleep Disorder?" For each diagnosis, participants were coded as 1 if they endorsed the diagnosis and 0 if they did not.

2.3 Analysis plan

Data were wrangled in R version 4.0.4 (R Core Team 2022) using tidyverse packages (Wickham et al. 2019). CERQ internal consistency metrics were calculated using the psych package (Revelle 2022) (see "Measures" for α and ω values). Prior to analyses, missing data mechanisms were assessed using the naniar package (Tierney et al. 2021) and Little's test suggested data were Missing Completely at Random ($\chi^2 = 2057.15$, $p = 0.996$). Rates of missing data on study variables ranged from 0.19 to 3.32%. Given the number of statistical tests conducted, alpha was specified as $p < 0.005$; although there is debate about significance thresholds in the behavioral sciences (e.g., Lakens et al. 2018), $p < 0.005$ was selected in the current study in order to balance the risk of Type I and Type II errors (Benjamin et al. 2018; Machery 2021).

The first analysis goal was to derive underlying latent factors for cognitive ERSs using ESEM. ESEM is a type of multivariate analysis that integrates advantages of Exploratory Factor Analysis (CFA), Confirmatory Factor Analysis (CFA), and structural equation modeling (Asparouhov and Muthén 2009; Marsh et al. 2014). Specifically, ESEM allows for a more realistic representation of the data than CFA by allowing cross-loadings to be estimated across latent factors, as in an EFA; fixing parameter estimates to zero in a CFA contributes to model misfit, since cross-loadings exist in most data (Asparouhov and Muthén 2009). Further, ESEM allows for estimation of *a priori* models, accounts for measurement error in latent constructs, and provides goodness-of-fit statistics (Marsh et al. 2014). ESEM was appropriate for the current study because previous research indicates that ERSs can vary across contexts (e.g., Aldao and Nolen-Hoeksema 2012a, 2012b), suggesting that constraining cross-loadings for each ERS to zero is likely too restrictive to accurately represent these constructs (e.g., Naragon-Gainey et al. 2017). Use of ESEM is also particularly appropriate for examining underlying factor structures of the nine CERQ ERSs. Sizeable correlations between some CERQ ERSs in previous studies (e.g., Ireland et al. 2017; Tuna and Bozo 2012) indicate a likelihood of underlying latent factors among these subscales. Previous studies have used traditional CFA or bi-factor modeling approaches to examine underlying two-factor structures for either all nine (e.g., Domínguez-Sánchez et al. 2013; Jermann et al. 2006) or a subset (Flores-Kanter et al. 2019) of the CERQ subscales. However, CFA and bi-factor models force variables to load onto a single factor, which could introduce misfit by not accounting for the context-dependent nature of cognitive ERSs. By allowing the ERSs to load onto multiple factors, ESEM may provide a more accurate depiction of the CERQ ERSs' underlying latent structure.

ESEMs were conducted in Mplus version 8 (Muthén and Muthén 1998–2022). Model indicators were the nine CERQ subscales, each calculated as the mean of its four items (Garnefski et al. 2001). It is important to note that some studies have identified poorly performing items, cross-loading items, and/or model misfit in the CERQ's nine-factor structure (e.g., Carvajal et al. 2022; Flores-Kanter et al. 2019; Ireland et al. 2017; McKinnon et al. 2020). However, the CERQ's originally published nine-factor structure has been most widely used internationally, is validated in several languages and populations (e.g., Tuna and Bozo 2012; Zhu et al. 2008), and demonstrated good internal consistency in the present sample. Structural model parameters are also generally robust to error from parceling items into manifest subscale scores (Rhemtulla 2016). Hence, we elected to model the CERQ's original nine subscales as indicators to make our results more translatable to broader use of the CERQ. Individual CERQ items were also not used as indicators because the primary study aim was to evaluate an underlying latent structure for ERSs as represented by the CERQ subscales, rather than a re-evaluation of the CERQ's item-level psychometric properties. Moreover, by allowing the nine original subscales to freely load onto each ESEM factor, ESEM models account for some misfit that could arise from measurement error within individual items and subscales of the CERQ.

We evaluated one- through four-factor models for the ESEM. Models with five or more factors were not tested due to statistical power considerations and to avoid single-indicator latent variables. The latent factors were allowed to correlate in all models. Model fit for the ESEM was evaluated with the comparative fit index (CFI), Tucker Lewis index (TLI), root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Values ≥ 0.90 indicate good fit and values ≥ 0.95 indicate excellent fit for

CFI and TLI, values < 0.06 represent good fit for RMSEA, and values < 0.08 represent good fit for SRMR (Hu and Bentler 1999; Tabachnick and Fidell 2013, p. 720–725). The sample-size adjusted Bayesian information criterion (BIC) was used to evaluate comparative fit across models, and smaller BIC values are preferred. We also evaluated model χ^2, in which a non-significant test statistic denotes good model fit to the sample. The χ^2 test is sensitive to sample size; the likelihood of having a significant test statistic increases with sample size (Tabachnick and Fidell 2013, p. 720). Factor loadings represent the strength of the relation between each indicator (CERQ subscale score) and the underlying latent factor. While factor loadings ≥ 0.162 can be statistically significant for sample sizes of 1000 or more (Field et al. 2012), in general, loadings ≥ 0.71 are considered excellent, ≥ 0.55 are considered good, and loadings ≤ 0.32 are considered poor (Comrey and Lee 1992).

The second analysis goal was to evaluate the utility of the identified ESEM factors in predicting mental health outcomes. Binary variables for the seven health-risk behaviors and seven mental health diagnoses were assessed in the ESEM using probit regression, in which each outcome was regressed onto the ERS factors. All 14 mental health outcomes were allowed to correlate. Though less commonly used in the behavioral sciences, probit regression is similar to logistic regression in that both focus on the proportions of responses across categories of a dependent variable. Probit models utilize a probit transformation in which observed proportions are replaced by the *z*-scores (i.e., values in the metric of standard deviations from the mean) below the observed proportion (Tabachnick and Fidell 2002, p. 458–459). Probit regression coefficients are interpreted as the change in *z*-score of the binary outcome for every one-unit increase in the predictor. Although logistic regression is preferable when outcomes are unbalanced (Tabachnick and Fidell 2002, p. 458–459), as in the current study, the logit link is not available for categorical outcomes within ESEM in Mplus (Muthén and Muthén 1998–2022). Measurement models used the Maximum Likelihood (ML) estimator (Muthén and Muthén 1998–2022). Because outcomes were categorical, the ESEM structural model used the Weighted Least Square Mean and Variance Adjusted (WLSMV) estimator (Muthén and Muthén 1998–2022). The ML estimator handles missing data using full information maximum likelihood, and WLSMV uses pairwise deletion in which all available data is used to estimate each model parameter.

The third analysis goal was to examine the utility of the identified ESEM ERS factors in predicting mental health outcomes when analyzed as observed, not latent, variables. This step aimed to determine if derived ERSs constructs displayed consistent relations with mental health outcomes when assessed in a non-multivariate regression framework without accounting for cross-loadings across factors, since some study designs may not be well-suited for structural equation modeling (e.g., due to small sample sizes). Using the R base package (R Core Team 2022), the seven health-risk behaviors and seven mental health diagnoses were regressed onto the identified ESEM ERS variables in logistic regressions (i.e., 14 binary logistic regressions total). Logistic regressions were estimated using complete cases.

Table 1 Goodness-of-fit indices for all ESEM models

	CFI	TLI	SRMR	RMSEA	χ^2	DF	BIC
Measurement model 1: One factor	0.607	0.476	0.149	0.209	2466.925***	27	41182.658
Measurement model 2: Two factors	0.884	0.780	0.057	0.136	740.601***	19	39491.972
Measurement model 3: Three factors	**0.978**	**0.934**	**0.016**	**0.074**	**148.950*****	**12**	**38931.506**
Measurement model 4: Four factors	0.997	0.980	0.006	0.041	26.607***	6	38835.892
Structural model	0.992	0.980	0.017	0.023	14303.600***	–	–

Note: ***$p<0.001$. CFI = comparative fit index, TLI = Tucker Lewis index, SRMR = standardized root mean square residual, RMSEA = root mean square error of approximation, BIC = sample-size adjusted Bayesian information criterion. DF = degrees of freedom for the χ^2 test of model fit. Bolded text represents the model selected as the final measurement model. Significant χ^2 tests across models was considered unremarkable given the large sample size in the present study (N = 2,077). BIC and DF are not shown for the structural model due to use of the Weighted Least Square Mean and Variance Adjusted estimator.

3 Results

3.1 ESEM Measurement Model

CERQ subscales were treated as continuous and met assumptions of normality. The ESEM was specified using geomin rotation. We ran a series of measurement models in order to select the best-fitting model from one- through four-factor solutions for the nine CERQ subscales. Goodness-of-fit indices and standardized factor loadings for all models are presented in Tables 1 and 2, respectively. The covariance matrix for model indicators is shown in Table 3. After taking into account multiple fit indices, factor loadings and cross-loadings, and parsimony considerations, the three-factor solution was selected as the final measurement model. While fit indices indicated improved fit in the four-factor model, this model had a factor that was characterized by a large loading from only one CERQ subscale (Putting Into Perspective) and generally had smaller target loadings than the three-factor solution, making the factors less interpretable. The three-factor solution was selected because we aimed to identify the most parsimonious model that adequately depicted the data, and all fit indices in the three-factor model were in the good to excellent range. The first factor was characterized by largest factor loadings from the CERQ ERSs Positive Refocusing, Positive Reappraisal, Refocus on Planning, and Putting into Perspective. Because these four subscales generally involve positive and/or solution-focused thinking, this factor was termed "Positive ERSs." The second factor was characterized by largest factor loadings from Rumination, Self-Blame, and Acceptance. These three subscales generally involve negative thoughts about oneself and resignation about difficult situations. Hence, this factor was termed "Internally-Oriented Negative ERSs." The third factor had largest factor loadings from Catastrophizing and Blaming Others, both of which involve negative thinking about factors outside of oneself, including comparing oneself to others or blaming others for troubles. This factor was therefore termed "Externally-Oriented Negative ERSs." Target factor loadings for the three ESEM factors were all significant and ranged from good to excellent (>0.55), and cross-loadings were generally either small (<0.30) or negative in the expected direction. Cross-loadings<0.32 were not substantively interpreted due to their small size (Comrey and Lee 1992). Nonetheless, the presence of small cross-loadings in the measurement model (Table 2) supports use of ESEM over traditional SEM, which would restrict all cross-loadings to zero, for modeling the structure of the CERQ ERSs.

Table 2 Standardized factor loadings for 1- through 4-factor ESEM measurement models

	Standardized factor loading (*SE*)			
	1-Factor Model	2-Factor Model	3-Factor Model	4-Factor Model
Factor 1				
Catastrophizing	−0.124 (0.024)	−0.137 (0.024)	−0.006 (0.002)	−0.042 (0.015)
Blaming Others	0.001 (0.024)	−0.011 (0.023)	0.213 (0.036)	0.044 (0.022)
Self-Blame	−0.002 (0.024)	−0.005 (0.003)	−0.418 (0.043)	0.068 (0.032)
Rumination	0.239 (0.023)	0.250 (0.024)	0.007 (0.005)	−0.046 (0.019)
Acceptance	0.380 (0.021)	0.387 (0.021)	0.066 (0.041)	0.209 (0.114)
Positive Refocusing	0.557 (0.017)	0.545 (0.017)	**0.731 (0.025)**[1]	0.104 (0.070)
Refocus on Planning	0.833 (0.010)	0.823 (0.010)	**0.818 (0.015)**[1]	−0.038 (0.033)
Positive Reappraisal	0.896 (0.008)	0.914 (0.009)	**0.857 (0.015)**[1]	0.161 (0.116)
Putting into Perspective	0.703 (0.013)	0.701 (0.013)	**0.549 (0.028)**[1]	1.002 (0.157)
Factor 2				
Catastrophizing		0.622 (0.020)	0.329 (0.038)	−0.052 (0.013)
Blaming Others		0.335 (0.025)	0.013 (0.004)	0.082 (0.042)
Self-Blame		0.660 (0.019)	**0.851 (0.031)**[2]	−0.27 (0.079)
Rumination		0.703 (0.018)	**0.659 (0.020)**[2]	0.142 (0.072)
Acceptance		0.432 (0.021)	**0.611 (0.030)**[2]	0.073 (0.040)
Positive Refocusing		0.017 (0.024)	−0.130 (0.030)	0.589 (0.079)
Refocus on Planning		0.015 (0.020)	0.046 (0.023)	0.886 (0.018)
Positive Reappraisal		−0.107 (0.021)	0.011 (0.005)	0.737 (0.081)
Putting into Perspective		−0.004 (0.007)	0.182 (0.026)	0.016 (0.006)
Factor 3				
Catastrophizing			**0.775 (0.029)**[3]	0.317 (0.043)
Blaming Others			**0.593 (0.030)**[3]	0.007 (0.016)
Self-Blame			0.004 (0.002)	0.764 (0.031)
Rumination			0.201 (0.029)	0.656 (0.027)
Acceptance			−0.079 (0.035)	0.527 (0.038)
Positive Refocusing			0.266 (0.027)	−0.111 (0.025)
Refocus on Planning			0.013 (0.011)	0.101 (0.024)
Positive Reappraisal			−0.104 (0.030)	0.024 (0.018)
Putting into Perspective			−0.190 (0.031)	0.014 (0.005)
Factor 4				
Catastrophizing				0.726 (0.043)
Blaming Others				0.583 (0.032)
Self-Blame				−0.003 (0.011)
Rumination				0.146 (0.035)
Acceptance				−0.041 (0.028)
Positive Refocusing				0.277 (0.026)
Refocus on Planning				−0.010 (0.009)
Positive Reappraisal				−0.074 (0.026)
Putting into Perspective				0.005 (0.007)

Note: N=2,077. Bolded text represents the primary factor interpretations in the final measurement model. [1] Positive ERS factor, [2] Internally-Oriented Negative ERS factor, [3] Externally-Oriented Negative ERS factor.

The Positive factor was positively correlated with the Internally-Oriented Negative Fac-

Table 3 Covariance matrix for the ESEM measurement model indicators

Indicator	1	2	3	4	5	6	7	8	9
1. Catastrophizing	0.596								
2. Blaming Others	0.222	0.396							
3. Self-Blame	0.248	0.055	0.755						
4. Rumination	0.245	0.100	0.340	0.643					
5. Acceptance	0.103	0.021	0.265	0.269	0.663				
6. Positive Refocusing	0.054	0.068	−0.060	0.093	0.110	0.740			
7. Refocus on Planning	−0.057	0.019	0.002	0.176	0.212	0.389	0.767		
8. Positive Reappraisal	−0.132	−0.026	−0.054	0.137	0.255	0.407	0.651	0.980	
9. Putting into Perspective	−0.109	−0.013	0.053	0.113	0.281	0.307	0.428	0.580	0.823

tor ($r=0.432$, $p<0.001$) and negatively correlated with the Externally-Oriented Negative Factor ($r=-.329$, $p<0.001$). The correlation between the Internally-Oriented Negative and Externally-Oriented Negative factors was null ($r=0.056$, $p=0.293$).

3.2 ESEM Structural Model

Prevalence rates for each mental health outcome in the sample were as follows: heavy alcohol use = 19.8%, uncommon drug use = 19.1%, suicide attempt = 11.3%, suicidal ideation = 26.4%, multiple engagement in NSSI = 26.2%, daily disordered eating = 21.8%, unprotected sex = 30.3%, depression = 24.9%, anxiety = 28.6%, PTSD = 5%, OCD = 3.2%, ADHD = 7.4%, eating disorder = 4.4%, and sleep disorder = 5.4%. The ESEM structural model that regressed mental health outcomes onto the latent ERS factors is presented in Fig. 1. Probit regression coefficients of the ERS factors predicting each mental health outcome are shown in Table 4. At $p<0.005$, the Positive latent ERS factor predicted lower likelihood of NSSI, suicidal ideation, attempted suicide, disordered eating, and self-reported diagnoses of depression, anxiety, PTSD, ADHD, an eating disorder, and a sleep disorder. The Internally-Oriented Negative latent ERS factor predicted higher likelihood of NSSI, suicidal ideation, attempted suicide, disordered eating, uncommon drug use, and self-reports of all seven mental health diagnoses (depression, anxiety, PTSD, OCD, ADHD, an eating disorder, and a sleep disorder). The Externally-Oriented Negative latent ERS factor predicted lower likelihood of NSSI. Effects on mental health outcomes were generally largest for the Internally-Oriented Negative strategy factor.

3.3 Logistic regressions of observed ERS variables Predicting Mental Health Outcomes

Logistic regression results for adaptive and maladaptive variables predicting mental health diagnoses are presented in Table 5. Each observed ERS variable was calculated as a *z*-score of the mean of the primary contributing CERQ subscales for each ESEM factor. The Positive ERS factor was calculated as the mean of the Positive Refocusing, Positive Reappraisal, Refocus on Planning, and Putting into Perspective subscales. The Internally-Oriented Negative ERS factor was calculated as the mean of the Rumination, Self-Blame, and Acceptance subscales, and the Externally-Oriented Negative ERS factor was calculated as a mean of the Catastrophizing and Blaming Others subscales. The three observed ERS variables met

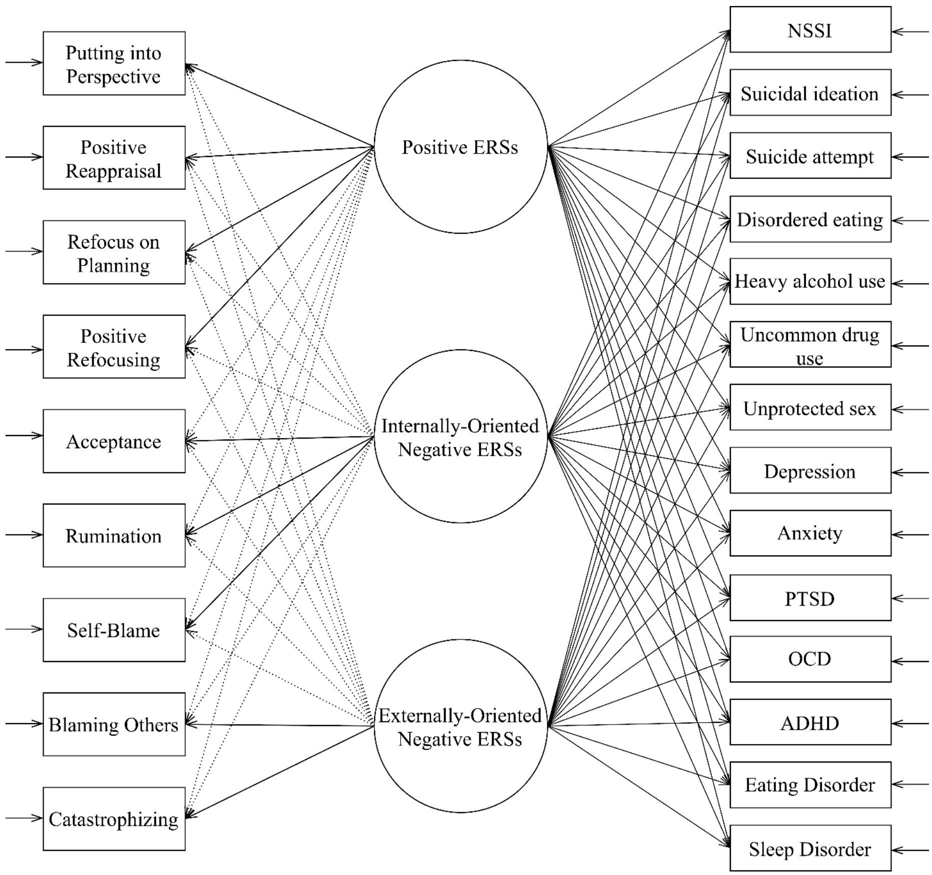

Fig. 1 ESEM structural model. Binary mental health outcomes were regressed onto the three latent ERS factors discerned by the ESEM. All outcomes were allowed to correlate. ERSs = emotion regulation strategies

assumptions of normality. At $p < 0.005$, the Positive ERS variable predicted lower likelihood of NSSI, suicidal ideation, attempted suicide, and diagnoses of depression, anxiety, and a sleep disorder. The Internally-Oriented Negative ERS variable predicted increased likelihood of NSSI, suicidal ideation, attempted suicide, disordered eating, uncommon drug use, and all seven mental health diagnoses (depression, anxiety, PTSD, OCD, ADHD, an eating disorder, and a sleep disorder). The Externally-Oriented Negative ERS variable predicted reduced likelihood of NSSI and increased likelihood of heavy alcohol use. Again, effects on mental health outcomes were generally largest for the Internally-Oriented Negative strategy variable.

Table 4 Probit regression statistics for the ESEM structural model

	Positive ERSs		Internally-Oriented Negative ERSs		Externally-Oriented Negative ERSs	
	B (*SE*)	95% CI	*B* (*SE*)	95% CI	*B* (*SE*)	95% CI
Health-risk behaviors						
NSSI	−0.503 (0.043)***	−0.588, 0.418	0.564 (0.040)***	0.486, 0.641	−0.192 (0.040)***	−0.270, −0.114
Suicidal ideation	−0.447 (0.041)***	−0.527, −0.366	0.556 (0.037)***	0.483, 0.630	−0.088 (0.040)°	−0.166, −0.011
Suicide attempt	−0.347 (0.050)***	−0.445, −0.250	0.451 (0.047)***	0.360, 0.543	−0.018 (0.046)	−0.108, 0.072
Disordered eating	−0.166 (0.044)***	−0.253, −0.080	0.243 (0.043)***	0.159, 0.327	0.008 (0.042)	−0.074, 0.090
Heavy alcohol use	−0.027 (0.045)	−0.116, 0.063	0.035 (0.044)	−0.051, 0.121	0.071 (0.045)	−0.017, 0.160
Uncommon drug use	−0.094 (0.045)°	−0.182, −0.007	0.179 (0.044)***	0.094, 0.265	−0.104 (0.045)°	−0.193, −0.016
Unprotected sex	−0.005 (0.040)	−0.083, 0.073	0.061 (0.040)	−0.017, 0.139	−0.041 (0.039)	−0.118, 0.035
Mental health diagnoses						
Depression	−0.418 (0.041)***	−0.498, −0.338	0.458 (0.039)***	0.381, 0.535	−0.079 (0.040)°	−0.157, −0.001
Anxiety	−0.319 (0.040)***	−0.398, −0.240	0.378 (0.040)***	0.300, 0.455	−0.022 (0.040)	−0.100, 0.055
PTSD	−0.232 (0.061)***	−0.351, −0.113	0.320 (0.061)***	0.201, 0.440	−0.020 (0.058)	−0.134, 0.095
OCD	−0.104 (0.072)	−0.246, 0.038	0.247 (0.068)***	0.114, 0.379	−0.078 (0.069)	−0.212, 0.056
ADHD	−0.147 (0.052)**	−0.248, −0.045	0.160 (0.054)**	0.054, 0.266	−0.113 (0.057)°	−0.224, −0.001
Eating disorder	−0.281 (0.066)***	−0.410, −0.153	0.443 (0.063)***	0.320, 0.566	−0.136 (0.060)°	−0.254, −0.019
Sleep disorder	−0.389 (0.059)***	−0.504, −0.274	0.380 (0.056)***	0.270, 0.489	−0.007 (0.050)	−0.104, 0.091

Note: °$p<0.05$, *$p<0.01$, ** $p<0.005$, ***$p<0.001$. CI = confidence interval. N=2,077. Model estimates are presented in the metric of z-scores.

4 Discussion

The current study developed a novel empirical method of examining general reliance on different domains of cognitive emotion regulation strategies (ERSs). Exploratory structural equation modeling (ESEM) successfully discerned a parsimonious underlying structure for the nine strategies measured by the Cognitive Emotion Regulation Questionnaire (CERQ). We initially hypothesized a two-factor solution would be identified to represent overall reliance on putatively adaptive versus maladaptive strategies. However, our results suggest a more nuanced underlying factor structure, particularly for strategies that have been previously identified as maladaptive. A three-factor solution was selected as the best-fitting model. The first factor, Positive ERSs, was characterized by four ERSs that generally involve positive or solution-focused thinking: Positive Refocusing, Positive Reappraisal,

Table 5 Logistic regression statistics for observed emotion regulation strategy constructs predicting mental health outcomes

		Positive ERSs		Internally-Oriented Negative ERSs		Externally-Oriented Negative ERSs	
	N	*B* (*SE*)	*OR* (95% CI)	*B* (*SE*)	*OR* (95% CI)	*B* (*SE*)	*OR* (95% CI)
Health-risk behaviors							
NSSI	1754	−0.541 (0.062)***	0.582 (0.515, 0.656)	0.772 (0.065)***	2.163 (1.908, 2.460)	−0.185 (0.062)**	0.831 (0.736, 0.937)
Suicidal ideation	1758	−0.520 (0.062)***	0.594 (0.526, 0.670)	0.772 (0.065)***	2.165 (1.908, 2.465)	0.002 (0.060)	1.002 (0.891, 1.126)
Suicide attempt	1755	−0.401 (0.078)***	0.670 (0.573, 0.780)	0.621 (0.080)***	1.861 (1.593, 2.179)	0.101 (0.077)	1.106 (0.949, 1.286)
Disordered eating	1743	−0.164 (0.060)*	0.849 (0.754, 0.955)	0.255 (0.063)***	1.291 (1.141, 1.460)	0.097 (0.061)	1.102 (0.977, 1.241)
Heavy alcohol use	1751	−0.042 (0.063)	0.958 (0.848, 1.084)	0.002 (0.067)	1.002 (0.878, 1.141)	0.179 (0.063)**	1.195 (1.055, 1.353)
Uncommon drug use	1685	−0.037 (0.064)	0.963 (0.850, 1.092)	0.202 (0.068)**	1.223 (1.071, 1.397)	−0.057 (0.067)	0.945 (0.827, 1.078)
Unprotected sex	1734	0.028 (0.054)	1.029 (0.926, 1.143)	0.063 (0.057)	1.065 (0.951, 1.191)	−0.003 (0.056)	0.997 (0.894, 1.112)
Mental health diagnoses							
Depression	1760	−0.485 (0.061)***	0.616 (0.546, 0.693)	0.590 (0.063)***	1.804 (1.596, 2.042)	−0.004 (0.060)	0.996 (0.885, 1.120)
Anxiety	1760	−0.341 (0.057)***	0.711 (0.636, 0.794)	0.472 (0.059)***	1.604 (1.429, 1.803)	0.054 (0.057)	1.055 (0.944, 1.179)
PTSD	1760	−0.236 (0.107)°	0.790 (0.639, 0.973)	0.520 (0.109)***	1.681 (1.358, 2.081)	0.032 (0.108)	1.032 (0.831, 1.272)
OCD	1760	0.010 (0.133)	1.010 (0.778, 1.312)	0.413 (0.138)**	1.511 (1.148, 1.978)	−0.097 (0.139)	0.907 (0.685, 1.184)
ADHD	1760	−0.162 (0.093)	0.850 (0.708, 1.021)	0.264 (0.095)**	1.303 (1.079, 1.568)	−0.187 (0.102)	0.829 (0.677, 1.008)
Eating disorder	1760	−0.147 (0.114)	0.863 (0.690, 1.079)	0.606 (0.118)***	1.833 (1.455, 2.309_	−0.055 (0.118)	0.947 (0.747, 1.187)
Sleep disorder	1760	−0.504 (0.108) ***	0.604 (0.488, 0.744)	0.448 (0.104)***	1.565 (1.275, 1.920)	0.232 (0.104)*	1.261 (1.027, 1.544)

Note: °$p<0.05$, *$p<0.01$, ** $p<0.005$, ***$p<0.001$. *OR* = odds ratio, CI = confidence interval for the odds ratio. Emotion regulation strategy predictors were *z*-scored. Models were estimated using complete cases.

Refocus on Planning, and Putting into Perspective. The second factor, Internally-Oriented Negative ERSs, was characterized by three ERSs that involve negative focus on self and a lack of control to change a negative situation: Rumination, Self-Blame, and Acceptance. The third factor, Externally-Oriented Negative ERSs, was primarily distinguished by two ERSs that involve negative cognitions about factors outside of oneself: Catastrophizing and Blaming Others. These three ERS constructs differentially predicted several health-risk behaviors and mental health diagnoses when examined as both latent and mean-scored variables. Results from the two modeling approaches in predicting mental health outcomes were largely corroborative.

The Positive ERS factor in our model mostly aligned with our hypothesis of an adaptive strategy factor. The four strategies that comprised this factor have been suggested to have protective effects against mental health concerns (e.g., Garnefski et al. 2001; Garnefski et al. 2004; Garnefski and Kraaij 2018). Study results were consistent with previous literature, with this factor predicting reduced likelihood of mental health diagnoses and health-risk behaviors. The Internally-Focused Negative ERS factor generally supported our hypothesis of a maladaptive factor, although the grouping of Acceptance with Rumination and Self-Blame was unexpected. Acceptance has often been identified as an adaptive ERS (e.g., Moumne et al. 2020; Naragon-Gainey et al. 2017; te Brinke et al. 2020). However, other studies have demonstrated inconsistent associations between the CERQ Acceptance subscale and mental health outcomes, possibly due to less specific construct validity (Ireland et al. 2017; Martin and Dahlen 2005). While acknowledging a locus of control can be helpful for reducing in-the-moment distress, perseverating on the fact that one must resign themselves to a negative situation may conversely increase distress. Thus, the Acceptance subscale of the CERQ is likely to be highly context dependent, and the present study suggests this strategy is more prone to serving a maladaptive than a protective function against psychopathology (Martin and Dahlen 2005). Researchers using the CERQ in the future may interpret the Acceptance subscale with these considerations in mind. Nonetheless, results corroborate previously reported positive associations between mental health concerns and the Rumination and Self-Blame subscales (e.g., Garnefski et al. 2001; Garnefski et al. 2004, Garnefski and Kraaij 2007; Garnefski and Kraaij 2018; Garnefski et al. 2017; Jermann et al. 2006; Martin and Dahlen 2005). This factor predicted increased likelihood of nearly all the mental health concerns assessed in our models.

The Externally-Focused Negative ERS factor represents another set of ERSs that are conventionally considered to be maladaptive, as both the Catastrophizing and Blaming Other subscales have predicted increased psychopathology, and especially anxious symptoms, in past studies (e.g., Garnefski and Kraaij 2007; Garnefski and Kraaij 2018). Therefore, it was surprising that this factor was generally observed to have null or protective effects against mental health concerns in our models, and was positively correlated with the Positive ERS factor. The exception was the Externally-Focused Negative factor predicting increased odds of heavy alcohol use in the logistic regression, but not in the ESEM. This may be related to externalizing of negative thoughts contributing to concomitant externalizing behavior (i.e., alcohol use). However, the inconsistency in this result across modes of analysis warrants replication before interpreting this effect with confidence. Overall, when comparing the Internally-Oriented and Externally-Oriented Negative factors, results suggest negative cognitions are primarily problematic when focused on oneself instead of others. This three-factor model of the CERQ somewhat resembles underlying factors identified in previous studies on the structure of ERSs. Naragon-Gainey and colleagues (2017) also identified a three-factor solution that included an adaptive factor that was mostly characterized by problem solving, as well as a factor that focused on negative cognitive perseveration, including rumination and worrying. A separate study identified distinct factors for cognitive adaptive ERSs, including re-evaluating stressors and negative thoughts, and cognitive maladaptive ERSs, which included rumination and self-devaluation (te Brinke et al. 2020). Although these two studies examined different set of ERSs than the CERQ, underlying factors characterized by internally-directed negative perseveration or adaptive cognitive functioning may be common across domains of ERSs. Replication of a similar Externally-Focused Negative ERS factor in future research on ERS structures would increase confidence in this third factor identified by our model.

Another contribution of the present study is extension of previous research on differences between putatively adaptive and maladaptive ERSs across a wide range of mental health concerns. Findings emphasize that the ERSs in the Positive and Internally-Focused Negative constructs are transdiagnostic features of a wide range of mental health concerns (Aldao et al. 2016). Both of these constructs predicted several self-reported psychiatric diagnoses and engagement in health-risk behaviors. Further, results suggest ERSs, like other emotion-based constructs, are more salient risk and protective factors for suicidality, NSSI, and disordered eating than for substance use and risky sexual behavior, as evidenced by non-significant or comparatively smaller effect sizes for the latter outcomes (e.g., Germain and Hooley 2012; Weinbach et al. 2018). Both the ESEM and logistic regressions using this novel definition of the CERQ support previous research suggesting that presence of maladaptive strategies has larger impacts on mental health outcomes than adaptive strategies (Aldao and Nolen-Hoeksema 2010; Aldao et al. 2010; Garnefski et al. 2017). Across analyses, effects for the Internally-Focused Negative ERSs construct were generally larger than those for the Positive and Externally-Focused Negative ERS constructs. As discussed in the introduction, presence of any maladaptive strategies appears to strongly influence health-risk behaviors and psychopathology; adaptive strategies may significantly reduce risk for negative outcomes only in the absence of maladaptive strategies (Aldao and Nolen-Hoeksema 2010; Aldao et al. 2010). Hence, interventions that target ERSs to reduce distress and unhealthy behaviors (e.g., Affect Regulation Therapy, Cognitive Behavior Therapy, and Dialectical Behavior Therapy) may be most effective when they specifically prioritize reduction of negative self-talk and perseveration about one's powerlessness to change negative experiences, while replacing these with adaptive strategies that emphasize re-appraisal, perspective taking, positive thinking, and solution-focused planning.

The identified three-factor structure may provide a useful alternative to traditional methods of examining strategies individually. It is important to note that collapsing ERSs reduces specificity and contextual utility for understanding how individuals are impacted by use of single strategies (Aldao and Nolen-Hoeksema 2012a, b; Sheppes et al. 2015). However, there may be value in using this parsimonious three-factor method in future studies that aim to predict important mental health outcomes so as to target at-risk groups for intervention, to examine general emotion regulation trends across development or between cultures or populations, and/or to address parsimony constraints for statistical analyses. By combining several strategies into a single measure, one can better address the limitation of comparing a single strategy (e.g., cognitive reframing) as the only adaptive strategy and a single strategy (e.g. expressive suppression) as the only maladaptive strategy, despite potential variability in the contexts being referenced by participants when answering a questionnaire (Aldao and Nolen-Hoeksema 2012a, b; Naragon-Gainey et al. 2017). Because results from the two modeling approaches for the three ERS constructs were largely corroborative, we suggest it is appropriate to use either approach to examine relations between ERSs and mental health outcomes; use of a structural equation modeling versus non-multivariate regression approach could be selected based on study design considerations, such as the ratio of number of predictors to sample size.

4.1 Limitations and future directions

Results from the current study should be interpreted in the context of several limitations. First, data came from university students with over-representation of self-reported dominant social identities. Thus, results may not generalize to other populations, cultures, and age groups, and should be replicated in other samples. Nonetheless, the high rates of psychopathology and health-risk behaviors in the present sample indicate that continued research on emotion regulation and mental health concerns among university students specifically is warranted. Second, we used the CERQ's originally published nine subscales as indicators in our ESEM models. While the CERQ's nine-factor structure has been supported in numerous publications, some studies have identified misfit and cross-loading items in the measure (e.g., Flores-Kanter et al. 2019, Ireland et al. 2017). We did not have sufficient sample size to model the individual CERQ items in the ESEMs, and parceling the items into their respective subscales could have introduced variability to the models (Sterba 2019). There were not indications of concerning misfit in our models, but it will be important to replicate the three-factor ERS structure in future studies, particularly in samples for which the CERQ's nine-factor structure has not been well-supported (e.g., western clinical samples; McKinnon et al. 2020).

Third, psychometric scales generally measure dispositional tendencies for ERSs as opposed to use in specific contexts, making these interpretations more generalizable to behaviors across time (Aldao et al. 2010). Self-report measures of ERSs may be confounded by individual differences in participants' ability to identify internal cognitive and emotional experiences (e.g., alexithymia). Incorporating multiple measurement methodologies, such as behavioral measures, self-report instruments, and physiological indices (e.g., Cuthbert and Insel 2013) would provide a more global understanding of relations between emotion regulation and mental health outcomes. Fourth, this study only included nine cognitive ERSs. While the strategies measured by the CERQ have demonstrated clear associations with mental health outcomes, there is robust evidence that many other ERSs also contribute to mental health (e.g., thought and expressive suppression, emotional and experiential avoidance, etc.) (Aldao et al. 2010). Future research on the structure of ERSs that accounts for additional strategy domains (e.g., behavioral emotion regulation) may increase model prediction accuracy for mental health outcomes (e.g., Naragon-Gainey et al. 2017).

Fifth, the present study assessed risk for individual health-risk behaviors and self-reported mental health diagnoses. Different factors may impact risk for co-occurrences of these concerns (e.g., Spinhoven et al. 2014), and future research assessing multi-morbidity of mental health concerns may increase understanding of how emotion regulation relates to complex mental health presentations. Sixth, use of single-item measures for mental health outcomes that primarily focused on lifetime or recent presence of each outcome does not provide information about the severity and diverse presentations of mental health symptoms and engagement in health-risk behaviors. Self-reported mental health diagnoses could also be inaccurate. Finally, as mentioned earlier, the CERQ contextualizes ERSs in threat situations that might evoke more internalizing than externalizing responses. Therefore, the ERS factors derived in this study may be less applicable to externalizing difficulties such as ADHD, conduct disorder, and/or antisocial personality disorder. The finding that the factors generally had smaller effects on substance use and ADHD compared to other mental health outcomes is consistent with this possibility.

4.2 Conclusion

The present study examined overall reliance on different domains of cognitive ERSs via generation of a novel three-factor structure for nine strategies measured by the CERQ, including Positive ERSs, Internally-Oriented Negative ERSs, and Externally-Oriented Negative ERSs. This parsimonious method comprehensively accounts for several ERSs and predicted a wide range of mental health diagnoses and health-risk behaviors. Results extend and support previous research indicating maladaptive ERSs have larger risk-increasing effects on transdiagnostic mental health concerns than the protective effects of adaptive strategies. Specifically, results suggest ERSs involving negative cognitions about oneself have larger effects on mental health than strategies involving positive cognitions in general or negative cognitions about others. Thus, thorough assessment and prioritization of internally-directed negative thinking is likely important for reducing and preventing mental health concerns. This three-factor modeling approach for ERSs may provide a useful measurement tool for researchers aiming to examine cognitive emotion regulation in etiology models for mental health concerns.

Tables.

5.1 Funding No funding was received for conducting this study.

Declarations

5.2 Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

5.3 Ethics approval All study procedures were approved by the Institutional Review Board of the participating institution.

5.4 Consent.

Informed consent was obtained from all study participants.
5.5 Data, Material and Code Availability.
The data, materials, and statistical code that support the findings of this study are available from the corresponding author upon request.

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