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Unveiling the Network and Community Structures of Emotion Dysregulation: Sex Differences and Implications for Anxiety

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Abstract

As aberrant emotion regulation is evident in anxiety disorders, elucidating the relationships between emotion dysregulation processes and anxiety symptoms is of great clinical and theoretical relevance. The goal of the current study is to investigate sex differences in the relationships between emotion dysregulation processes and between emotion dysregulation and anxiety symptoms, using graph-based analyses. Using data from a large and diverse sample (N = 1373, M_{age} = 19.6 years, female: 67.4%, Hispanic/Latinx: 58.7%) collected in 2021-2022 at a regional university, the findings indicated that: 1) "limited access to emotion regulation strategies" was most strongly associated with the other aspects of emotion dysregulation; 2) emotion dysregulation processes were clustered into antecedent- and response-focused dimensions; 3) there existed minimal biological sex differences in the relationships between different emotion dysregulation processes and how they clustered; and 4) "worrying too much about different things and "becoming easily annoyed or irritable" were the most salient anxiety symptoms associated with emotion dysregulation. The potential directional effects between emotion dysregulation processes and anxiety symptoms were explored. The findings suggested that "limited access to emotion regulation strategies" was the most influential aspect of emotion dysregulation, especially in the context of anxiety, which should be the target for intervention.

Keywords: emotion dysregulation; network analysis; sex differences; anxiety.

Introduction

Problems in emotion regulation are present in many psychological disorders, and investigating how the dynamic processes involved in regulating emotions contribute to psychopathological symptoms is pivotal to understanding the emotion regulatory processes underlying mental health, as well as to identifying intervention and treatment targets (Lincoln et al., 2022; Sheppes et al., 2015). As emotion dysregulation is evident in anxiety disorders, it is of great relevance to elucidate the complex interrelationships between emotion regulatory processes and anxiety symptoms (Mennin et al., 2004, 2005, 2006).

The emergence of network analysis provides a valuable opportunity to achieve this goal by examining the interplay between different psychological phenomena, such as symptoms of a disorder

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(Epskamp & Fried, 2018; Mcnally, 2021). Meanwhile, sex differences are evident in emotion regulatory strategies and processes (Goubet & Chrysikou, 2019; Kaur et al., 2022; Nolen-Hoeksema & Aldao, 2011; van Middendorp et al., 2005). However, how the interplay, or relationships, between different emotion regulatory processes differs between males and females remains unknown. Hence, the present study aimed to examine the network and dimensional structures of emotion dysregulation, sex differences in such structures, and the relationships between emotion dysregulation and anxiety symptoms.

Emotion Dysregulation

Emotion regulation refers to the processes by which we influence which emotions we have, when we have them, and how we experience and express them (Gross, 1998b). As emotion regulation involves a series of processes, it is critical to examine how these processes operate together. Identifying the temporal structure of emotion regulation processes will permit targeted intervention at specific times. Several models exist that suggest a temporal and/or hierarchical organization of emotion regulation processes. According to the extended process model of emotion regulation, difficulties in specific emotion regulatory stages (i.e., identification, selection, implementation, and monitoring) and elements (i.e., perception, valuation, action, stopping, and switching) may result in different clinical symptoms and conditions. For example, impairments in the perception regulatory element (i.e., the representation of emotional and regulated states) during the identification regulatory stage (i.e., determining whether to regulate emotion or not) may lead to sustained attention to threatening information, which is characteristic of anxiety disorders (Lincoln et al., 2022; Sheppes et al., 2015).

One way of classifying the multifaceted emotion regulatory processes is based on whether the input or output of the emotion regulatory system is manipulated. Whereas antecedent-focused emotion regulation manipulates the input of the system, which includes processes such as attention deployment and cognitive appraisal, response-focused emotion regulation manipulates the output, which includes processes such as strategy selection and suppression. These two classes of emotion regulation were demonstrated to result in distinct psychological and physiological consequences. To illustrate, previous research found that whereas using suppression (a response-focused emotion regulation strategy) led to higher sympathetic nervous system activation when watching a disgust-evoking film, using reappraisal (an antecedent-focused strategy) did not impact physiology (Gross, 1998a). In terms of psychosocial consequences, one study found response-focused emotion dysregulation to be related to both psychopathology and social relationship problems, but antecedent-focused emotion dysregulation to only be associated with problems in social relationships (Berzenski, 2019). These findings highlight the importance of examining antecedent- and response-focused emotion (dys)regulation as two distinct sets of processes.

The Adaptive Coping with Emotions (ACE) model (Berking & Whitley, 2014) provides further justification for a temporal-focus classification of emotion regulatory processes. According to this model, adaptive emotion regulation is deemed as the complex situation-dependent interactions between several regulatory processes. When unconscious emotion regulation processes fail to alleviate negative emotions, individuals typically become aware of their emotions, which helps with conscious regulatory processes, like emotion identification and labeling. Being able to identify and label emotions contributes to understanding the causal and maintaining factors of negative emotions, which can result in either actively modifying or accepting and tolerating negative emotions, further leading to the readiness to confront new situations that are likely to evoke negative emotions. These adaptive emotion regulation processes are driven by effective self-support, which also fosters emotional awareness and understanding. The ACE model emphasizes the temporal order of emotion regulation skills and the complex interplay between the skills and provides a useful framework for examining (mal)adaptive consequences as emotion regulation unfolds along the theorized order of regulatory processes.

Given the multiple theoretical models described above that support a temporal process orientation, it is necessary to identify measurement tools that capture the full range of emotion regulation components that operate across this process. The Difficulties in Emotion Regulation Scale (DERS; Gratz & Roemer, 2004) provides the opportunity to capture the crosstalk between emotion regulation processes and their temporal order. The DERS assesses 6 aspects of emotion dysregulation, including "nonacceptance of emotional responses," "difficulty engaging in goal-directed behavior," "impulse control difficulties," "lack of emotional awareness," "limited access to emotion regulation strategies," and "lack of emotional clarity." Previous research, using factor analysis, showed that the 6 aspects of the DERS formed 2 clusters, which corresponded to antecedent-focused (including "lack of emotional awareness" and "lack of emotional clarity") and response-focused (including the remaining 4 aspects and "lack of emotional clarity" [cross-loaded]) emotion dysregulation, and these two clusters had distinct associations with psychosocial adjustment (Berzenski, 2019). These 6 aspects also map onto some of the processes proposed in the ACE model; to illustrate, "lack of emotional clarity" in the DERS may represent difficulties in identifying and labeling emotions in the ACE model, and "nonacceptance of emotional responses" in the DERS may represent problems in accepting and tolerating negative emotions in the ACE model. Hence, the DERS can be utilized to provide evidence for both the antecedent- and response-focused categorization of emotion regulation and the ACE model and is useful for examining aberrant regulatory processes and associated detrimental consequences.

Emotion Dysregulation and Anxiety

There is ample evidence that problems in emotion regulation are associated with psychopathology, especially anxiety (see Amstadter, 2008, for review). Mennin and colleagues (2004, 2005, 2006) proposed an emotion dysregulation model of generalized anxiety disorder (GAD) that conceptualized GAD as a syndrome involving difficulties in regulating emotions in various temporal processes, ranging from limited emotion understanding to negatively reacting to one's own emotions. They noted that individuals with GAD also experience heightened emotional intensity and overly rely on maladaptive cognitive regulatory strategies (e.g., worry). In addition, research suggests that all the DERS dimensions, except "lack of emotional awareness," differed significantly between analogue GAD and non-GAD samples and were significantly associated with analogue GAD diagnostic status, even after controlling for general negative affect (Salters-Pedneault et al., 2006). Notably, "limited access to emotion regulation strategies" had the largest effect size when comparing the two samples and strongest association when examining correlations (Salters-Pedneault et al., 2006). Moreover, as Cisler et al. (2010) reviewed, emotion dysregulation is significantly associated with anxiety disorder symptoms even after accounting for constructs such as general anxiety and depression, and the chronic and inflexible use of maladaptive emotion regulation strategies (e.g., suppression) may result in increasing fear and avoidance and thus lead to functional impairment that typically defines anxiety disorders. Hence, probing the relationships between anxiety symptoms and aberrant emotion regulation processes can provide critical insight into the affective etiology of anxiety, as well as intervention and treatment targets.

Emotion Dysregulation Network

In recent years, network analysis has garnered increasing attention and stimulated scientific progress in understanding behavior from a new perspective. In the network analysis framework, psychological constructs are conceptualized as a complex interplay between their components, rather than caused by an underlying latent entity (Epskamp et al., 2018; Epskamp & Fried, 2018). In a psychological network, we can estimate not only the strength of the relationship between pairs of variables but also the importance of a variable in the network, indicated by centrality indices. Applying such an approach to emotion dysregulation allows us to examine the interaction between different regulatory processes, whether specific processes are more influential than the others, and whether specific processes are more connected to psychopathological symptoms than the others. In addition, some variables (or nodes) in a psychological network may cluster together to represent an underlying dimension of a construct. Such dimensions are referred to as "communities," representing coherent sub-networks within the larger network. How well a node within a community is connected to nodes in the other communities can be calculated, and this statistic can help identify the candidates for intervention.

However, extant network analysis research on emotion dysregulation is sparse, and among the few studies on emotion dysregulation networks, many of them only examined static emotion regulation processes (i.e., focused on certain types of regulation strategy; Guo et al., 2023; Zhang et al., 2022). Hence, as dynamic emotion regulatory processes were considered the novel focus of the current study, we only reviewed emotion dysregulation network studies that permit the scrutinization of such dynamic processes. A prior study, using data from 463 community women and a brief version of the DERS, suggested that the most influential node in the emotion dysregulation network was an aspect of "limited access to emotion regulation strategies," followed by aspects of "impulse control difficulties" and "nonacceptance of emotional responses" (Haws et al., 2022). Another study constructed a network involving emotion dysregulation, depression, and anxiety using the DERS in 209 adolescent mental health patients (Ruan et al., 2023). Within the emotion dysregulation community (i.e., subnetwork or group), the strongest edge was between "limited access to emotion regulation strategies" and "difficulties engaging in goal-directed behavior." In addition, "limited access to emotion regulation strategies" was the most central node in the network, indicated by both centrality and bridge centrality indices, revealing its pivotal role in emotion dysregulation and internalizing symptoms. "Lack of emotional clarity" also showed a strong connection to anxiety and depression symptoms. Within the anxiety community, "worry" and "relax" were the most strongly connected to the other two communities. Taken together, the prior emotion dysregulation network analytic work suggests that "limited access to emotion regulation strategies" was the most important aspect of emotion dysregulation both among different emotion dysregulation processes and in the context of internalizing psychopathology, including anxiety symptoms. Hence, this element of emotion dysregulation represents an important potential target for intervention and a candidate mechanism for explaining the way in which management of negative emotions may specifically influence the development and maintenance of internalizing problems.

These two studies were great endeavors to scrutinize the intricate relationships between different emotion regulatory processes and their relationships with internalizing psychopathology, but they also suffered from limitations such as limited generalizability (due to the female-only sample) and centrality instability (i.e., results were less reliable due to the limited sample size). These limitations precluded us from understanding the network structure of emotion dysregulation in males and whether such structure differs between males and females. Also, no study, to our knowledge, has explored whether the antecedent- and response-focused emotion regulation communities (which resemble factors in factor analysis) would emerge in an emotion (dys)regulation network.

Sex Differences in Emotion Regulation

Sex and gender differences in emotion regulation have been documented. Prior research suggested that women were more likely to utilize a variety of emotion regulation strategies than men (e.g., rumination, problem-solving, reappraisal; Nolen-Hoeksema & Aldao, 2011). Using the DERS, Kaur and colleagues (2022) reported that while males scored higher on "nonacceptance of emotional responses" and "impulse control difficulties," females scored higher on "lack of emotional clarity." In addition, gender-specific associations between emotion regulation styles and perceived health were stronger in females than males, particularly for the affective domain of health, in physical health patients (van Middendorp et al., 2005). Moreover, women were found to utilize more emotion regulation strategies and be more flexible when using such strategies on average; however, men were more likely to engage in acceptance and suppression strategies than women (Goubet & Chrysikou, 2019). These findings underscored the importance of examining sex and gender differences in emotion regulation and highlighted the need for sex- and gender-specific prevention, intervention, and treatment for psychopathology related to emotion dysregulation.

However, most of the prior studies examined sex and gender differences in emotion regulation at the strategy-specific level (i.e., probing mean differences in the use of specific strategies), so the relationships and interactions between different temporal processes of emotion regulation were largely overlooked. The network analysis approach would complement extant research findings by investigating sex differences in the associations between different emotion regulation processes, the relative importance of these processes to the entire network, and how these processes cluster, to further explore and validate sex-specific intervention targets.

The Present Study

Hence, the aims of the current study were to examine the network and community (or dimensional) structures of emotion dysregulation using the DERS, whether sex differences exist in such structures, and the relationship between emotion dysregulation and anxiety symptoms using a large and diverse sample. Although the present study is exploratory in nature, we did hypothesize that 1) "limited access to emotion regulation strategies" would emerge as the most central node in the emotion dysregulation network given the prior results reviewed above; 2) corroborating the previous findings, the antecedent- and response-focused emotion regulation communities would appear; and 3) there would be sex differences in the network and community structures. The present study would provide critical insights into which emotion dysregulation process(es) should be the targets of intervention by identifying the most influential nodes in the network, especially in the context of anxiety. Exploring sex differences in the network and community structures of emotion dysregulation would advance the theoretical understanding of emotion dysregulation and inspire sex-specific interventions and treatments, achieving precision mental health.

Methods

Participants and Procedures

A total of 1444 participants were recruited from introductory-level psychology courses at a regional comprehensive university to complete online questionnaires as part of a large study examining emotional adjustment in emerging adults in 2021 to 2022. The full study took participants a median of 85.55 minutes to complete and contained six attention checking questions [e.g., 'Please click on "3 (Slightly Agree)"]. Participants' data were removed if more than half of the attention checking questions attempted were failed (N = 58). Of note, the two measures used in the current study were the second and fourth measures in the survey, so fatigue effects were unlikely. Data from participants who began but did not complete the survey was retained on a measure-by-measure basis (e.g., a participant who completed the first two attention checks correctly but then left the rest of the survey blank had data retained for the portion of the survey they completed). As relevant to these analyses, 13 people did not complete either measure used here. Hence, data from 1373 participants (M_{age} = 19.6 years, *SD* = 2.98) were retained and used in the present study. The current sample is diverse (female: 67.4%; Hispanic/Latinx: 58.7%); see Table 1 for demographic information. The sex variable in the current study refers to biological sex, and participants were asked "What is your sex?" with options 'Female' and 'Male' (or the option to not respond). Questionnaires were administered online through Qualtrics. Participants were required to electronically sign the informed consent form at the beginning of the survey in order to proceed, and no identifiable data were collected. Participants received research credits to fulfill their course requirements as compensation for their participation. The study was approved by the Institutional Review Board of the university.

Table 1. Demographic Statistics

	N	Percentage (%)
Age	M = 19.61, *SD* = 2.98	
Sex		
Female	926	67.6
Male	422	30.7
Did not report	25	1.8
Ethnicity		
Hispanic/Latino	791	57.6
Asian/Asian American	149	10.9
Multiethnic	117	8.5
White/Caucasian of European Descent	105	7.6
Black/African American	81	5.9
White/Caucasian of Middle Eastern Descent	73	5.3
Native Hawaiian, Pacific Islander	4	.3
Native American/Alaska Native	1	.1
Other	27	2
Did not report	25	1.8

Measures

Difficulties in Emotion Regulation Scale (DERS; Gratz & Roemer, 2004).

Emotion dysregulation was measured by the DERS, a 36-item scale measuring 6 different facets of ED: nonacceptance of emotional responses (6 items; e.g., "When I'm upset, I become angry with myself for feeling that way."), difficulty engaging in goal-directed behavior (5 items; e.g., "When I'm upset, I have difficulty getting work done."), impulse control difficulties (6 items; e.g., "I experience my emotions as overwhelming and out of control."), lack of emotional awareness (6 items; e.g., "When I'm upset, I take time to figure out what I'm really feeling [reverse-scored]."), limited access to emotion regulation strategies (8 items; e.g., "When I'm upset, I believe that I will remain that way for a long time."), and lack of emotional clarity (5 items; e.g., "I have no idea how I am feeling."). The items were rated on a 5-point scale, ranging from 1 (almost never) to 5 (almost always). Composite scores of the 6 facets of emotion dysregulation were calculated and used in the network analyses. Reliability analysis demonstrated excellent reliability (Cronbach's α = .94).

Generalized Anxiety Disorder 7-item Scale (GAD-7; Spitzer et al., 2006).

Seven anxiety symptoms were assessed using the GAD-7: 1) feeling nervous, anxious, or on edge, 2) not being able to stop or control worrying, 3) worrying too much about different things, 4) trouble relaxing, 5) being so restless that it's hard to sit still, 6) becoming easily annoyed or irritable, and 7) feeling afraid as if something awful might happen. The 7 items were rated on a 4-point scale, ranging from 0 (not at all) to 3 (nearly every day). Reliability analysis indicated excellent reliability (Cronbach's α = .90).

Patient Health Questionnaire-9 (PHQ-9; Kroenke et al., 2001).

PHQ-9 is a 9-item measure with each item rated on a 0 (not at all)-to-3 (nearly every day) scale. A composite score of the PHQ-9 was calculated for the measure of depression. Reliability analysis indicated excellent reliability (Cronbach's α = .90).

Data Preparation and Power Analysis

Descriptive statistics and missing value analysis were conducted using SPSS Statistics (Version 27). No variables had more than 1% missing data, and Little's MCAR test suggested that data were missing completely at random (χ^2 = 84.77, *df* = 70, *p* = .11). All of the following procedures were conducted in R (R Core Team, 2022). After confirming that missing data were missing completely at random, missing data were imputed using the *mice* R package (van Buuren & Groothuis-Oudshoorn, 2011). The predictive mean matching method was chosen given that this method performs well with large samples, produces the least biased estimates of missing data, and is preferrable when missing data are less than 50% and are not MNAR (missing not at random; Kleinke, 2017; Marshall et al., 2010a; Marshall et al., 2010b).

One key assumption of the Graphical Gaussian Model is multivariate normality (Epskamp & Fried, 2018). Hence, multivariate normality was assessed using the *MVN* package (Korkmaz et al., 2014). The Mardia's test was conducted to determine multivariate normality by calculating Mardia's multivariate skewness and kurtosis coefficients; $p > .05$ indicates multivariate normality. Both the emotion dysregulation and combined networks (see below for information about the networks) violated the multivariate normality assumption (skewness and kurtosis *p*'s < .05). Hence, Spearman's correlations, as nonparametric measures, were used in Graphical Gaussian Models (including exploratory graph analysis, detailed below) to address the violation of the assumption.

Power analysis was conducted to determine the minimum sample sizes for the emotion dysregulation and combined networks (see below for information about the networks). This analysis was carried out after data collection, given that the data used in the current analyses were part of a larger study. Following Epskamp & Fried (2018), we used the *netSimulator* function of the *bootnet* package (Epskamp et al., 2018) to simulate data with varying sample sizes (i.e., N's = 100, 250, 500, 1000, 2500) and examine the sensitivity (the true-positive rate for edges), specificity (the true-negative rate for edges), and correlations between edge weights and expected influences of the true and estimated networks as the properties of interest. The results suggested that, for a network including only the emotion dysregulation nodes, a sample size of 100 already resulted in moderate to high on these properties, and these properties improved as the sample size increased, although the specificity maintained moderate across the simulated samples. For a network including emotion dysregulation and anxiety nodes, similarly, these properties improved as the sample size increased (with the exception of specificity, which was moderate across the simulated samples). A sample size of 1000 was determined to be the most harmonious as it achieves excellent edge weight and expected influence correlations, great sensitivity, and moderate specificity. Taken together, for a network containing only emotion dysregulation nodes, the sample size should be at least 100, and for a network including emotion dysregulation and anxiety nodes, the sample size should be around 1000. See Supplemental Figures S1 and S2 for the visualization of the simulated results.

Network Analysis

The emotion dysregulation networks and combined (i.e., emotion dysregulation and anxiety) network were estimated using the Graphical Gaussian Model via the *qgraph* package (Epskamp et al., 2012). The graphical least absolute shrinkage and selection operator (glasso) was implemented with the extended Bayesian Information Criterion (EBIC), tuned by the hyperparameter gamma (γ), which was set to .05 (by default), to select the optimal regularized parameters. The *bootnet* package (Epskamp et al., 2018) achieves this estimation process automatically in *qgraph* with the default "EBICglasso" argument. This procedure returns a sparse network structure by eliminating extremely small partial correlations, which are likely to be spurious. Because the multivariate normality assumption was violated, Spearman's correlations were used. In these networks, nodes represent variables (e.g., an aspect of emotion dysregulation), and edges represent the regularized partial correlations between two nodes. The color of the edges in the network graphs indicates the sign of the correlations (blue: positive;

red: negative), and the thickness of the edges indicates the strength of the regularized partial correlations.

The importance of a node in a given network was measured by the centrality measure, expected influence (EI), which sums the weights of edges connecting the node with other neighboring nodes (Robinaugh et al., 2016). It considers the signs of the correlations, instead of using the absolute values (as in the case of node strength, another centrality measure), and thus presents the overall cumulative influence of a node on all other nodes in the network. Because the combined network has more than one community (i.e., subgroup or sub-network), (one-step) bridge EI was calculated to represent the extent to which a node in one community was connected to the other community. The calculation of bridge EI is identical to EI, but it sums the edge weights connecting the node with nodes in the other community. Nodes with high bridge EIs are recognized as bridge nodes (Jones et al., 2019). Both EI and bridge EI were calculated using the *networktools* package (Jones, 2022).

To complement the expected influence values of the nodes in the combined network, node predictability, defined as the percentage of variance of a node explained by all other nodes connected to it, was calculated (Haslbeck & Waldorp, 2018). Node predictability can inform the degree to which a node can be influenced by intervening on its connecting nodes, as well as whether important variables are missing in the network (i.e., low predictability suggests a node is less explained by the other nodes in the network). For the relevance of the present study, we focus on the predictability of the anxiety nodes in the network.

Community Detection

In order to detect whether the six emotion dysregulation elements would form one or more communities in the emotion dysregulation network, exploratory graph analysis (Golino et al., 2019; Golino & Epskamp, 2017), a graph-based dimension reduction technique using community detection, was conducted using the *EGAnet* package (Golino & Christensen, 2022). A simulation study demonstrated that, compared to traditional dimension reduction methods (e.g., exploratory factor analysis), exploratory graph analysis is more accurate, less biased, and easier to carry out and interpret (i.e., can discern dimensional structure upon visual inspection of the graph; Golino et al., 2019). In exploratory graph analysis, nodes in a community (akin to "factor" in factor analysis) are highly interconnected and weakly connected to other nodes in the other community or communities. In the current analysis, the Louvain community detection algorithm was utilized as it was demonstrated to outperform other community detection algorithms commonly used in network analysis research, such as the Walktrap algorithm (Christensen et al., 2020). Standardized network loadings, which resemble factor loadings, were obtained for each node to represent the degree to which a given node contributes to the emergence of a coherent dimension, and network loadings of 0.15 (small), 0.25 (moderate), and 0.35 (large) were used as the effect size guidelines (Christensen et al., 2020; Christensen & Golino, 2021a). Moreover, structural consistency and item stability statistics were produced by using a parametric bootstrap approach with the "bootEGA" function of the *EGAnet* package.

Structural consistency of a community refers to the degree to which the nodes within the community are homogeneous and interrelated in the presence of the other community or communities, and item stability represents the robustness of, or the proportion of times, a node's placement within each of the derived communities across the bootstrap samples (Christensen et al., 2020; Christensen & Golino, 2021b). The structural consistency statistics range from 0 to 1; however, as Christensen et al. (2020) suggested, a recommended guideline for interpreting structural consistency has not yet been developed. Nevertheless, we chose to report the statistics for readers to interpret them when the recommended guideline is developed based on simulation studies in the future. Following Christensen & Golino (2021b), item stability should be above 0.7 to be regarded as acceptable. Structural consistency and item stability are complementary measures as item stability provides insight into which nodes lead to structural (in)consistency (Christensen & Golino, 2021a).

Network Comparison

To examine sex differences in the network structure between females and males, network comparison was conducted using the *NetworkComparisonTest* package with 1000 permutations (van Borkulo et al., 2022). Invariance of network structure was first tested as the omnibus test to see whether all edges were equal across the two networks (i.e., equal network structure); if the result suggested that the networks were unequal (i.e., at least one edge significantly differed between the networks), indicated by a significant maximum statistic (M) when $p < .05$, post-hoc invariance of specific edge strength was then examined. Because of the exploratory nature of the current study, we reported statistics both adjusted and non-adjusted for multiple comparisons when comparing edges, as van Borkulo and colleagues (2022) suggested that correcting for multiple comparisons, although ideal, is not necessary in exploratory settings. The Holm-Bonferroni correction method was implemented as recommended. In addition, global expected influence invariance test was conducted to see whether the overall level of connectivity was the same across females and males, indexed by a significant S statistic when $p < .05$. Finally, a centrality invariance test was conducted to examine whether the expected influence of certain nodes differed across the two networks, indicated by a significant statistic C when $p < .05$. Similar to testing edge differences, both adjusted and non-adjusted results were reported. Of note, because the sample size of the female network was more than 2 times larger than that of the male network, the power of the network comparison test was similar to if the two groups had the same sample size of the male network (van Borkulo et al., 2022).

Network Stability

The stability of edges, expected influence, and bridge expected influence was estimated using the *bootnet* package (Epskamp et al., 2018). Case-dropping subset bootstrapping was used to obtain correlation stability coefficients (CS-coefficients). CS-coefficients represent, with 95% probability, the maximum proportion of cases that can be dropped in order to retain a correlation of 0.7 (by default) between the parameters of interest (e.g., expected influence) in the original sample and in the subset. It was recommended that CS-coefficients should be at least .25 and preferably larger than .5 (Epskamp et al., 2018).

Directed Acyclic Graph Analysis

Finally, directed acyclic graph (DAG) analysis, a Bayesian network analysis, was conducted as an exploratory analysis with all the ED and anxiety variables on the whole sample. Whereas edges in Graphical Gaussian Models are undirected, the DAG analysis gives the directions of the edges, which are noncircular (Briganti et al., 2022). In a DAG, if node A points to node B, it means that the presence of node B strongly implies the presence of node A, but not the opposite (Mcnally, 2021). Hence, the DAG analysis provides insights into the potential causal relationships between the nodes and thus is instrumental to identifying intervention and treatment targets. The present study used the completed partially DAG analysis in which only edges that appeared in a set proportion of the models based on an optimal significance threshold for inclusion (i.e., 51.4%; Scutari & Nagarajan, 2013) are accepted, with the bootstrapping-based (1000 times) hill-climbing algorithm via the *bnlearn* package (Scutari, 2017). In this DAG, the thickness of an edge indicates the probability of obtaining the direction of the edge in the graph in at least 51.4% of the bootstrapped samples (Mcnally, 2021); as such, thin edges imply that the direction of the arrows depicted in the graph is more often the opposite in the bootstrapped samples than thick edges.

Analytic Procedures and Order

The emotion dysregulation network was first constructed on the whole sample to investigate the network structure of emotion dysregulation, and then community detection was conducted. Next, network comparison was implemented to explore sex differences in the network structure of emotion dysregulation, followed by a community detection on both the female and male networks. Following, the combined (emotion dysregulation and anxiety) network was estimated. Given that emotion dysregulation variables are summed scores of individual items and anxiety variables are single items, to avoid the potential influence of variability on network statistics, standardized scores were used in the combined network. Based on the results of the community detection, emotion dysregulation variables were compartmentalized into two communities. In order to control for the impact of depression, the sum-scored depression variable was included as a covariate. Individual items of the depression scale were not used in the analysis in order to maintain statistical power. Bridge EI was calculated between one emotion dysregulation community and the anxiety community and between the other emotion dysregulation and anxiety communities separately; doing so, the calculation of the bridge EI of a node in a given emotion dysregulation community would not be affected by the other emotion dysregulation community and thus purely represented the degree to which this node connected to the anxiety community, while controlling for depression. The stability of all the networks above was assessed. Finally, the DAG analysis was conducted. Similar to the combined network, variables in the DAG analysis were standardized.

Transparency and Openness

We reported how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. The data used in the present study are not available to the public due to not obtaining permission in the initial Institutional Review Board application. Analytic code and materials are available online (https://osf.io/uz3gj/?view_only=343d4675f5534777836f199aa1c79b1f). The present study was not pre-registered.

Results

Emotion Dysregulation Network

The emotion dysregulation network is depicted in Figure 1a. The edge and EI CS-coefficients were both .75, indicating excellent stability (Figure S3). The strongest edges were "lack of emotional awareness"-to-"lack of emotional clarity" (standardized edge weight = .46) and "nonacceptance of emotional responses"-to-"limited access to emotion regulation strategies" (.41). Figure 1c shows the EI of the nodes in the network. "Limited access to emotion regulation strategies" (standardized EI = 1.62) and "lack of emotional clarity" (.5) emerged as the most influential nodes, and "lack of emotional awareness" (-1.17) and "difficulty engaging in goal-directed behavior" (-.87) emerged were the least influential.

Community detection (Figure 1b) suggested a two-dimension solution. The median number of communities that emerged in the 1000 bootstrapped samples was two; the two-community solution emerged 999 times. Community 1 included "limited access to emotion regulation strategies," "impulse control difficulties," "nonacceptance of emotional responses," and "difficulty engaging in goal-directed behavior," which corresponded with response-focused emotion dysregulation. Community 2 contained "lack of emotional clarity" and "lack of emotional awareness," which corresponded with antecedent-focused emotion dysregulation. The structural consistency of response-focused and antecedent-focused emotion dysregulation networks were 1 and .99, respectively, and the average item stability were 1 and .99, respectively, indicating excellent item stability. See Figure S4 for the item stability graph and Table S1 for network loadings.

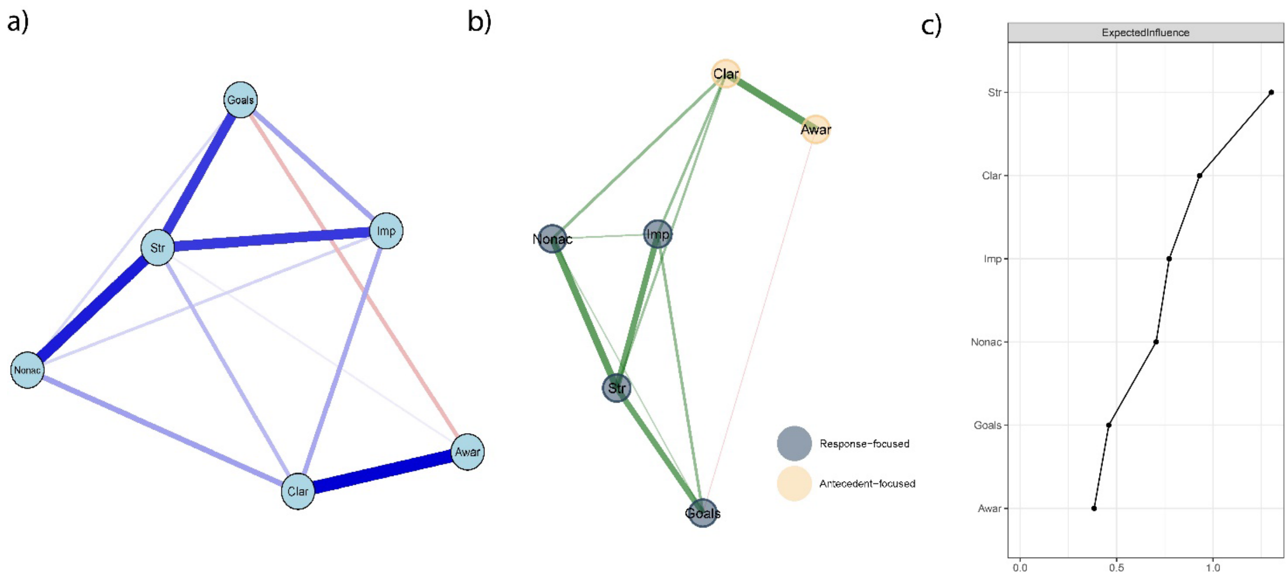

Figure 1. Network structure and dimensions of emotion regulation. a) the network graph of emotion dysregulation; b) community detection graph; c) expected influence of the emotion dysregulation nodes. Awar: lack of emotional awareness; Clar: lack of emotional clarity; Goals: difficulty engaging in goal-directed behavior; Imp: impulse control difficulties; Nonac: nonacceptance of emotional responses; Str: limited access to emotion regulation strategies. The color of the edges in the network graphs indicates the sign of the correlations (blue: positive; red: negative), and the thickness of the edges indicates the strength of the regularized partial correlations.

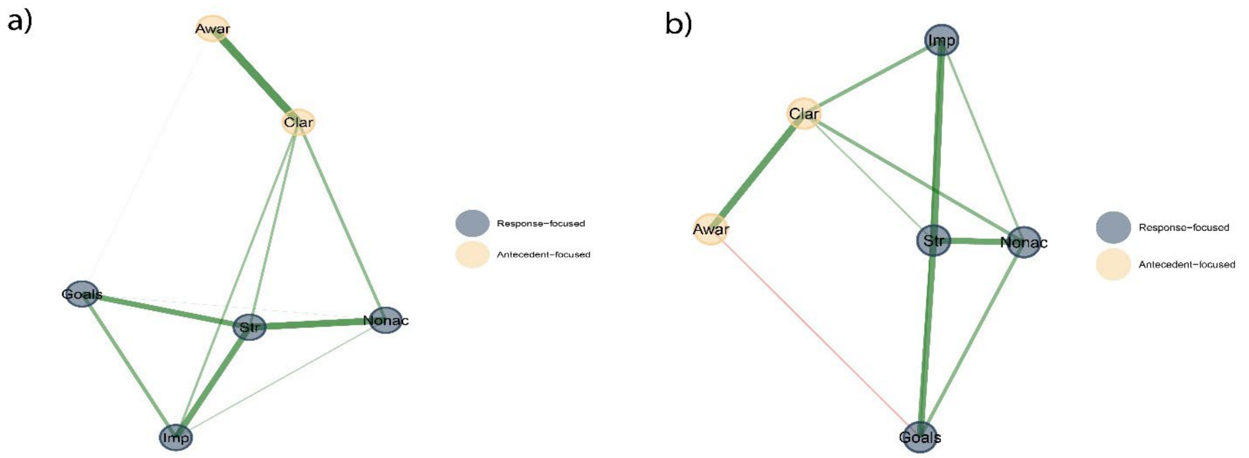

Figure 2. Community detection graphs for females (a) and males (b). Awar: lack of emotional awareness; Clar: lack of emotional clarity; Goals: difficulty engaging in goal-directed behavior; Imp: impulse control difficulties; Nonac: nonacceptance of emotional responses; Str: limited access to emotion regulation strategies. The color of the edges in the network graphs indicates the sign of the correlations (blue: positive; red: negative), and the thickness of the edges indicates the strength of the regularized partial correlations.

Network Comparison

The edge and EI CS-coefficients of the female and male networks were all .75, indicating excellent stability. The network invariance test suggested that at least one edge significantly differed between the two networks (M = .17, p_{adjusted} = .03, $p_{non\text{-adjusted}}$ = .03). With and without adjustment for multiple comparison, "nonacceptance of emotional responses"-to-"difficulty engaging in goal-directed behavior" was significantly different between the networks (p_{adjusted} = .03, $p_{non\text{-adjusted}}$ = .003). The edge weights of this edge in the female and male networks were .02 and .19, respectively, indicating that the relationship between these two nodes was significantly stronger in males. The global expected influence invariance test was not significant, S = .1, p = .13, meaning that the overall connectivity of the networks was equal. Finally, the centrality invariance test indicated that only the expected influence value of "lack of emotional awareness" (C = .16, $p_{non\text{-adjusted}}$ = .01; female EI: -1.05, male EI: -1.45) was significantly different between females and males without adjusting for Holm-Bonferroni multiple comparison. After correcting for multiple comparison, it was still significant (p_{adjusted} = .5).

Community detection revealed the same community structures in females and males. Both female and male networks returned a two-community solution identical to that of the emotion dysregulation network on the whole sample (Figure 2); the median number of communities that emerged in the 1000 bootstrapped samples was two. The two-community solution emerged in most of the bootstrapped samples (Female: 99.3%; Male: 95.3%). The communities had excellent structural consistency in both females (response-focused: 1; antecedent-focused: .99) and males (response-focused: 97; antecedent-focused: .95). Similarly, the item stability of the communities was excellent in both females (response-focused: 1; antecedent-focused: .99) and males (response-focused: 99; antecedent-focused: .95). See Tables S2&3 for network loadings of the female and male emotion dysregulation networks.

Combined Network

The combined network is depicted in Figure 3. Given the community structure of emotion dysregulation was identical in both females and males, we assigned two communities to the emotion dysregulation nodes in the combined network. The edge and EI CS-coefficients were both .75, indicating excellent stability. The bridge EI CS-coefficients between the first emotion dysregulation community (i.e., antecedent-focused) and anxiety community and between the second emotion dysregulation community (i.e., response-focused) and anxiety community were both .44, suggesting moderate stability. "Lack of emotional clarity" had the highest bridge EI (standardized bridge EI = .07) in the antecedent-focused emotion dysregulation community, while "worrying too much about different things" (.02) and "becoming easily annoyed or irritable" (.01) had the highest bridge EIs in the anxiety community. "Impulse control difficulties" (.16) had the highest bridge EI in the response-focused emotion dysregulation community, and "becoming easily annoyed or irritable" (.13) had the highest bridge EI in the anxiety community, followed by "worrying too much about different things" (.02). Node predictability of the anxiety nodes ranged from .39 (i.e., 39% of the variance explained) to .67. See Table S4 for the predictability of all the anxiety nodes.

DAG Analysis

The directed acyclic graph of the combined network is depicted in Figure 4. "Limited access to emotion regulation strategies" (Str) emerged as the most important node; being the most upstream node (i.e., not triggered by any other node), it directly triggered four other types of emotion dysregulation and four anxiety symptoms. "Not being able to stop or control worrying" was the most upstream node among the anxiety symptoms, and it was directly triggered by Str and triggered four other anxiety symptoms. The most downstream node (i.e., only being triggered by other nodes but not triggering any other node) within the anxiety community was "becoming easily annoyed or irritable", which was directly triggered by one emotion dysregulation nodes and four other anxiety symptoms. Interestingly, some anxiety symptoms pointed to emotion dysregulation processes. "Worrying too much about different things" directly pointed to "nonacceptance of emotional responses" and "difficulty engaging in goal-directed behavior," and "trouble relaxing" pointed to "lack of emotional clarity."

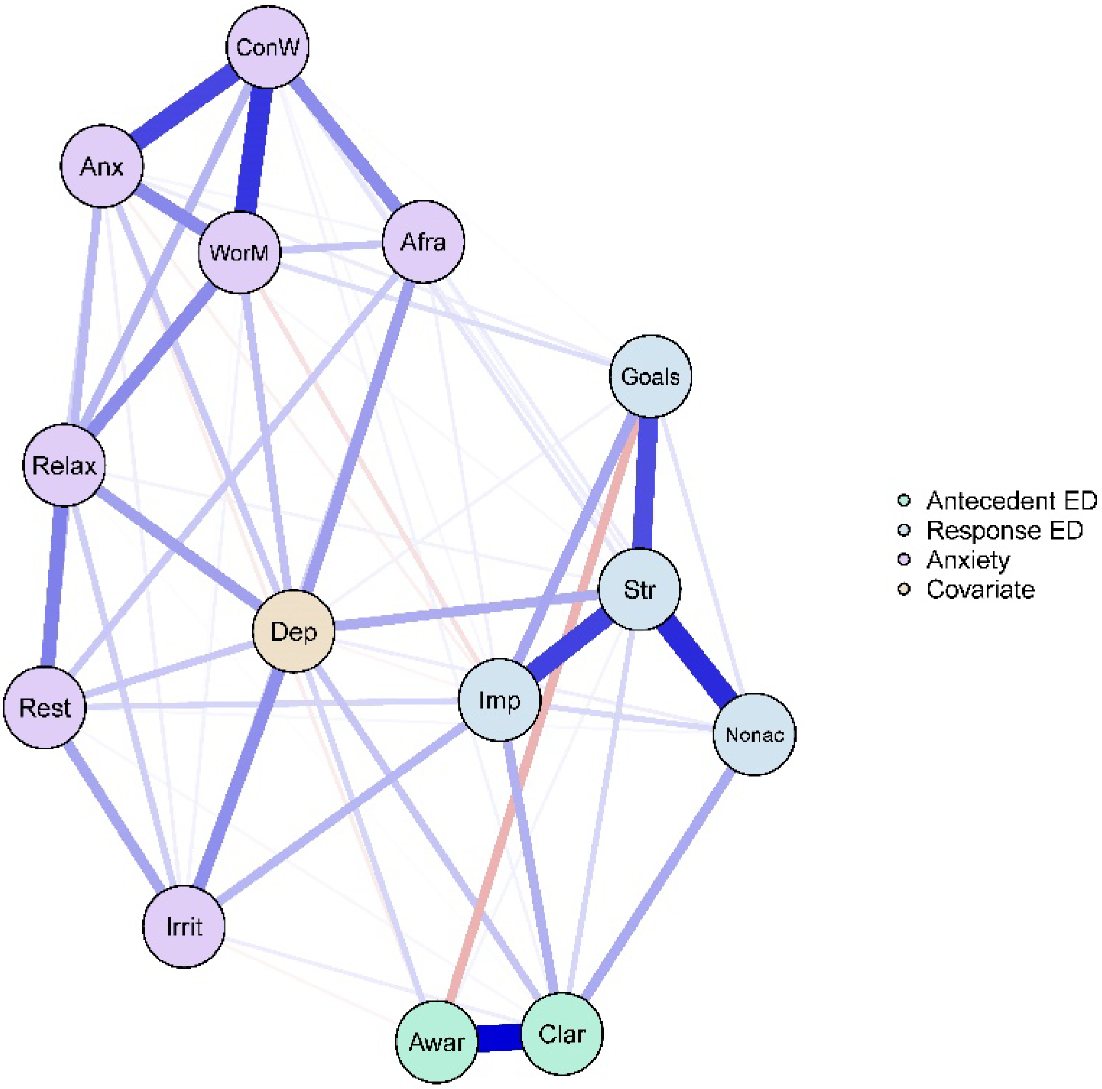

Figure 3. The network structure of the combined network. Emotion dysregulation-related abbreviations: Awar: lack of emotional awareness; Clar: lack of emotional clarity; Goals: difficulty engaging in goal-directed behavior; Imp: impulse control difficulties; Nonac: nonacceptance of emotional responses; Str: limited access to emotion regulation strategies. Anxiety-related abbreviations: Anx: feeling nervous, anxious, or on edge; Afra: feeling afraid as if something awful might happen; ConW: not being able to stop or control worrying; Irrit: becoming easily annoyed or irritable; Relax: trouble relaxing; Rest: being so restless that it's hard to sit still; WorM: worrying too much about different things. Dep: depression. The color of the edges in the network graph indicates the sign of the correlations (blue: positive; red: negative), and the thickness of the edges indicates the strength of the regularized partial correlations.

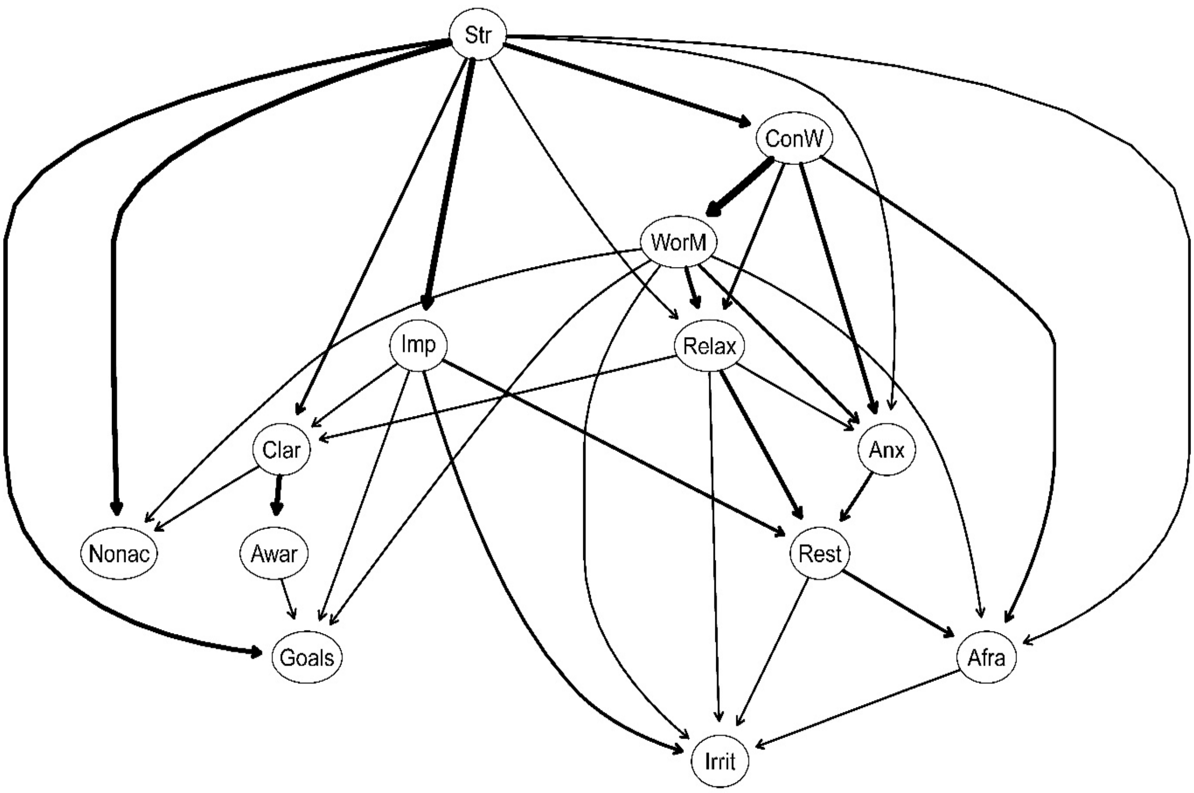

Figure 4. Direct acyclic graph (DAG) of the combined network. Emotion dysregulation-related abbreviations: Awar: lack of emotional awareness; Clar: lack of emotional clarity; Goals: difficulty engaging in goal-directed behavior; Imp: impulse control difficulties; Nonac: nonacceptance of emotional responses; Str: limited access to emotion regulation strategies. Anxiety-related abbreviations: Anx: feeling nervous, anxious, or on edge; Afra: feeling afraid as if something awful might happen; ConW: not being able to stop or control worrying; Irrit: becoming easily annoyed or irritable; Relax: trouble relaxing; Rest: being so restless that it's hard to sit still; WorM: worrying too much about different things.

Discussion

Using network analysis and community detection, the present study aimed to unveil the network and community structures of emotion dysregulation, sex differences in such structures, as well as the relationship between emotion dysregulation and anxiety. Corroborating our hypotheses, "limited access to emotion regulation strategies" was the most important aspect of emotion dysregulation, and emotion dysregulation processes were clustered into antecedent- and response-focused emotion dysregulation communities. The network structures showed some, but not substantial, sex differences, and community structures were identical between females and males. In addition, the combined (emotion dysregulation and anxiety) network revealed that "worrying too much about different things" and "becoming easily annoyed or irritable" were the symptoms most strongly associated with both emotion dysregulation communities. The DAG analysis further validated the importance of "limited access to emotion regulation strategies" in emotion dysregulation and anxiety.

The results from the whole-sample emotion dysregulation network suggested that, as expected, "limited access to emotion regulation strategies" emerged as the most influential node in the network, followed by "lack of emotional clarity." It is well-established in the literature that having and knowing how to apply emotion regulation strategies is pivotal to many aspects of well-being. Emotion regulation strategies, such as cognitive reappraisal, can help individuals manage unwanted feelings in certain contexts (McRae et al., 2012; Siemer et al., 2007). We posit that the importance of having access to emotion regulation strategies outweighs that of emotional clarity because emotional clarity may not be necessary for, and does not guarantee, successful emotion regulation. Needless to say, emotion clarity is important to many aspects of affective experience and subjective well-being (Lischetzke & Eid, 2017). Recent evidence revealed that emotional clarity can be divided into *type clarity* (the ability to identify and distinguish different types of emotion) and *source clarity* (the ability to discern the causes of emotions; Boden & Berenbaum, 2011). Individuals who experience a negative emotion may not need to specify the category of negative emotion being experienced (e.g., anger vs. frustration), nor do they need to discern the cause of that emotion, in order to manage it using emotion regulation strategies, such as acceptance.

Moreover, corroborating prior research (Berzenski, 2019), community detection revealed that "limited access to emotion regulation strategies," "impulse control difficulties," "nonacceptance of emotional responses," and "difficulty engaging in goal-directed behavior" clustered together, representing response-focused emotion dysregulation, while "lack of emotional clarity" and "lack of emotional awareness" formed a separate cluster, representing antecedent-focused emotion dysregulation. These findings provided additional support for the process model of emotion regulation that emotion regulation processes can be compartmentalized based on when these processes happened, further validating the need for examining the differential influences of antecedent- and response-focused emotion regulation on later consequences separately.

As an exploratory endeavor, results of the network comparison indicated that the relationship between "nonacceptance of emotional responses" and "difficulty engaging in goal-directed behavior" was significantly stronger in males than females. This difference pointed out that intervening anyone of these nodes may result in a larger effect on the other one in males than in females. On the other hand, the expected influence value of "lack of emotional awareness" differed between males and females, even after adjusting for multiple comparison. However, "lack of emotional awareness" was the least influential node in both female and male networks and thus is unlikely to be an intervention target. "Limited access to emotion regulation strategies" was the most influential node in both females and males, and its expected influence value did not differ in terms of sex, again underscoring the importance of having access to emotion regulation strategies. Community detection revealed a two-community structure, which resembled that of the whole-sample network, in both male and female emotion dysregulation networks. This result further solidified the evidence that emotion (dys)regulation can be divided into antecedent- and response-focused emotion regulation, in both females and males.

Together, network comparison suggested that there are minimal differences in the relationships between emotion dysregulation processes, as well as no differences in how they cluster, between females and males, and access to emotion regulation strategies was the most important aspect of emotion dysregulation in both sexes. We postulate that the reason why the results did not support our hypothesis regarding sex differences is that mean-level differences in emotion regulation, as well as the frequency of the use of regulatory strategies, are distinct from the *relationships* between emotion regulation processes (i.e., network structure). Even if (for example) one sex scores higher on all emotion regulation processes than the other sex, how these processes are related to each other can remain identical.

In the combined network, emotion dysregulation nodes were grouped into two communities based on the two-community solution discovered: antecedent- and response-focused emotion dysregulation. Within the antecedent-focused emotion dysregulation community, "lack of emotional clarity" was most strongly connected to the anxiety community, and within the anxiety community, "worrying too much about different things" and "becoming easily annoyed or irritable" were the most strongly connected to the antecedent-focused emotion dysregulation community. Within the response-focused emotion dysregulation community, "impulse control difficulties" was the most strongly associated to the anxiety community, while within the anxiety community, "becoming easily annoyed or irritable" and "worrying too much about different things" were most strongly associated with the response-focused emotion dysregulation community. These findings suggested that, in the antecedent-focused emotion regulation processes, having trouble with emotional clarity may particularly put individuals at risk of developing anxiety, while during the response-focused phase of emotion regulation, impulse control may be particularly protective against anxiety.

Interestingly, "becoming easily annoyed or irritable" and "worrying too much about different things" had the highest bridge EIs linking anxiety to both antecedent- and response-focused emotion dysregulation, making them the most salient anxiety symptoms associated with emotion dysregulation. Combined with the results from the DAG analysis (details see below), we posit that the reason why "worrying too much about different things" is strongly associated with emotion dysregulation is that, as it likely stems from difficulties in controlling worrying, it in turn may trigger two aspects of emotion dysregulation (i.e., "difficulty engaging in goal-directed behavior" and "nonacceptance of emotional response"). As for irritability, in addition to being triggered by other aspects of emotion dysregulation, it is also likely to be triggered by impulse control difficulties, according to the DAG analysis. Node predictability of the anxiety nodes in the combined network ranged from .39 to .67. Although the significance of the explained variance remains unknown, it suggested that the network could explain a reasonable amount of variance of the anxiety symptoms.

The findings from the DAG analysis should be interpreted with caution, as cross-sectional DAGs only characterize probabilistic dependence, which suggests, but cannot confirm, temporal precedence (Mcnally, 2021). In other words, X pointing to Y indicates that X could be present without Y, but the presence of Y strongly implies the presence of X. The findings of the present study indicate that if someone lacks emotional clarity, it was likely triggered by limited access to emotion regulation strategies, but having limited access to emotion regulation strategies will not always eventuate in a lack of emotional clarity. Clarity then triggered several other aspects of emotion dysregulation. These results corroborate the ACE model that emotional clarity (e.g., identification and labeling) is a critical aspect of adaptive emotion regulation and expand on the model that does not explicitly characterize the role of *access* to emotion regulation strategies (as separate from their enaction), which was suggested to be the most important aspect of emotion (dys)regulation by the present study. In addition, the results show that the lack of emotional awareness is present downstream from lack of emotional clarity, in contrast to the ACE model, which proposes that being aware of one's emotions precedes emotional clarity. We posit that lacking the ability to recognize and label specific emotions may present a critical obstacle to conscious awareness of emotions.

In terms of the crosstalk between emotion dysregulation and anxiety, the presence of "not being able to stop or control worrying," the most upstream anxiety node, strongly implies the presence of "limited access to emotion regulation strategies," highlighting the significance of having access to emotion regulation strategies. Combined with the findings from the combined network that emotional clarity and impulse control are particularly relevant to symptoms of irritability and worrying too much about different things, the DAG analysis suggested that access to emotion regulation strategies may be the most important target for intervention, as it pointed to not only other emotion dysregulation nodes but also the most upstream anxiety node. Finally, several anxiety symptoms pointed to emotion dysregulation nodes. For example, the presence of "difficulty engaging in goal-directed behavior" likely stems from "worrying too much about different things." It demonstrated that anxiety symptoms may not solely be the consequences of emotion dysregulation, but rather, anxiety symptoms (or more broadly, psychopathological symptoms) can also lead to emotion dysregulation, providing further evidence for a transactional relationship between emotion dysregulation and psychopathology (Bardeen et al., 2013; Masters et al., 2019; Robinson et al., 2019). Overall, the DAG analysis indicated that "limited access to emotion regulation strategies" may be a cardinal intervention target to foster healthy emotion regulation and alleviate anxiety symptoms. Again, these findings require longitudinal data to confirm the temporal precedence and potential causal implications.

Constraints on Generality and Other Limitations

The findings of the present study should be interpreted with the following limitations in mind, and future research should attempt to address these issues. First, the DERS does not capture all the processes involved in regulating emotion, and there are more detailed and nuanced emotion regulation models. To illustrate, based on the temporal order, emotion regulation processes can also be divided into five stages: situation selection, situation modification, attentional deployment, cognitive change, and response modulation (Gross, 1998a, 1998b; Sheppes et al., 2015). The extended process model of emotion regulation states that regulatory stages and dynamics involve identification, selection, implementation, and monitoring, and within each stage, there are regulatory elements, such as perception, valuation, and action (see Sheppes et al., 2015 for a review on the model and its relationship with psychopathology). The DERS does not fully capture all the intricate processes involved in emotion regulation, leaving room for future inquiry in such processes, how they interact, and their relationships with anxiety symptoms.

In terms of outcome variables, the measure GAD-7 does not capture all the symptoms, such as fatigue and other somatic symptoms. Further, a sum score of depression was used as a covariate in the combined network in order to preserve enough power for the analysis. Future research should leverage a larger sample and include depressive symptoms as nodes (as supposed to one depression node) to capture and account for the nuanced impact of specific depressive symptoms. Moreover, the combined network analysis was conducted with the whole sample, instead of in females and males separately, again to maintain enough power for the analysis. Although the community structure of emotion dysregulation did not differ between females and males, it is possible that the relationships between emotion dysregulation processes and communities and anxiety symptoms are distinct between the sexes. Hence, larger samples of females and males are also required for future investigation.

There are several methodological issues that need to be improved in future inquiry. The current study utilized cross-sectional data, and although we do not make any statement about the causal relationships between the nodes in the networks, we warn that the results from the regularized partial correlation networks do not imply any directional effect. Future research should utilize longitudinal data to elucidate the directions of the associations in the networks. Additionally, the questionnaires were not randomized during study administration to ensure that participants paid enough attention while completing questionnaires that were of the greatest interest of the large study (to minimize fatigue effects). It should be noted that this, on the other hand, could increase the possibility of order effects. Lastly, the current sample of college students, although diverse, is not representative, and the focus on biological sex may have prevented gender minorities to participate in the study. Future research should investigate whether the findings could be replicated in other populations (e.g., other age groups, clinical populations, genders), and whether the findings would change across age, reflecting developmental differences.

Conclusion

Taken together, the present study utilized data from a large and diverse sample to interrogate the network and community structures of emotion dysregulation and its relationship with anxiety symptoms. The findings highlighted the cardinal role of having access to emotion regulation strategies to maintain mental health, indicated by both the network and DAG analyses, especially in the context of anxiety. Community detection revealed an antecedent-focused and a response-focused emotion dysregulation community in both females and males, providing evidence for the temporal organization of emotion regulation processes. With the stability of our network analyses and the diversity of our sample, the findings are instrumental to both advancing theoretical understanding of emotion (dys)regulation processes and identifying intervention and treatment targets for emotion regulation problems implicated in anxiety.

Additional Information

Supplementary Material

https://osf.io/uz3gj/?view_only=343d4675f5534777836f199aa1c79b1f

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Conflict of Interest

The authors declare that there is no conflict of interest.

Ethical approval

The study was approved by the Institutional Review Board of California State University, Northridge.

Data Availability

The data used in the present study are not available to the public due to not obtaining permission in the initial Institutional Review Board application.

Author CRediT Statement

Conceptualization: CL & SRB; methodology: CL, SP, & YZ; formal analysis, writing-original draft: CL; visualization: CL & SP; data collection and curation: SRB; supervision: SRB; writing-review and editing: all the authors.

References

Bardeen, J. R., Kumpula, M. J., & Orcutt, H. K. (2013). Emotion regulation difficulties as a prospective predictor of posttraumatic stress symptoms following a mass shooting. *Journal of Anxiety Disorders*, *27*(2). https://doi.org/10.1016/j.janxdis.2013.01.003

Berking, M., & Whitley, B. (2014). *Affect Regulation Training: A Practitioners' Manual*. Springer.

Berzenski, S. R. (2019). Distinct emotion regulation skills explain psychopathology and problems in social relationships following childhood emotional abuse and neglect. *Development and Psychopathology*, *31*(2), 483–496. https://doi.org/10.1017/S0954579418000020

Boden, M. T., & Berenbaum, H. (2011). What you are feeling and why: Two distinct types of emotional clarity. Personality and Individual Differences, 51(5). https://doi.org/10.1016/j.paid.2011.06.009

Briganti, G., Scutari, M., & McNally, R. J. (2022). A Tutorial on Bayesian Networks for Psychopathology Researchers. *Psychological Methods*. https://doi.org/10.1037/met0000479

Christensen, A. P., Garrido, L. E., Guerra-Peña, K., & Golino, H. (2020). *Comparing community detection algorithms in psychological data: A Monte Carlo simulation*. https://doi.org/10.31234/OSF.IO/HZ89E

Christensen, A. P., & Golino, H. (2021a). Estimating the Stability of Psychological Dimensions via Bootstrap Exploratory Graph Analysis: A Monte Carlo Simulation and Tutorial. *Psych*, *3*(3), 479–500. https://doi.org/10.3390/psych3030032

Christensen, A. P., & Golino, H. (2021b). On the equivalency of factor and network loadings. *Behavior Research Methods*, *53*(4), 1563–1580. https://doi.org/10.3758/s13428-020-01500-6

Christensen, A. P., Golino, H., & Silvia, P. J. (2020). A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires. *European Journal of Personality*, *34*(6), 1095–1108. https://doi.org/10.1002/per.2265

Cisler, J. M., Olatunji, B. O., Feldner, M. T., & Forsyth, J. P. (2010). Emotion regulation and the anxiety disorders: An integrative review. In *Journal of Psychopathology and Behavioral Assessment* (Vol. 32, Issue 1, pp. 68–82). https://doi.org/10.1007/s10862-009-9161-1

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). Qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*. https://doi.org/10.18637/jss.v048.i04

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, *23*(4), 617–634. https://doi.org/10.1037/met0000167

Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS ONE*, *12*(6). https://doi.org/10.1371/journal.pone.0174035

Golino, H., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Sadana, R., Thiyagarajan, J. A., & Martínez-Molina, A. (2019). Investigating the performance of Exploratory Graph Analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods*, *25*(3), 292–320. https://doi.org/10.1037/met0000255

Goubet, K. E., & Chrysikou, E. G. (2019). Emotion Regulation Flexibility: Gender Differences in Context Sensitivity and Repertoire. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.00935

Gratz, K. L., & Roemer, L. (2004). Multidimensional Assessment of Emotion Regulation and Dysregulation: Development, Factor Structure, and Initial Validation of the Difficulties in Emotion Regulation Scale. *Journal of Psychopathology and Behavioral Assessment*, *26*(1). https://doi.org/10.1023/B:JOBA.0000007455.08539.94

Gross, J. J. (1998a). Antecedent-and Response-Focused Emotion Regulation: Divergent Consequences for Experience, Expression, and Physiology. *Journal of Personality and Social Psychology*, *74*(1), 224–237.

Gross, J. J. (1998b). The Emerging Field of Emotion Regulation: An Integrative Review. *Review of General Psychology*, *2*(5), 271–299.

Guo, Z., Cui, Y., Yang, T., Liu, X., Lu, H., Zhang, Y., & Zhu, X. (2023). Network analysis of affect, emotion regulation, psychological capital, and resilience among Chinese males during the late stage of the COVID-19 pandemic. *Frontiers in Public Health*, *11*, 1144420. https://doi.org/10.3389/fpubh.2023.1144420

Haslbeck, J. M. B., & Waldorp, L. J. (2018). How well do network models predict observations? On the importance of predictability in network models. Behavior Research Methods, 50(2), 853–861. https://doi.org/10.3758/s13428-017-0910-x

Haws, J. K., Brockdorf, A. N., Gratz, K. L., Messman, T. L., Tull, M. T., & DiLillo, D. (2022). Examining the associations between PTSD symptoms and aspects of emotion dysregulation through network analysis. *Journal of Anxiety Disorders*, *86*. https://doi.org/10.1016/j.janxdis.2022.102536

Jones P (2022). _networktools: Tools for Identifying Important Nodes in Networks. R package version 1.5.0, <https://CRAN.R-project.org/package=networktools>.

Jones, P. J., Ma, R., & McNally, R. J. (2019). Bridge Centrality: A Network Approach to Understanding Comorbidity. *Multivariate Behavioral Research*, *56*(2), 353–367. https://doi.org/10.1080/00273171.2019.1614898

Kaur, A., Kailash, S. Z., Sureshkumar, K., C, S., & Rumaisa, N. (2022). Gender differences in emotional regulation capacity among the general population. *International Archives of Integrated Medicine*, *9*(1), 22–28. http://iaimjournal.com/

Kleinke, K. (2017). Multiple Imputation Under Violated Distributional Assumptions: A Systematic Evaluation of the Assumed Robustness of Predictive Mean Matching. Journal of Educational and Behavioral Statistics, 42(4). https://doi.org/10.3102/1076998616687084

Korkmaz, S., Goksuluk, D., & Zararsiz, G. (2014). MVN: An R package for assessing multivariate normality. R Journal, 6(2). https://doi.org/10.32614/rj-2014-031

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. Journal of General Internal Medicine, 16(9). https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Lincoln, T. M., Schulze, L., & Renneberg, B. (2022). The role of emotion regulation in the characterization, development and treatment of psychopathology. *Nature Reviews Psychology*, *1*(5), 272–286. https://doi.org/10.1038/s44159-022-00040-4

Lischetzke, T., & Eid, M. (2017). The functionality of emotional clarity: A process-oriented approach to understanding the relation between emotional clarity and well-being. In The Happy Mind: Cognitive Contributions to Well-Being. https://doi.org/10.1007/978-3-319-58763-9_20

Marshall, A., Altman, D. G., & Holder, R. L. (2010a). Comparison of imputation methods for handling missing covariate data when fitting a Cox proportional hazards model: A resampling study. BMC Medical Research Methodology, 10. https://doi.org/10.1186/1471-2288-10-112

Marshall, A., Altman, D. G., Royston, P., & Holder, R. L. (2010b). Comparison of techniques for handling missing covariate data within prognostic modelling studies: A simulation study. BMC Medical Research Methodology, 10. https://doi.org/10.1186/1471-2288-10-7

Masters, M. R., Zimmer-Gembeck, M. J., & Farrell, L. J. (2019). Transactional Associations Between Adolescents' Emotion Dysregulation and Symptoms of Social Anxiety and Depression: A Longitudinal Study. *Journal of Early Adolescence*, *39*(8). https://doi.org/10.1177/0272431618806053

Mcnally, R. J. (2021). Network Analysis of Psychopathology: Controversies and Challenges. *Annual Review of Clinical Psychology*. https://doi.org/10.1146/annurev-clinpsy-081219

McRae, K., Jacobs, S. E., Ray, R. D., John, O. P., & Gross, J. J. (2012). Individual differences in reappraisal ability: Links to reappraisal frequency, well-being, and cognitive control. Journal of Research in Personality, 46(1). https://doi.org/10.1016/j.jrp.2011.10.003

Mennin, D. S., Heimberg, R. G., Turk, C. L., & Fresco, D. M. (2005). Preliminary evidence for an emotion dysregulation model of generalized anxiety disorder. *Behaviour Research and Therapy*, *43*(10), 1281–1310. https://doi.org/10.1016/j.brat.2004.08.008

Mennin, D. S., Heimberg, R. G., Turk, C. L., & Fresco, D. M. (2006). Applying an Emotion Regulation Framework to Integrative Approaches to Generalized Anxiety Disorder. *Clinical Psychology: Science and Practice*, *9*(1), 85–90. https://doi.org/10.1093/clipsy.9.1.85

Mennin, D. S., Turk, C. L., Heimberg, R. G., & Carmin, C. (2004). Focusing on the regulation of emotion: a new direction for conceptualizing and treating generalized anxiety disorder. In *Cognitive Therapy Across the Lifespan: Evidence and Practice*.

Nolen-Hoeksema, S., & Aldao, A. (2011). Gender and age differences in emotion regulation strategies and their relationship to depressive symptoms. *Personality and Individual Differences*, *51*(6), 704–708. https://doi.org/10.1016/j.paid.2011.06.012

R Core Team (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://R-project.org/.

Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology*, *125*(6). https://doi.org/10.1037/abn0000181

Robinson, K., Garisch, J. A., Kingi, T., Brocklesby, M., O'Connell, A., Langlands, R. L., Russell, L., & Wilson, M. S. (2019). Reciprocal Risk: the Longitudinal Relationship between Emotion Regulation and Non-suicidal Self-Injury in Adolescents. *Journal of Abnormal Child Psychology*, *47*(2). https://doi.org/10.1007/s10802-018-0450-6

Ruan, Q. N., Chen, Y. H., & Yan, W. J. (2023). A network analysis of difficulties in emotion regulation, anxiety, and depression for adolescents in clinical settings. *Child and Adolescent Psychiatry and Mental Health*, *17*(1). https://doi.org/10.1186/s13034-023-00574-2

Salters-Pedneault, K., Roemer, L., Tull, M. T., Rucker, L., & Mennin, D. S. (2006). Evidence of broad deficits in emotion regulation associated with chronic worry and generalized anxiety disorder. *Cognitive Therapy and Research*, *30*(4), 469–480. https://doi.org/10.1007/s10608-006-9055-4

Scutari, M. (2017). Bayesian network constraint-based structure learning algorithms: Parallel and optimized implementations in the bnlearn R package. *Journal of Statistical Software*, *77*(1). https://doi.org/10.18637/jss.v077.i02

Scutari, M., & Nagarajan, R. (2013). Identifying significant edges in graphical models of molecular networks. *Artificial Intelligence in Medicine*, *57*(3). https://doi.org/10.1016/j.artmed.2012.12.006

Sheppes, G., Suri, G., & Gross, J. J. (2015). Emotion regulation and psychopathology. *Annual Review of Clinical Psychology*, *11*, 379–405. https://doi.org/10.1146/annurev-clinpsy-032814-112739

Siemer, M., Mauss, I., & Gross, J. J. (2007). Same Situation-Different Emotions: How Appraisals Shape Our Emotions. Emotion, 7(3). https://doi.org/10.1037/1528-3542.7.3.592

Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. *Archives of Internal Medicine*, *166*(10). https://doi.org/10.1001/archinte.166.10.1092

van Borkulo, C. D., van Bork, R., Boschloo, L., Kossakowski, J. J., Tio, P., Schoevers, R. A., Borsboom, D., & Waldorp, L. J. (2022). Comparing network structures on three aspects: A permutation test. *Psychological Methods*. https://doi.org/10.1037/met0000476

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3). https://doi.org/10.18637/jss.v045.i03

van Middendorp, H., Geenen, R., Sorbi, M. J., Hox, J. J., Vingerhoets, A. J. J. M., van Doornen, L. J. P., & Bijlsma, J. W. J. (2005). Gender differences in emotion regulation and relationships with perceived health in patients with rheumatoid arthritis. *Women and Health*, *42*(1), 75–97. https://doi.org/10.1300/J013v42n01_05

Zhang, D., Liu, S., Wu, X., & Tian, Y. (2022). Network analysis of cognitive emotion regulation strategies and depressive symptoms in young adults after recent stressful events: The moderation of childhood maltreatment. *Journal of Affective Disorders*, *301*. https://doi.org/10.1016/j.jad.2022.01.044