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Relations between emotion regulation and depression and anxiety symptoms: a network analysis

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Symptoms seem to be constitutive parts of a complex clinical problem, rather than the expressions of a disease, as traditionally considered. Network analysis has proved to be useful to identify correlations amongst them. This study addresses associations regarding regulation strategies and depressive and anxious symptoms, as well as emotion regulation strategies' risk and protective ability, in a sample of 1103 adults from Buenos Aires City and Greater Buenos Aires aged between 18 and 65 (M= 31.96; SD= 10.32). Results showed that CR and ES might be differentially associated with anxiety and depression symptoms, yet both exhibited negative bridge expected influence across the networks, suggesting a protective role. These findings have several implications for treatments.
Keywords: emotion regulation, depression symptoms, anxiety symptoms, network analysis.

Relaciones entre la regulación de las emociones y los síntomas de depresión y ansiedad: un análisis de redes

Los síntomas parecen ser partes constitutivas de un problema clínico complejo, más que expresiones de una enfermedad, como se consideraba tradicionalmente. El análisis de redes ha demostrado ser útil para identificar correlaciones entre ellos. Este estudio aborda las asociaciones entre estrategias de regulación y síntomas depresivos y ansiosos, así como el riesgo y la capacidad protectora de las estrategias de regulación de las emociones, en una muestra de 1103 adultos de la Ciudad de Buenos Aires y el Gran Buenos Aires con edades entre 18 y 65 años (M= 31,96; DE = 10,32). Los resultados mostraron que la reevaluación cognitiva (RC) y la supresión expresiva (SE) podrían estar asociadas de manera diferente con los síntomas de ansiedad y depresión, aunque ambas mostraron una influencia esperada negativa como nodos puente en las redes, lo que sugiere un rol protector. Estos hallazgos tienen varias implicaciones para los tratamientos.
Palabras clave: regulación emocional, síntomas de depresión, síntomas de ansiedad, análisis de redes

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Relações entre regulação emocional e sintomas de depressão e ansiedade: uma análise de redes

Os sintomas parecem ser partes constitutivas de um problema clínico complexo, e não expressões de uma doença, como tradicionalmente se considera. A análise de redes provou ser útil para identificar correlações entre elas. Este estudo aborda associações relativas a estratégias de regulação e sintomas depressivos e ansiosos, bem como risco e capacidade protetora de estratégias de regulação emocional, em uma amostra de 1.103 adultos da cidade de Buenos Aires e Grande Buenos Aires com idade entre 18 e 65 anos (M = 31,96; DP = 10,32).Os resultados mostraram que a reavaliação cognitiva (RC) e a supressão expressiva (SE) podem estar associadas de forma diferenciada aos sintomas de ansiedade e depressão, embora ambas tenham apresentado influência esperada negativa como nós-pontes nas redes, sugerindo um papel protetor. Essas descobertas têm várias implicações para os tratamentos.

Palavras-chave: regulação emocional, sintomas de depressão, sintomas de ansiedade, análise de redes

In the field of psychopathology, comorbidity has been considered the rule rather than the exception for years (Kessler et al., 2005). Comorbidity is often investigated by considering composite measures of items representing latent constructs that share a causal root (Boorsboom et al., 2011). Traditionally, psychology has defined the different psychopathological entities as latent structures represented by symptoms. However, it has been found that half of the symptoms in the DSM-IV network are connected, and the architecture of these connections features a high degree of clustering but a short average path length. The distances between disorders predict empirical comorbidity rates (Borsboom et al., 2011). The emergence of the network model coincides with a movement that has occurred in recent years within the field of Psychopathology, where dimensional models are being proposed as alternatives to classic categorical models (Insel et al., 2010; Krueger et al., 2018; Kotov et al., 2017; Lahey et al., 2021).

Classifications of mental disorders are intended to facilitate organization, communication, description, prediction, theory construction, clinical utility, and scientific accuracy (Forbes et al., 2024). Based on these objectives, the way mental disorders are classified has been the subject of a debate that has increased in recent years (Lahey et al., 2021; Rief et al., 2023). Limitations of categorical systems include a wide range of difficulties: the distinction between diagnostic categories is not as clear due to overlapping symptoms and the presence/absence limits are imprecise for the comparison of symptom levels of different people with the same disorder and the categories have low inter-rater reliability. These are problematic, considering comorbidity between disorders is the norm and several mechanisms are transdiagnostic; or that the data do not support the categorization proposed by the manuals (Borsboom et al., 2011; Clark et al., 2017; Cuthbert & Kozak, 2013; Eaton et al., 2023; Forbes et al., 2024)

Variations in human behavior can be explained in dimensional or categorical terms (Lahey et al., 2021; Rief et al., 2023). Network analysis is presented as an alternative that could be complementary to categorical models that conceive clinical entities as factors represented by different symptoms. This relationship could be analyzed, for example, from the point of view of structural equations, through which it could be said that symptoms have a causal relationship with disorders (Borsboom & Cramer, 2013). Within the network approach, symptoms have an active causal role as interrelated entities interacting with each other and with other variables (Cramer et al., 2010; Borsboom & Cramer, 2013; Henry et al., 2022; Lunansky & Garay, 2022). Symptoms are not expressions of a disease but constitutive parts of the clinical problem (Lunansky & Garay, 2022) and are causally connected through innumerable biological, psychological and social mechanisms (Borsboom, 2017).

In classical experimental designs, causality is established through the controlled manipulation of an independent variable and the observation of its effects on a dependent variable, which allows for the isolation of unidirectional relationships under controlled conditions (Shadish et al., 2002). In contrast, the psychopathological network approach assumes that symptoms are not simple indicators of a latent entity, but rather nodes in a dynamic system that influence each other in reciprocal interactions (Borsboom & Cramer, 2013). However, in empirical practice, many network studies use cross-sectional data, implying that observed associations between symptoms reflect static correlations at a single point in time, without allowing for the inference of causal directionality or dynamic changes (Bringmann & Eronen, 2018). Thus, while experimental causality requires manipulation and control to establish causal inferences, causality in psychopathological networks is often based on patterns of covariation between symptoms that suggest possible mechanisms, but do not reach the status of causal evidence in the experimental sense (Robinaugh et al., 2019).

The network approach has been essential in psychopathology (Epskamp et al., 2017). A recent review (Fried et al., 2017) showed that prediction studies have found that symptom networks of people with mental disorders are different from those of healthy individuals. They also expose that networks of healthy people may show early warning signals before becoming a disordered network. Regarding intervention, targeting the most central symptoms could offer novelties at the psychotherapeutic level. In addition, this approach proposes a relevant framework to analyze the relationships between symptoms at the clinical level and new quantitative methods at the research level (Lunansky & Garay, 2022).

Anxiety and mood disorders are the most prevalent worldwide (Dattani et al., 2021) and in Argentina (Cía et al., 2018). Accordingly, the symptoms of anxiety and depression present a high prevalence (Etchevers et al., 2021). Previous studies carried out from the perspective of network analysis reported the relevance of symptoms such as loss of interest (Bos et al., 2018), loss of pleasure (Bringmann et al., 2015), and sad/depressed mood (Boschloo et al., 2016; Briganti et al., 2021; Cramer et al., 2010; Fried et al., 2016; Hakulinen et al., 2020; Kaiser et al., 2021) in depression networks; and worry (Beard et al., 2016; Hoffard et al., 2021) in anxiety networks. A better understanding of common mechanisms of depressive and anxiety symptoms may lead to developing early detection and intervention strategies (Liang et al., 2022).

From a transdiagnostic approach, there are common etiological and maintenance processes and cognitive-affective, interpersonal, and behavioral variables (Fusar-Poli et al., 2019). One of the most addressed transdiagnostic processes has been emotion regulation (ER) due to its ubiquity in psychopathology (Cludius et al., 2020). ER emerged as one of the most studied topics in psychology due to its transdiagnostic nature (Aldao et al., 2016). It is fundamental in triggering and maintaining different clinical conditions (Aldao et al., 2010; Sloan et al., 2017). ER refers to how individuals influence their emotions when they have them and how they experience and express them (Gross, 1998, 2015). ER is crucial when there is a conflict between a person's emotional responses and goals (Bargh & Williams, 2007), as it allows people to manage all their emotionally charged states, including emotional specific, affect, mood and stress.

It has been suggested that difficulties in ER are associated with the identification of the need to regulate emotions; the selection of one among the different strategies available to regulate emotions; the implementation of a strategy to regulate emotions once it has been selected; and the monitoring of the ER implemented over time (Sheppes et al., 2015). The most widespread model of ER is the Process Model (Gross, 1998, 2015). This model incorporates stages where a regulatory need is identified after a discrepancy between someone's goal and current state. Then, a strategy is selected and implemented, and follow-up is performed to track success. ER strategies are classified based on when they intervene in generating the emotional response (Gross, 2001; Gross, 2015). Antecedent-focused ER strategies are performed before activating and changing the emotional response's course. In contrast, response-focused ER strategies are implemented after the emotional response and require more effort to deal with the consequences of the emotional response (Gross, 2015).

The process model highlights two ER strategies: cognitive reappraisal and expressive suppression. Cognitive reappraisal is an antecedent-focused strategy that implies a reinterpretation of the emotional meaning of a situation to modify the emotional response (Gross & John, 2003). According to research literature, habitual use of cognitive reappraisal is positively associated with well-being, positive emotions, and positive functioning and negatively with psychological symptoms and negative emotions (Gross & John, 2003; McRae & Gross, 2020). On the contrary, expressive suppression is a response-focused strategy that inhibits emotional expression to influence outcomes rather than the emotion itself (Gross, 1998). As shown in the research literature, frequent use of expressive suppression is related to less positive emotions, more negative emotions, more perceived stress, weaker expressivity, and greater psychological symptoms (Aldao et al., 2010; Aldao et al., 2016; Gross & John, 2003; Sloan et al., 2017).

Regarding the research literature on the relationship between ER and symptoms of anxiety and depression, most published studies have operationalized the constructs through the latent constructs approach, with depression and anxiety severity indexed by sum scores of symptoms (Liang et al., 2022). This approach may overlook the existing relationships at the symptom level (Fried & Nesse, 2015). However, in recent years, different investigations have been carried out from a network approach, which considered the symptoms of anxiety and depression as causal entities interrelated with ER.

Everaert and Joormann (2019) examined the associations among repetitive negative thinking, positive reappraisal, and individual symptoms of depression and anxiety disorders through the estimation of models of regularized partial-correlation networks using cross-sectional data from 468 participants who were 18 years or older and resided in the United States. They found that repetitive negative thinking and reappraisal were differentially related to affective, cognitive, and somatic symptoms of depression and anxiety. Regarding depression symptoms, the authors found that repetitive negative thinking was positively related to guilty feelings, changes in appetite, agitation, self-criticalness, and sadness. Positive reappraisal was negatively related to pessimism. Regarding anxiety symptoms, they stated that repetitive negative thinking was positively related to fear of losing control, fear of the worst happening, inability to relax, and nervousness. Positive reappraisal was negatively related to fear of the worst happening.

Liang et al. (2022) considered the strategies specified in the Process Model (Gross, 1998) and examined depression symptoms, anxiety symptoms and emotion regulation among 420 medical staff from Xijing Hospital, China, during the late stage of the COVID-19 pandemic via network analysis. They constructed two networks: an ER-depression network and an ER-anxiety network and calculated the bridge centrality index for each variable within the two networks. They reported that cognitive reappraisal and expressive suppression showed distinct connections to symptoms of depression and anxiety. Considering bridge centrality, the authors informed that CR had a negative bridge expected influence value in both networks while ES had a positive one.

Moreover, Liang et al. (2022) informed that cognitive reappraisal was negatively related to five depression symptoms that capture fatigue: anhedonia, sleep difficulties, fatigue, psychomotor agitation/retardation and concentration difficulties. Also, they identified a strong positive edge between expressive suppression and the symptom of thought of death. Within the emotion regulation-anxiety network, they found that the symptom of trouble relaxing was negatively linked to cognitive reappraisal and positively linked to expressive suppression. Furthermore, expressive suppression was negatively linked to one anxiety symptom of irritability. To quantify the protective or risk ability of cognitive reappraisal and expressive suppression on depression and anxiety symptoms, the authors calculated the bridge expected influence of each network. In both, cognitive reappraisal has had a negative bridge expected influence value. In contrast, expressive suppression has had a positive bridge expected influence value, indicating cognitive reappraisal may be a protective factor and expressive suppression may be a risk factor for depression and anxiety among medical staff (Liang et al., 2022).

The research literature offers much information about the relationship between ER and symptoms of anxiety and depression. However, most of the research has been carried out from the approach of latent constructs, possibly ignoring the role of symptoms (Liang et al., 2022). The investigations on the relationship between ER and anxiety and depression symptoms from the network approach have only been carried out with samples from the United States and China. So, there is still much research to be done to know the behavior of the variables in different contexts from the network approach.

Under consideration of the construct of ecological validity (Kihlstrom, 2021) and the biases that generalization of results to other populations may cause, is that this research was carried out to address these topics in the local context. The present study aimed 1) to explore differential links between emotion regulation strategies and symptoms of depression and anxiety in a sample of adults from Buenos Aires City and Greater Buenos Aires; 2) to assess ER strategies risk and protective ability of the CR and ES on depression and anxiety symptoms in a sample of adults from Buenos Aires City and Greater Buenos Aires and 3) to examine whether CR and/or ES act as bridges connecting anxiety and depression symptoms.

Method

Sample

Through intentional non-probabilistic sampling, a sample of 1103 participants aged between 18 and 65 (M= 31.96; SD= 10.32) was collected. 65% (n= 718) reported living in the Buenos Aires suburbs and 35% (n= 385) in Buenos Aires City. Regarding gender, 63% (n= 696) reported female, 36% male (n= 396) and 1% (n= 11) non-binary. Regarding the level of education, 46.4% (n=512) reported incomplete university or in progress, 29.1% (n=321) complete university, 15.5% (n= 171) complete secondary school, 4.4% (n= 49) postgraduate, 3.9% (n= 43) incomplete or ongoing secondary school, 0.5% (n= 5) complete primary school, and 0.2% (n= 2) incomplete or ongoing primary school. Regarding marital status, 50.4% (n= 546) reported being single, 45.9% (n= 506) being married, in a relationship or cohabiting, 3.2% (n= 35) separated or divorced and 0.5% (n= 6) widowed.

Participants had to meet the following requirements: be between 18 and 65 years old, reside in the City of Buenos Aires or the Buenos Aires suburbs, and complete the informed consent. The exclusion criteria were that the people were minors, that they were over 65 years of age and that they had not completed the informed consent. The classification of age groups is the one elaborated by Cuijpers et al. (2020), according to which adults can be divided into young adults (18 to 24 years), middle-aged adults (24 to 55 years) and older adults (55 to 65 years).

Table 1

Sociodemographic data

Variable	Number	%
Age		
18 - 24 years	287	26.0
25 - 55 years	757	68.6
56 - 65 years	59	5.3
Gender		
Female	696	63
Male	396	36
Non-binary	11	1
Education		
Complete university	321	29.1
Incomplete or ongoing university	512	46.4
Complete secondary school	171	15.5
Incomplete or ongoing secondary school	43	3.9
Complete primary school	5	0.5
Incomplete or ongoing primary school	2	0.2
Marital status		
Single	546	50.4
Married, in a relationship or cohabiting	506	45.9
Separated or divorced	35	3.2
Widowed	6	0.5

Instruments

Sociodemographic questionnaire

A sociodemographic questionnaire that inquired about gender (female, male, non-binary), age, educational level (incomplete primary, complete primary, incomplete secondary, complete secondary, incomplete tertiary or university, complete tertiary or university and postgraduate education), and marital status (single, married, with a partner, common-law marriage, divorced, widowed).

Beck Anxiety Inventory (BAI; Beck et al., 1988; Argentine adaptation: Vizioli & Pagano, 2020; 2022a)

It is a self-administered instrument with 21 items that measure characteristic symptoms of anxiety, which is scored using a four-option Likert scale (0 to 3). The instrument has evidence of construct validity through confirmatory factor analysis; invariance according to gender, educational level, age and region; as well as adequate values of internal consistency through different coefficients, namely, α = .94; ω = 95; algebraic GLB = .97; GLB factorial = .96; β= .86; H = 91; θ = .88 (Pagano & Vizioli, 2021; Vizioli, 2024a; Vizioli & Pagano, 2020; 2022a). It also presents evidence of discriminant validity in relation to depressive symptoms, with a correlation of r= .56, exploratory factor analysis that shows a two-factor solution, and a HTMT proportion = .66 (95% CI = .55 - .74), and evidence of temporal stability in a three-month interval through an intraclass correlation of .82 (95% CI = .69 - .90) (Pagano & Vizioli, 2021a).

Beck Depression Inventory (BDI-II; Beck et al., 2006; Argentine adaptation: Brenlla & Rodríguez, 2006)

It is a self-administered instrument consisting of 21 items that refer to characteristic symptoms of depression. Items are scored on a 4-option Likert scale (0 to 3), with total scores ranging from 0 to 63, with cut-off points based on severity and intensity of depressive symptoms: 0-13 = minimal depression, 14-19 = mild depression; 20-28 = moderate depression and 29-63 = severe depression. The BDI presents adequate psychometric properties for the Argentine population, with an internal consistency of Cronbach's α = .88.

Emotional Regulation Questionnaire (ERQ; Gross & John, 2003; Argentine adaptation: Pagano & Vizioli, 2021b)

It is a self-administered questionnaire consisting of 9 items, which measures two emotional regulation strategies: cognitive reappraisal (6 items) and expressive suppression (3 items). Responses are given on a 7-point Likert scale, ranging from 1 = totally disagree to 7 = totally agree. The questionnaire presents adequate psychometric properties for the Argentine population, with evidence of construct validity through confirmatory factor analysis, which indicates a structure that measures two independent factors. Through multi-group confirmatory factor analysis, it was found that the instrument presented invariance according to gender and age (Vizioli, 2024b). It also exhibits adequate reliability values: α ordinal = .81 and ω ordinal = .87 for cognitive reappraisal, and α ordinal = .72 and ω ordinal = .79 for expressive suppression. Likewise, it has evidence of convergent and incremental validity with measures of anxious and depressive symptomatology, and temporal stability in a 3-month interval (Vizioli & Pagano, 2022b)

Data analysis

Regarding the descriptive statistics, the means and standard deviations of the variables of interest were calculated. To address the objectives proposed in this research, three networks were examined following previous research (Everaert & Joormann, 2019; Liang et al., 2022): ER-anxiety symptoms (ER-AS); ER-depression symptoms (ER-DS) and a network combining both anxiety and depression symptoms (ER-ADS). The estimation and interpretation of the networks, as well as the analysis of their precision, were carried out following the guidelines proposed by Epskamp and Fried (2018), Epskamp et al. (2018), and Havey (2018). The information reported in this section follows the standards proposed by Burger et al. (2022) for network analysis, in such a way that data is provided about the structure of the network, its visualization and its stability, including specificities about the estimation and graphing of the network, statistics to examine its stability and the precision of the nodes, as well as centrality measures.

The networks were estimated through the Gaussian graphical model (GGM; Costantini et al., 2015), using the least absolute shrinkage and selection operator (LASSO; Friedman et al., 2008; Tibshirani, 1996). After LASSO regularization, a network was selected using Extended Bayesian Information Criterion (EBIC; Chen & Chen, 2008), with the tuning parameter set to $\gamma = 0.5$ (Epskamp et al., 2018; Epskamp & Fried, 2018; Havey, 2018). This estimation procedure was conducted using the *qgraph* package (Epskamp et al., 2012) in the R software.

Traditional centrality measures were calculated to indicate the structure of the networks (Epskamp & Fried, 2018; Fonseca-Pedrero, 2018): a) strength, b) closeness and c) betweenness. a) strength refers to the magnitude of the association between the nodes; b) closeness indicates if a node can predict other nodes; and c) betweenness quantifies how important a node is in the average path between two other nodes (Epskamp et al., 2018; Fonseca-Pedrero, 2018). Bridge expected influence was used to estimate and interpret the importance of the nodes, as it accounts for the presence of negative edges, unlike traditional indices (Robinaugh et al., 2016; Jones et al., 2021). Higher values of expected influence indicate greater importance of the nodes in the networks.

To assess the networks' accuracy, the edge weights and stability of centrality indices were tested (Epskamp et al., 2018). The accuracy of the edge weights was tested by plotting the 95% confidence intervals (CIs) using non-parametric bootstrap with 2000 bootstrap samples. To interpret edge weights accuracy, CIs width was considered. When the bootstrapped CIs are wide, the strength of an edge is harder to interpret (Epskamp et al., 2018). To test the stability of the centrality measures, correlation stability coefficients (CS-coefficients) were calculated after performing *m out of n* bootstrap with 2500 samples. This method drops proportions of cases from the original data to assess the correlation between the original centrality indices and those obtained from subsets and enables to obtain CS-coefficients, as a way to quantify the stability of centrality indices using subset bootstraps (Epskamp et al., 2018). CS-coefficient indicates the percentage of our sample that can be dropped to maintain correlation of r = 0.7 between sample's centrality values and bootstrapped samples' centrality values with 95% confidence interval. To interpret CS, suggested thresholds were used: CS should be, preferable, above 0.5 (Epskamp et al., 2018). Descriptive statistics, were performed with JASP software (JASP team, 2022), while the network estimations and the CS-coefficients calculations were performed in R (4.3.2 version), using *qgraph* (Epskamp et al., 2012) and *bootnet* (Epskamp et al., 2018) packages. The R codes proposed by Epskamp et al. (2018) in their tutorial were used to analyze the data.

Procedure

The data was collected through the use of virtual platforms. The sample was collected from the use of social networks and messages sent by cell phone. Prior to the administration of the instruments, the participants completed an informed consent, which specified the objectives of the research, explained the guarantees of confidentiality and anonymity, and explained that participation was voluntary and without compensation, and that the participants could leave the study participation at any time.

The procedures carried out in this investigation were based on the recommendations and principles of the American Psychological Association (2010), and on the ethical aspects specified by the Declaration of Helsinki (World Medical Association, 2013), which establishes the principles and ethics for research with humans.

Results

Descriptive results

Table 2 shows abbreviation, means and standard deviations for each variable analyzed in the networks.

Table 2

Abbreviations and descriptive statistics for each variable analyzed in the networks

Variable	Abbreviation	Mean	Standard Deviation
Cognitive reappraisal	CR	4,73	1,29
Expressive suppression	ES	4,17	1,65
Numbness or tingling	bai1	1,01	0,92
Feeling hot	bai2	1,15	0,95
Wobbliness in legs	bai3	1,02	0,92
Unable to relax	bai4	1,90	1,07
Fear of worst happening	bai5	1,67	1,15
Dizzy or lightheaded	bai6	0,96	0,92
Heart pounding/racing	bai7	1,17	1,02
Unsteady	bai8	1,37	1,08
Terrified or afraid	bai9	1,15	1,02
Nervous	bai10	1,96	1,01
Feeling of choking	bai11	1,01	0,99
Hands trembling	bai12	0,85	0,87
Shaky / unsteady	bai13	1,08	0,94
Fear of losing control	bai14	1,16	1,03
Difficulty in breathing	bai15	0,96	0,92
Fear of dying	bai16	0,89	0,97
Scared	bai17	1,10	1,00
Indigestion	bai18	1,50	1,11
Faint / lightheaded	bai19	0,64	0,69
Face flushed	bai20	0,90	0,89

Variable	Abbreviation	Mean	Standard Deviation
Hot/cold sweats	bai21	0,97	0,94
Sadness	bdi1	0,52	0,68
Pessimism	bdi2	0,62	0,70
Past Failure	bdi3	0,64	0,86
Loss of Pleasure	bdi4	0,75	0,76
Guilty Feelings	bdi5	0,84	0,80
Punishment Feelings	bdi6	0,40	0,83
Self-Dislike	bdi7	0,81	1,10
Self-Criticalness	bdi8	0,92	0,92
Suicidal Thoughts or Wishes	bdi9	0,34	0,61
Crying	bdi10	0,76	1,04
Agitation	bdi11	0,59	0,73
Loss of interest	bdi12	0,85	0,81
Indecisiveness	bdi13	0,84	0,97
Worthlessness	bdi14	0,72	0,93
Loss of Energy	bdi15	1,05	0,82
Changes in Sleeping Pattern	bdi16	1,18	0,89
Irritability	bdi17	0,73	0,83
Changes in Appetite	bdi18	0,87	0,92
Concentration Difficulty	bdi19	1,03	0,89
Tiredness or Fatigue	bdi20	0,98	0,89
Loss of Interest in Sex	bdi21	0,79	0,94

Note. ER-anxiety symptoms network

The ER-AS network structure is shown in Figure 1. The strongest edges were between bai15 and bai11 (weight= 0.52), bai17 and bai9 (weight= 0.38), bai4 and bai10 (weight= 0.33), bai12 and bai13 (weight= 0.32), and bai5 and bai9 (weight= 0.29). CR was negatively linked with bai5 (weight= -0.046), bai8 (weight= -0.02) and bai10 (weight= -0.02). ES was negatively linked with bai19 (weight= -0.03), bai16 (weight= -0.01) and bai9 (weight= -0.01).

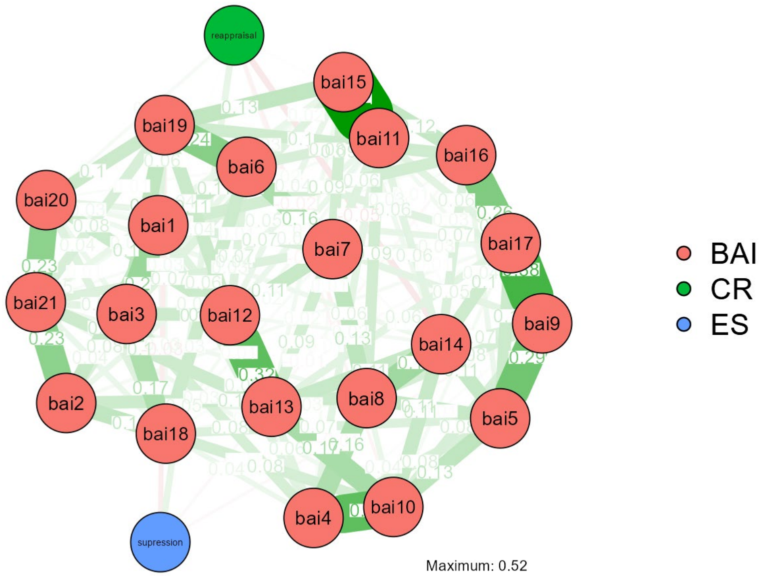

Figure 1. Emotion regulation – anxiety symptoms network

Note: CR= cognitive reappraisal; ES= expressive suppression; AS= anxiety symptoms. Green edges represent positive links, and red edges negative links. The thickness of the edge refers to the magnitude of the correlation.

Through the calculation of the CS-coefficient, it was found that connections were stable for strength, bridge expected influence and closeness with values of CS (cor = 0.7) > 0.75, but not for betweenness that presented values of CS (cor = 0.7) = 0.05. Therefore, strength, bridge expected influence and closeness are interpretable but betweenness is not. Table 3 indicates that CR and ES were the most important nodes, due to their relatively high expected influences. Both CR (bridge expected influence= -2,97) and ES (bridge expected influence= -2,96) bridge expected influences were negative.

Table 3

ER-anxiety symptoms network centrality measures per variable

Variable	Betweenness	Closeness	Strength	Bridge expected influence
CR	-0,86	-1,73	-2,26	-3,41
ES	-1,15	-2,43	-2,17	-1,66
bdi1	1,46	1,29	0,85	0,80
bdi2	0,40	0,58	0,02	-0,58
bdi3	0,11	0,72	0,90	0,23
bdi4	1,65	1,23	1,00	0,90
bdi5	-1,06	-0,49	-0,15	-0,01
bdi6	0,11	0,33	-0,14	0,10
bdi7	1,56	1,03	1,22	1,07
bdi8	-0,57	0,49	0,56	0,44
bdi9	0,78	1,01	0,47	0,53
bdi10	-0,28	0,46	-0,16	0,09
bdi11	-0,86	-0,84	-0,98	-0,49
bdi12	2,33	1,24	0,65	0,66
bdi13	-0,86	-0,38	0,18	0,33
bdi14	-0,77	0,54	1,01	0,92
bdi15	0,40	0,17	0,67	0,55
bdi16	-1,15	-1,58	-0,73	-0,48
bdi17	-0,48	-0,48	-0,36	-0,19
bdi18	0,11	-0,45	-0,14	-0,04
bdi19	0,20	0,00	0,24	0,37
bdi20	0,01	0,01	1,02	0,88
bdi21	-1,06	-0,71	-1,70	-1,01

Note. CR= cognitive reappraisal; ES= expressive suppression. ER-depression symptoms network

The ER-DS network structure is shown in Figure 2. The strongest edges were between bdi15 and bdi20 (weight= 0.41), bdi4 and bdi12 (weight= 0.28), bdi5 and bdi6 (weight= 0.24), bdi1 and bdi9 (weight= 0.23), and bdi7 and bdi14 (weight= 0.22). CR was negatively linked with bdi2 (weight= -0.12), bdi3 (weight= -0.09), bdi16 (weight= -0.03), bdi8 (weight= 0.03), bdi15 (weight= -0.02) and bdi5 (weight= 0.02). ES was negatively linked with bdi18 (weight= 0.02), and bdi17 (weight= 0.02).

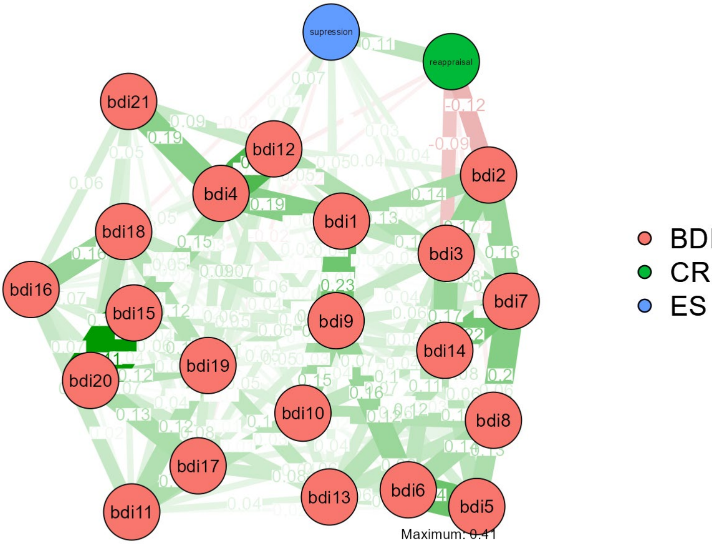

Figure 2. Emotion regulation – depression symptoms network

Note. CR= cognitive reappraisal; ES= expressive suppression; DS= depression symptoms. Green edges represent positive links, and red edges negative links. The thickness of the edge refers to the magnitude of the correlation.

Through the calculation of the CS-coefficient, it was found that connections were stable for strength, bridge expected influence with values of CS (cor = 0.7) > 0.75, as well as values for and closeness CS (cor = 0.7) = 0.67, but not for betweenness that presented values of CS (cor = 0.7) = 0.21. Therefore, strength, bridge expected influence and closeness are interpretable but betweenness is not. Table 4 indicates that CR and ES were the most important nodes, due to their relatively high expected influences. Both CR (bridge expected influence= -3,41) and ES (bridge expected influence= -1,66) bridge expected influences were negative. bdi7 and bdi21 also present relatively high bridge expected influences.

bdi7 bridge expected influence was positive (bridge expected influence= 1,07) and bdi21 bridge expected influence was negative (bridge expected influence = -1,01). CR and ES also had the highest strength (-2.26 amd -2,17 respectively) and closeness (-1,73 and -2,43 respectively) values.

Table 4

ER-depression symptoms network centrality measures per variable

Variable	Betweenness	Closeness	Strength	Bridge expected influence
CR	-0,86	-1,73	-2,26	-3,41
ES	-1,15	-2,43	-2,17	-1,66
bdi1	1,46	1,29	0,85	0,80
bdi2	0,40	0,58	0,02	-0,58
bdi3	0,11	0,72	0,90	0,23
bdi4	1,65	1,23	1,00	0,90
bdi5	-1,06	-0,49	-0,15	-0,01
bdi6	0,11	0,33	-0,14	0,10
bdi7	1,56	1,03	1,22	1,07
bdi8	-0,57	0,49	0,56	0,44
bdi9	0,78	1,01	0,47	0,53
bdi10	-0,28	0,46	-0,16	0,09
bdi11	-0,86	-0,84	-0,98	-0,49
bdi12	2,33	1,24	0,65	0,66
bdi13	-0,86	-0,38	0,18	0,33
bdi14	-0,77	0,54	1,01	0,92
bdi15	0,40	0,17	0,67	0,55
bdi16	-1,15	-1,58	-0,73	-0,48
bdi17	-0,48	-0,48	-0,36	-0,19
bdi18	0,11	-0,45	-0,14	-0,04
bdi19	0,20	0,00	0,24	0,37
bdi20	0,01	0,01	1,02	0,88
bdi21	-1,06	-0,71	-1,70	-1,01

Note. CR= cognitive reappraisal; ES= expressive suppression. ER- anxiety and depression symptoms network

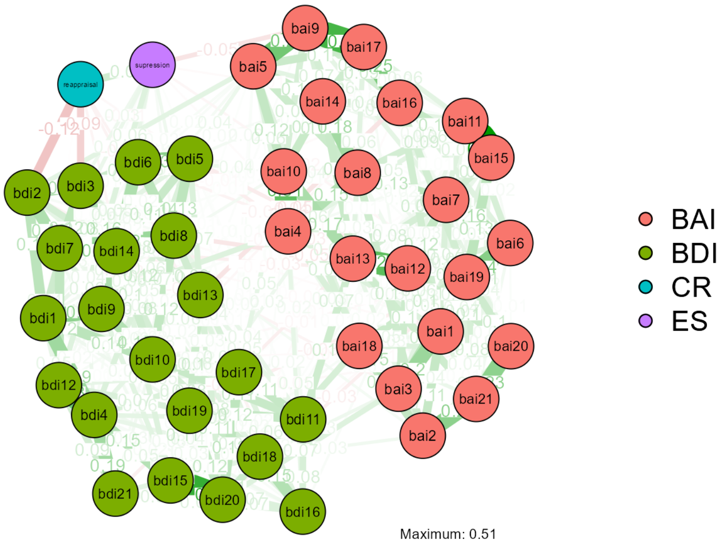

Figure 3. Emotion regulation – depression symptoms network.

Note. CR= cognitive reappraisal; ES= expressive suppression. network colors were fixed to be colorblind friendly, with blue meaning positive and red meaning negative edge weights. The thickness of the edge refers to the magnitude of the correlation.

Graphical representation of the ER-ADS network can be visualized in figure 3. The network consisted of 44 nodes. The strongest edges were between bai5 and bai9 (weight= .29), bai9 and bai17 (weight= .37), bai11 and bai15 (weight= 0.51), bai20 and bai21 (weight= 0.23), bdi15 and bdi20 (weight= 0.40). CR was negatively linked with bdi2 (weight= -0.12) and bdi3 (weight= -0.09).ES was negatively linked with bai9 (-0.05).

Through the calculation of the CS-coefficient, it was found that connections were stable for strength and bridge expected influence with values of CS (cor = 0.7) > 0.75, but not for betweenness and closeness that presented values of CS (cor = 0.7) = 0.13 and CS (cor = 0.7) = 0.28, respectively. Therefore, strength and bridge expected influence are interpretable but betweenness and closeness are not. As seen in Table 5, CR (bridge expected influence = -4,50 had the highest value of bridge expected influence followed by ES (bridge expected influence = -2,58).

Table 5

ER-anxiety and depression symptoms network centrality measures per variable

Variable	Betweenness	Closeness	Strength	Expected influence
bai1	-0,38	-0,03	-0,19	-0,12
bai2	-0,70	-0,92	-0,71	-0,21
bai3	1,47	0,86	0,10	0,21
bai4	1,65	1,76	-0,05	0,28
bai5	1,10	0,63	0,62	0,77
bai6	-0,85	-0,14	-0,31	0,08
bai7	-1,10	-0,48	0,00	0,31
bai8	0,64	0,73	0,45	0,64
bai9	0,85	-0,11	0,94	0,58
bai10	0,56	1,49	0,56	0,73
bai11	-1,03	-1,52	0,65	0,79
bai12	0,09	0,88	0,75	0,36
bai13	1,93	1,53	0,88	0,71
bai14	-1,24	-0,23	-0,06	0,27
bai15	-0,20	-1,15	0,91	0,95
bai16	0,49	-0,45	-0,39	-0,75
bai17	0,20	-0,37	0,90	0,99
bai18	0,17	0,50	-0,43	0,00
bai19	1,83	0,88	1,37	-0,25
bai20	-1,28	-1,51	-1,11	-0,85
bai21	-0,99	-1,31	-0,06	0,20
bdi1	2,48	1,40	0,87	0,95
bdi2	1,00	0,26	-0,08	-0,96
bdi3	-0,66	-0,29	0,70	0,08
bdi4	0,35	0,21	0,82	0,77
bdi5	-1,10	-0,51	0,14	-0,30
bdi6	-0,59	-0,20	-0,28	-0,09
bdi7	0,67	0,42	1,11	1,06
bdi8	0,35	0,66	0,54	0,12

Variable	Betweenness	Closeness	Strength	Expected influence
bdi9	-0,27	0,50	0,09	0,38
bdi10	-0,41	0,44	-0,35	-0,27
bdi11	0,71	1,44	-1,12	-0,60
bdi12	0,45	0,12	0,34	0,53
bdi13	-0,56	-0,16	0,16	-0,01
bdi14	-1,10	-0,35	1,03	0,73
bdi15	0,06	0,21	0,39	0,45
bdi16	-1,28	-0,93	-1,19	-0,77
bdi17	-0,99	0,12	-0,84	-0,31
bdi18	0,35	0,70	-0,19	0,18
bdi19	-0,16	0,71	0,12	0,14
bdi20	1,03	0,66	1,25	0,92
bdi21	-1,28	-1,44	-2,20	-1,59
CR	-1,21	-2,67	-3,24	-4,50
ES	-1,06	-2,34	-2,90	-2,58

Note. CR= cognitive reappraisal; ES= expressive suppression.

Discussion

The present study explored differential links between emotion regulation strategies and symptoms of depression and anxiety in a sample of adults from Buenos Aires City and Greater Buenos Aires. Results showed that CR and ES might be differentially related to anxiety and depression symptoms, as reported by previous studies (Everaert & Joormann, 2019; Liang et al., 2022). Regarding ER strategies and anxiety symptoms, CR was negatively linked with fear of the worst happening, unsteadiness, and nervousness. Since CR is an antecedent-focused strategy that implies a reinterpretation of the emotional meaning of a situation to modify the emotional response (Gross & John, 2003), it is logical that a greater use of CR is related to less nerves, unsteadiness and fear of the worst happening.

In this sense, less use of CR could be associated with more negative thoughts which are characteristic of several mental disorders, such as anxiety and depression (Everaert & Joormann, 2019; Roepke & Selligman, 2016). CR has a positive impact in the affective domain by decreasing negative emotions without increases in physiological activation, which causes an impact in mood and anxiety disorders, as they are usually characterized by emotion dysregulation (Cutuli, 2014). ES was negatively linked with faint/lightheaded, fear of dying and being terrified or afraid. Also, ES was negatively linked with the depressive symptoms of changes in appetite and irritability. These results are similar to the ones reported by Liang et al. (2022), which showed ES as a risk factor for depression and anxiety.

While a frequent use of ES can be effective in reducing these symptoms, it is worth mentioning that expressive suppression principally modifies the behavioral aspect of the emotional responses. It does not help reducing the subjective and physiological experience of negative emotion and may thus continue to be unresolved, as explained by Cutuli (2014). ES is a response-focused strategy that inhibits emotional expression to influence outcomes (Gross, 1998), and may lead to social difficulties and anxious relational behaviors (Cutuli, 2014; Gross & John, 2003).

As regards to CR and depressive symptoms, CR was negatively linked with sadness, past failure, changes in sleeping patterns, self-criticalness, loss of energy, and guilty feelings. The use of CR is related to affective benefits like more internally felt and outwardly expressed positive emotions and less internally felt and outwardly expressed negative emotions (Dryman & Heimberg, 2018). Additionally, CR is associated with more perceived self-esteem and life satisfaction, and overall mental health (Hu et al., 2014).

Examining the importance of CR and ES in separate networks showed that both CR and ES had high values of expected influence in both anxiety and depression networks, suggesting that CR and ER are highly connected with depression and anxiety symptoms. In inspecting whether CR and/or ES act as bridges connecting depression and anxiety symptoms, it was found that CR and ES had the highest expected influences of the anxiety and depression symptoms network. These results indicate that CR and ES are important in connecting anxiety and depression symptoms. These findings suggest that emotion regulation strategies, and particularly CR and ES are important mechanisms explaining the high co-occurrence of anxiety and depression, according to previous literature about transdiagnostic mechanism (Aldao et al.,2010; Aldao et al., 2016; Cludius et al., 2020; Sloan et al., 2017).

The present study assessed ER strategies' risk and protective ability on depression and anxiety by calculating the bridge expected influence of CR and ES on each network. CR and ES exhibited negative bridge expected influence on both anxiety and depression networks, as well as in the anxiety and depression symptoms networks These results differ from previous investigations that reported a positive bridge expected influence for CR and a negative for ES on both networks (Liang et al., 2022). The results of the present investigation show that both strategies can function as protective factors. Likewise, excessive dependence on SE could be maladaptive, as shown by Dryman and Heimberg (2018), because of the negative consequences in both social and emotional aspects, particularly in the case of social anxiety disorder. The effectiveness of ES may depend on the emotion to be regulated and the situation in which a person finds himself: sometimes, the expression can be harmful, or the suppression can be beneficial (Fernandes & Tone, 2021).

These findings have several implications for treatments. The consideration of ER strategies has been pivotal to different kinds of psychotherapy, as in the use of cognitive restructuring in Cognitive Therapy (Clark, 2022), the approach to emotion regulation strategies by certain techniques in Schema Therapy and Dialectical Behaviour Therapy (Fassbinder et al., 2016) or the study of patterns of emotion dysregulation in trauma therapies (González et al., 2017).

CR and ES showed negative links with symptoms of anxiety and depression, emerged as an important connection between symptoms of anxiety and depression, and both have been found to be protective factors. Previous literature suggested that CR may be adaptive and healthy (Gross & John, 2003; McRae & Gross, 2020), while ES is presented as maladaptive strategy related to negative outcomes (Aldao et al., 2010; Aldao et al., 2016; Gross & John, 2003; Sloan et al., 2017). However, the efficacy of the use of ES may depend on the situation and the emotion to regulate (Fernandes & Tone, 2021). In this sense, effective use of both CR and ES should be targets of psychological treatments. Considering the prevalence of elevated symptoms of anxiety and depression, the assessment of the forms of emotional regulation may be important to work with populations at risk, to prevent the development of pathological conditions. In addition, this study contributed to obtaining new knowledge about ER and the symptoms of anxiety and depression from the network approach. This approach allows obtaining data that could be overlooked with the latent constructs approach (Fried & Nesse, 2015).

This study has several limitations that may lead to future directions. The use of cross-sectional data does not allow conclusions about the causal direction of the variables. Future investigations could focus on longitudinal data to correctly assess the influence of ER in anxiety and depression symptoms. Second, this research was conducted in a general population sample and generalizations of the conclusions may be limited for use in clinical settings. While the dimensional approach used makes it possible to evaluate the different possible degrees in the use of ER, and is in line with current dimensional diagnostic approaches (Everaert & Joormann, 2019), it is recommended to carry out more investigations in clinical populations. Third, the present study focused on two of the most widely used and researched ER strategies in the research literature, CR and ES. However, there are other strategies whose relationship with psychological symptoms should be investigated from the network approach. Finally, the symptoms considered for the present investigation are those evaluated by the BAI and the BDI. So there could be variations depending on the measurement used, and new information could even be provided with the use of other instruments.

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