



# Examining the relationships between emotional disorder symptoms in a mixed sample of community adults and patients: A network analysis perspective

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## Abstract

According to the literature, comorbidity rates observed on emotional disorders are linked to how the main diagnostic classification systems have traditionally defined these disorders. This paper aims to analyze the structure of symptoms evaluated with the Inventory of Depression and Anxiety Symptoms-II (IDAS-II) with network analysis. A mixed sample ( $n = 2021$ ) of 1692 community adults and 329 patients was used. 14.79% ( $n = 299$ ) of the sample met the diagnostic criteria for at least one DSM-5 mental disorder and 5.29% ( $n = 107$ ) had diagnostic comorbidity. The sample was randomly divided into two sub-samples: estimation sample ( $n = 1010$ ) and replication sample ( $n = 1011$ ). The detection of community structures was carried out on estimation sample using the walktrap algorithm. Four local inference measures were estimated: Strength, one-step Expected Influence, two-step Expected Influence, and node predictability. Exploratory graphic analysis of modularity yielded an optimal solution of two communities on estimation sample: first linked to symptoms of depression and anxiety and second grouping symptoms of bipolar disorder and obsessive – compulsive disorder. Mania, Panic, Claustrophobia, and Low Well-Being Bridge emerged as bridge symptoms, connecting the two substructures. Networks estimated on replication subsamples did not differ significantly in structure. Dysphoria, Traumatic Intrusions and Checking and Ordering were the symptoms with greatest number of connections with rest of the network. Results sheds light on specific links between emotional disorder symptoms and provides useful information for the development of transdiagnostic interventions by identifying the influential symptoms within the internalizing spectrum.

**Keywords** Emotional disorders · Comorbidity · IDAS-II · HiTOP · Transdiagnostic · Network analysis

## Introduction

Depression and anxiety affect 4.4% and 3.6% of the world's population respectively, having serious consequences for health, quality of life and severe negative

clinical outcomes such as suicidal behavior (World Health Organization, 2017). Although previous studies have identified neurobiological factors that explain the complexity of suicide (Orsolini et al., 2020) and provide advances in treatments (De Berardis et al., 2018), suicidal behavior still remains a real challenge associated with mental disorders comorbidity (Quevedo et al., 2020). According to empirical literature (e.g., Skodol, 2012), high rates of co-morbidity are linked to the way in which diagnostic classification systems have traditionally defined disorders. These systems, which use polythetic criteria, establish categorical classifications according to an observed set of symptoms, resulting in patients with different symptoms receiving the same diagnosis (Skodol, 2012).

In order to overcome the limitations of this taxonomic approach, transdiagnostic proposals look beyond the traditional classification schemes (Barlow et al., 2017; Kotov

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et al., 2017). The translation of this conceptualization into the applied field has allowed for the development of unified intervention protocols, yielding more effective and cheaper interventions (Barlow et al., 2017). Whilst these are promising findings, the transdiagnostic approach still requires a better understanding of the relationships between symptoms.

Past decade, empirical network models have provided a complementary approach to understanding the interaction between symptoms (Cramer et al., 2010). The analysis of bridge symptoms connecting different substructures offers a complementary view of the comorbidity phenomenon (Jones et al., 2019). At the same time, network analysis allows us to analyze the influence that each symptom has on the other symptoms in a network (Robinaugh et al., 2016), identifying which will have the greatest potential to influence the overall network (Borsboom, 2017). This information could then be useful for designing transdiagnostic interventions.

Network analysis has already been applied to the study of comorbid emotional disorders, with interesting results (see review by Contreras et al. (2019)). Overall, a high connectivity between depression and anxiety symptoms has been observed (Bekhuis et al., 2016; McElroy et al., 2018). The symptoms of post-traumatic stress disorder (PTSD) are, however, shown in a different cluster, and are connected to the depression cluster by the symptoms of "irritability" or "sleep problems" (Afzali et al., 2017; Choi et al., 2017). McNally et al. (2017) have also shown the lack of connection between the symptoms linked to depression and the symptoms of obsessive–compulsive disorder (OCD), which appear solely connected through "sadness" but not through sleep problems. The results of previous work have also identified dysphoria and lassitude to be the most influential symptoms in the networks obtained for depression (e.g., Funkhouser et al., 2020), whilst traumatic intrusions are the most influential for PTSD (Contractor et al., 2020; Gilbar, 2020) and the checking and ordering symptoms for OCD networks (Zhang et al., 2019).

Whilst these results are of interest, to our knowledge, studies of this type use different instruments to assess each group of symptoms (e.g. Choi et al., 2017), involving different instructions and time frames for evaluation (Watson et al., 2012). This affect measurement and network estimation (Bekhuis et al., 2016). Only Afzali et al. (2017) explored the relationship between major depressive disorder and PTSD with the same instrument (the ICD) although it provides a categorical measure of the evaluated symptomatology.

In this regard, the Inventory of Depression and Anxiety Symptoms (IDAS; Watson et al., 2007) and the IDAS-II (Watson et al., 2012) have been identified as effective tools for measuring several symptoms and spectra of the transdiagnostic models of psychopathology (Kotov et al., 2017).

Funkhouser et al. (2020), found consistent connections between the symptoms of dysphoria and lassitude, as well as between dysphoria and social anxiety, evaluated with the IDAS, although this work did not specifically aim to analyze the bridge symptoms that could explain comorbidity. The analysis of the structure of IDAS-II could further provide a broader perspective on the configuration of the relationships between emotional disorders, as it additionally measures symptoms of bipolar disorder (BD) and OCD as well as contains more expansive coverage of PTSD and social anxiety symptoms.

Given the above, this work examines, through empirical networks: 1) the structure of the relationships between the dimensional symptoms involved in the emotional disorders evaluated with the IDAS-II; 2) the bridge symptoms between the identified substructures; and 3) the influence that each symptom has on the rest of the network. According to previous studies we expected that: 1) the symptoms of depression and anxiety will be highly connected in a cluster that, in turn, will show less connections with the symptoms of BD and OCD; 2) the symptoms acting as a bridge between these will be related to irritability and sadness; and 3) the symptoms with the strongest influence will be dysphoria for depression, traumatic intrusions for PTSD, and checking and ordering for OCD.

## Material and Methods

### Participants

In order to increase the variability of the scores and thus represent the dimensional continuum from normality to pathology, the study was conducted on a mixed sample of 2021 persons, composed of both adults from the community population ( $n = 1692$ ) and patients ( $n = 329$ ).

The community adults were recruited in two phases of data collection: a) Wave 1, 620 adults selected by means of non-probability sampling in the province of Huelva (Spain); and b) Wave 2, 1,072 adults recruited by stratified random sampling, proportionally represented in the Spanish population according to age group, sex, and geographic area. The equivalence between both samples was verified. Inclusion criteria on community sample was being between 18 and 80 years old and not having a diagnose on any mental disorder.

The patient sample consisted of 329 patients from public and private mental health services in the province of Huelva (Spain). Inclusion criteria on clinical sample was being between 18 and 80 years old and being under treatment in a mental health service during the data collection. Those who met any of the following characteristics were excluded from both

samples (community adults and patients): having been diagnosed with a medical or psychological disorder that disqualified them from taking the tests, or not signing the informed consent form.

Of the total number of participants ( $n = 2,021$ ), 51.6% were women, and aged between 18 and 80 years ( $M = 42.90$ ;  $SD = 14.64$ ). 1.8% had not completed primary education, 8.5% had completed primary education, 16.5% had completed secondary education, 34.3% had completed post-compulsory education, 37.6% had completed university studies, and 1.2% had completed a university doctorate. With regard to employment status, 55.6% were working. 14.79% ( $n = 299$ ) of the sample met the diagnostic criteria for at least mental one disorder mental disorder according to Diagnostic and Statistical Manual of Mental Disorders, fifth edition (DSM-5) and 5.29% ( $n = 107$ ) had diagnostic comorbidity. Table 1 shows the diagnoses present in the sample. The most frequent diagnostic categories were Depressive Disorders (5.84%) and Anxiety Disorders (5.10%).

## Measures

The IDAS-II (Watson et al., 2012) was administered in its Spanish version (De la Rosa-Cáceres et al., 2020). The 99 items with a Likert response format from 1 ("not at all") to 5 ("extremely") are grouped in 18 specific scales. Participants scored the severity of their symptoms during the last two weeks, where higher scores indicate greater severity of symptoms. In the present study, this instrument was found to be internally consistent (Cronbach's  $\alpha = 0.91$ ). Internal consistency of all subscales are presented in Table 2.

In addition, questions regarding sociodemographic variables related to sex, age, educational level, employment, and marital status were included.

## Procedure

Community adults from wave 2 completed the IDAS-II in an online format, whilst a psychologist administered the Spanish version of IDAS-II in paper and pencil format to the rest of the community and patient samples ( $n = 949$ ). The latter completed the IDAS-II in rooms set up in the centers where they were recruited. All participants were informed about the anonymous and voluntary nature of their participation in the study and gave their written informed consent which remained in the custody of the research group. This study has the approval of the Bioethics Committee of Biomedical Research of Andalusia (Spain) (file number PI 040/18).

## Data Analysis

Results revealed the absence of multivariate normality for asymmetry (Mardia = 8092.19) and kurtosis (Mardia = 89.62). The estimation of the network and its properties was conducted using the Graphical Least Absolute Shrinkage and Selection Operator (GLASSO; Friedman et al., 2008) algorithm in combination with the Extended Bayesian Information Criterion (EBIC; Chen & Chen, 2008) selection model applied to the nonparanormal transformation (Liu et al., 2009) of the data set. The EBIC hyperparameter  $\gamma$  was set at 0.5. The arrangement of the nodes was established using the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991).

**Table 1** DSM-5 Diagnoses distribution

	<i>n</i>	% over patients ( <i>n</i> = 329)	% over complete sample ( <i>n</i> = 2021)
Neurodevelopmental Disorders	25	7.60	1.24
Schizophrenia Spectrum and Other Psychotic Disorders	23	6.99	1.14
Bipolar and Related Disorders	12	3.65	0.59
Depressive Disorders	118	35.87	5.84
Anxiety Disorders	103	31.31	5.10
Obsessive–Compulsive and Related Disorders	9	2.74	0.44
Trauma- and Stressor-Related Disorders	77	23.40	3.80
Dissociative Disorders	2	0.61	0.10
Somatic Symptom and Related Disorders	2	0.61	0.10
Feeding and Eating Disorders	6	1.82	0.29
Disruptive, Impulse-Control, and Conduct Disorders	5	1.52	0.25
Substance-Related and Addictive Disorders	11	3.34	0.54
Personality Disorders	30	9.12	1.48
Do not meet diagnostic criteria	30	9.12	1.48

The selected sample was randomly divided into two subsamples: estimation sample ( $n = 1010$ ) and replication sample ( $n = 1011$ ). The sample size of the estimation sample ( $n = 1010$ ) was adequate for the estimation of the network based on simulation analyses (Epskamp et al., 2018) (see Online Resource 1). The detection of community structures was carried out on estimation sample using the walktrap algorithm (Pons & Latapy, 2005) and the optimal number of steps was set using the highest cluster's modularity. The modularity index resulting from the exploratory graphic solution was compared with obtained of the three-factor structure presented in De la Rosa-Cáceres et al. (De la Rosa-Cáceres et al., 2020).

Four local inference measures were estimated: Strength, one-step Expected Influence (EI1), two-step Expected Influence (EI2), and node predictability Haslbeck & Waldorp, 2018; Robinaugh et al., 2016). Strength and EI are relative measures of centrality that provide information about the relationships between each node and the rest of the network. EI2 takes into account, besides, the relations with the nodes that are of an indirect nature (Robinaugh et al., 2016). Further, the predictability of the node is an absolute measurement of interconnection that indicates the proportion of variance of each node that is explained by its neighboring nodes (Haslbeck & Waldorp, 2018).

Participation Coefficient (PC) and Participation Ratio (PR) (Letina et al., 2019) were applied to analyze the heterogeneity of the network nodes. The PC analyzes how the nodes distribute their edges among the different communities, where higher values of PC indicate that the nodes distribute their edges more equally among the network communities. The PR takes into account both the number and strength of the edges connected to each node, so that higher values of PR are indicative of nodes with more numerous and stronger edges. The PC and PR values were transformed to the same scale of values between 0 and 1 to facilitate their interpretation.

To increase the understanding of comorbidity, three bridge centrality indices were estimated (Jones, 2020; Jones et al., 2019): bridge strength, which indicates the total connectivity of the node with nodes of other communities with which it is directly related; bridge EI1, which indicates the general increase in activation of the node with nodes of other communities with which it is directly related; and bridge EI2, which, like bridge EI1, indicates the general increase in the activation of other communities, but in this case by also taking into account the effect on nodes of other communities with which it is indirectly related. Finally, bridge nodes/symptoms were identified by applying a blind cut-off point at the 80th percentile of bridge strength (Jones et al., 2019).

The precision of the estimated relationships in the network was estimated by calculating the values of the edge

weights with a 95% confidence interval (CI) from a non-parametric bootstrap with subsamples repeated 1,000 times (Epskamp et al., 2018). The stability of the network centrality indices was evaluated by means of a person-dropping bootstrap procedure that provides a correlation-stability coefficient (CS-coefficient). Values  $> 0.5$  indicate strong stability and interpretability (Epskamp et al., 2018).

Once the network was estimated on the estimation sample ( $n = 1010$ ), results were mirrored on the replication sample ( $n = 1011$ ) and both networks were compared using the network comparison test (van Borkulo et al., 2017) (5000 times repeated subsampling). We analyzed the network structure invariance, regarding to the differences in the connections of the edges of both networks (statistic  $M$ ); and the global strength invariance, based on the difference in global strength (the weighted absolute sum of all edges) between the two networks (statistic  $S$ ). Additionally, if the omnibus network invariance test is significant, the test of edge invariance will also be estimated (van Borkulo et al., 2017).

The R packages used were: mvn version 5.8 (Korkmaz et al., 2014) to calculate the Mardia coefficient; bootnet version 1.3 (Epskamp et al., 2018) to perform the simulation analyses, to estimate the network, network stability and accuracy, and the strength of each node; igraph version 1.2.5 (Csardi & Nepusz, 2006) to perform the modularity analysis; networktools version 1.2.2 (Jones, 2020) to estimate EI and bridge centrality indices; mgm version 1.2.7 (Haslbeck & Waldorp, 2016) to estimate the explained variance ratio of each node; and Network-ComparisonTest 2.2.1 (van Borkulo et al., 2017) to test network invariance. All analyses were conducted using R version 3.6.3 and R-Studio version 1.2.5033.

## Results

The descriptive statistics for each of the IDAS-II scales are shown in Table 2. The Cronbach's alpha coefficients were higher than 0.70 for all the IDAS-II scales and above 0.80 for 13 of the 18 scales.

## Network Estimation and Community Detection

Table 3 shows the partial correlations and zero-order correlations between symptoms on estimation sample ( $n = 1010$ ). The number of estimated edges with a partial correlation value that differed from zero was 93 out of 153 possible edges. The edge weights ranged from -0.46 (Euphoria—Low Well-Being) to 0.30 (Ordering – Checking, and Cleaning – Claustrophobia). Online Resource 2 shows the partial edge correlations estimated by bootstrapping with a 95% CI.

**Table 2** Results of the analysis of the scales and reliability of the IDAS-II ( $n = 2021$ )

IDAS-II Scales	M (SD)	Skewness	Kurtosis	Coefficient $\alpha$
Appetite Gain	5.87 (2.87)	1.17	0.84	0.78
Appetite Loss	4.85 (2.51)	1.48	1.76	0.86
Checking	5.76 (2.72)	1.10	0.71	0.77
Claustrophobia	8.03 (4.36)	1.64	2.15	0.87
Cleaning	11.51 (5.12)	0.95	0.57	0.85
Dysphoria	21.43 (8.81)	0.81	-0.06	0.91
Euphoria	8.44 (3.53)	1.30	1.47	0.76
Ill Temper	9.77 (4.54)	1.08	0.59	0.86
Insomnia	13.18 (6.11)	0.81	-0.18	0.90
Lassitude	12.24 (4.70)	0.84	0.37	0.78
Low Well-Being	25.61 (6.26)	0.09	-0.41	0.85
Mania	9.76 (4.38)	0.92	0.10	0.80
Ordering	10.05 (3.95)	0.82	0.36	0.75
Panic	13.33 (6.57)	1.56	1.85	0.91
Social Anxiety	10.42 (4.84)	1.38	1.58	0.83
Suicidality	7.72 (3.55)	3.09	10.68	0.84
Traumatic Avoidance	8.50 (4.02)	0.73	-0.27	0.84
Traumatic Intrusions	6.93 (3.87)	1.48	1.46	0.88

The estimated network in the estimation sample is shown in Fig. 1. Exploratory graphic analysis of modularity yielded an optimal solution of two communities. The first community includes the symptoms Dysphoria, Lassitude, Insomnia,

Suicidality, Appetite Loss, Appetite Gain, Ill Temper, Panic, Social Anxiety, and Traumatic Intrusions, while the second community includes Low Well-Being, Mania, Euphoria, Claustrophobia, Traumatic Avoidance, Checking, Ordering, and Cleaning. Figure 1 also shows the bridge nodes between both communities, which are Low Well-Being, Mania, Panic, and Claustrophobia.

### Network Inference

The modularity index of this grouping was 0.25 while that obtained with the confirmatory factor analysis (CFA) presented in De la Rosa-Cáceres et al. (2020), based on the organization of the internal structure of IDAS-II and its correspondence with the Hierarchical Taxonomy of Psychopathology (HiTOP) model, was -0.06 (the latter network is presented in Online Resource 3).

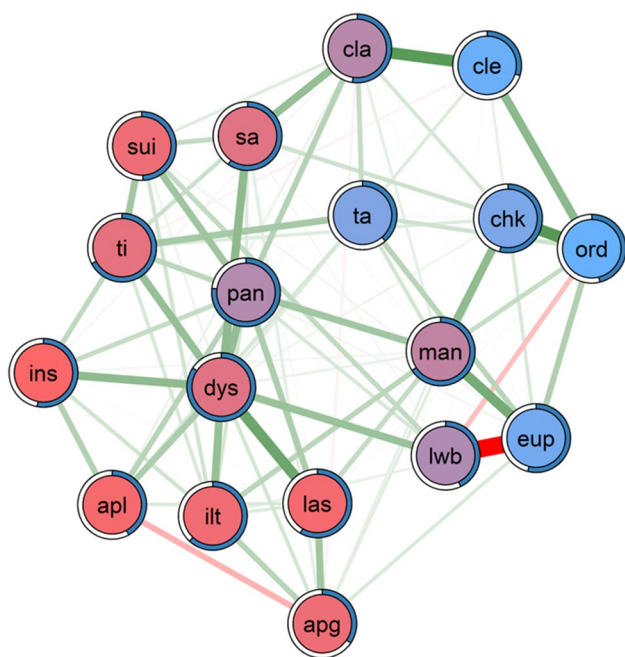
The standardized scores estimated for the centrality indices of the nodes are shown in Table 4. The symptoms or nodes that present higher values of Strength, EI1, and EI2 are Dysphoria, Panic, and Mania (standardized values of Strength were between 2.95 and -1.01; standardized values of EI1 were between 2.26 and -2.31; and standardized values of EI2 were between 2.21 and -2.18).

CS-coefficient ( $\text{cor} = 0.7$ ) was 0.75 for Strength and EI (see Online Resource 4 and Online Resource 5,

**Table 3** Partial and zero-order correlations between network symptoms on estimation sample ( $n = 1010$ )

Nodes	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Appetite Gain		0.09	0.36	0.19	0.13	0.44	0.29	0.46	0.31	0.44	0.02	0.40	0.20	0.33	0.36	0.24	0.23	0.34
2. Appetite Loss	-0.14		0.31	0.38	0.15	0.58	0.18	0.42	0.52	0.47	0.17	0.39	0.17	0.55	0.44	0.40	0.36	0.46
3. Checking	0.05	-		0.46	0.37	0.51	0.48	0.47	0.40	0.43	-0.04	0.61	0.57	0.50	0.48	0.36	0.43	0.49
4. Claustrophobia	-0.03	0.03	0.07		0.44	0.52	0.31	0.43	0.44	0.40	0.10	0.51	0.34	0.61	0.56	0.48	0.42	0.47
5. Cleaning	-	-	0.04	0.30		0.18	0.25	0.18	0.20	0.18	-0.08	0.29	0.42	0.22	0.22	0.15	0.30	0.17
6. Dysphoria	0.08	0.15	0.03	-	0.03		0.25	0.73	0.69	0.74	0.35	0.65	0.27	0.81	0.72	0.61	0.48	0.77
7. Euphoria	0.06	-	0.07	0.01	-	-		0.35	0.22	0.28	-0.42	0.54	0.49	0.33	0.28	0.24	0.40	0.29
8. Ill Temper	0.12	-	-	-	-	0.19	0.04		0.56	0.62	0.17	0.62	0.28	0.68	0.60	0.53	0.38	0.64
9. Insomnia	0.01	0.13	-	0.02	-	0.20	-	0.08		0.53	0.22	0.52	0.24	0.64	0.54	0.46	0.39	0.62
10. Lassitude	0.17	0.07	-	-	-	0.26	-	0.06	0.01		0.18	0.59	0.24	0.65	0.56	0.44	0.39	0.58
11. Low W-B	-	-	-	-	-0.01	0.18	-0.46	-	-	-		0.00	-0.23	0.26	0.22	0.26	-0.02	0.21
12. Mania	0.04	-	0.20	0.05	-	0.04	0.25	0.12	0.02	0.10	-		0.49	0.67	0.55	0.46	0.50	0.58
13. Ordering	-	-	0.30	-	0.21	-	0.14	-	-	-0.01	-0.11	0.10		0.27	0.29	0.20	0.39	0.27
14. Panic	-	0.13	-	0.13	0.01	0.19	0.02	0.07	0.10	0.15	0.07	0.17	-		0.68	0.66	0.45	0.73
15. Social Anxiety	0.05	-	0.09	0.19	-	0.20	-	0.05	-	0.01	0.02	0.02	-	0.06		0.56	0.41	0.65
16. Suicidality	-	-	-	0.05	-	0.03	0.02	0.08	-	-	0.11	-	-	0.17	0.12		0.31	0.62
17. Trauma. Avoidance	-	0.07	0.03	0.10	0.06	0.05	0.12	-	-	-	-	0.08	0.09	-	-	-		0.48
18. Trauma. Intrusions	-	-	0.06	-	-0.02	0.19	-	0.07	0.11	0.01	-	0.02	-	0.12	0.09	0.16	0.16	

Partial correlations are shown on the lower diagonal and zero-order correlations on the upper diagonal. The dashes represent correlation values = 0



**Fig. 1** Empirical network model (network structure estimated from a walktrap modularity analysis) apg: Appetite Gain, apl: Appetite Loss, chk: Checking, cla: Claustrophobia, cle: Cleaning, dys: Dysphoria, eup: Euphoria, ilt: Ill Temper, ins: Insomnia, las: Lassitude, lwb: Low Well-Being, man: Mania, ord: Ordering, pan: Panic, sa: Social Anxiety, sui: Suicidality, ta: Traumatic Avoidance, ti: Traumatic Intrusions. Each node represents a symptom. The edges represent the relationships (partial correlations) between the symptoms. Positive relationships are represented in green, and negative relationships in red. The thickness of the edge reflects the strength of the association, so that the most strongly related symptoms are connected by thicker edges. The blue pie chart surrounding each node represents the predictability of each node (a higher proportion of blue indicates greater predictability). The membership of the nodes to the different communities is represented by a red-blue gradient according to the bridge strength values: the symptoms of Community 1 are shown in red tones, the bridge symptoms in purple tones and the symptoms of Community 2 in blue tones. The arrangement of the nodes was established based on the Fruchterman-Reingold algorithm

respectively), indicating strong stability and interpretability of the estimates in both cases.

The standardized scores estimated for the bridge centrality indices of the nodes are shown in Table 4. The symptoms or nodes with higher values of Bridge Strength, Bridge EI1 and Bridge EI2 are Mania (standardized values of Bridge Strength = 2.04; standardized values of Bridge EI1 = 2.09; and standardized values of Bridge EI2 = 2.39), Claustrophobia (1.50, 1.24, and 1.09), Panic (1.14, 1.08, and 0.88), and Low Well-Being (0.99, 1.08, and 1.02).

The predictability of each node is shown in Fig. 1 and Table 4. The predictability values ranged from 0.30 (Cleaning) to 0.84 (Dysphoria), with a mean value of 0.54. The symptoms with the least explained variance — and therefore

the most independent — were Cleaning ( $R^2=0.30$ ), Appetite Gain ( $R^2=0.35$ ), Traumatic Avoidance ( $R^2=0.39$ ) and Appetite Loss ( $R^2=0.42$ ). The symptoms with the greatest explained variance were Dysphoria ( $R^2=0.84$ ), Panic ( $R^2=0.77$ ), Traumatic Intrusions ( $R^2=0.67$ ), and Mania ( $R^2=0.66$ ).

The PC and PR values are shown in Table 4. The highest PC values corresponded to Traumatic Avoidance (PC = 0.43), Social Anxiety (PC = 0.39), and Claustrophobia (PC = 0.35), these being the nodes that distribute their edges most equally among the network communities. The network nodes that presented the strongest and most numerous edges, according to PR values, were Dysphoria (PR = 1), Panic (PR = 0.77), and Mania (PR = 0.60).

The invariance test showed that the networks estimated on estimation ( $n=1010$ ) and replication subsamples ( $n=1011$ ) did not differ significantly in structure (i.e., differences in the edge connections of the two networks,  $M=0.08$ ;  $p=0.989$ ) nor in overall strength (i.e., differences in the sum of the absolute weights between the two networks,  $S=0.24$ ;  $p=0.418$ ). The overall strength of the network estimated over the first half of the sample was 8.69, while that of the network estimated over the second half of the sample was 8.45.

## Discussion

The present work examined the relationships between the dimensional symptoms assessed by the IDAS-II improving our understanding of comorbidity between emotional disorders. Results showed that emotional disorders symptoms groups in two communities: first linked to symptoms of depression and anxiety and second grouping symptoms of bipolar disorder and obsessive-compulsive disorder. Mania, Panic, Claustrophobia, and Low Well-Being emerged as bridge symptoms, connecting the two substructures. Finally, results suggest that Dysphoria is the symptom with greatest number of connections with rest of depression dimensions; Traumatic Intrusions the one with most connections for PTSD, and Checking and Ordering for OCD. The invariance analysis failed to find significant differences between the structure and global strength of estimation and replication subsample networks. Next, we analyze the results in more detail.

Congruent with our first hypothesis, the structure of the network provides evidence of a stronger relationship between the symptoms of depression and anxiety (Dysphoria, Lassitude, Insomnia, Suicidality, Appetite Loss, Appetite Gain, Ill Temper, Panic and Social Anxiety) that are grouped in the first community. This substructure, previously described (Bekhuis et al., 2016; McElroy et al., 2018) supports the observed relationship between these two sets of disorders. Based on this body of evidence, various authors

**Table 4** Standardized values of centrality indices and bridge centrality indices, explained variance, Participation Coefficient, and Participation Ratio of each node on estimation sample ( $n = 1010$ )

Nodes	Strength	Expected Influence 1	Expected Influence 2	Bridge Strength	Bridge Expected Influence 1	Bridge Expected Influence 2	$R^2$	PC	PR
Appetite Gain	-0.77	-0.85	-1.02	-0.33	-0.50	-0.73	0.35	0.11	0.15
Appetite Loss	-0.87	-0.80	-0.77	-0.89	-0.70	-0.78	0.42	0.07	0.03
Checking	-0.12	0.35	0.21	-0.06	0.09	0.28	0.54	0.09	0.32
Claustrophobia	0.04	0.34	0.18	1.50	1.24	1.09	0.52	0.35	0.35
Cleaning	-1.01	-0.59	-0.91	-1.17	-1.75	-1.62	0.30	0.01	0
Dysphoria	2.95	2.26	2.21	0.62	0.36	0.13	0.84	0.12	1
Euphoria	0.79	-1.19	-0.79	-0.57	-0.39	-0.76	0.54	0.02	0.42
Ill Temper	-0.29	0.24	0.33	-0.48	-0.30	-0.17	0.62	0.17	0.29
Insomnia	-0.97	-0.22	-0.14	-1.29	-1.08	-0.86	0.53	0.01	0.11
Lassitude	-0.39	0.11	0.32	-0.80	-0.77	-0.46	0.58	0.08	0.22
Low Well-Being	-0.02	-2.31	-2.18	0.99	1.08	1.02	0.43	0.18	0.10
Mania	0.80	0.96	0.88	2.04	2.09	2.39	0.66	0.33	0.60
Ordering	0.00	-0.17	-0.35	-1.48	-1.46	-1.34	0.46	0.00	0.17
Panic	1.48	1.36	1.54	1.14	1.08	0.88	0.77	0.26	0.77
Social Anxiety	-0.28	0.24	0.40	0.58	0.70	0.64	0.60	0.39	0.35
Suicidality	-0.80	-0.10	-0.27	-0.32	-0.16	-0.51	0.48	0.17	0.04
Traumatic Avoidance	-0.72	0.06	-0.29	0.34	0.47	0.60	0.39	0.43	0.16
Traumatic Intrusions	0.17	0.43	0.63	0.18	0.18	0.21	0.67	0.22	0.38

$R^2$  = explained variance;  $PC$  = Participation Coefficient;  $PR$  = Participation Ratio

have questioned whether these disorders should be defined as a single clinical entity and not as distinct disorders (Borsboom, 2017; Kotov et al., 2017; McElroy et al., 2018).

The structure of the network also shows, in a separate community, the symptoms of BD (Euphoria and Mania) and OCD (Checking, Ordering, and Cleaning). The co-occurrence of these disorders has been reported in several studies and meta-analyses (e.g., Ferentinos et al., 2020). The grouping of this set of symptoms is of interest, as Tonna et al. (2016) point out that the appearance of OCD symptoms could be a risk factor for increased BD symptoms.

Interestingly, the two PTSD symptom dimensions appear separately. In line with Gilbar (2020) and Levi-Belz et al. (2020), Traumatic Intrusions appear in Community 1, linked to symptoms of anxiety and depression, whilst Traumatic Avoidance is linked to OCD symptoms. This evidence supports the connection between PTSD and depressive disorder (Afzali et al., 2017; Levi-Belz et al., 2020) through intrusive thoughts. In contrast, strategies to reduce anxiety had the most direct connection with OCD. OCD and PTSD share avoidance of stimuli as a means of reducing stress (American Psychiatric Association, 2013; Franklin & Raines, 2019). From a behavioral perspective, Gershuny et al. (2003) point out that, in patients with comorbid OCD and PTSD, the avoidance strategies in OCD could reduce the emotional distress generated by a traumatic event, thus explaining the comorbidity of these disorders.

Concerning our second hypothesis, the results indicate that the bridge symptoms differ from those hypothesized. Although Ill Temper has been pointed out as a bridge symptom (Afzali et al., 2017; Choi et al., 2017), the connections observed in the present work between this symptom and PTSD occur within the same community. In the present work, the bridge nodes obtained are Claustrophobia, Low Well-Being, Mania, and Panic. It can be observed that whilst Panic connects the symptoms of depression and anxiety, Mania has been shown to connect the symptoms of depression with BD. Niitsu et al. (2015) highlight panic attacks as one of the strongest predictors of the change from depression to mania in BD. In relation to the other two bridge symptoms (Low Wellbeing and Claustrophobia), to our knowledge, this is the first work that includes these dimensions in network analysis. The inclusion of a greater number of symptoms can modify community organization and, therefore, the identification of bridge symptoms (Jones et al., 2019). For Claustrophobia, the observed relationships with Panic and Social Anxiety provide further empirical support for the organization proposed by HiTOP (Kotov et al., 2017) where these symptoms are grouped within the Fear factor. With regard to Low Well-Being, differential activation is observed in the network structure, with activation

of Community 1 and inhibition of Community 2. For several decades, numerous studies have provided evidence for the relationship between Low Well-Being and depression (Kotov et al., 2017; Watson et al., 2007).

Finally, regarding the symptoms with the greatest influence, our results support the third hypothesis. Similar to Funkhouser et al. (2020), Dysphoria presents the highest centrality values for depression. Likewise, Traumatic Intrusions showed greater centrality than did Traumatic Avoidance for PTSD (Contractor et al., 2020; Gilbar, 2020), and Checking and Ordering showed greater centrality for OCD (Zhang et al., 2019). Although Dysphoria is the most central node of the network, the low PC values and location indicate that their edges are primarily related to Community 1. This should be regarded as an important symptom in the initiation and maintenance of depression and anxiety disorders (Boschloo et al., 2016).

In clinical terms, some authors suggest that clinicians should pay attention to the presence of bridging symptoms and intervene on them to prevent comorbidity (Fried et al., 2017; Jones et al., 2019; Kaiser et al., 2021). In this sense, the intervention on panic and claustrophobia—identified as bridge symptoms on present study—, supports the inclusion of some of the modules of the Unified Protocol for Transdiagnostic Treatment of Emotional Disorders (UP) Barlow et al., (2017), successfully applied to a wide range of disorders. Specifically, both modules 5—aimed on changing the action tendencies related to strong emotions, and 7—emotion exposures—, appear as central modules of the UP. Related to this, Jones et al. (2019) suggest that deactivation of bridging symptoms could prevent comorbidity to a greater extent than the deactivation of more central symptoms in the network. Thus, Dysphoria could be considered as a target of intervention for depressive disorders, rather than a symptom which intervention could prevent comorbidity.

## Conclusions

From a clinical perspective, this study provides useful information. According to previous studies (Afzali et al., 2017; Borsboom, 2017; Jones et al., 2019), interventions that target bridge symptoms could be relevant due to their role in the activation of different communities. From the analysis of the heterogeneity, results suggest that interventions aimed at Panic, Mania, and Claustrophobia may generate more global changes because their edges are distributed more equally among the communities. Moreover, Panic and Mania have stronger and more numerous edges. In congruence with this result, a systematic review conducted by González-Robles et al. (2018) found that Panic is the symptom most frequently targeted in transdiagnostic

treatments of emotional disorders. Treatment of these symptoms could help to reduce the severe consequences associated with comorbidities, such as greater functional impairment, higher rates of chronicity, and increased disability (Hofmeijer-Sevink et al., 2012).

Finally, several studies suggest that treatments applied to nodes with high values of strength, IE, and predictability could generate global changes in the structure of the network and could be considered as priority interventions (Haslbeck & Waldorp, 2018; Robinaugh et al., 2016; Zhang et al., 2019). According to this idea, one of the priority targets of the network could be Dysphoria. This result is consistent with the notion that negative affect is the common component of emotional disorders related to the internalizing spectrum (Kotov et al., 2017). However, Santos et al. (2017) point out the need to also intervene in other less central symptoms when they cause clinically significant discomfort.

Although this study makes several contributions to the literature, it is not without limitations. First, the use of a transversal design does not allow for making causal inferences about the direction of associations between symptoms, which was the reason for using undirected networks in present study. In this regard, it would be worthwhile to conduct future longitudinal studies to clarify the directionality of the associations in the network.

Second the resulting IDAS-II network does not include other symptoms of depression such as concentration or psychomotor problems which, although not diagnostic criteria of the DSM, could be equally relevant (Fried et al., 2016). As mentioned above, the inclusion of different symptoms can produce changes on the community organization and, therefore, the identification of bridge symptoms (Jones et al., 2019). However, it should be mentioned that this is one of the studies evaluating the greatest number of internalizing symptoms within the same instrument, using a dimensional approach.

Finally, it should be noted that different sampling procedures have been used to select the subsamples: community adults were recruited by random sampling, while, patients were selected by non-probability sampling. The use of non-probabilistic sampling may limit the generalizability of patient responses, though the accessibility of this kind of patients difficult the use of random sampling procedures.

In general terms, we believe the present study contributes providing relevant information for a better understanding of emotional disorders comorbidities, one of the most persistent problems associated with mental disorders (Cramer et al., 2010; Hofmeijer-Sevink et al., 2012; Kotov et al., 2017), and also for the development of transdiagnostic interventions for various emotional disorders by identifying the core symptoms within the internalizing spectrum (Barlow et al., 2017).

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**Authors' Contributions** CDB, FFC and ADC has contributed on the conception and design of study. ADC, FFC and MSG has contributed on the acquisition of data. ADC, MSG and PSJ had participated on the analysis of data. ADC, SSO, CDB had participated on the interpretation of data. ADC, CDB, SSO had drafted the manuscript. All authors have revised the manuscript critically for intellectual content and approved the final version of the manuscript submitted.

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**Data Availability** The datasets analysed during the current study are available in Arias Montano, the Institutional Repository of the University of Huelva, <http://hdl.handle.net/10272/20199>

## Declarations

**Ethics Approval** This study was approved by the Bioethics Committee of Biomedical Research of Andalusia (Spain) (No. PI 040/18). The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

**Consent to Participate** Informed consent was obtained from all individual participants included in the study.

**Informed Consent** Informed consent was obtained from all individual participants included in the study.

**Competing Interests** The authors have no relevant financial or non-financial interests to disclose.

**Research Involving Human Participants and/or Animals** This study was approved by the Bioethics Committee of Biomedical Research of Andalusia (Spain) (No. PI 040/18). The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

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