

## RESEARCH ARTICLE

# The network structure of psychopathological and resilient responses to the pandemic: A multicountry general population study of depression and anxiety

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## Abstract

Commonly identified patterns of psychological distress in response to adverse events are characterized by resilience (i.e., little to no distress), delayed (i.e., distress that increases over time), recovery (i.e., distress followed by a gradual decrease over time), and sustained (i.e., distress remaining stable over time). This study aimed to examine these response patterns during the COVID-19 pandemic. Anxiety and depressive symptom data collected across four European countries over the first year of the pandemic were analyzed ( $N = 3,594$ ). Participants were first categorized into groups based on the four described patterns. Network connectivity and symptom clustering were then estimated for each group and compared. Two thirds (63.6%) of the sample displayed a resilience pattern. The sustained distress network (16.3%) showed higher connectivity than the recovery network (10.0%) group,  $p = .031$ ; however, the resilient network showed higher connectivity than the delayed network (10.1%) group,  $p = .016$ . Regard-

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ing symptom clustering, more clusters emerged in the recovery network (i.e., three) than the sustained network (i.e., two). These results replicate findings that resilience was the most common mental health pattern over the first pandemic year. Moreover, they suggest that high network connectivity may be indicative of a stable mental health response over time, whereas fewer clusters may be indicative of a sustained distress pattern. Although exploratory, the network perspective provides a useful tool for examining the complexity of psychological responses to adverse events and, if replicated, could be useful in identifying indicators of protection against or vulnerability to future psychological distress.

Psychological reactions to potentially traumatic events (PTEs) are highly heterogeneous; commonly identified trajectories include (a) low-to-moderate distress which increases over time (i.e., *delayed distress*); (b) elevated distress and functional impairment, followed by a gradual decrease or return to normal baseline over time (i.e., *recovery*); (c) moderate or severe distress that remains stable over time (i.e., *sustained distress*); and (d) a stable state of little to no distress (i.e., *resilience*; Bonanno et al., 2011). Despite reports that there has been an overall increase in psychological distress in the general population during the COVID-19 pandemic (Santomauro et al., 2021), these established mental health responses have also been identified in the general population during this time (e.g., Ahrens et al., 2021; Chen & Bonanno, 2020; Gambin et al., 2021; Kimhi et al., 2021; Pierce et al., 2021; Shevlin et al., 2021; Valiente et al., 2021). Thus, based on the conceptualization of the COVID-19 pandemic as a PTE (Shevlin et al., 2020), research has shown that the most common pattern in the general population during COVID-19 is marked by resilience, characterized by low levels of psychological distress and dysfunction over time, consistent with the broader research on PTE exposure (Galatzer-Levy et al., 2018).

Although there is no single accepted definition of resilience, most proposals agree on the presence of a process of adaptation and recovery from adversity (see Bonanno et al., 2011, and Southwick et al., 2014, 2015, for a detailed review). Thus, resilience can be understood as a stable trajectory of healthy functioning after a highly adverse event (Southwick et al., 2015; Valiente et al., 2021). Consequently, the study of dynamic indicators of resilience could be useful for monitoring risk or anticipating possible systemic disturbances in individuals (see Scheffer et al., 2018, for further discussion).

Network analysis is an analytic approach that has grown in popularity in the field of psychology over the last decade (Contreras et al., 2019; Robinaugh et al., 2019). From this perspective, mental health conditions can be conceptual-

ized as a dynamic system of interacting elements—that is, a network structure of variables (e.g., symptoms), represented by circles also known as *nodes*, and their mutual associations, represented by edges, or lines linking the nodes (Borsboom, 2017). The network theory of mental disorders postulates that both symptom activation and network structure play key roles in the onset and maintenance of psychological distress such that symptoms in strongly interconnected networks (i.e., higher connectivity) are more likely to be activated by their neighbors than those belonging to a network with low connectivity (Robinaugh et al., 2019). Thus, from this perspective, resilience could be seen as a stable state in which relatively few symptoms are activated or in which low connectivity prevents active symptoms from triggering others (Borsboom & Cramer, 2013; Boschloo et al., 2015; Robinaugh et al., 2019). Additionally, clusters of densely connected nodes (i.e., communities or subgroups of symptoms) can also be examined using network analysis (Borsboom, 2017). However, few studies have examined resilience from a network perspective generally (Kalisch et al., 2019; Lunansky et al., 2021) or investigated how symptoms may cluster as a function of resilience (Groen et al., 2019). It seems plausible that as the severity of psychopathology increases, the association between symptoms may become more specific, and more clusters will appear (Van Os, 2013).

Recent studies have applied network analysis to study psychopathology during the COVID-19 pandemic (Gibson-Miller et al., 2022; Taylor, 2020; Williamson et al., 2021; Zavlis et al., 2021); however, these studies have focussed on symptoms in the general population broadly rather than within the distinct response groups known to emerge following PTE exposure (i.e., resilience, delayed distress, recovered, and sustained distress).

Therefore, the aim of the current study was to (a) identify these four patterns of responses to the COVID-19 pandemic using two different time points and (b) model and visualize the complex symptom-to-symptom

associations at their starting point to examine whether they reflect distinct psychological response patterns during the COVID-19 pandemic. Specifically, networks of psychological distress (i.e., symptoms of depression and anxiety) were modeled for each of the four symptom-based response patterns, and differences in terms of connectivity and psychopathological symptoms clustering (i.e., communities) were examined. For these network comparisons, the resilient and delayed distress groups (i.e., the two groups characterized by the absence of distress at Time 1) and the recovered and sustained distress groups (i.e., the two groups characterized by the presence of distress at Time 1) were compared to one another.

Based on network theory, densely connected networks with high symptom activation are considered to give rise to psychopathology. Therefore, we hypothesized that mental health networks would be less densely connected with increasing levels of resilience (i.e., connectivity hypothesis). In other words, the connectivity of the resilient group network would be lower compared to the delayed distress group, and, similarly, the connectivity of the recovered group network would be lower compared to the sustained distress group. In addition, consistent with the literature, we anticipated as resilience levels increased, fewer symptom clusters would be identified in the networks and, instead, anxiety and depressive symptoms would be represented as more unified and homogeneous constructs (i.e., clustering hypothesis). Specifically, we expected that fewer symptom clusters would be observed in the recovered and resilient networks compared to the sustained distress and delayed distress networks, respectively.

## METHOD

### Participants

Data used in the current study belong to a larger project (COVID-19 Psychological Research Consortium—C19PRC Panel Study; [osf.io/v2zur/](https://osf.io/v2zur/)). For the present study, we used a combined sample of 3,594 participants from four different countries (United Kingdom:  $n = 1,162$ ; Ireland:  $n = 390$ ; Spain:  $n = 1,498$ ; Italy:  $n = 544$ ). Sample characteristics are depicted in Table 1.

### Procedure

Established in March 2020, the COVID-19 Psychological Research Consortium (C19PRC) is a longitudinal multicountry study that aims to monitor and evaluate the psychological, socioeconomic, and political impacts of the COVID-19 pandemic on the lives of adults living in the United Kingdom, Ireland, Spain, and Italy (McBride et al.,

2021). Participants were recruited via online research panels and completed an online survey. All participants gave their informed electronic consent to participate in the survey, and ethical approval was sought in each country (see [Supplementary Materials](#) for detailed information). The current study used data collected over the course of the first year of the COVID-19 pandemic. To categorize patterns of psychological responses during this time, only individuals who participated in the first survey wave in each country (Time 1 [T1]; United Kingdom, Ireland: March 2020; Spain: April 2020; Italy: July 2020) and the most recent follow-up survey at the time of analysis (Time 2 [T2]; United Kingdom, Ireland: March 2021; Spain, Italy: April 2021) were included. See the [Supplementary Materials](#) for a detailed description of the sample, fieldwork procedures, and survey timelines.

### Measures

The depression, anxiety, and COVID-19 anxiety items used to estimate the networks were measured at T1 in each country.

#### Depressive symptoms

The Patient Health Questionnaire–9 (PHQ-9; Kroenke et al., 2001) is a nine-item scale that is used to assess the severity of depressive symptoms over the last 2 weeks. Responses are scored on a 4-point Likert scale ranging from 0 (*not at all*) to 3 (*nearly every day*) and summed, with higher scores indicating more severe symptoms. The PHQ-9 has shown acceptable diagnostic properties (Kroenke et al., 2001; Manea et al., 2012), and its Spanish version has demonstrated good psychometric properties (see Díez-Quevedo et al., 2001). Of note, PHQ-9 scores have shown measurement invariance in the United Kingdom, Ireland, Spain, and Italy (Shevlin et al., 2022). In the present sample, the PHQ-9 demonstrated excellent internal consistency, Cronbach's  $\alpha = .90$ .

#### Anxiety symptoms

The seven-item Generalized Anxiety Disorder scale (GAD-7; Spitzer et al., 2006) was used to assess anxiety symptoms over the past 2 weeks. Participants were asked to report how often they were bothered by each symptom, scoring responses on a 4-point Likert scale ranging from 0 (*not at all*) to 3 (*nearly every day*). Scores are summed, with higher scores indicating higher levels of anxiety symptoms. The GAD-7, including the Spanish version (see García-Campayo et al., 2010), has demonstrated good psychometric properties, and the measure has been

**TABLE 1** Sample characteristics

|                                                                                                             | <i>M</i> | <i>SD</i> |
|-------------------------------------------------------------------------------------------------------------|----------|-----------|
| Worry about the degree to which household finances have been affected by the COVID-19 pandemic <sup>a</sup> | 6.06     | 2.79      |
| Age <sup>b</sup>                                                                                            | 49.02    | 14.12     |
|                                                                                                             | <i>n</i> | %         |
| Age (years)                                                                                                 |          |           |
| 18–24                                                                                                       | 196      | 5.5       |
| 25–34                                                                                                       | 465      | 12.9      |
| 35–44                                                                                                       | 673      | 18.7      |
| 45–54                                                                                                       | 855      | 23.8      |
| 55–64                                                                                                       | 845      | 23.5      |
| ≥ 65                                                                                                        | 560      | 15.6      |
| Gender                                                                                                      |          |           |
| Male                                                                                                        | 1,873    | 52.1      |
| Female                                                                                                      | 1,717    | 47.8      |
| Other                                                                                                       | 4        | 0.1       |
| United Kingdom                                                                                              | 1,162    | 32.3      |
| Ireland                                                                                                     | 390      | 10.9      |
| Spain                                                                                                       | 1,498    | 41.7      |
| Italy                                                                                                       | 544      | 15.1      |
| Educational attainment                                                                                      |          |           |
| Did not attend postsecondary education                                                                      | 1,079    | 30.0      |
| Postsecondary education                                                                                     | 2,515    | 70.0      |
| Religion                                                                                                    |          |           |
| Agnostic or atheist                                                                                         | 1,249    | 34.8      |
| Any religion                                                                                                | 2,345    | 65.2      |
| Urbanicity of residential location                                                                          |          |           |
| Suburb/town/rural                                                                                           | 1,730    | 48.1      |
| City                                                                                                        | 1,864    | 51.9      |
| Household composition                                                                                       |          |           |
| Not living alone                                                                                            | 3,060    | 85.1      |
| No children in household                                                                                    | 2,424    | 67.4      |
| Estimated gross annual household income                                                                     |          |           |
| Lowest income category measured in each country                                                             | 957      | 26.6      |
| All other income categories                                                                                 | 2,637    | 73.4      |
| Health conditions (diabetes, lung disease, heart disease)                                                   |          |           |
| Self                                                                                                        | 521      | 14.5      |
| Family member                                                                                               | 1,149    | 32.0      |
| Pregnant                                                                                                    |          |           |
| Self                                                                                                        | 403      | 11.2      |
| Family member                                                                                               | 220      | 6.1       |

<sup>a</sup>Range: 1–10.

<sup>b</sup>Range: 18–87 years.

recommended for use in clinical research and primary care (Hinz et al., 2017). Of note, GAD-7 scores have shown measurement invariance in the United Kingdom, Ireland, Spain, and Italy (Shevlin et al., 2022). In the present sample, the GAD-7 demonstrated excellent internal consistency, Cronbach's  $\alpha = .94$ .

## COVID-19 anxiety

Participants were asked to report their degree of specific anxiety about the COVID-19 pandemic with a single item: “How anxious are you about the coronavirus/COVID-19

pandemic?”. Responses were rated on a slider scale ranging from 0 (*not at all anxious*) to 100 (*extremely anxious*).

## Data analysis

### Psychological responses during the pandemic categorization

Psychological responses during the pandemic were categorized following the previous symptom-based definition of resilience (Valiente et al., 2021) according to two criteria (i.e., distress and time). Firstly, we categorized participants according to whether they showed the absence or presence of distress (i.e., whether they met the standard cutoff scores of 10 or higher on the PHQ-9 or GAD-7) and, second, based on the time of the assessment (i.e., T1 or T2). The combination of these two variables provided four different categories describing the pattern of responses following traumatic events (Bonanno, 2004; Galatzer-Levy et al., 2018): resilience, categorized by the absence of distress at both T1 and T2 ( $n = 2,284$ , 63.6%; delayed distress, categorized by the absence of distress at T1 and the presence of distress at T2 ( $n = 364$ , 10.1%; recovered, categorized by the presence of distress at T1 and the absence of distress at T2 ( $n = 359$ , 10.0%); and sustained distress, categorized by the presence of distress at both T1 and T2 ( $n = 587$ , 16.3%; see the Supplementary Materials for further details).

Given that the network comparison technique used can be influenced by sample size (Boschloo et al., 2015; Terluin et al., 2016), before groups could be compared, random subsamples were drawn from the sustained and resilient groups to match the sample sizes, controlling for age and gender, of the recovered ( $n = 359$ ) and delayed ( $n = 364$ ) groups, respectively. All network analyses in the main manuscript were conducted using these age- and gender-matched samples (for a detailed description, see the Supplementary Materials).

### Validation of patterns of response categories with levels of impairment

Following previous work (Valiente et al., 2021), an objective, evidence-based validation of the groups' classifications was conducted by analysing the levels of impairment each subgroup experienced, measured using the International Trauma Questionnaire (Cloitre et al., 2018). We conducted a 4 (Group: resilient, delayed distress, recovered, and sustained distress)  $\times$  2 (Time: T1, T2) repeated-measures analysis of variance in SPSS (Version 22) with Group being a between-subject factor and Time

a within-subject factor. A detailed description and results are provided in the Supplementary Materials.

## Network estimation and visualization

A network structure consists of nodes (i.e., circles in the network graph representing observed variables or symptoms in this case) and edges (i.e., lines linking the nodes to indicate the degree of the association between them). Networks were estimated for each of the four age- and gender-matched groups. Networks included all PHQ-9, GAD-7, and COVID-19 anxiety items as nodes and were estimated using a Gaussian graphical model (GGM) in which edges represent partial correlation coefficients (Epskamp, Borsboom, & Fried, 2018).

Analyses were conducted in *R Studio* (R Version 4.1.0). There were no missing data (see R code in the Supplementary Materials). The Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991) was used to visualize the networks using the *qgraph* package (Version 1.6.9), which places nodes that are strongly connected closer together. Thicker edges indicate a stronger connection. Blue edges indicate positive correlations, and red indicates negative correlations. To avoid spurious edges and produce a more parsimonious network, regularization techniques were used (Epskamp, Borsboom, & Fried, 2018; Epskamp, van Borkulo, et al., 2018). Specifically, the graphical least absolute shrinkage and selection operator (LASSO; Friedman et al., 2008) was employed to shrink small edges to exactly 0, meaning only the most relevant edges were present. The “tuning” hyperparameter gamma ( $\gamma$ ) was selected using the extended Bayesian information criteria (EBIC). The default ( $\gamma = 0.5$ ) was selected to ensure a more conservative network estimation. Networks were estimated using the R package *bootnet* (Version 1.4.3). For ease of visual comparison, all four networks have been constricted to an “average layout.”

A number of additional network tests were conducted to specifically address our study aims. First, to examine whether network connectivity would vary as a function of resilience, we relied on the *NetworkComparisonTest* package (Version 2.2.1) to compare the overall network connectivity and structure between (a) the resilient and delayed distress subgroups and (b) the recovered and sustained distress subgroups. Differences in network structure were assessed using the network invariance test, whereas global strength (GS) was estimated by comparing the summed edge weights within a network (i.e., invariant GS; van Borkulo, 2018). Second, to investigate whether psychopathology symptom clustering varied as a function of resilience, we applied the *walktrap* algorithm (Pons & Latapy, 2005), implemented in the *igraph*

package (Version 1.2.6), to detect the presence of clusters within each network. Briefly, this algorithm finds similar nodes based on random walks over the network's edges, searching for densely connected sections of that network (Newman & Girvan, 2004). We selected this algorithm for use in this study because it has been reported to have high accuracy (Demetriou et al., 2017; Golino & Epskamp, 2017; Smith et al., 2020) compared to other existing algorithms, such as *spinglass*, which may produce different results (Briganti et al., 2018). We also calculated the modularity ratio ( $Q$  index) to evaluate the goodness of fit of these communities;  $Q$  index values typically fall between 0.3 and 0.7, with higher values reflecting strong community structures (Newman & Girvan, 2004), and values below 0.3 are considered most likely random. We compared the number and content of clusters between the resilient and delayed groups as well as between the recovered and sustained groups.

## Supplementary analyses

Supplementary analyses related to network expected influence centrality and network robustness were also carried out. A detailed description of the procedure and results is provided in the Supplementary Materials.

## RESULTS

Mean symptom scores for each psychological response group are provided in Table 2. Network models for each of the psychological response groups are presented in Figures 1 and 2. Results from supplementary analyses suggest that network estimated parameters were robust—that is, edge-weight analyses revealed accurate estimations, whereas centrality indexes showed relative stability (see Supplementary Materials). Overall, in all four network structures, symptoms were mostly positively connected. The networks also showed the presence of a negative association between COVID-19 anxiety and appetite problems (PHQ-9, Item 5) and COVID-19 anxiety and suicidal ideation (PHQ-9, Item 9) in the resilient network, with the latter negative association also replicated in the recovered group network structure.

### Does network connectivity vary as a function of resilience?

We first compared the resilient (57% of potential edges above 0; edge weight range: 0.13–.42) and delayed distress

subgroups (49% of potential edges above 0; edge weight range: 0.01–0.23; see Figure 1). The network invariance test showed no differences in the network structure, maximum difference ( $M$ ) = 0.189,  $p$  = .485. Conversely, for connectivity, results of the GS invariance test showed significant differences between both groups,  $S$  = 1.26,  $p$  = .016. GS values, per group, revealed that the connectivity in the resilient network was higher,  $GS$  = 6.48, than in the delayed network,  $GS$  = 5.23.

Next, we compared the recovered (34% of potential edges above 0; edge weight range: -0.03–0.33) and sustained distress subgroups (48% of potential edges above 0; edge weight range: 0.002–0.39; see Figure 2). The network invariance test showed no differences in the network structure between these groups,  $M$  = 0.147,  $p$  = .667. However, regarding connectivity, results from the GS invariance test showed significant differences between both groups,  $S$  = 1.061,  $p$  = .031, revealing that connectivity in the sustained network,  $GS$  = 6.59, was higher than in the recovered network,  $GS$  = 5.52. Therefore, the connectivity hypothesis was partially supported, as the recovered group network showed lower connectivity than the network representing the sustained distress group. However, the resilient group network did not show lower connectivity than the delayed distress group network, as expected; instead, the opposite was observed.

### Does psychopathology symptom clustering vary as a function of resilience?

In the resilient group, four symptom clusters emerged (see Figure 3). The first cluster was composed of the PHQ-9 items measuring reductions in mood, interest, and energy (both physical and cognitive; red nodes); the second comprised the PHQ-9 items related to restlessness and self-image thoughts (purple nodes); the third was composed of the PHQ-9 items reflecting a loss of appetite, suicidal ideation, and the COVID-19 anxiety item (brown nodes); and the fourth community comprised all the GAD-7 items (green nodes). An analysis of modularity suggested a most likely random clustering,  $Q$  = 0.24. In the delayed group, we observed two communities (see Figure 3): one composed of the COVID-19 anxiety item and the majority of GAD-7 items (green nodes), except for restlessness and irritability, which, together with all the PHQ-9 items formed a second community (red nodes). The  $Q$  index also suggested a most likely random clustering,  $Q$  = 0.28.

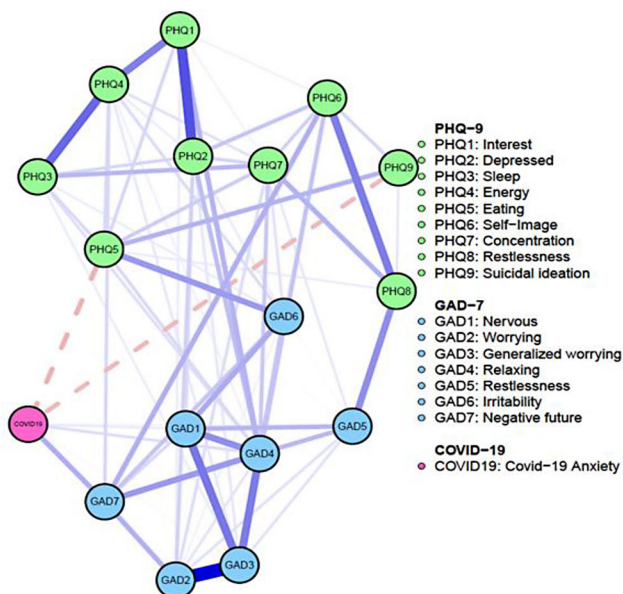
For the recovered network, three communities emerged (Figure 4). In this case, PHQ-9 items were divided into two separate communities. One community contained the first five items of the scale, which are related to

TABLE 2 Mean item scores, by response group, and group comparison tests<sup>a</sup>

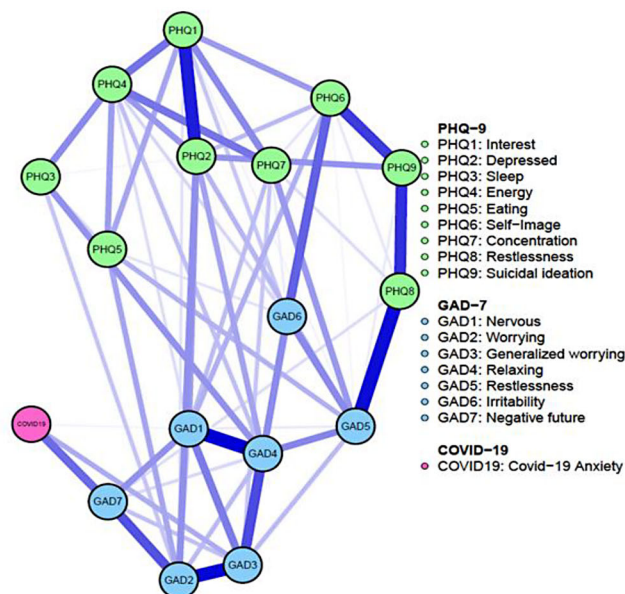
| T1 item             | Description                         | (a) Sustained<br>(n = 359) |       | (b) Recovered<br>(n = 359) |      | (c) Delayed<br>(n = 364) |       | (d) Resilient<br>(n = 364) |       | Kruskal–Wallis test <sup>b</sup> | p      | Post hoc test <sup>c</sup> |
|---------------------|-------------------------------------|----------------------------|-------|----------------------------|------|--------------------------|-------|----------------------------|-------|----------------------------------|--------|----------------------------|
|                     |                                     | M                          | SD    | M                          | SD   | M                        | SD    | M                          | SD    |                                  |        |                            |
| PHQ1                | Low interest or pleasure            | 1.70                       | 0.88  | 1.56                       | 0.86 | 0.80                     | 0.73  | 0.57                       | 0.74  | 394.791                          | < .001 | a = b > c > d              |
| PHQ2                | Feeling down, hopeless              | 1.87                       | 0.78  | 1.55                       | 0.75 | 0.71                     | 0.61  | 0.44                       | 0.60  | 635.330                          | < .001 | a > b > c > d              |
| PHQ3                | Sleep problems                      | 1.90                       | 0.95  | 1.70                       | 0.96 | 0.79                     | 0.78  | 0.59                       | 0.79  | 436.194                          | < .001 | a = b > c > d              |
| PHQ4                | Tired or little energy              | 1.91                       | 0.86  | 1.56                       | 0.88 | 0.79                     | 0.71  | 0.53                       | 0.64  | 501.208                          | < .001 | a > b > c > d              |
| PHQ5                | Appetite problems                   | 1.56                       | 1.03  | 1.29                       | 0.98 | 0.58                     | 0.73  | 0.39                       | 0.67  | 343.312                          | < .001 | a > b > c > d              |
| PHQ6                | Worthlessness/guilt                 | 1.47                       | 1.04  | 1.08                       | 0.96 | 0.37                     | 0.58  | 0.15                       | 0.38  | 459.318                          | < .001 | a > b > c > d              |
| PHQ7                | Trouble concentrating               | 1.52                       | 0.94  | 1.31                       | 0.93 | 0.49                     | 0.62  | 0.23                       | 0.45  | 500.203                          | < .001 | a > b > c > d              |
| PHQ8                | Moving or speaking slowly/restless  | 0.92                       | 0.99  | 0.73                       | 0.90 | 0.18                     | 0.42  | 0.05                       | 0.24  | 312.946                          | < .001 | a > b > c > d              |
| PHQ9                | Suicidal ideation                   | 0.72                       | 0.99  | 0.48                       | 0.78 | 0.12                     | 0.32  | 0.03                       | 0.21  | 215.433                          | < .001 | a > b > c > d              |
| GAD1                | Nervous, anxious, on edge           | 1.88                       | 0.87  | 1.65                       | 0.86 | 0.76                     | 0.62  | 0.46                       | 0.56  | 579.607                          | < .001 | a > b > c > d              |
| GAD2                | Uncontrollable worry                | 1.98                       | 0.89  | 1.85                       | 0.85 | 0.73                     | 0.68  | 0.45                       | 0.65  | 636.691                          | < .001 | a = b > c > d              |
| GAD3                | Worry about different things        | 1.97                       | 0.85  | 1.83                       | 0.82 | 0.68                     | 0.62  | 0.40                       | 0.59  | 701.504                          | < .001 | a = b > c > d              |
| GAD4                | Trouble relaxing                    | 1.98                       | 0.85  | 1.76                       | 0.84 | 0.67                     | 0.63  | 0.37                       | 0.53  | 705.528                          | < .001 | a = b > c > d              |
| GAD5                | Restless                            | 1.43                       | 0.98  | 1.19                       | 0.88 | 0.37                     | 0.54  | 0.14                       | 0.35  | 529.192                          | < .001 | a = b > c > d              |
| GAD6                | Irritable                           | 1.64                       | 0.98  | 1.49                       | 0.87 | 0.65                     | 0.65  | 0.42                       | 0.61  | 449.183                          | < .001 | a = b > c > d              |
| GAD7                | Afraid something awful might happen | 1.60                       | 0.98  | 1.55                       | 0.92 | 0.54                     | 0.64  | 0.29                       | 0.51  | 538.848                          | < .001 | a = b > c > d              |
| Total PHQ-GAD score |                                     | 26.06                      | 7.99  | 22.59                      | 6.46 | 9.24                     | 4.86  | 5.51                       | 4.75  | 1067.316                         | < .001 | a > b > c > d              |
| COVID-19 anxiety    |                                     | 73.50                      | 23.46 | 75.74                      | 20.9 | 63.25                    | 22.92 | 57.27                      | 26.51 | 147.628                          | < .001 | a = b > c = d              |

Notes: T1 = Time 1; PHQ = nine-item Patient Health Questionnaire; GAD = Generalized Anxiety Disorder–7 scale.  
<sup>a</sup>Age- and gender-matched a–b and c–d samples: (a) is age- and gender-matched to (b), and (d) is age- and gender-matched to (c).  
<sup>b</sup>All Kruskal–Wallis tests were significant at the  $p < .001$  level.  
<sup>c</sup>Nonparametric correction applied the  $p = .50$ .

Resilient sample network N=364

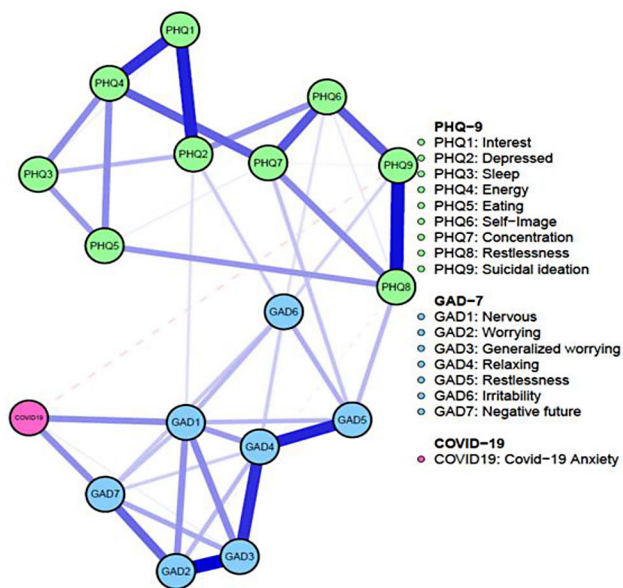


Delayed sample network N=364

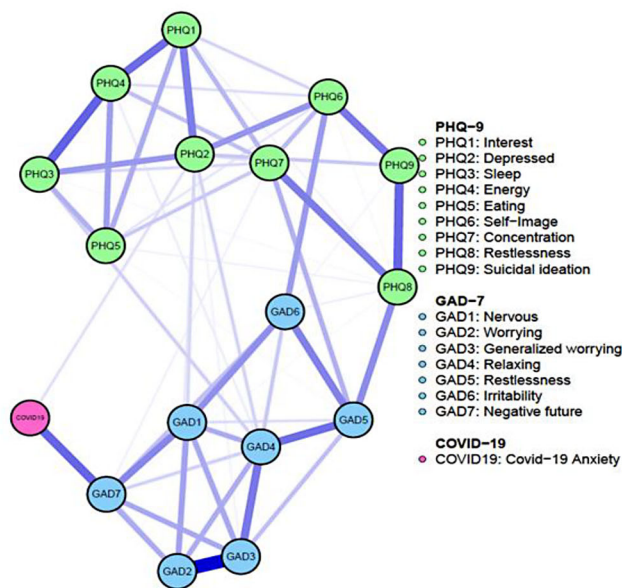


**FIGURE 1** Combined plot comparing network connectivity between Resilient and Delayed distress groups  
Note: PHQ-9 = nine-item Patient Health Questionnaire; GAD-7 = Generalized Anxiety Disorder-7 scale.

Recovered sample network N=359



Sustained sample network N=359

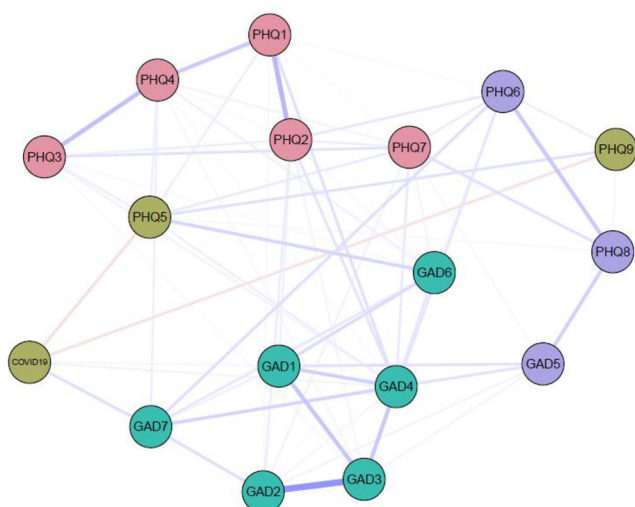


**FIGURE 2** Combined plot comparing network connectivity between Recovered and Sustained distress groups  
Note: PHQ-9 = nine-item Patient Health Questionnaire; GAD-7 = Generalized Anxiety Disorder-7 scale.

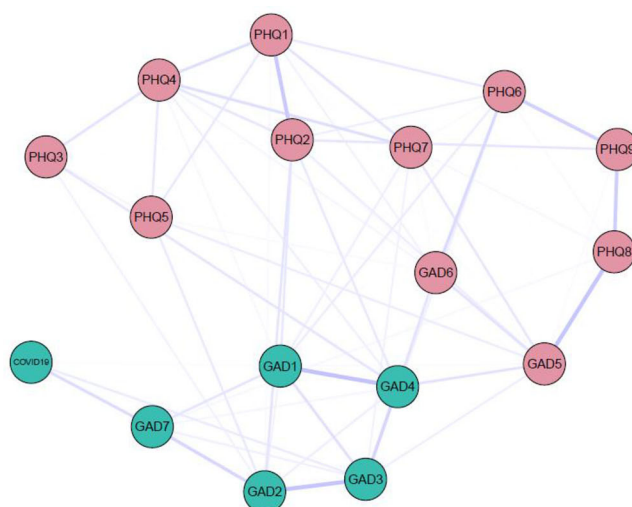
anhedonia; low mood; and problems with sleep, tiredness, and appetite, respectively, whereas the second community comprised the remaining four PHQ-9 items (i.e., items related to negative self-view, concentration

problems, restlessness, and thoughts of suicide). A third community was made up of the COVID-19 anxiety item and GAD-7 symptoms. For the sustained network, two communities emerged: one composed of all PHQ-9 items

Resilient group

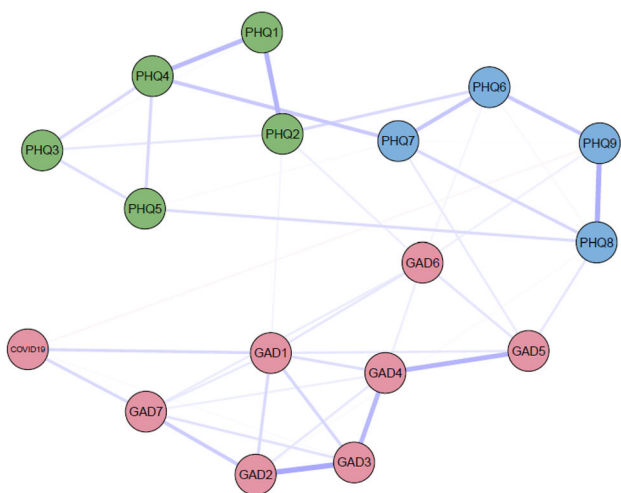


Delayed group

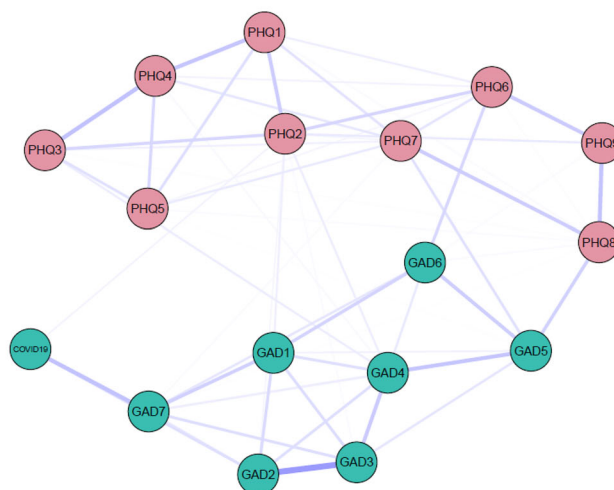


**FIGURE 3** Plot comparing communities between the resilient and delayed distress groups  
*Note:* PHQ = nine-item Patient Health Questionnaire; GAD = Generalized Anxiety Disorder-7 scale.

Recovered group



Sustained distress



**FIGURE 4** Plot comparing communities between the recovered and sustained distress groups  
*Note:* PHQ = nine-item Patient Health Questionnaire; GAD = Generalized Anxiety Disorder-7 scale.

and one that mirrored the recovered network and included all the GAD-7 items and the COVID-19 anxiety item.  $Q$  index analyses revealed that clustering in both the recovered,  $Q = 0.45$ , and sustained distress networks,  $Q = 0.37$ , was nonrandom. Overall, therefore, the findings did not support the clustering hypothesis, which predicted that fewer symptom clusters would be observed with increasing levels of resilience.

## DISCUSSION

The present study aimed to analyze the distinct patterns of psychological responses to the COVID-19 pandemic in several European countries. To this end, we followed previous research that empirically identified four patterns of psychological responses (i.e., resilient, delayed distress, recovered, and sustained distress) and utilized network

analytical techniques to study symptom-level expression at baseline within each of these groups and compare them in terms of connectivity and clustering. We expected to observe that with increasing levels of resilience, mental health networks would be (a) less densely connected and (b) comprise fewer symptom clusters.

The COVID-19 pandemic has posed a major threat to the well-being of individuals, although it is best conceptualized as a distressing event or PTE (Samuelson et al., 2022). Mounting evidence has indicated that being exposed to a PTE can lead to a wide variety of psychological responses ranging from showing no distress to experiencing a substantial number of symptoms (Bonanno, 2021). Results from the current study showed that, out of 3,594 individuals, almost two thirds of the sample exhibited a resilient response pattern ( $n = 2,284$ , 63.6%), understood as the absence of anxiety and depression over a 1-year period, whereas 16.3% of the sample showed a sustained distress pattern ( $n = 587$ ). These results echo existing empirical evidence indicating that in the aftermath of trauma exposure, a large proportion of individuals show no symptoms (Bonanno, 2021), which other COVID-19 studies have also confirmed (Ahrens et al., 2021; Chen & Bonanno, 2020), reflecting the dynamic aspect of individual psychological functioning.

The findings partially supported our hypothesis about network connectivity. First, the network comparison test (NCT) for structural invariance (i.e., network structure) indicated the resilient group did not significantly differ from the delayed group, nor did the recovered and sustained groups differ, suggesting that there were no significant differences in the symptom structure of psychological responses. In line with our hypotheses, the NCT for GS (i.e., the sum of edge weights or connectivity) revealed that the sustained distress group had a more strongly connected network than the recovered group. However, this result was not replicated with the resilient and delayed networks, with the former being more highly connected than the latter. Thus, increased symptom connectivity was observed among the resilient and sustained groups compared to the delayed and recovered groups, respectively. Both groups, resilient and sustained showed consistent or stable patterns of mental health throughout the study period (i.e., although the resilient group showed an absence of distress and the sustained group showed the presence of distress, both groups maintained their responses over a year).

Network theory postulates that if an event activates a network of elements that are strongly connected (e.g., symptoms), this activation might remain even after the event that has generated this network is no longer present, known as the “hysteresis phenomenon” (Borsboom, 2017). According to this theory, if a network is

active despite the absence of the triggering event, it means that the network has high connectivity and might reflect a psychological problem. Following this rationale, a network could be considered to reflect pathology when its nodes appear highly connected, which would, therefore, maintain that mental health problem. In sum, research has suggested that connectivity may be a benchmark of pathological networks. Contrary to this proposal, our longitudinal data suggest that connectivity may function as an indicator of response stability (i.e., a stable pattern over time regardless of whether a given trajectory includes the presence or absence of distress) rather than a direct indicator of psychopathology (i.e., the presence or absence of distress). Although this finding does not align with the network theory-informed connectivity hypothesis, it may be interpretable from a latent variable perspective, which would suggest that correlations among variables may stay similar irrespective of severity level.

Our findings show some similarities with those obtained by previous studies that have applied NCT (McGlinchey et al., 2021). For example, van Borkulo et al. (2015) compared the connectivity of networks of depressive symptoms among individuals with persistent and remitted major depressive disorder (MDD) over 2 years. The authors found that the network of participants with persistent MDD showed more connectivity than the network representing participants whose MDD had remitted after 2 years. Although van Borkulo et al.'s (2018) findings align with the network theory proposal that pathological networks may be strongly connected, they may also indicate that individuals who maintain the same pattern of response over time (i.e., the stability of depressive symptoms over 2 years) have the highest connectivity. Hence, the findings related to connectivity in the current study may suggest that the concept of hysteresis could apply to network models of individuals who show a stable pattern of psychological response, including resilient individuals.

Contrary to our hypothesis, the results revealed that mental health networks did not comprise fewer symptom clusters with increasing levels of resilience. In this study, the resilient and recovered group networks showed more symptom clusters than the networks for the delayed and sustained distress groups, respectively. The findings revealed that only the clusters that emerged in the recovered and sustained networks were considered to have satisfactory goodness of fit (i.e., nonrandom clustering). It is important to note, however, that values were only slightly above the randomness threshold and, thus, should be interpreted with caution. Although previous literature suggests that more severe levels of psychopathology may be associated with specificity (i.e., more clusters; McGorry & Van Os, 2013), a recent study by Groen et al. (2019) that used network analysis to explore this phenomenon

did not support this; instead, the authors observed similarities in the number and structure of communities in four groups along the severity continuum of psychopathology. Our results did not support this pattern either, as we found that the groups showing high levels of distress at 1-year follow-up presented a smaller number of clusters than those that showed no distress. Despite a lack of support for this hypothesis, our findings revealed a few interesting patterns when comparing recovered and sustained distress network structures.

First, we observed that all GAD-7 items clustered together with the COVID-19 anxiety item, reflecting that the pandemic outbreak triggered a wave of general anxiety symptoms. Secondly, differences in the community structure of PHQ-9 (i.e., depressive symptom) items were observed between the recovered and sustained distress group networks. In the recovered group, depressive symptom items formed two distinct clusters, one comprising items related to affect, sleep, fatigue, and appetite, and another comprising cognitive items as well as psychomotor and concentration items. However, although strong evidence for both one- and two-factor models of the PHQ-9 exists (Lamela et al., 2020), the two depression clusters in the recovered group did not match previously reported factor structures (Lamela et al., 2020), whereas in the sustained network, items perfectly clustered into depression (i.e., all PHQ-9 items) and anxiety (i.e., all GAD-7 and COVID-19 anxiety items). Interestingly, these two clearly defined communities found in the sustained network were almost replicated in the delayed network. This similar pattern of clustering between the two groups of individuals who displayed high levels of distress 1 year into the pandemic could indicate alignment with current diagnostic classifications, such as those in the *Diagnostic and Statistical Manual of Mental Disorders* (5th ed; American Psychiatric Association, 2013), where symptoms are clustered within different psychological domains (e.g., depressive disorders, anxiety disorders). However, it is worth mentioning that only the modularity of the recovered and sustained groups suggested nonrandom clustering, which indicates that firm conclusions cannot be drawn from this finding, and, thus, further research is needed to examine how symptoms cluster as a function of resilience.

On balance, a large body of literature suggests that indices proposed by network analysis, such as node centrality (i.e., those nodes of greatest importance in the network; McNally, 2016), could function as predictors of psychopathology. However, the present study suggests that indicators of specificity, such as connectivity and clustering, may also function as predictors of the stability of psychological responses (i.e., higher connectivity) and

long-term high levels of distress (i.e., fewer clusters) to PTEs, such as the COVID-19 pandemic.

This study had several limitations. Although the strategy of matching subsamples between groups made them more homogenous, the networks presented were based on a between-subjects design; thus, caution should be taken when generalizing the results to individuals or groups that might not be homogeneous. Additionally, despite being theory-driven, the strategy of using cutoff scores to create subgroups may imply some loss of information.. Moreover, we adopted a dynamic perspective by considering two time points to create the psychological response groups; however, the data modeled in the network are cross-sectional (i.e., T1), thus precluding us from drawing inferences about causal relationships. Future research would benefit from adding more assessment points or utilizing intensive longitudinal data, which would allow the application of, for instance, panel data analysis (Mertens et al., 2017) or temporal network approach (Blanchard et al., 2022), respectively, that could reveal temporal predictions closer to causality. Likewise, future research would benefit from applying different data-driven models, such as latent growth mixture modeling or latent class growth analysis (Shevlin et al., 2023). Also, addressing the lack of information on COVID-19-related stressors in the current study (e.g., the degree of exposure, having been infected, having lost a loved one) may help future researchers to contextualize these findings within a traumatic stress perspective (see Shevlin et al., 2020, for further discussion).

Finally, this study should be considered exploratory, and the networks of the response patterns were estimated only from symptoms of anxiety and depression. Future research replicating these findings, as well as examining other relevant aspects that might be implicated in resilient responses (e.g., personality, socioeconomic and demographic factors, community characteristics, lifetime trauma history, or past and current stressors; Bonanno, 2021; Chen & Bonanno, 2020; van der Wal et al., 2021), is needed. Applying novel metrics proposed to study risk and protective factors that might affect the resilience of the network, such as expected symptoms activity and symptoms activity stability (Lunansky et al., 2021), would be extremely useful to gain knowledge to predict resilient responses over time.

Several strengths stand out. We adopted an Open Science Practice (OSF) perspective and preregistered the study on the OSF. Also, to encourage replicability, all the materials, such as data and scripts, have been included as part of the Supplementary Materials. Furthermore, we followed the current theoretical perspective, which incorporates the combination of two core aspects (i.e., the presence or absence of distress and symptom stability over time) when defining resilience, which might overcome

the limitations of previous conceptualizations (Denckla et al., 2020). Moreover, the data analyzed in this study are diverse and nationally representative of the four countries involved. In addition, the application of the network approach allowed us to adopt a symptom-level perspective, providing a fine-grained picture of the component-to-component association within and between the four mental health response patterns which, ultimately, may be useful in identifying potential indicators associated with resiliency and other psychological responses to PTEs. Finally, following recommendations in the field (Espkamp et al., 2018), we applied several approaches to test the robustness of our analysis (see Supplementary Materials).

To conclude, this is the first study to examine four types of psychological response patterns during the pandemic at the symptom level using a network approach. Although these findings are preliminary, the present study suggests that higher levels of network connectivity may be a predictor of stable responses, regardless of the level of distress, whereas fewer clusters might be a feature characterizing long-term distress. This analytic strategy afforded the opportunity to identify differences in these distinct response patterns of anxiety and depression, which, if replicated, may help researchers and clinicians to better understand the onset, maintenance, and course of psychological distress during a time of great uncertainty and, in the long-term, how best to intervene and treat such distress. If replicated, these results could assist with the early identification of different psychological response patterns through the examination of symptom configurations and, therefore, may contribute to public mental health policies.

## OPEN PRACTICES STATEMENT

The current study was preregistered via the Open Science Framework (<https://osf.io/85um2>). Furthermore, data and R code can be found in the Supplementary Materials.

## AUTHOR NOTE

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## OPEN RESEARCH BADGES



This article has earned Open Materials and Preregistered Research Design badges. The preregistered design and materials are available at <https://osf.io/95m4j/>, and <https://osf.io/xbsnj>, respectively.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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