RESEARCH PAPER

ANXIETY, DEPRESSION, EMOTION REGULATION, AND DAYTIME SLEEPINESS: ARE THERE LINKS BETWEEN THESE FACTORS? NETWORK ANALYSIS ON AN ITALIAN SAMPLE DURING THE COVID-19 PANDEMIC

Alberto Sardella, Giorgia Varallo, Mirian Agus, Vittorio Lenzo, Andrea Zagaria, Grazia Terrone, Alessandro Musetti, Gianluca Castelnuovo, Maria C. Quattropani, Christian Franceschini

Citation: Sardella, A., Varallo, G., Agus, M., Lenzo, V., Zagaria, A., Terrone, G., Musetti, A., Castelnuovo, G., Quattropani, M. C., & Franceschini, C. (2023). Anxiety, depression, emotion regulation, and daytime sleepiness: are there links between these factors? Network analysis on an Italian sample during the COVID-19 pandemic. *Clinical Neuropsychiatry, 20*(5), 395-404.

doi.org/10.36131/cnfioritieditore20230501

Funding: None.

Competing interests: None.

Corresponding author
Christian Franceschini, PhD.
Department of Medicine and Surgery, University of Parma, Via Volturno 39, 43126 Parma, Italy

Abstract

Objective: The COVID-19 pandemic has contributed to the occurrence of psychological disturbances, such as depressive and anxiety symptomatology, thereby significantly impacting individuals' lifestyles by disrupting sleep patterns. This study aimed to elucidate the interconnections between emotion regulation, depression, anxiety, and daytime sleepiness.

Method: We recruited 632 community adults who underwent an online survey of self-report questionnaires, including the Depression Anxiety Stress Scale (DASS-21), the Difficulties in Emotion Regulation Scale (DERS), and the Epworth Sleepiness Scale (ESS).

A network analysis was performed to examine and visually represent the pattern of relationships between psychological distress, emotion regulation, and daytime sleepiness.

Results: The DERS Strategy dimension showed high values across all centrality indices, indicating it as the most influential node in the network. In addition, the DASS Depression and DERS Goals dimensions exhibited high betweenness values, emerging as points of connection between the other nodes within the network structure.

Conclusions: Our primary findings underscore the connection between psychological distress and emotion regulation, specifically between depressive symptoms, a lack of emotional clarity, and difficulty in the flexible use of emotional strategies. These specific constructs hold promising potential as valuable targets for both assessment and the development of effective interventions during highly challenging situations such as the COVID-19 pandemic.

Key words: anxiety, depression, emotion regulation, daytime sleepiness, COVID-19, network analysis

Alberto Sardella[a]*, Giorgia Varallo[b]*, Mirian Agus[c], Vittorio Lenzo[d], Andrea Zagaria[e], Grazia Terrone[f], Alessandro Musetti[g], Gianluca Castelnuovo[h,i], Maria C. Quattropani[d], Christian Franceschini[l]**

[a] Department of Clinical and Experimental Medicine, University of Messina, Messina, Italy
[b] Department of Biomedical, Metabolic and Neural Sciences, University of Modena and Reggio Emilia, Modena, Italy
[c] Department of Pedagogy, Psychology, Philosophy, Faculty of Humanistic Studies, University of Cagliari
[d] Department of Educational Sciences, University of Catania, Catania, Italy
[e] Department of Psychology, Sapienza University of Rome, Rome, Italy
[f] Department of History, Cultural Heritage, Education and Society, University of Rome Tor Vergata, Rome, Italy
[g] Department of Humanities, Social Sciences and Cultural Industries, University of Parma, Parma, Italy
[h] Psychology Research Laboratory, Istituto Auxologico Italiano IRCCS, Milan, Italy
[i] Department of Psychology, Catholic University of Milan, Milan, Italy
[l] Department of Medicine and Surgery, University of Parma, Parma, Italy
* Joint first author

Introduction

The Coronavirus Disease 2019 (COVID-19) pandemic has emerged as an enduring and stressful phenomenon exerting a significant influence on the global population. National governments have imposed restrictive measures since the pandemic was declared in March 2020 (WHO, 2020) to contain the spread of COVID-19 and protect the most vulnerable populations. National lockdown, quarantine, and social distancing have been the most widely implemented preventive strategies (R. Rossi et al., 2020a). Citizens, on the other hand, have paid the price of confinement in terms of social isolation, estrangement from relatives and friends, a lack of social support, and limited access to the healthcare system. These circumstances have resulted in detrimental effects on both physical and psychological well-being (Forte et al., 2020; Lee et al., 2021).

The negative impact of the COVID-19 pandemic on psychological health has become a growing concern in the last two years. According to recent Italian population-based studies, the pandemic has significantly exacerbated individual psychological distress; specifically, increased levels of depressive symptoms, anxiety, and stress were reported as a result of the lockdown and social isolation (Lenzo et al., 2020; Musetti et al., 2021).

Nonetheless, previous evidence has underlined the significant role of individual characteristics in shaping the response to distressing experiences (A. Rossi et al., 2020b). Indeed, *how* people cope with stress determines the trajectory of its impact (Wang & Saudino, 2011). Thus, during and after stressful events, the ability to regulate emotions is especially important to maintain psychological well-being and promote adaptive behaviors. Specifically, emotion regulation refers to a repertoire of physiological, behavioral, or cognitive processes through which individuals modulate their emotional experiences and expression (Ochsner & Gross, 2005).

According to Gratz and Roemer (Gratz & Roemer, 2004), emotion regulation encompasses four broad facets: (a) awareness and understanding of emotions; (b) acceptance of emotions; (c) the ability to control impulses and behave in accordance with goals in the presence of negative affect; and (d) access to emotion regulation strategies that are perceived to be useful for feeling better.

Importantly, emotion regulation difficulties have been proposed as a core mechanism underlying anxiety and depressive disorders (Hermann et al., 2009). Individuals suffering from depression and anxiety disorders, for example, face difficulties in selecting and implementing appropriate emotion regulation strategies that might mitigate the harmful effects of stressful experiences (Liu & Thompson, 2017).

Emerging research highlights the paramount importance of emotion regulation in fostering psychological well-being amidst the COVID-19 pandemic, encompassing both clinical and non-clinical cohorts. Notably, recent findings propose a link between heightened psychological distress and challenges in emotion regulation among individuals who have recovered from SARS-CoV-2 infection (Janiri et al., 2020).

Furthermore, it has been elucidated that emotion regulation serves as a mediating factor in the relationship between loneliness and both depression and anxiety (Velotti et al., 2021), as well as the association between psychological distress and emotion-driven behaviors during the pandemic (Guerrini Usubini et al., 2021).

The prolonged experiences of quarantine and lockdown have yielded notable transformations in individual daily routines (e.g., forced implementation of remote work and reduction of social activities), with a profound impact on the sleep-wake cycle (Cellini et al., 2020). Specifically, reduced physical activity, daylight exposure, and changes in sleep-wake habits with delayed bedtime, light off time, and sleep onset time due to quarantine and lockdown may have negatively affected sleep, both in terms of quality and quantity (Altena et al., 2020; Cellini et al., 2020). The occurrence of sleep disturbances during the COVID-19 pandemic has become a growing concern, mainly due to their negative consequences on individual physical and mental health (Partinen et al., 2021). Notably, sleep disturbances contribute to daytime sleepiness, a widely reported symptom associated with the ongoing pandemic (Guerrini Usubini et al., 2022; Partinen et al., 2021). For example, a study by Gupta et al. (2020) revealed a noteworthy escalation in daytime napping during the pandemic, possibly as a compensatory response to overcome daytime sleepiness resulting from insufficient nocturnal rest. Increased daytime sleepiness is associated with lower quality of life, psychological well-being, and physical functioning and could also contribute to the disruption of social life and work performance (Bjorvatn et al., 2014). It is worth noting that stress and mood disturbances, such as depression and anxiety, can precipitate daytime sleepiness (Lin et al., 2021). Nonetheless, in studies conducted during the COVID-19 pandemic, daytime sleepiness was neglected despite its potential negative effects on multiple aspects of health.

Hence, within a context like the COVID-19 pandemic, which has profoundly impacted all these dimensions, daytime sleepiness assumes significance as an important yet frequently overlooked factor warranting consideration.

The present study

Considering these premises, in the present study, a network analysis was performed to provide an exploratory empirical conceptualization of the interrelationships between the experiences of COVID-19, anxiety, depression, emotion regulation, and daytime sleepiness during the pandemic. The network analytic approach was chosen because it offers a comprehensive and visual representation of the complex relationships between variables in our study. It allows for a deeper understanding of the interplay among COVID-19 experience, anxiety, depression, emotion regulation, and daytime sleepiness, which would be challenging to capture using more traditional multivariate techniques. One of the critical advantages of network analysis is its ability to capture and visualize the direct and indirect associations between variables from a data-driven perspective. This is particularly relevant when studying phenomena where multiple variables interact and influence each other simultaneously.

Moreover, network analysis offers the advantage of identifying central and influential nodes within a network structure, providing valuable information about key variables or factors that play a critical role in the overall system. This information can inform targeted interventions and strategies to address the interconnectedness of these variables. This statistical approach has gained increasing interest in the last few years, and it has been employed in previous studies during the COVID-19 pandemic (Cheung et al., 2021; Martìn-Brufau et al., 2020) to investigate the associations between different psychological disturbances that occurred.

First, the structures that the above-mentioned indicators assume in a network (i.e., whether dimensions of anxiety, depression, emotion regulation, daytime sleepiness, and experience of COVID-19 establish some distinct clusters or overlap) were investigated;

second, the central nodes in the network, the potential "bridge" nodes that connect the cluster of different variables, were identified; and finally, the stability of the network was evaluated.

Methods

Participants and Procedure

Participants were 632 Italian adults recruited from October to November 2020 as part of a large-scale assessment (involving 720 subjects). The excluded participants (n = 90) are those who received and opened the survey link but did not provide informed consent. To recruit participants, a combination of convenience and snowball sampling techniques was employed. Initially, participants were recruited through online advertisements and invitations disseminated across multiple social media platforms, email lists, and online communities. Subsequently, these participants were encouraged to share the survey link with their acquaintances, thereby facilitating the snowball sampling process. The online survey was administered through the Microsoft Azure platform. Stringent measures were implemented to ensure comprehensive data collection, as all participants were obliged to respond to all questions, resulting in the absence of any missing data. All participants signed an informed consent form, and anonymity was guaranteed. The study was approved by the Ethics Committee of the Center for Research and Psychological Intervention (CERIP) of the University of Messina.

The sample consisted of 70.4% female participants, with a mean age of 31.01±10.83.

A detailed overview of the demographic characteristics of the sample can be found in **table 1**.

Measures

Demographic Form

The initial section of the protocol focused on evaluating demographic variables. Specifically, we collected data concerning age, gender, marital status, educational level, occupational status, geographic location, number of cohabitants during the pandemic, size of the house/apartment they resided in during the pandemic, and their experiences related to the pandemic (e.g., personal experience of contracting COVID-19, quarantine, presence of neighbors infected by COVID-19).

Depression, anxiety, and stress

The Depression Anxiety Stress Scale (DASS-21) (Lovibond & Lovibond, 1996) was used to assess psychological distress. This self-report questionnaire comprises 21 items rated on a 4-point Likert scale ranging from 0 to 3, which results in 3 subscales: depression, anxiety, and stress. Higher scores correspond to higher levels of depression, anxiety, and stress. We used the Italian version of the DASS-21 (Bottesi et al., 2015), demonstrating good psychometric properties. The Cronbach's alpha in our sample was 0.95.

Difficulties in Emotional Regulation

The Difficulties in Emotion Regulation Scale (DERS) (Gratz & Roemer, 2004) was used to assess difficulties in emotion regulation. This self-report scale has 36 items rated on a 5-point Likert scale, extending from 1 ("almost never") to 5 ("almost always"), with higher scores suggesting greater difficulties in emotion regulation. The DERS is divided into six subscales: (a) lack of emotional awareness; (b) lack of emotional clarity; (c) difficulty regulating behavior when distressed; (d) difficulty engaging in goal-directed cognition and behavior when troubled; (e) rejection to accept certain emotional responses; (f) lack of access to strategies to feel restored when concerned. The Italian validation of the scale conducted by Giromini et al. (2012) showed good psychometric properties. In our sample, the overall Cronbach alpha was 0.93.

Daytime sleepiness

The Epworth Sleepiness Scale (ESS), developed by Johns (1991) was administered to assess daytime sleepiness. We used the Italian-validated version developed by Vignatelli et al. (2003). The ESS consists of 8 items, rated from 0 ("I never fall asleep") to 3 ("I have a high probability of falling asleep"), with higher scores indicating higher levels of daytime sleepiness. In the protocol, some further questions investigated sleep habits: consequences on bedtime, consequences on waking time, and consequences on afternoon naps.

Statistical analyses

Data were analyzed using JASP (Version 0.16) (JASP Team, 2022).

Network analysis (NA) was employed to elucidate the interconnections between emotion regulation, depression, anxiety, and daytime sleepiness. A three-step analysis was performed (Epskamp et al., 2018). In the first step, an undirected network model was estimated. The second step involved analyzing the network structure by evaluating a series of centrality indices. In the third step, the stability of network parameters was assessed. Step one involved the use of a pairwise Markov Random Field (PMRF) (Robinaugh et al., 2016). Specifically, we used a Mixed Graphical Model (MGM) via a regularized estimation technique applying the extended Bayesian information criterion (EBIC) to select the tuning parameter (Epskamp et al., 2018). MGM is recommended to deal with data containing both continuous and categorical variables (Haslbeck & Waldorp, 2020). In a PMFR network nodes represent variables, while the relationships among observed variables are defined as edges. Edges are undirected and define a conditional dependence given all other nodes in the network (Hevey, 2018). For the layout, the Fruchterman-Reingold's algorithm (1991) was adopted to organize the network according to the strength of the connections between nodes, in which the fundamental and central nodes are those that manifest strong impacts on the overall network because of the high number of edges (Beard et al., 2016). In the second step, to gain insights into the relevance of each node, four centrality indices (i.e., *betweenness, closeness, strength, expected influence*) were estimated (Epskamp et al., 2018). Nodes with high values of centrality indices are considered the most relevant nodes in the network. The *Betweenness* index evaluates the number of times a node lies on the shortest pathway between two other nodes, identifying nodes that act as "bridges" between other nodes in the network. With bridges we refer to nodes representing the only point of connection between two other nodes within the network structure. *Closeness* index (i.e., the reciprocal of the sum of the shortest paths from the considered node to others) quantifies how well a node is indirectly connected to other nodes. The *Strength* index (i.e., a sum of the absolute edge weights that are associated with a specific node) indicates which node has the most solid direct connections. The *Expected influence* (i.e., the sum of edge weights accounting for both positive and negative associations) was also computed to overcome the potential unreliability of traditional centrality measures in the case of weighted networks with both positive and negative edges. In this regard, Robinaugh and colleagues (2016) demonstrated the usefulness of expected influence as an additional index. All centrality indices were reported as standardized z-scores. Moreover, we calculated Zhang's clustering coefficients (Costantini & Perugini, 2014; Zhang & Horvath, 2005) in order to evaluate the locally redundant nodes in the network. Lastly, following Hevey's (2018) recommendations, we examined the stability of both centrality indices and edge weights employing the case-dropping subset bootstrap procedure grounded on 1000 iterations (Epskamp et al., 2018). This bootstrap method was applied for various proportions of dropped cases to assess the correlations between the original estimates and those derived from sub-samples with fewer cases.

Results

Summary of the network

The descriptive statistics of the investigated variables are summarized in **table 1**.

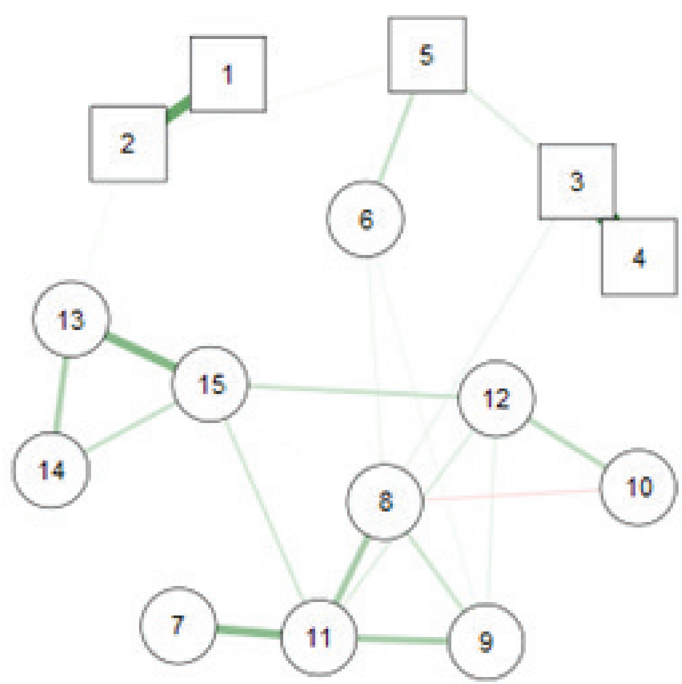
The following variables were included in the network model: COVID-19 diagnosis (binary: 0= no, 1=yes), someone close was positive for COVID-19 (binary: 0= no, 1=yes); consequences on bedtime (binary: 0= no, 1=yes); consequences on waking time (binary: 0= no, 1=yes); consequences in the afternoon nap (binary: 0= no, 1=yes); total ESS (continuous); DERS NONACCEPT (continuous); DERS GOALS (continuous); DERS IMPULSE (continuous); DERS AWARENES (continuous); DERS STRATEGY (continuous); DERS CLARITY (continuous); DASS_STRESS (continuous); DASS_ANXIETY (continuous); DASS_DEPRESSION (continuous).

The network model is depicted in **figure 1**. Nodes are represented as circles if continuous and squares if categorical. Edges are represented as lines: green lines indicate positive inter-connections among variables; red lines indicate negative inter-connections. The stronger the conditional dependence between two nodes, the thicker the edge presented in the plot. The position of the nodes in the network was organized by placing the nodes with more solid average associations nearer to the midpoint of the chart, through the application of Fruchterman-Reingold's algorithm (1991).

Overall, the network model showed a lack of strong relationships between the COVID-19-related nodes and the other dimensions. This can be extended to the nodes concerning daytime sleepiness that did not present substantial associations with the remaining nodes. On the other hand, the distress and emotional dysregulation nodes appear to be related to each other.

Specifically, observing the topology of the model, we showed that Node 1 (i.e., individual COVID-19 positivity experience) and Node 2 (i.e., presence of neighbors who were COVID-19 positive) were strongly and positively related, but they did not exhibit strong relationships with the other nodes (i.e., daytime sleepiness, emotion regulation, and psychological distress). Node 6 (i.e., total ESS score) exhibited a positive association with Node 5 (i.e., consequences in the afternoon nap), while a lack of associations was

Figure 1. *Summary of the network*



Notes: 1 = COVID-19 diagnosis (binary: 0= no, 1=yes), 2 = someone close was positive for COVID-19 (binary: 0= no, 1=yes); 3= implications at bedtime (binary: 0= no, 1=yes); 4= consequences on waking time (binary: 0= no, 1=yes); 5= consequences in the afternoon nap (binary: 0= no, 1=yes); 6 = total ESS (continuous); 7= DERS NONACCEPT (continuous); 8= DERS GOALS (continuous); 9 =DERS IMPULSE (continuous); 10 = DERS AWARENES (continuous); 11= DERS STRATEGY (continuous); 12 =DERS CLARITY (continuous); 13= DASS_STRESS (continuous); 14= DASS_Anxiety (continuous); 15 =DASS_DEPRESSION (continuous).

Table 1. *Descriptive statistics of the assessed variables (n = 632)*

Variable	n	%	Mean	SD
Age, years (mean, SD)			31.01	10.83
Female (n, %)	445	70.4		
Geographic area, northern-center (n, %)	591	93.8		
Employed (n, %)	427	67.6		
Education				
Secondary school and lower (n, %)	46	7.3		
High school (n, %)	397	62.8		
Bachelor's degree (n, %)	76	12.0		
Master's degree (n, %)	101	16.0		
PhD. (n, %)	12	1.9		
Marital status				
Single / unmarried (n, %)	222	35.1		
Married (n, %)	135	21.4		
Remarried (n, %)	3	0.5		
In a relationship (n, %)	189	29.9		
Divorced / separated / widowed (n, %)	24	3.8		
Cohabiting (n, %)	59	9.3		
Presence of offspring (n, %)	172	27.2		
Cohabitants during the lockdown (mean, SD)			2.58	1.26
Apartment dimension, m^2 (mean, SD)			139.41	82.59
Subjects not infected by COVID-19 (n, %)	606	95.9		
Subjects experiencing quarantine (n, %)	65	10.4		
Subjects with relatives positive for COVID-19 (n, %)	96	15.2		
Consequences on bedtime				
I maintained my habits (n, %)	303	47.9		
I anticipated (n, %)	48	7.6		
I postponed (n, %)	281	44.5		
Consequences on waking time				
I maintained my habits (n, %)	308	48.7		
I anticipated (n, %)	67	10.6		
I postponed (n, %)	257	40.7		
Consequences on afternoon nap				
I kept my habits (n, %)	243	38.4		
+ Naps (n, %)	129	20.4		
- Naps (n, %)	37	5.9		
I do not take naps (n, %)	223	35.3		
ESS Total score (mean, SD)			6.25	3.47
Emotion dysregulation				
DERS Non-accept (mean, SD)			13.44	5.95
DERS Goals (mean, SD)			13.22	4.98
DERS Impulse (mean, SD)			11.86	5.27
DERS Awareness (mean, SD)			9.42	5.18
DERS Strategy (mean, SD)			17.29	7.13
DERS Clarity (mean, SD)			9.94	4.44
DERS Total score (mean, SD)			75.18	23.65
Psychological distress				
DASS Stress (mean, SD)			7.87	5.59
DASS Anxiety (mean, SD)			3.83	4.43
DASS Depression (mean, SD)			5.91	5.27

Note: ESS: Epworth Sleepiness Scale; DERS: Difficulties in Emotion Regulation Strategies; DASS: Depression Anxiety Stress Scale found with Node 3 (i.e., consequences on bedtime) and with Node 4 (i.e., consequences on waking time). Node 4 (i.e., consequences on waking time) was only related to Node 3 (i.e., consequences on bedtime). The DASS nodes were strongly related to each other; however, only Node 15 (i.e., the DASS depression scale) was related to the emotional regulation dimensions, such as Node 11 (i.e., DERS strategy scale) and Node 12 (i.e., DERS CLARITY scale). Lastly, Node 10 (i.e., DERS Awareness scale) appeared in a peripheral position in the network, showing a positive relationship with Node 12 (i.e., DERS Clarity) and a negative relationship with Node 8 (i.e., DERS Goals).

Centrality indices

With the aim to evaluate the relevance of each node, four centrality indices (i.e., above mentioned: strength, closeness, betweenness, and expected influence) and the clustering Zhang's index were calculated. As shown in **table 2**, the most relevant node in the network was the number 11 (i.e., DERS_STRATEGY), which reported high values of betweenness, closeness, strength, and expected influence. Also, Node 8 (i.e., DERS-GOALS) exhibited high coefficients of betweenness and closeness; contraryly, the values of strength and expected influence were low. Considering betweenness, higher values were observed for Node 11 (i.e., DERS Strategy) and for Node 15 (i.e., DASS DEPRESSION), which may be considered as the "bridges" connecting the communities of nodes. Considering closeness, the higher values were registered for Node 11 (i.e., DERS strategy), Node 8 (i.e., DERS goals) and Node 15 (i.e., DASS depression), which exhibited the strongest connections to the nodes nearby. Also, high coefficients of strength and expected influence emerged for Node 11 (i.e., DERS strategy) and Node 3 (i.e., consequences on bedtime) demonstrating their central roles in the network. With respect to Zhang's clustering index, Node 14 (i.e., DASS_Anxiety) and Node 7 (i.e., DERS_non accept) reported the highest values and thus may be considered as the most locally redundant nodes in the network.

Stability of findings

The case-dropping subset bootstrap procedure grounded on 1000 iterations was employed to observe the stability of both centrality indices and edge weights. **figure 2** (i.e., centrality indices) and **figure 3** (i.e., edge weights) depict the correlations between the original estimates and those obtained from subsets with various proportions of dropped cases. The correlations was large in magnitudes and decreased slowly even after dropping large proportions of the sample (i.e., until nearly 40% of the sample on the x-axis). Hence, the estimations of both centrality indices and edge weights seem to be sufficiently stable to be reasonably interpreted (Hevey, 2018).

Discussion

To the best of our knowledge, this study represents the first population-based investigation conducted during the COVID-19 pandemic, employing network analysis to examine the relationships among variables associated with the COVID-19 experience, anxiety, depression, emotion regulation, and daytime sleepiness. The resulting network model showed good stability and substantially reported the presence of associations involving anxiety, depression, and emotion regulation. Conversely, the network did not indicate any direct connections between COVID-19-related factors or daytime sleepiness and the other psychological variables. Rather, these factors were only linked with

Table 2. *Centrality measures and clustering Zhang index per variable*

		Network				
	Variable	Betweenness	Closeness	Strength	Expected influence	Clustering Zhang index
1	COVID-19 diagnosis	-0.831	-1.819	-0.469	-0.342	-0.719
2	Someone close was positive for COVID-19	0.128	-1.604	-0.125	-0.024	-0.719
3	Implications at bedtime	0.128	-0.262	1.550	1.523	-0.719
4	Consequences on waking time	-0.831	-0.508	0.846	0.873	-0.719
5	Consequences in the afternoon nap	-0.241	-0.930	-1.126	-0.949	-0.719
6	ESS	-0.167	-0.540	-1.257	-1.070	-0.494
7	DERS NONACCEPT	-0.831	0.603	-0.805	-0.652	1.984
8	DERS GOALS	1.603	1.262	0.249	-0.363	-0.047
9	DERS IMPULSE	-0.831	0.649	0.038	0.127	0.586
10	DERS AWARENESS	-0.831	-0.189	-1.226	-1.726	-0.719
11	DERS STRATEGY	2.120	1.569	2.028	1.965	-0.311
12	DERS CLARITY	-0.462	0.259	-0.268	-0.156	-0.313
13	DASS_STRESS	0.349	0.635	0.334	0.400	0.445
14	DASS ANXIETY	-0.831	-0.236	-0.679	-0.536	2.445
15	DASS_DEPRESSION	1.529	1.111	0.909	0.932	0.020

Note: 1 = COVID-19 diagnosis (binary: 0= no, 1=yes), 2 = Someone close was positive for COVID-19 (binary: 0= no, 1=yes); 3= Implications at bedtime (binary: 0= no, 1=yes); 4= Consequences on waking time (binary: 0= no, 1=yes); 5= Consequences in the afternoon nap (binary: 0= no, 1=yes); 6 = Total ESS (continuous); 7= DERS NONACCEPT (continuous); 8= DERS GOALS (continuous); 9 =DERS IMPULSE (continuous); 10 = DERS AWARENES (continuous); 11= DERS STRATEGY (continuous); 12 =DERS CLARITY (continuous); 13= DASS_STRESS (continuous); 14= DASS_Anxiety (continuous); 15 =DASS_DEPRESSION (continuous).

Figure 2. *Centrality indices stability. Lines indicate the means and areas indicate the range from the 2.5th quantile to the 97.5th quantile*

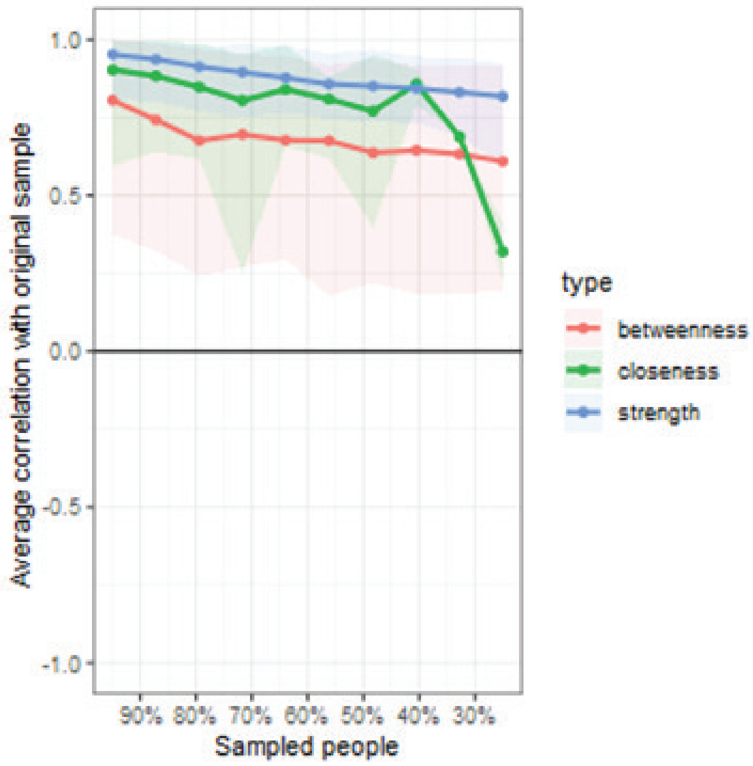
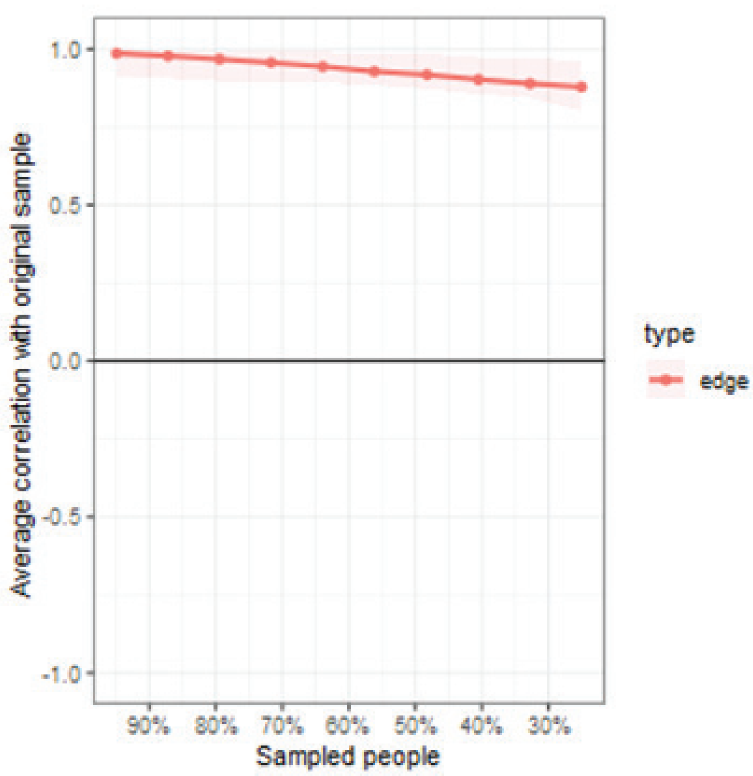


Figure 3. *Edge stability. Lines indicate the means and areas indicate the range from the 2.5th quantile to the 97.5th quantile*



other nodes within their respective domains.

Our results might indicate that in our sample having contracted or having a neighbor who had contracted COVID-19 may not be associated with anxious and depressive symptoms Our results are in contrast to previous evidence in the Italian population, which has reported an association between depressive symptoms and having a family member with COVID-19 (Delmastro & Zamariola, 2020).Furthermore, daytime sleepiness did not emerge as a significant factor linking anxiety, depression, and emotion regulation processes. One possible explanation for this is that other sleep-related variables, such as insomnia, may serve as stronger connectors among these factors. Consequently, future research should examine this hypothesis, as the role of sleep could play a significant role in interconnecting symptom clusters within anxiety and depressive disorders, potentially representing a transdiagnostic target for intervention (Dolsen et al., 2014).

On the other hand, depressive symptoms, as expressed by the DASS Depression score, resulted linked to both the DERS Clarity (i.e., lack of emotional clarity) and the DERS Strategy scores (i.e., lack of access to strategies for feeling better when distressed). According to the model proposed by Gratz and Roemer (2004), emotional clarity refers to an individual's ability to accurately recognize and differentiate their experienced emotions. Access to emotion regulation strategies defines the ability to use flexible emotion regulation strategies, appropriate to the context and to situational demands (Gratz & Roemer, 2004). Our results underlined the significant association between emotional clarity and depression in line with previous evidence. For example, lack of emotional clarity was associated with depressive symptoms among college students (Di Schiena et al. 2011), as well as among individuals with psychological disorders (see, e.g., Bamonti et al., 2010). Furthermore, lower levels of emotional clarity have been found to be associated with poor psychosocial adjustment (Salguero, Palomera, & Fernández-Berrocal, 2012). Greater emotional clarity, on the other hand, has been linked to better coping and higher levels of well-being (Gohm & Clore, 2002). Our findings combined with these previous evidence suggest that the ability to identify and describe one's own emotions is critical for psychosocial well-being.

In addition, the ability to use flexible emotion regulation strategies that are appropriate to the context and situational demands is another pivotal aspect of psychological well-being because different situations require a completely different approach to effectively dealing with emotions. Current frameworks go beyond a static view of the functionality or dysfunctionality of specific emotion regulation strategies and instead consider adaptive the flexible use of emotion regulation strategies across time as a result of the interplay of personal characteristics and specific situational demands (Aldao et al., 2015; Bonanno & Burton, 2013). Fixed and inflexible emotion regulation strategies are often maladaptive, while greater flexibility is associated with improved psychological adaptation (Aldao et al., 2015) and better coping (Levy-Gigi et al., 2016). Indeed, has been suggested that psychological disturbances may be characterized by deficits in the flexibility of emotion regulation strategies (Bonanno & Burton, 2013). Interestingly, the association between depressive symptoms and difficulties in emotion regulatory processes has been recently demonstrated in a study on community adults during the COVID-19 pandemic which highlighted emotion dysregulation as a predictor of severe depressive symptoms (Moccia et al., 2020).

Our analysis revealed that the DERS Strategy factor (i.e., lack of access to strategies for feeling better when distressed) was the central node of the network, since it showed the highest values of betweenness, closeness, strength, and expected influence, compared to the other nodes. Furthermore, both the DERS Strategy and the DASS Depression nodes represented the bridges, which connected most nodes.

This evidence remarks the importance of having a flexible range of emotion regulation strategies to rely on, in order to avoid psychological distress, especially during extremely distressing situations such as living during a pandemic (Tyra et al., 2021).

We acknowledge the presence of some limitations in the study. The first limitation regards the use of self-report measures for collecting data, even though they are well-established and standard instruments. The second limitation concerns the cross-sectional design, which did not allow us to infer causal relationships between the variables considered. Morover, the oversampling of certain characteristics (i.e., the female gender) may limit the generalizability of the results to the population. Lastly, during the data collection period, Italy witnessed a notable upsurge in COVID-19 cases following the initial wave in spring. The Autumn season was marked by implementing several containment measures, such as regional lockdowns, limitations on movement, and alterations in social interactions. Although this particular timeframe holds its distinctiveness, analyzing individuals' experiences allows us to obtain valuable insights into their psychological and sleep-related reactions to a challenging and highly stressful situation.

Despite the aforementioned limitations, this study provides stimulating implications for the planning of further preventive interventions based on emotion regulation and psychological distress, aimed at promoting psychological well-being. In this regard, the implementation of the remote evaluation in this study appears to be in line with the actual contingencies. Specifically, due to the restrictions caused by the pandemic emergency, access to assistance services has been progressively reduced. In this context, the use of remote strategies has facilitated not only the assessment of pandemic-related psychological consequences (Sardella et al., 2021), but also the possibility of providing effective telematic psychological support in response to various issues among different populations (Gorenko et al., 2021; Moshe et al., 2021; Yuan, 2021).

In conclusion, the present network analysis explored associations between anxiety, depression, emotion regulation, and daytime sleepiness in community subjects during the COVID-19 pandemic. The main finding was the existing link between psychological distress and emotion regulation, precisely between depressive symptoms, difficulty in emotional clarity, and difficulty in using flexible emotional strategies.

The COVID-19 pandemic has contributed to the occurrence of psychological disturbances, and it has affected individual life habits. Implementing integrated interventions appears to be increasingly necessary, with the aim of improving psychological and emotional adaptation to such a dramatic event as the pandemic. According to our results, intervention aimed at promoting better emotion regulation (specifically, emotional clarity and flexible use of emotion regulation strategies) might have a positive impact on depressive symptomatology. Finally, future studies should go in the direction of a deeper and more accurate understanding of which antecedent factors can expose individuals to a greater risk of adverse psychological outcomes, or conversely which might act as protective factors (e.g., psychological resilience).

References

Aldao, A., Sheppes, G., & Gross, J. J. (2015). Emotion regulation flexibility. *Cognitive Therapy and Research, 39*, 263–278. https://doi.org/10.1007/s10608-014-9662-4

Altena, E., Baglioni, C., Espie, C. A., Ellis, J., Gavriloff, D., Holzinger, B., Schlarb, A., Frase, L., Jernelöv, S., &

Riemann, D. (2020). Dealing with sleep problems during home confinement due to the COVID-19 outbreak: Practical recommendations from a task force of the European CBT-I Academy. *Journal of Sleep Research, 29*(4), e13052. https://doi.org/10.1111/jsr.13052

Bamonti, P. M., Heisel, M. J., Topciu, R. A., Franus, N., Talbot, N. L., & Duberstein, P. R. (2010). Association of alexithymia and depression symptom severity in adults aged 50 years and older. *The American Journal of Geriatric Psychiatry: Official Journal of the American Association for Geriatric Psychiatry, 18*(1), 51–56. https://doi.org/10.1097/jgp.0b013e3181bd1bfe

Beard, C., Millner, A. J., Forgeard, M. J., Fried, E. I., Hsu, K. J., Treadway, M. T., Leonard, C. V., Kertz, S. J., & Björgvinsson, T. (2016). Network analysis of depression and anxiety symptom relationships in a psychiatric sample. *Psychological medicine,* 46(16), 3359–3369. https://doi.org/10.1017/S0033291716002300

Bonanno, G. A., & Burton, C. L. (2013). Regulatory flexibility: An individual differences perspective on coping and emotion regulation. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science, 8*(6), 591–612. https://doi.org/10.1177/1745691613504116

Bottesi, G., Ghisi, M., Altoè, G., Conforti, E., Melli, G., & Sica, C. (2015). The Italian version of the Depression Anxiety Stress Scales-21: Factor structure and psychometric properties on community and clinical samples. *Comprehensive Psychiatry, 60*, 170–181. https://doi.org/10.1016/j.comppsych.2015.04.005

Bjorvatn, B., Pallesen, S., Grønli, J., Sivertsen, B., & Lehmann, S. (2014). Prevalence and correlates of insomnia and excessive sleepiness in adults with obstructive sleep apnea symptoms. *Perceptual and Motor Skills, 118*(2), 571–586. https://doi.org/10.2466/15.06.pms.118k20w3

Cellini, N., Canale, N., Mioni, G., & Costa, S. (2020). Changes in sleep pattern, sense of time and digital media use during COVID-19 lockdown in Italy. *Journal of Sleep Research, 29*(4), e13074. https://doi.org/10.1111/jsr.13074

Cheung, T., Jin, Y., Lam, S., Su, Z., Hall, B. J., & Xiang, Y. T., International Research Collaboration on COVID-19 (2021). Network analysis of depressive symptoms in Hong Kong residents during the COVID-19 pandemic. *Translational psychiatry, 11*(1), 460. https://doi.org/10.1038/s41398-021-01543-z

Costantini, G., & Perugini, M. (2014). Generalization of clustering coefficients to signed correlation networks. *PLoS ONE, 9*(2), e88669. https://doi.org/10.1371/journal.pone.0088669

Delmastro, M., & Zamariola, G. (2020). Depressive symptoms in response to COVID-19 and lockdown: a cross-sectional study on the Italian population. *Scientific Reports, 10*(1), 22457. https://doi.org/10.1038/s41598-020-79850-6

Di Schiena, R., Luminet, O., & Philippot, P. (2011). Adaptive and maladaptive rumination in alexithymia and their relation with depressive symptoms. *Personality and Individual Differences, 50*(1), 10–14. https://doi.org/10.1016/j.paid.2010.07.037

Dolsen, M. R., Asarnow, L. D., & Harvey, A. G. (2014). Insomnia as a transdiagnostic process in psychiatric disorders. *Current Psychiatry Reports, 16*(9), 471. https://doi.org/10.1007/s11920014-0471-y

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

Forte, G., Favieri, F., Tambelli, R., & Casagrande, M. (2020). COVID-19 Pandemic in the Italian Population: Validation of a Post-Traumatic Stress Disorder Questionnaire and Prevalence of PTSD Symptomatology. *International Journal of Environmental Research and Public Health, 17*(11), 4151. https://doi.org/10.3390/ijerph17114151

Franceschini, C., Musetti, A., Zenesini, C., Palagini, L., Scarpelli, S., Quattropani, M. C., Lenzo, V., Freda, M. F., Lemmo, D., Vegni, E., Borghi, L., Saita, E., Cattivelli, R., De Gennaro, L., Plazzi, G., Riemann, D., & Castelnuovo, G. (2020). Poor Sleep Quality and Its Consequences on Mental Health during the COVID-19 Lockdown in Italy. *Frontiers in Psychology, 11*, 574475. https://doi.org/10.3389/fpsyg.2020.574475

Fruchterman, T.M.J. and Reingold, E.M. (1991). Graph Drawing by Force-directed placement. *Software – Practice and Experience*, 21 (11):1129-1164.

Giromini, L., Velotti, P., De Campora, G., Bonalume, L., & Cesare Zavattini, G. (2012). Cultural Adaptation of the Difficulties in Emotion Regulation Scale: Reliability and Validity of an Italian Version. *Journal of Clinical Psychology, 68*(9), 989–1007. https://doi.org/10.1002/jclp.21876

Gohm, C. L., & Clore, G. L. (2002). Four latent traits of emotional experience and their involvement in well-being, coping, and attributional style. *Cognition and Emotion, 16*(4), 495–518. https://doi.org/10.1080/02699930143000374

Gorenko, J. A., Moran, C., Flynn, M., Dobson, K., & Konnert, C. (2021). Social Isolation and Psychological Distress Among Older Adults Related to COVID-19: A Narrative Review of Remotely-Delivered Interventions and Recommendations. *Journal of Applied Gerontology: The Official Journal of the Southern Gerontological Society, 40*(1), 3–13. https://doi.org/10.1177/0733464820958550

Gratz, K. L., & Roemer, L. (2004). Multidimensional assessment of emotion regulation and dysregulation. *Journal of Psychopathology and Behavioral Assessment, 26*(1), 41–54. https://doi.org/10.1023/B:JOBA.0000007455.08539.94

Guerrini Usubini, A., Terrone, G., Varallo, G., Cattivelli, R., Plazzi, G., Castelnuovo, G., Schimmenti, A., Musetti, A., & Franceschini, C. (2022). The Mediating Role of Emotion Dysregulation and Problematic Internet Use in the Relationship Between Negative Affect and Excessive Daytime Sleepiness: A Structural Equation Model. *Nature and Science of Sleep, 14*, 291–302. https://doi.org/10.2147/NSS.S346485

Guerrini Usubini, A., Cattivelli, R., Varallo, G., Castelnuovo, G., Molinari, E., Giusti, E. M., Pietrabissa, G., Manari, T., Filosa, M., Franceschini, C., & Musetti, A. (2021). The Relationship between Psychological Distress during the Second Wave Lockdown of COVID-19 and Emotional Eating in Italian Young Adults: The Mediating Role of Emotional Dysregulation. *Journal of Personalized Medicine, 11*(6), 569. https://doi.org/10.3390/jpm11060569

Gupta, R., Grover, S., Basu, A., Krishnan, V., Tripathi, A., Subramanyam, A., Nischal, A., Hussain, A., Mehra, A., Ambekar, A., Saha, G., Mishra, K. K., Bathla, M., Jagiwala, M., Manjunatha, N., Nebhinani, N., Gaur, N., Kumar, N., Dalal, P. K., … Avasthi, A. (2020). Changes in sleep pattern and sleep quality during COVID-19 lockdown. *Indian Journal of Psychiatry, 62*(4), 370–378. https://doi.org/10.4103/psychiatry.IndianJPsychiatry_523_20

Haslbeck, J. M. B., & Waldorp, L. J. (2020). mgm: Estimating Time-Varying Mixed Graphical Models in High-Dimensional Data. *Journal of Statistical Software, 93*(8), 1–46. https://doi.org/10.18637/jss.v093.i08

Hermann, A., Schäfer, A., Walter, B., Stark, R., Vaitl, D., & Schienle, A. (2009). Emotion regulation in spider phobia: role of the medial prefrontal cortex. *Social Cognitive and Affective Neuroscience, 4*(3), 257–267. https://doi.org/10.1093/scan/nsp013

Hevey, D. (2018). Network analysis: a brief overview and tutorial. *Health Psychology and Behavioral Medicine, 6*(1), 301–328. https://doi.org/10.1080/21642850.2018.1521283

Janiri, D., Kotzalidis, G. D., Giuseppin, G., Molinaro, M., Modica, M., Montanari, S., Terenzi, B., Carfì, A., Landi, F., Sani, G., & Gemelli against COVID-19 Post-acute

Care Study Group (2020). Psychological Distress after Covid-19 Recovery: Reciprocal Effects With Temperament and Emotional Dysregulation. An Exploratory Study of Patients Over 60 Years of Age Assessed in a Post-acute Care Service. *Frontiers in Psychiatry, 11*, 590135. https://doi.org/10.3389/fpsyt.2020.590135

JASP Team. (2022). *JASP* (0.16). University of Amsterdam. http://jasp-stats.org/

Johns, M. W. (1991). A New Method for Measuring Daytime Sleepiness: The Epworth Sleepiness Scale. *Sleep, 14*(6), 540–545. https://doi.org/10.1093/sleep/14.6.540

Lee, E., Man, R., Gan, T., Fenwick, E. K., Aravindhan, A., Ho, K. C., Sung, S. C., Wong, T. Y., Ho, C., Gupta, P., & Lamoureux, E. L. (2021). The longitudinal psychological, physical activity and financial impact of a COVID-19 lockdown on older adults in Singapore: The PIONEER-COVID population-based study. *International Journal of Geriatric Psychiatry, 37*(1), 10.1002/gps.5645. Advance online publication. https://doi.org/10.1002/gps.5645

Lenzo, V., Quattropani, M. C., Musetti, A., Zenesini, C., Freda, M. F., Lemmo, D., Vegni, E., Borghi, L., Plazzi, G., Castelnuovo, G., Cattivelli, R., Saita, E., & Franceschini, C. (2020). Resilience Contributes to Low Emotional Impact of the COVID-19 Outbreak Among the General Population in Italy. *Frontiers in Psychology, 11*, 576485. https://doi.org/10.3389/fpsyg.2020.576485

Levy-Gigi, E., Bonanno, G. A., Shapiro, A. R., Richter-Levin, G., Kéri, S., & Sheppes, G. (2016). Emotion Regulatory Flexibility Sheds Light on the Elusive Relationship Between Repeated Traumatic Exposure and Posttraumatic Stress Disorder Symptoms. Clinical Psychological Science, 4(1), 28-39. https://doi.org/10.1177/2167702615577783

Lin, C.-Y., Imani, V., Griffiths, M. D., Broström, A., Nygårdh, A., Demetrovics, Z., & Pakpour, A. H. (2021). Temporal associations between morningness/eveningness, problematic social media use, psychological distress and daytime sleepiness: Mediated roles of sleep quality and insomnia among young adults. *Journal of Sleep Research, 30*(1), e13076. https://doi.org/10.1111/jsr.13076

Liu, D. Y., & Thompson, R. J. (2017). Selection and implementation of emotion regulation strategies in major depressive disorder: An integrative review. *Clinical Psychology Review, 57*, 183–194. https://doi.org/10.1016/j.cpr.2017.07.004

Lovibond, S. H., & Lovibond, P. F. (1996). *Manual for the depression anxiety stress scales*. Psychology Foundation of Australia.

Martín-Brufau, R., Suso-Ribera, C., & Corbalán, J. (2020). Emotion Network Analysis During COVID-19 Quarantine - A Longitudinal Study. *Frontiers in Psychology, 11*, 559572. https://doi.org/10.3389/fpsyg.2020.559572

Moccia, L., Janiri, D., Giuseppin, G., Agrifoglio, B., Monti, L., Mazza, M., Caroppo, E., Fiorillo, A., Sani, G., Di Nicola, M., & Janiri, L. (2020). Reduced Hedonic Tone and Emotion Dysregulation Predict Depressive Symptoms Severity during the COVID-19 Outbreak: An Observational Study on the Italian General Population. *International Journal of Environmental Research and Public Health, 18*(1), 255. https://doi.org/10.3390/ijerph18010255

Moshe, I., Terhorst, Y., Philippi, P., Domhardt, M., Cuijpers, P., Cristea, I., Pulkki-Råback, L., Baumeister, H., & Sander, L. B. (2021). Digital interventions for the treatment of depression: A meta-analytic review. *Psychological Bulletin, 147*(8), 749–786. https://doi.org/10.1037/bul0000334

Musetti, A., Franceschini, C., Pingani, L., Freda, M. F., Saita, E., Vegni, E., ... & Schimmenti, A. (2021). Maladaptive daydreaming in an adult Italian population during the COVID-19 lockdown. *Frontiers in Psychology, 12*, 838. https://doi.org/10.3389/fpsyg.2021.631979

Ochsner, K. N., & Gross, J. J. (2005). The cognitive control of emotion. *Trends in Cognitive Sciences, 9*, 242–249. https://doi.org/10.1016/j.tics.2005.03.010

Partinen, M., Holzinger, B., Morin, C. M., Espie, C., Chung, F., Penzel, T., Benedict, C., Bolstad, C. J., Cedernaes, J., Chan, R. N. Y., Dauvilliers, Y., De Gennaro, L., Han, F., Inoue, Y., Matsui, K., Leger, D., Cunha, A. S., Merikanto, I., Mota-Rolim, S., … Bjorvatn, B. (2021). Sleep and daytime problems during the COVID-19 pandemic and effects of coronavirus infection, confinement and financial suffering: a multinational survey using a harmonized questionnaire. *BMJ Open, 11*(12), e050672. https://doi.org/10.1136/bmjopen-2021-050672

Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology, 125*(6), 747–757. https://doi.org/10.1037/abn0000181

Rossi, R., Socci, V., Talevi, D., Mensi, S., Niolu, C., Pacitti, F., Di Marco, A., Rossi, A., Siracusano, A., & Di Lorenzo, G. (2020a). COVID-19 Pandemic and Lockdown Measures Impact on Mental Health Among the General Population in Italy. *Frontiers in Psychiatry, 11*, 790. https://doi.org/10.3389/fpsyt.2020.00790

Rossi, A., Panzeri, A., Pietrabissa, G., Manzoni, G. M., Castelnuovo, G., & Mannarini, S. (2020b). The anxiety-buffer hypothesis in the time of COVID-19: When self-esteem protects from the impact of loneliness and fear on anxiety and depression. *Frontiers in Psychology, 11*, 2177. https://doi.org/10.3389/fpsyg.2020.02177

Salguero, J. M., Palomera, R., & Fernández-Berrocal, P. (2012). Perceived emotional intelligence as predictor of psychological adjustment in adolescents: a 1-year prospective study. *European Journal of Psychology of Education, 27*(1), 21–34. https://doi.org/10.1007/s10212-011-0063-8

Sardella, A., Lenzo, V., Bonanno, G. A., Basile, G., & Quattropani, M. C. (2021). Expressive Flexibility and Dispositional Optimism Contribute to the Elderly's Resilience and Health-Related Quality of Life during the COVID-19 Pandemic. *International Journal of Environmental Research and Public Health, 18*(4), 1698. https://doi.org/10.3390/ijerph18041698

Tyra, A. T., Griffin, S. M., Fergus, T. A., & Ginty, A. T. (2021). Individual differences in emotion regulation prospectively predict early COVID-19 related acute stress. *Journal of Anxiety Disorders, 81*, 102411. https://doi.org/10.1016/j.janxdis.2021.102411

Velotti, P., Rogier, G., Beomonte Zobel, S., Castellano, R., & Tambelli, R. (2021). Loneliness, Emotion Dysregulation, and Internalizing Symptoms During Coronavirus Disease 2019: A Structural Equation Modeling Approach. *Frontiers in Psychiatry, 11*, 581494. https://doi.org/10.3389/fpsyt.2020.581494

Vignatelli, L., Plazzi, G., Barbato, A., Ferini-Strambi, L., Manni, R., Pompei, F., & D'Alessandro, R. (2003). Italian version of the Epworth sleepiness scale: external validity. *Neurological Sciences, 23*(6), 295–300. https://doi.org/10.1007/s100720300004

Wang, M., & Saudino, K. J. (2011). Emotion Regulation and Stress. *Journal of Adult Development, 18*, 95–103. https://doi.org/10.1007/s10804-010-9114-7

World Health Organization. (2020). *Coronavirus Disease 2019 (COVID-19).* Situation Report – 116. Geneva: World Health Organization

Yuan, Y. (2021). Mindfulness training on the resilience of adolescents under the COVID-19 epidemic: A latent growth curve analysis. *Personality and Individual Differences, 172*, 110560. https://doi.org/10.1016/j.paid.2020.110560

Zhang, B., & Horvath, S. (2005). A General Framework for Weighted Gene Co-Expression Network Analysis. *Statistical Applications in Genetics and Molecular Biology, 4*(1). https://doi.org/10.2202/1544-6115.1128