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ORIGINAL ARTICLE

Identifying Central Negative Thoughts Using Experience Sampling and Network Analysis

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Abstract

Purpose Network analysis has promised to inform clinical practice about what should be prioritised in treating different psychological disorders. However, the pure phenomenological approach adopted by network analysis did not help advance this goal considerably. We propose a theoretical approach based on the cognitive model of psychopathology.

Method We used a multivariate vector-autoregression model to analyse the networks of anxious symptoms, depressive symptoms, and negative automatic thoughts. In a preliminary study, we identified the most common negative thoughts and then monitored them alongside symptoms of anxiety and depression in a sample of undergraduate students three times per day for three weeks.

Results Results revealed that negative thoughts have a high bridge outdegree in the temporal network (predict the occurrence of symptoms), while symptoms have a high bridge outdegree (are predicted by thoughts). Thoughts related to self-criticism, like "There is something wrong with me", were the most central for both anxiety and depression and could be considered priority targets for cognitive interventions.

Conclusions Adopting a theoretical approach has proven helpful in providing concrete targets for therapy instead of just identifying central symptoms, as it is typically done in network studies. Future network studies could also consider adopting an approach based on a psychotherapeutic theory about the aetiology of psychopathology.

Keywords Network analysis · Negative automatic thoughts · Cognitive-behavioural therapy · Depression · Anxiety

Introduction

According to the cognitive theory of psychopathology, people's reactions to events are mediated by thoughts and beliefs or, otherwise said, by their perception of events (Beck, 2011, pp. 30–45; Joeng & Turner, 2015). For example, after failing a task, one could think, "I did a terrible job", and feel sad because of evaluating the situation as "terrible". Thus, sadness is not a direct response to the event per se but a consequence of the appraisal of the event as "terrible". Alternatively, someone in a similar situation could think, "I will do better next time", and have a completely different experience. In the above example, "I did a terrible job" is called in Cognitive-Behavioural Therapy (CBT) an automatic negative thought, which is simply an immediate cognitive response to an event (e.g., a situation, an emotion, or a body sensation). Negative automatic thoughts are ubiquitous in mental disorders and are responsible for the associated emotional distress of mental disorders. Plenty of empirical research supports this core theoretical assumption in cognitive therapy. For instance, Flouri and Panourgia (2014) have shown that negative automatic thoughts (NAT) mediate the relationship between life stress and emotional and behavioural problems. Another study showed that NAT mediates the influence of self-compassion and childhood maltreatment on the development of depression and anxiety (Hou et al., 2020). Schniering and Rapee (2004) also showed that NAT led to psychopathological symptoms and that these pathways are content-specific. For example, depression is best predicted by thoughts related to personal failure or loss, anxiety is predicted by automatic thoughts of

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social threat or negative evaluation, and externalising symptoms are best predicted by thoughts related to hostility and revenge (Schniering & Rapee, 2004). Additionally, group comparisons between depressive patients, bipolar patients, and healthy controls have shown that depressive and bipolar patients have significantly higher levels of anxious and depressive thoughts (Yesilyaprak et al., 2019).

As presented above, cross-sectional studies frequently show an association or a mediating effect of NAT on emotional problems. However, automatic thoughts are rather momentary experiences than a construct that can be conceptualised at the group level. Very few studies have inspected the momentary within-subject effects of automatic thoughts or cognitions in general situations. A review of Experience Sampling studies on depression has presented a similar conclusion recommending investigating the influence of NAT on inducing negative mood, pointing towards a lack of such studies in the literature (Telford et al., 2012). We identified only two studies that are close to the proposed framework. One study showed that anxiety sensitivity thoughts predict anxiety symptoms at the following assessment moment (Hong, 2010). The second study focused on ruminations (repetitive thoughts about one's emotional state) and demonstrated that an increase in rumination is associated with increased depressive symptoms without directly influencing the negative mood (Pasyugina et al., 2015). To the best of our knowledge, there are no experience sampling studies to investigate specifically the interplay between NATs and depressive and anxiety symptoms. Such an exploration will elucidate the within-subject dynamic between NAT and anxiety/depression, which might not necessarily follow the same dynamic pattern found in a between-subject approach.

The Network Approach to Mental Disorders

Mental disorders are conceptualised in the DSM-5 as latent variables that can be identified only indirectly by observing the co-occurrence of a specific set of symptoms (American Psychiatric Association, 2013). The limitations of this approach, such as having low utility for treatment (Hofmann & Hayes, 2019); artificially inflating the comorbidity rates (van Loo & Romeijn, 2015); the over-medicalising of normal human experiences (Pickersgill, 2014); and others, have motivated multiple recent efforts to explore new ways of conceptualising mental disorders, one of which is the network approach (Bringmann et al., 2022; Hofmann et al., 2016).

From the network point of view, mental disorders are systems in which each element (i.e., symptom) is causally related to each other, as opposed to the traditional perspective in which observable elements of a disorder are mere symptoms of a latent common cause. Originally, network analysis focused on estimating networks of psychopathological symptoms from cross-sectional data (Robinaugh et al., 2020), which allowed the modelling of mental disorders as networks and the identification of central symptoms but did not allow the identification of the directions of relationships. To address this limitation, new methodological approaches have been developed to estimate networks on intensive longitudinal data collected through Ecological Momentary Assessments (EMA) (Epskamp, 2020). The EMA approach conceptualises psychological phenomena as momentary experiences by assessing them multiple times during the day. For instance, in a pioneer study in the field of EMA networks, Bringmann et al. (2013) modelled the dynamic interaction of four emotions (Cheerful, Fearful, Sad, Relaxed), worry, and the pleasantness of the event experienced by the participants during the assessment moments. Participants had to answer six questions over 12 days, ten times per day. An interesting result reported in this study was the effect of worry on affectivity. Negative affect (Fearful, Sad) was higher when worry was high, while positive affect (Cheerful, Relaxed) was associated with reduced worries. In another study that looked closely into participants' daily routines, Winkel et al. (2017) identified a specific mechanism characteristic for the prodromal phase of participants who transitioned to depression at 20 months follow-up. Particularly, participants who developed depression tended to isolate themselves after negative appraisal of a social company, preferring to be alone rather than to remain in the company. Many other examples of studies on momentary dynamics of emotions and psychopathological symptoms exist. However, no studies currently explore the role of cognitions (i.e., thoughts or beliefs) at a momentary level. As cognitions play an essential role in the emergence and treatment of mental disorders, it is possible that anxiety and depression symptoms will show temporal dependencies on negative automatic thoughts, which will translate into high levels of the centrality of negative automatic thoughts in the network. Centrality indices are measures of how correlated a particular node is with the rest of the network and are usually used to make inferences about the importance of symptoms in the network structure. Bridge centrality refers to indices that estimate centrality based on the community from which the nodes are part (Jones et al., 2021). As our estimated networks of anxiety and depression will consist of two communities (symptoms and negative automatic thoughts), bridge centrality indices will help consider only directed connections between nodes from different communities (thoughts towards symptoms and symptoms towards thoughts).

Network analysis usually has a phenomenological approach to their study variables, as psychopathological networks consist of nodes that represent symptoms that are concrete manifestations of mental disorders. Although a phenomenological approach has many advantages in terms of objectivity and comprehensiveness and is helpful for the description of mental disorders, it is by far not enough to provide solutions for treatment. Every form of psychotherapy usually has an assumption about the aetiology of mental distress that helps guide therapeutical interventions. For example, cognitive-behavioural therapy assumes that dysfunctional thoughts cause psychological distress (Beck, 2011); acceptance and commitment therapy considers psychological inflexibility the root of mental distress (Levin et al., 2014); while in emotion-focused therapy, the explanation for the emergence of mental disorders is considered the inability to manage emotions and the lack of strong emotional ties to others (Greenman & Johnson, 2022). Assumptions regarding the aetiology of psychopathology are critical because one of the primary driver of network analysis is identifying the most relevant targets for psychotherapeutic interventions through psychological networks. However, acknowledging the presence of a symptom and its level of centrality does not provide any solution to guide therapy. Even symptom-focused approach in psychotherapy do not necessarily target symptoms but rather monitor their improvement and posits this as an indicator of therapeutical success. For example, cognitive-behavioural therapy (a symptom-focused approach) targets eeuîthe dysfunctional cognitions since their alteration will improve the overall symptomatology. We argue that a theoretical view of the aetiology of symptoms is required for network analysis to guide treatment.

This Study

This study aimed to examine the role of negative automatic thoughts in a dynamic network of symptoms of anxiety and depression. We adopted the DSM-5 conceptualisation of anxiety and depression symptoms and applied a novel time-series network analysis methodology to inspect their relationships with negative automatic thoughts at the level of momentary experiences. Following the cognitive theory of psychopathology, we expected that automatic negative thoughts would have higher levels of bridge centrality than psychopathological symptoms. Finally, we explored specific edges between thoughts and symptoms to identify pathways that maintain the psychopathological network and understand how central nodes influence the rest of the network.

Methods

Participants

One hundred forty-five undergraduate students have initially completed the study, rewarded with course credits. We removed five respondents due to having less than 20 measurements (Epskamp et al., 2021) and another 29 respondents due to having zero variance on multiple variables. The final sample consisted of 111 participants. All demographic characteristics are presented in Table 1.

Measures

Anxiety symptoms Generalised Anxiety Disorder Questionnaire – IV (GAD-Q; Newman et al., 2002) was administered to measure baseline anxiety symptoms before the ESM phase. GAD-Q has 13 items, of which 10 are dichotomous ("Yes" or "No") items that assess GAD symptomatology, 2 are numeric items that ask the respondent about the impairment level on a scale from 0 = None to 8 = Very Severely, and one open-ended question that ask the respondent to offer examples of their worries. The ten dichotomous items had a good baseline internal consistency with α = 0.78.

Depression symptoms Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001; Romanian Version: Lupascu et al., 2019) was administered before the ESM phase to measure baseline levels of depressive symptomatology. PHQ-9 comprises nine items, each referring to a DSM-5 symptom of Major Depressive Disorder. The items are measured on a 4-point Likert scale ranging from 0 = "Not at all" to 3 = "Nearly every day". The scale had a good baseline level of internal consistency α = 0.88.

Experience Sampling Measures

Negative automatic thoughts We used principal component analysis to identify clusters of items from the Automatic

Table 1 Demographics

Demographic characteristic	Percentage
Age (median, IQR, range)	22.33 (20, 18–46)
Sex	
Male	9.91
Female	90.09
Educational level	
Secondary Education	84.68
Bachelor	7.21
Master	8.11
Employed	5.11
Marital status	
Never married	63.96
Married	5.41
In a relationship	29.73
Divorced	0.90
ESM characteristics	
Measurements per participant (mean, SD)	57.79 (4.45)
Total skipped measurements (mean)	8.26

Thoughts Questionnaire (ATQ-15; Hollon & Kendall, 1980) and Cognition Checklist (CCL-Q; Beck et al., 1987) administered to a sample of 135 participants. Thirteen clusters of items were identified and renamed to form a new set of items. Items were measured on a 4-point scale: 1 = "Never"; 2 = "Once"; 3 = "Several times"; 4 = "Many times", asking participants how frequently they had a particular thought. Results of the principal component analysis are presented in the supplementary materials.

Depression and anxiety symptoms We adapted the items of PHQ-9 and GAD-Q to be suitable for the momentary assessment by asking the participants in the instruction to answer referring to the last 4 h and phrasing the questions in the past tense. Items were measured on a scale from 1 to 4, where 1 = "Not at all", 2 = "A short time", 3 = "A long time", and 4 = "Most of the time". Within-subject and between-subjects alpha Cronbach were good to excellent for anxiety ($\alpha_{within} = 0.86$, $\alpha_{between} = 0.94$), depression ($\alpha_{within} = 0.80$, $\alpha_{between} = 0.94$), thoughts ($\alpha_{within} = 0.92$, $\alpha_{between} = 0.96$). English translation of all items used for ESM is presented in the supplementary materials.

Procedure

The West University of Timișoara Scientific Council granted ethics approval to conduct the study. Participants completed a baseline questionnaire containing demographic questions and questions about their typical levels of anxious-depressive symptomatology and negative thoughts. In the baseline questionnaire, participants were informed about all the study details and asked to provide informed consent before enrolling. In the next phase, participants completed the ESM questionnaires three times per day for 21 days, with a fixed interval of 4 h between measurements. To avoid an overlap between sleeping hours and ESM beeps, we asked participants to provide an estimation of their typical waking hours. Each participant had an individualised schedule of notifications synchronised with their waking hours and academic schedule. We used *PIEL survey* open-source smartphone application to collect the experience sampling data (Jessup et al., 2012).

Analysis

Preliminary Analyses

We analysed within-person variance and identified cases with zero variance on some variables. Participants in the fourth quantile of cases with zero variances, either on thoughts (zero variance on more than nine variables) or symptoms (zero variance on more than four variables), were considered extreme cases and were not included in the analysis. A detailed description of item variance analysis is presented in the supplementary materials. Symptoms and negative thoughts included in the study are presented in Table 2, along with descriptive statistics.

Network Analysis

We analysed the data as a lag-1 multilevel vector-autoregression model with orthogonal random effects implemented in the *mlVAR* package version 0.5 (Epskamp et al., 2021) in R (R Core Team, 2022). This analysis allows the computation of three types of networks: temporal, contemporaneous, and between-subjects, each indicating a different type of relationship between nodes. The temporal network is estimated through a series of univariate multilevel models for each variable, in which each variable is sequentially predicted by all other variables and by itself at previous timepoints. Edges in the temporal network indicate that a node at time t predicts another node (or itself) at the next moment in time, $t+1$, controlling for all other nodes at time t. The contemporaneous network is estimated by performing another series of multilevel regressions on the residuals of the temporal model. In the contemporaneous network, edges indicate the associations between nodes at the same moment after controlling for temporal relationships and other contemporaneous relationships. Estimating the contemporaneous network on the residuals allows the exclusion of temporal effects rendering "pure" contemporaneous effects because the variables are unbiased by the possible influence of other variables at time $t-1$. The between-subject network encodes relationships among mean levels of variables across participants, controlling for the typical level of the other nodes. An edge in this network indicates that the typical level of two nodes is associated across participants, controlling for the typical level of the other nodes. In the figures, we visualised only significant edges ($p < 0.05$). In some previous studies, authors employed methods, such as Benjamini and Hochberg's (1995) False Discovery Rate method, to adjust the significance threshold and reduce the rate of Type 1 errors (Bringmann et al., 2013, 2015; Epskamp, 2020; Marian et al., 2023). However, we were more concerned with type 2 errors (false negatives) because we had a relatively smaller sample size than previous studies, making it harder to identify weaker but true edges. Thus, to increase the model's sensitivity, we opted for a discovery approach letting the significance threshold be $p < 0.05$.

The data must meet two main assumptions for this type of model: (1) Approximately equal time intervals between assessments; (2) Stationarity = the parameters of the data must not change over time (Bringmann et al., 2013). The first assumption was met by setting fixed time intervals of 4 h between assessments. Additionally, *the mlVAR* function from R deletes the first measurement of each day in the lagged

Table 2 Descriptive statistics of ESM variables

Name	Node	Content	Mean	Wp SD	ICC
Symptoms					
Excessive worry	Exc	A	1.43	0.55	0.31
Difficulties controlling worry	DCW	A	1.35	0.50	0.32
Restlessness	Res	A	1.51	0.61	0.29
Fatigability	Fat	A/D	1.71	0.61	0.41
Difficulty concentrating	DiC	A/D	1.54	0.53	0.44
Irritability	Iri	A	1.52	0.64	0.27
Muscle tension	Mus	A	1.38	0.46	0.42
Anhedonia	Anh	D	1.69	0.65	0.44
Depressed mood	Dep	D	1.55	0.65	0.30
Decrease or increase in appetite	App	D	1.58	0.62	0.42
Worthlessness	Wor	D	1.27	0.38	0.38
Psychomotor agitation or retardation	Psy	D	1.18	0.28	0.44
Suicidal ideation	Sui	D	1.14	0.23	0.40
Thoughts					
There's something wrong with me	T1	A/D	1.35	0.47	0.41
I don't think I can go on like this	T2	A/D	1.36	0.48	0.39
I don't like myself	T3	D	1.35	0.46	0.42
I'm no good	T4	D	1.27	0.37	0.38
Nobody likes me	T5	D	1.19	0.29	0.40
I am alone	T6	D	1.29	0.41	0.39
What if I get sick?	T7	A	1.21	0.32	0.41
Something awful is going to happen	T8	A	1.25	0.39	0.36
Life isn't worth living	T9	D	1.12	0.20	0.39
Nobody cares about me	T10	D	1.17	0.26	0.40
I can't stand this anymore	T11	D	1.39	0.52	0.38
I'll never make it	T12	D	1.28	0.36	0.43
Something has to change	T13	D	1.60	0.64	0.40

Note Content indicates if the node is related to depression or anxiety

A anxious; *D* depression; *ICC* intraclass correlation; *Node* network plots; *Wp SD* within-person standard deviation

variables to avoid overnight prediction. The second assumption was tested with the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS), applied to each variable individually for each participant. For this analysis, we used the function *kpss.test* from *tseries* package, version 0.10–52 (Kwiatkowski et al., 1992). The KPSS test indicated that out of 2886 existent time-series (26 variables × 111 participants), 80.77% were level stationary, and 83.85% were trend stationary. The results of the KPSS indicate that for most cases, the mean and variance have remained unchanged throughout the 21 days of data collection. When time-series data is stationary, it describes a relatively stable period of time, and the interpretation of results can apply to the entire period. As the data was highly stationary, similar to the study of Bringmann et al. (2013), no detrending procedure was applied.

Centrality

To answer our research questions about the centrality of negative thoughts, we investigated several bridge centrality (Jones et al., 2021) using package *networktools* (Jones, 2021) and regular centrality indices using package *qgraph* version 1.9.3. *Bridge Out-Strength* and *Bridge In-strength* indicate how frequently a node is associated with another node from another community by considering the direction of the relationship. *Bridge Out-Strength* is the sum of absolute values of all edges' weights pointing from a node towards all other nodes from opposing communities. In our case, it will indicate how strongly a node temporally predicts other nodes. *Bridge In-Strength* is the sum of absolute values of all edges' weights pointing towards a node from nodes from opposing communities. It indicates how strongly a node is predicted by nodes from opposing communities. *Bridge Strength* is the sum of all edges connecting (in and out) a node with other communities. *Bridge Expected Influence* is the sum of all edges pointing from a node (out-edges) to nodes from other communities. In networks with negative edges, using absolute values to compute *In-/Out-Strength* could lead to inflated estimates of centrality and false conclusions about the importance of a node. When using raw values to compute *Expected influence*, positive and negative edges' weights cancel each other and offer a more accurate centrality index for weighted networks. A node with multiple negative edges will have high *Strength* and low *Expected Influence*.

Results

Figures 1 and 2 illustrate temporal and contemporaneous networks of anxious and depressive symptoms and negative automatic thoughts. In the temporal networks, self-directed edges were the strongest, followed by edges within the communities of nodes. In the contemporaneous network, edges within the communities were also the strongest. However, multiple edges connecting symptoms and thoughts were also identified. Out of 400 possible edges in the temporal anxiety network, 72 (18.00%) were included in the final network, and 76 out of 441 (17.23%) in the temporal depression network. Regarding the contemporaneous networks, 65 out of 190 (34.21%) edges were significant in the anxiety network and 75 out of 210 (35.71%) in the depression network (Figs. 3 and 4).

Anxiety Network

The thoughts “I can’t stand this anymore”, “I don’t like myself”, and “I don’t like myself” had the highest bridge outdegree in the network. However, “I don’t like myself” also had a low bridge expected influence which shows that it is negatively connected to the network and will not activate other nodes but will inhibit them. Anxiety symptoms generally had low bridge outdegree and high bridge indegree, denoting that symptoms temporally come after negative thoughts. “Irritability” had the highest values of *Indegree*, meaning that this symptom was the most likely to occur at the next timepoint as a consequence of a negative automatic thought. In the contemporaneous network, there is no particular pattern of centrality of symptoms and thoughts, as both communities have a relatively equal number of central nodes. “Restlessness” and “Difficulties concentrating” had the highest bridge strength in the contemporaneous network, indicating that these symptoms were associated the strongest with negative thoughts.

Depression Network

Similar to the anxiety network, in the depression network, three negative automatic thoughts were the most central “I am no good", "There's something wrong with me", and "I don’t like myself”. Once again, the thought “I don’t like myself” had low bridge expected influence, indicating that numerous negative edges inflated its strength centrality. As opposed to the anxiety network, where the centrality of

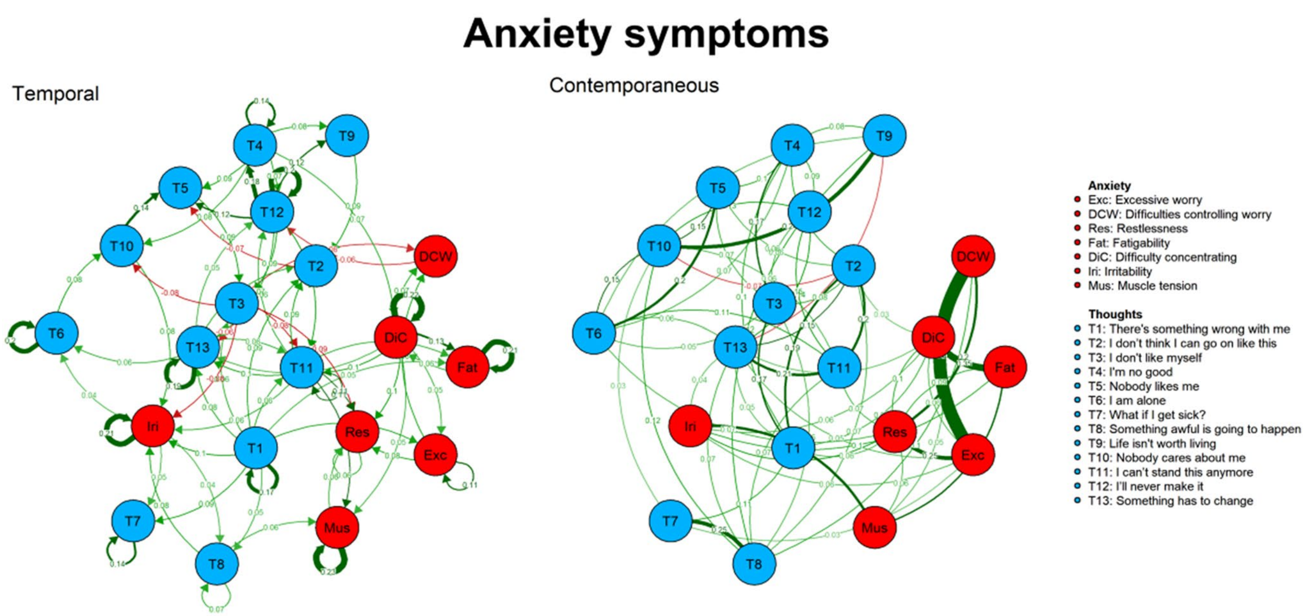

Fig. 1 Temporal and contemporaneous networks of anxiety symptoms and negative thoughts

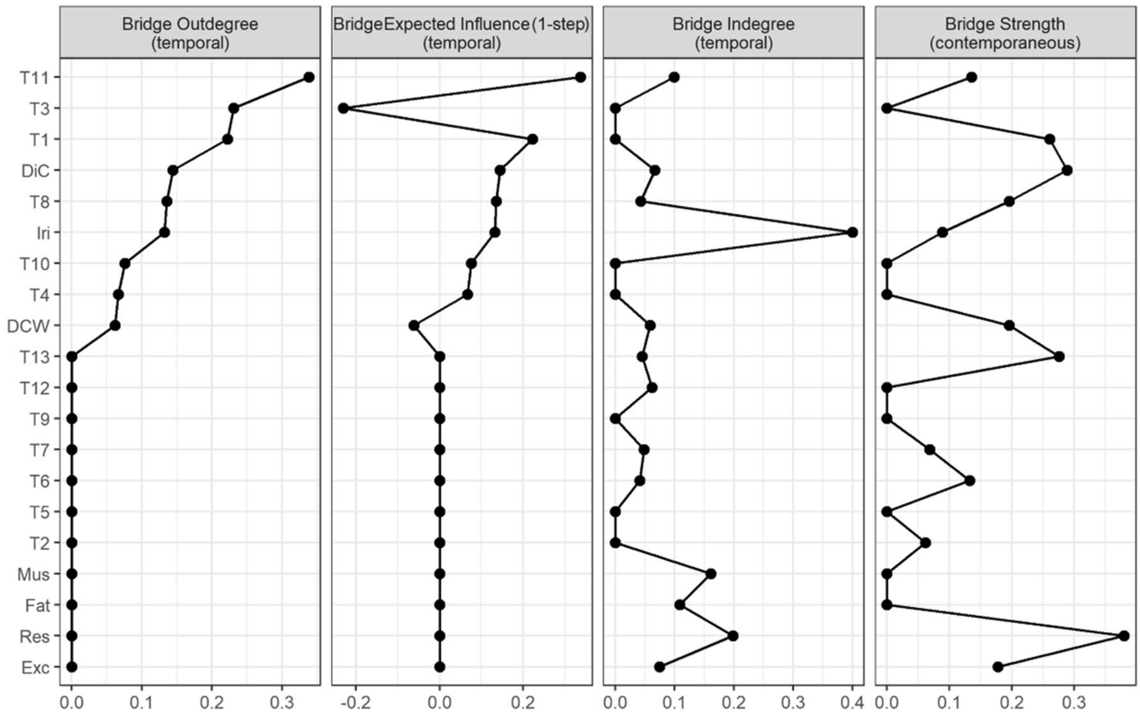

Fig. 2 Bridge centrality of temporal and contemporaneous anxiety networks

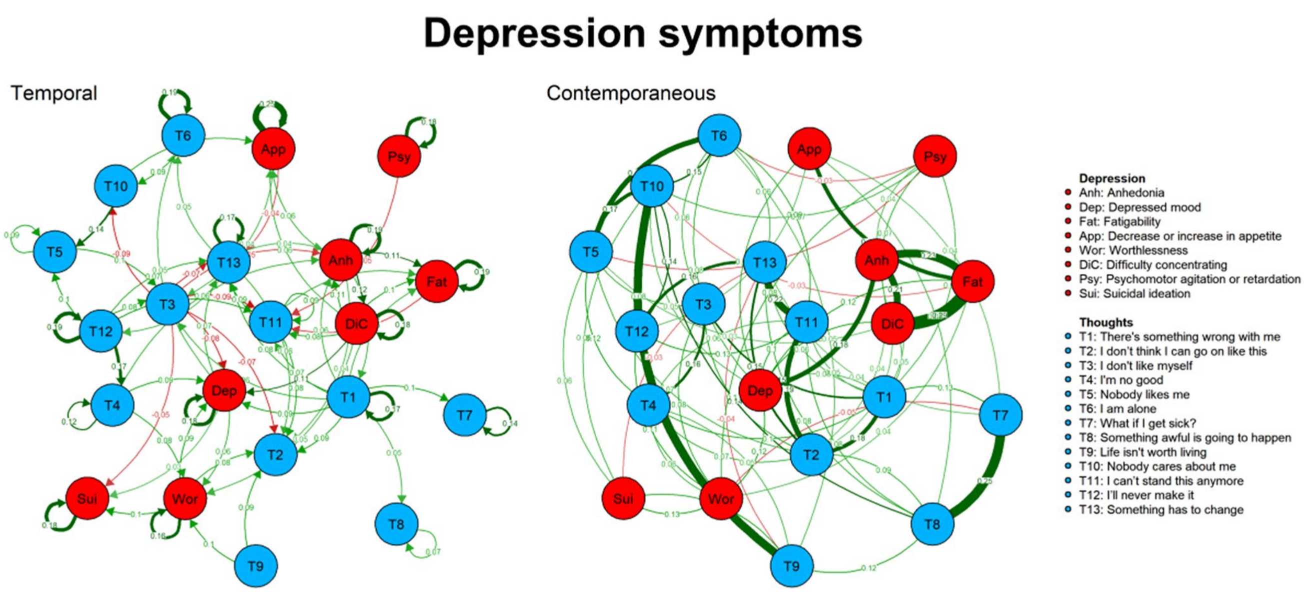

Fig. 3 Temporal and contemporaneous networks of depression symptoms and negative thoughts

symptoms was generally low, in the depression network, "Depressed mood" and "Anhedonia" had relatively high centrality levels denoting that in the case of depression, symptoms are also predictive of negative thoughts. "Worthlessness" and "Depressed mood" were the most bridge central in the contemporaneous network. The symptom "Depressed mood" had high Bridge Indegree centrality showing that this symptom is more likely than others to appear after an automatic negative thought. The thought "There's something wrong with me" and symptoms "Depressed mood" and "Worthlessness" had the highest bridge centrality in the contemporaneous network.

In conclusion, in both the case of the anxiety network and depression network, negative automatic thoughts have

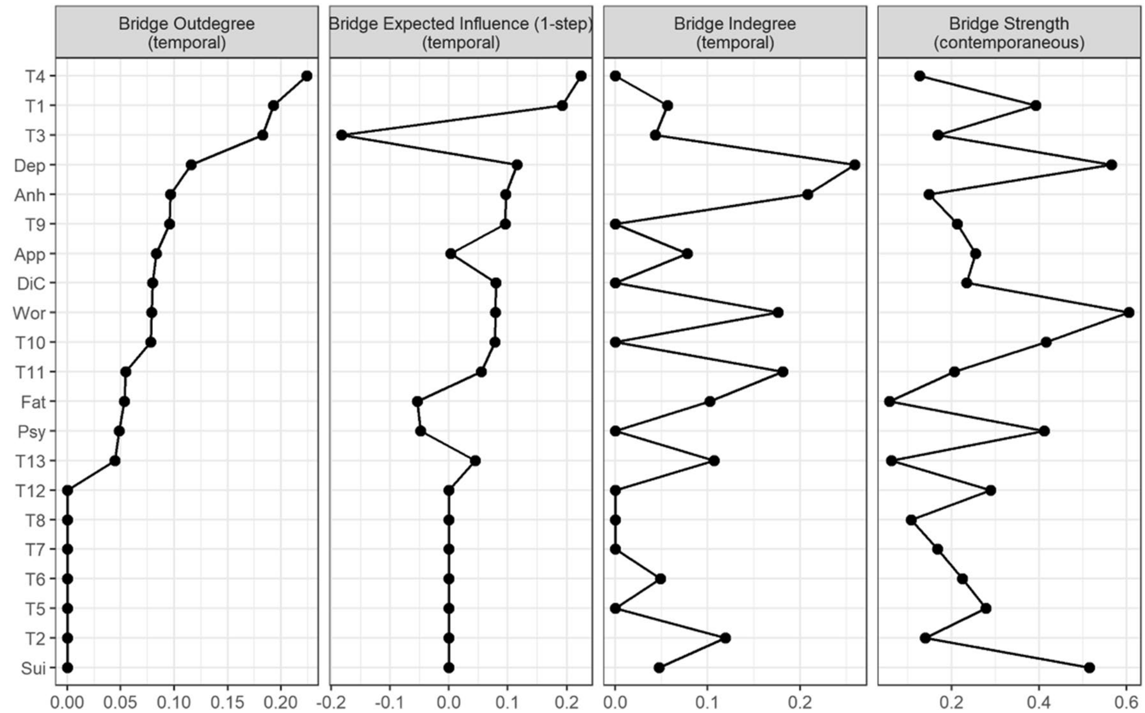

Fig. 4 Bridge centrality of temporal and contemporaneous depression networks

higher bridge centrality levels than symptoms. In the depression network, however, some symptoms also proved to have high centrality levels.

Discussion

In this study, we monitored during 21 days the anxiety-depressive symptoms and negative thoughts in a sample of undergraduate students. We applied network analysis to analyse the data and extract the most influential nodes. Based on the cognitive model of psychopathology (Beck, 2011), we hypothesised that negative thoughts would be more central in the network than symptoms. Therefore, we used bridge centrality metrics to separate the nodes into two communities (i.e., symptoms and thoughts) and analyse the most influential nodes by considering directed relationships that point from one community to another. Results were congruent with the cognitive model, as both in the anxiety and depression network, as in both temporal networks, the first three most central nodes were negative thoughts. Negative thoughts had a high bridge outdegree while symptoms had generally high bridge indegree, which can be interpreted as the severity of symptoms is predicted by negative automatic thoughts at a previous measurement point. Negative thoughts and symptoms had multiple edges connecting them, the network emerging as a single interconnected system rather than two separate groups of nodes. Further, we provide guidelines for interpreting results and discuss the most influential nodes and their connections.

Interpretation of Temporal and Contemporaneous Edges and Centrality Metrics

Centrality indices should be interpreted carefully (Bringmann et al., 2019; Dablander & Hinne, 2019). We used centrality measures to identify the most influential thoughts and symptoms. However, referring to nodes as “influential" implies a causal relationship, which is inappropriate for longitudinal data. On the other hand, interpreting a directed temporal relationship as a mere association between nodes is also inappropriate, as it reduces the meaning of that relationship by neglecting the temporal dependencies between variables. Although time-series data will not elucidate true causality, it can indicate how variables depend on each other. This is especially obvious in the case of strong auto-correlations that are typically present in time-series data, often referred to as *inertia* (Jongerling et al., 2015). For example, take "Fatiguability", which can be caused by many life events outside the network (e.g., sleep quality, workload, emotional exhaustion after a breakup). No matter what the full set of causes is, how tired one feels now depends on how tired one felt before (in our case, during the previous four hours). If one is very tired at moment 1, one will also feel very tired at moment 2. Alternatively, if one is just a little tired at moment 1, at moment 2, one will also be just a little tired. Suppose one takes a 15-min break between moment 1 and moment 2. Same as before, the break has an evident causal influence on the tiredness at moment 2. However, the effect of the break depends on the initial tiredness levels. If one is extremely tired at moment 1, after a 15-min break, one will feel just a little less tired, as opposed to the situation where one is moderately tired at moment 1, after the same break, one will feel a little tired.

The same principle applies to directed edges between different nodes. For example, in our network, "Difficulties concentrating" at moment 1 predicts "Fatiguability" at moment 2. Let us assume we know the actual cause of the two variables: quality of sleep of the night before. Even though the low quality of sleep causes "Fatiguability" at moment 2, it also depends on how difficult it was to concentrate at moment 1 (i.e., struggling to concentrate on tasks is even more tiresome than just concentrating). Therefore, when referring to the centrality of a node and its influence on other nodes in the temporal network, we imply this type of temporal dependency. Bridge Outdegree and Bridge Expected Influence will indicate the influence of a node on other nodes from different communities. In contrast, bridge indegree will indicate how dependent a node is on nodes from other communities. For example, in the anxiety network, the thought “I can't stand this anymore” had the highest bridge outdegree centrality, indicating that the intensity of anxiety symptoms at moment 2 depends significantly on the presence of this thought at moment 1, even if we cannot be sure this thought is the true cause.

In the contemporaneous network, the interpretation is more straightforward. Contemporaneous networks illustrate the associations of nodes at the same moment in time. Thus, high centrality refers to the connectedness of a node with other nodes assessed at the same moment. For example, in the contemporaneous anxiety network, “Restlessness” had the highest Bridge Strength, which indicates that when someone reported having felt more restless than usual since the last beep, they were also more likely to report more negative thoughts than usual in the same time span. In contrast, the symptom “Muscle tension” had very low centrality, indicating that experiencing this symptom was very unlikely to be accompanied by a negative thought.

Given that our observations were spaced 4-h apart, it is also important to take into account the time frame of the proposed psychological processes when interpreting the results. The timeframe necessary for a thought to trigger an emotion is typically considered to be instantaneous (Beck, 2011, Chapter 3). Therefore, the temporal resolution of our design might be insufficient to capture the longitudinal component of these relationships, which might be better reflected in an undirected edge in the contemporaneous network (Epskamp et al., 2018). However, negative emotions (e.g., sadness, worthlessness) can persist for an extended period after the negative thought that triggered them. Additionally, negative thoughts are known to be repetitive and persist through worrying and rumination (Calmes & Roberts, 2007). That is, ruminating over the thought “I am no good” will entertain the emotion of worthlessness throughout the entire time of having this thought. In the same way, one will continue feeling anxious as long as that person worries that “I will fail”. Relationships between cognitions and emotions that unfold over a longer timespan can result in edges in the temporal network.

Centrality of Thoughts

The most central negative thought in both temporal networks of anxiety and depression was “There's something wrong with me”. Participants that reported having this thought were more likely to experience worry, irritability, depressed mood, worthlessness, and anhedonia at the next measurement moment. As this thought can be considered oriented towards the self, this result is congruent with the already documented effect of low self-esteem on anxiety and depression (Sowislo & Orth, 2013). Other thoughts related to the inadequacy of the self were also highly central in the depression network: "I'm no good" and "I don't like myself". In contrast, in the anxiety network, central negative thoughts generally referred to the adversity of present or future events: “I can't stand this anymore”, “Something awful is going to happen”. In the contemporaneous network, there was no clear superiority in the centrality of thoughts or symptoms. “Restlessness” and “Difficulties concentrating” were the most central in the contemporaneous anxiety networks, while “Depressed mood” and “Worthlessness” were the most central symptoms in the contemporaneous depressive network, meaning that these symptoms are the most strongly associated with the presence of negative thoughts.

Regarding the centrality of thoughts, “There's something wrong with me” and “Something has to change” were the most central in the anxiety contemporaneous network. At the same time, “Nobody cares about me” and "There is something wrong with me" were the most central in the depression network, indicating that these thoughts were associated the most with the presence of symptoms, or in other words, they were associated with the highest level of distress.

The thought “I don't like myself” was central in both temporal networks but had many negative symptoms indicating that it predicts the decrease of some symptoms (“Restlessness”, “Irritability”, “Difficulties controlling worries”, “Depressed mood”, “Suicidal ideation”) and negative thoughts. A previous study has shown that internalised self-criticism is associated negatively with depression when controlling for self-compassion (Joeng & Turner, 2015).

In other words, self-criticism has a small protective effect against depression, but because it is also associated with low self-compassion, it worsens depressive symptomatology. It is possible that having the thought "I don't like myself" reflects this mechanism. However, as expected, most thoughts reflecting self-criticism were positively associated with anxious-depressive symptomatology. Different participants might interpret some thoughts differently, even though they have generally negative content. For example, "I don't like myself" could be interpreted as a need to improve and induce a temporary superficial sense of being motivated, while "There is something wrong with me" could be interpreted as an inability to change anything and lead directly to feeling depressed.

Centrality of Symptoms

In the temporal network, symptoms generally had higher bridge Indegree than thoughts. "Irritability" had the highest indegree centrality in the anxiety network, and "Depressed mood", "Anhedonia", and "Worthlessness" had the highest Indegree in the depression networks. This indicates that these symptoms are the most common reactions to an automatic negative thought from a preceding measurement occasion. It is important to emphasise that the symptoms mentioned above represent emotional responses and were highly Indegree central, while symptoms that represent physiological responses (e.g., "Difficulty concentrating", "Psychomotor agitation or retardation", "Muscle tension", "Fatiguability") had low Indegree, which indicates that their presence and severity depend less on negative cognitions. It is possible that physiological symptoms of anxiety and depression are an effect of the previous night's sleeping difficulties, which we were not able to account for because of different levels of variation of sleeping difficulties (from one day to another) and all other variables (from one measurement occasion to another) (Tkachenko et al., 2014). Another plausible explanation could be that physiological symptoms depend on negative emotions (Flett et al., 2012) and have low centrality in our network because we accounted only for connections between negative thoughts and all the symptoms.

Limitations

The main limitation of this study is the low diversity of the sample. We used a non-clinical convenience sample composed mainly of young females. Thus, it is unclear if our results are generalisable outside the female student population. For example, the high centrality levels of thoughts referring to self-criticism could be explained by the fact that self-criticism is generally more present in young people than in adults and elders (Kopala-Sibley et al., 2013). As another example, high centrality levels of "Difficulties concentrating" could be attributed to the high stakes the inability to concentrate has in students' academic performance. This symptom might be less distress-inducing in other age categories that are not constantly required to engage in tasks that involve the concentration of attention or have already developed necessary attentional resources to engage with more ease in such tasks. Despite having a non-clinical sample, we obtained an adequate level of variance, which was possible to be modelled into a network. Even with a sample as homogeneous as we had, we were able to achieve the purpose of this study, namely, to analyse temporal interactions between negative automatic thoughts and anxiety-depressive symptoms and identify negative thoughts that could be more relevant to be targeted in therapy. Another limit is the inability to include "Sleeping difficulties" in our network model. As mentioned before, "Sleeping difficulties" cannot vary within a day, similar to all other variables included in the network. Including variables with different levels of variation in time-series networks is currently a methodological challenge for network analysis and cannot be easily addressed (Bringmann et al., 2022).

Strengths and Implications

The main strength of this study was the introduction of a theoretical framework to guide the selection of nodes included in the network, as opposed to the traditional phenomenological approach in network analysis studies. By doing so, we showed that through longitudinal network analysis, it is possible to identify thoughts that are much more distressful than others and that can be prioritised in cognitive therapeutical interventions. Of course, the cognitive content that individuals can come up with is difficult to nearly impossible to be summarised in a few thoughts. Instead, it might be more beneficial to consider the thought that we identified as the most central "There's something wrong with me" to be a mere indicator of a higher category of cognitions involving self-criticism, and the prioritised targets for cognitive therapeutical interventions should be negative thoughts related to self-criticism. Future research could adopt a dimensional conceptualisation of thoughts to provide more generalisable recommendations. For example, The Children's Automatic Thoughts Scale groups negative thoughts into four categories: Physical Threat, Social Threat, Personal Failure, and Hostility (Sun et al., 2015). Applying a similar analysis to these four categories would help gain insight into which negative thoughts are the most distress-inducing and should be prioritised in children's psychotherapy. Studying individual thoughts could be more relevant for idiographic $n = 1$ network studies. In the case of a network built after intensively monitoring a single individual, focusing on single thoughts will be much more relevant as it will directly give insight into what thoughts can be targeted in therapy.

Another strength of this study is the reasonably well representation of anxious and depressive symptoms. While most time-series network studies include only a few core aspects of studied disorders due to the complexity of administering multiple times per day a large number of questions, we successfully measured and modelled the daily dynamics of almost all MDD and GAD DSM-5 symptoms. Additionally, we were able to do so while also having a reduced rate of dropouts, uncommon for ESM studies (Wrzus & Neubauer, 2022).

Conclusion

Per CBT's cognitive theory of psychopathology, negative thoughts had high levels of outdegree centrality, while symptoms of anxiety and depression had high levels of Indegree. We were able to identify which thoughts are the best predictors of the occurrence of psychopathological symptoms during the day. By introducing a theoretical approach to the aetiology of diseases, we were able to show how network analysis could provide specific targets for cognitive interventions. We hope our example will serve as a basis for future studies to adopt a theoretical perspective to aid network analysis studies in finding central targets for psychotherapy interventions.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10608-023-10400-w.

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Data Availability The data used in this study is available on PsychArchives repository for public use, with sharing level 0+, under a CC-BY-SA 4.0 licence. The link to the data is: https://doi.org/10.23668/psycharchives.12932.

Declarations

Conflict of Interest Ştefan Marian and Florin Alin Sava have no known conflict of interest to disclose.

Informed Consent Informed consent was obtained from all individual participants included in the study. Participants also consented their data to be used anonymously in the study.

Animal Rights No animal studies were carried out by the authors for this article.

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