A network perspective on real-life threat, anxiety, and avoidance

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ABSTRACT

Anxiety, approach and avoidance motivation crucially influence mental and physical health, especially when environments are stressful. The interplay between anxiety and behavioral motivation is modulated by multiple individual factors. This proof of concept study applies graph-theoretical network analysis to explore complex associations between self-reported trait anxiety, approach and avoidance motivation, situational anxiety, stress symptoms, perceived threat, perceived positive consequences of approach, and self-reported avoidance behavior in real-life threat situations. 541 participants (218 patients, 323 community) completed an online survey assessing these factors in response to the COVID-19 pandemic. The resulting cross-sectional psychological network revealed a complex pattern with multiple positive (e.g., between trait anxiety, avoidance motivation, and avoidance behavior) and negative associations (e.g., between approach and avoidance motivation). The patient and community subsample networks did not differ significantly, however, descriptive differences may inform future research.

Key words: network analysis, graph analysis, anxiety, approach, avoidance, threat

Introduction

Flexible adaptations to potential threats are essential for survival in dynamic environments. Perceived threats elicit subjective feelings of fear, anxiety, and behavioral avoidance (e.g., Craske & Stein, 2016). These responses fulfill adaptive functions as they reduce the probability of physical (e.g., illness or injury) and psychological harm (e.g., perceived helplessness). However, persistent and intense avoidance, which is out of proportion to the objective threat, can contribute to the development and maintenance of anxiety disorders (e.g., Craske et al., 2017; Pittig, Wong et al., 2020). Flexibly approaching potentially positive outcomes, on the other hand, is also essential for health, survival, and well-being. Thus, complex interactions between motivational tendencies to avoid and to approach environmental situations or stimuli, cognitive and emotional psychological states (e.g., threat perception or stress), and psychological traits (e.g., trait anxiety), are vital for understanding functional and dysfunctional behavioral adaptations in environments with varying levels of potentially aversive (i.e., threatening) or positive (i.e., rewarding) environmental outcomes.

A wide variety of trait factors may be relevant for these behavioral adaptations. For example, high trait anxiety has been associated with stronger negative responses in a threatening situation (Chambers et al., 2004; Spielberger, 1972, 1975). Moreover, physiological characteristics such as high age or pre-existing medical conditions, which contribute to physiological vulnerability, may increase avoidance motivation by elevating state anxiety in situations with relevant physical threats. The threat of contracting COVID-19 is a naturalistic example of a physical threat that is especially dangerous for individuals with certain pre-existing medical conditions. Individuals with high trait anxiety or physiological risk factors for a severe COVID-19 course may be more vulnerable to experience highly anxious states. Potentially, this may be connected to a higher motivation to avoid situations with elevated COVID-19 infection risk.

Individual threat-related responses to potentially life-threatening events (i.e., anxiety and avoidance behavior) are also associated with individual cognitive states. Threat evaluations, such as the perceived risk and dangerousness of a situation, play an especially important role (Lazarus & Folkman, 2006; Mogg & Bradley, 2009). A higher perceived risk for contracting COVID-19 in a specific situation may, for instance, induce a higher level of situation-specific anxiety and avoidance. Risk evaluations and trait factors may thus, together and interactively, shape situational anxiety levels. In turn, situation-specific anxiety levels may influence both individual avoidance motivation and overt avoidance behavior.

Notably, anxiety and anxiety-related avoidance tendencies are not the only determinants of overt behavior. For example, positive outcomes linked to approach behavior can down-regulate avoidance motivation despite high levels of anxiety (Pittig, 2019). This down-regulation through competing positive outcomes is reduced in individuals with anxiety disorders and even in healthy individuals with high trait anxiety (Pittig, Boschet et al., 2020; Pittig & Scherbaum, 2020). Such findings highlight the role of appetitive factors, such as competing goals, rewards, and approach motivation, in the regulation of avoidance behavior.

The development of anxiety and avoidance in interactions with a variety of factors goes beyond bivariate associations. Thus, a comprehensive approach to capture the whole complexity of these psychological interactions is of help. Graph-theoretical network analysis is an adequate tool to analyze complex interactions between different variables. The interacting elements in a network are called *nodes*, while their interconnections are called *edges*. Nodes and edges together define the so-called graph (i.e., the network) that can be analyzed with specific graph-theoretical measures (e.g., centrality), providing nuanced insights into the network structure (e.g., the relative importance of a node). Graph-theoretical network analysis has been established over the past years as a fruitful approach in neuroimaging (Bullmore & Sporns, 2009) and has recently been introduced to clinical psychological research (Borsboom,

2017; Fried et al., 2017; Heeren & McNally, 2016). Here, different symptoms or symptom classes are typically defined as network nodes, and network edges are computed based on the nodes' associations across participants (e.g., Robinaugh et al., 2019; Taylor et al., 2020).

In this study, we explored the complex interplay between self-reported trait anxiety, individual differences in approach and avoidance motivation, situational anxiety, stress symptoms, perceived levels of threat, perceived positive consequences, and the frequency of avoidance behavior in situations of real-life threat. We applied network analyses to cross-sectional data from an online survey focused on affective and behavioral responses to naturally arising threatening situations during the COVID-19 pandemic. Our main goal was to exploratively analyze the psychological network across all participants, without testing specific hypotheses. Additionally, we aimed to investigate network differences between a psychotherapy patient and a matched community sample to explore potential aberrations in psychologically vulnerable individuals concerning their response pattern in threatening environments.

Methods

Participants

The sample consisted of 541 participants and was recruited in Germany from mid of May 2020 until the beginning of August 2020, i.e., during the first months of the COVID-19 pandemic (see Table 1). Sample size was based on a trade-off between higher statistical power (large N) and a short recruitment duration to minimize changes in COVID-related factors (e.g., infection rates, restrictions and regulations of social distancing), as a longer recruitment period may have compromised comparability across participants. The sample included two subsamples: a) a community sample ($N = 323$) that was recruited from the general community of Germany via online advertisements (e.g., via a platform for online surveys, local social media

groups, and the online participant recruitment tool of the University of Würzburg, and b) a patient sample ($N = 218$) that was recruited from the outpatient clinic for psychotherapy at the University of Würzburg. Four hundred and ninety-six patients who had provided written consent to be contacted for research studies were invited, 286 patients started the survey, and 218 patients were included in data analysis as they answered items with respect to at least one of the four specific situations (see Online Survey description in the Methods section). The main primary diagnoses in the invited patient sample were affective disorders (33.4%), anxiety disorders (23.7%), adjustment disorder (15.3%), somatoform disorders (7.4%), obsessive-compulsive disorder (5.0%), posttraumatic stress disorder (3.9%), eating disorders (2.9%), and others (8.4%). To protect the patient's privacy, we refrained from collecting any psychological diagnoses of individual patients. Concerning the community sample, 503 participants started the survey, and 342 participants provided data for at least one specific situation. Nineteen participants did not provide any information about their risk group status or COVID-19 related variables and were excluded prior to data analysis, resulting in a final sample of $N = 541$. The survey was implemented using the platform SoSci Survey (Leiner, 2018, www.soscisurvey.de).

Study Procedure

All study procedures were conducted in accordance with the declaration of Helsinki (1975, revised in 2008), and were approved by the local ethics committee (GZEK 2020-31). Before completion of the online survey, the participants were informed about their anonymity, the use of the data, and their right to withdraw from participation. Informed consent was signed via an opt-in procedure. All participants confirmed to be ≥ 18 years of age. As an incentive for participation, participants could take part in a lottery for shopping vouchers (20 €) or receive course credits. The survey was presented in German.

Threat-relevant situations for the online survey (see below) were chosen due to their relevance in the COVID-19 pandemic. The situation's relevance was reflected by various

official regulations during the recruitment period (Steinmetz et al., 2020). Such regulations concerned behavior (e.g., physical distancing, use of face masks) in many public situations (e.g., supermarkets, shops, and public transport), and prohibited large gatherings. At the time of recruitment, the reported 7-day incidence in Germany varied between 2.9 and 5.8 cases per 100,000 population (Robert Koch Institute, 2021), with a reported number of deaths between 0 and 83 per day (Robert Koch Institute, 2020a).

Table 1.*Demographic and Questionnaire Data*

	<i>Complete sample</i>		<i>Matched community subsample</i>		<i>Matched patient subsample</i>		<i>t^a</i>	<i>p</i>	<i>d</i>
<i>N</i>	541		218		218		-	-	-
Females (%)	354	(65.4%)	135	(61.9%)	133	(61.0%)	-	-	-
Age	35.61	(14.58)	37.26	(14.80)	39.11	(14.49)	1.32	.186	0.13
Trait anxiety (NEO-PI-R-N1)	17.70	(5.69)	15.84	(5.80)	19.87	(5.02)	7.75	< .001	0.74
<i>DASS symptoms</i>									
Anxiety (0-42)	6.39	(7.43)	4.59	(6.26)	9.00	(8.24)	6.30	< .001	0.60
Depression (0-42)	10.33	(10.10)	8.52	(9.47)	12.93	(10.88)	4.51	< .001	0.43
Stress (0-42)	12.88	(9.95)	10.51	(9.39)	16.22	(10.06)	6.13	< .001	0.59
<i>COVID-19 ratings</i>									
Risk group (<i>n</i>)	174	(32.2%)	73	(33.5%)	73	(33.5%)	-	-	-
Dangerousness (1-5)	3.55	(0.95)	3.41	(0.97)	3.69	(0.98)	3.00	.003	0.29
Likelihood of infection (1-5)	2.72	(0.98)	2.62	(0.97)	2.75	(1.00)	1.41	.159	0.14
<i>Anxiety, Approach-Avoidance</i>									
Situational anxiety (0-4)	1.13	(0.90)	1.04	(0.88)	1.21	(0.95)	1.94	.054	0.19
Avoidance frequency (0-4)	1.81	(1.01)	1.77	(1.07)	1.80	(1.00)	0.27	.790	0.03
Avoidance motivation (0-4)	1.74	(0.97)	1.72	(0.94)	1.73	(1.05)	0.07	.943	0.01
Approach motivation (0-4)	1.52	(0.65)	1.60	(0.69)	1.47	(0.62)	1.97	.050	0.19
Positive consequences (0-4)	1.52	(0.67)	1.48	(0.64)	1.58	(0.73)	1.58	.115	0.15

Note. Means (and standard deviations). Significant differences between subsamples are marked in bold. DASS = Depression Anxiety Stress Scales (Lovibond & Lovibond, 1995); NEO-PI-R-N1 = Anxiety subscale of the NEO-PI-R (Costa & McCrae, 1992). *d* = effect size as indicated by Cohen's *d*. ^a all *t*(434)

Measures

The online survey (for a detailed description see (Pittig et al., 2021)) included a) basic sociodemographic variables (i.e., age, sex, employment status), b) measures of trait anxiety, c) general symptoms of anxiety, stress, and depression, d) COVID-19 related variables (risk group status, perceived dangerousness of COVID-19, perceived risk of infection), and e) situation-specific variables (anxiety, approach and avoidance motivation, and avoidance frequency) towards four specific public situations relevant to the pandemic.

Trait anxiety was assessed with the German version of the NEO-PI-R anxiety subscale (N1 subscale; Costa & McCrae, 1992; Ostendorf & Angleitner, 2004. General symptoms of anxiety, depression, and stress during the previous week were assessed with the German short version of the Depression Anxiety Stress Scales (DASS-21; Lovibond & Lovibond, 1995; Nilges & Essau, 2015). DASS-21 subscale scores were multiplied by a factor of 2 (Lovibond & Lovibond, 1996). Of note, anxiety, as assessed with the DASS, represents anxious symptomatology in the last week rather than a stable trait anxiety measure, providing information different from trait anxiety and situation-specific anxiety. Being part of a risk group for a severe course of COVID-19 was defined according to the official criteria of the Robert Koch Institute in May 2020: Age > 60, and/or suffering from a suppressed immune system, cardiovascular disease, kidney disease, or cancer (Robert Koch Institute, 2020b). Risk group status (i.e., a binary yes/no variable) was assumed positive when participants themselves belonged to the risk group or when they indicated to live in a shared household with a risk group member. The perceived dangerousness of COVID-19 was rated on a 5-point Likert scale from 1 = *very harmless* to 5 = *very dangerous*. The perceived probability of infection was rated on a 5-point Likert scale from 1 = *very unlikely* to 5 = *very likely*.

Situation-specific anxiety and approach-avoidance motivation were assessed for four public situations assumed to pose a realistic threat during the COVID-19 pandemic. These

situations were: “Going to a supermarket”, “Staying in a crowded public area”, “Taking a bus”, and “Talking to others”. We previously reported an increase in situational anxiety for each of these situations, supporting their utility as a paradigmatic model for naturalistic threat situations during the COVID-19 pandemic (Pittig et al., 2021). For each of these four situations, participants rated a) their situational anxiety in the previous two weeks (5-point Likert scale: 0 = *no anxiety at all* to 4 = *very strong anxiety*), b) their motivation to avoid the situation (5-point Likert scale: 0 = *not at all*, 4 = *very strongly*), c) their motivation to approach the situation (5-point Likert scale: 0 = *not at all*, 4 = *very strongly*), d) whether they expected positive consequences of approaching the situation (5-point Likert scale: 0 = *not at all*, 4 = *very strongly*), and, finally, e) the actual frequency of avoiding the situation in the previous two weeks (5-point Likert scale: 0 = *very rarely*, 4 = *very often*). Regarding their situation-specific anxiety, participants were instructed to imagine being in the described situation if they did not face it within the last two weeks. Average values across all four situations for these five situation-specific variables were used in all analyses (Cronbach’s α : 0.65 - 0.87). The rating of the perceived positive consequences of approach for each situation was subdivided into six life domains, i.e., a) friendships or relationships, b) family or partnership, c) work or career, d) physical or mental health, e) leisure, and f) supply with daily goods. Analyses were carried out with the across-domain average value for perceived positive consequences (Cronbach’s α = 0.93).

Network Analyses

The complex patterns of associations between psychological trait variables and situational state factors were modeled as a psychological network using graph theory. The main goal was to explore this approach for its usefulness in analyzing an overall whole-sample network. We defined the network nodes as 1) trait anxiety, 2) symptoms of depression, 3) symptoms of stress, 4) symptoms of anxiety, 5) perceived dangerousness of COVID-19, 6)

perceived risk of infection with COVID-19, 7) risk group status, 8) situational anxiety, 9) avoidance motivation, 10) approach motivation, 11) perceived positive consequences of approach, and 12) avoidance frequency. For the purpose of visualization, these nodes were grouped into six different node groups, which are highlighted in distinct colors in all figures: 1) DASS node group (symptoms of depression, stress, and anxiety), 2) COVID-19 node group (perceived dangerousness, perceived risk of infection, risk group status), 3) avoidance node group (avoidance motivation, avoidance frequency), 4) approach node group (approach motivation, positive consequences), 5) trait anxiety (single node), and 6) situational anxiety (single node). Of note, the assignment of nodes to the node groups did not affect the computations of the psychological networks. In addition, further analyses were conducted to test for the ability of the network approach to compare networks of two different groups. Specifically, we compared the network of a patient sample with the network of a community sample. Therefore, to reduce sampling bias, we created two matched subsamples using nearest neighbor matching (Ho et al., 2011). Thus, the closest neighbors to the smaller sample were selected, resulting in two equally sized subsamples (each $n = 218$) matched on age, sex, risk group status and employment status (see Table 1).

Network analyses were implemented using Mixed Graphical Models (MGMs), as MGMs explicitly account for mixed measurement scales of variables as present in the current study (Haslbeck & Waldorp, 2020). Specifically, LASSO (Least Absolute Shrinkage and Selection Operator)-regularized regressions were estimated, using the Extended Bayesian Information Criterion (EBIC) with the default tuning parameter $g = 0.25$. Note that this approach balances the level of sparsity by shrinking weak connections to zero (for a detailed discussion, see Epskamp & Fried, 2018; Foygel & Drton, 2010). As the MGM results in two regression parameters for each pair of nodes (i.e., edge), the AND-Rule (in contrast to the OR-Rule) was used to obtain edge-weights (w) for each pairwise interaction. The AND-Rule takes

the arithmetic mean of both parameters, requiring each of them to be non-zero. If at least one regression parameter is zero, the final edge-weight is set to zero, resulting in a sparser network (e.g., Haslbeck & Waldorp, 2020; van Borkulo et al., 2014). All networks were computed as weighted and signed networks, i.e., information about the strength and valence of the associations was kept, to gain the most comprehensive insights. To assess the stability of regularized edge-weights of the MGM networks, nonparametric bootstrapping with 1000 iterations was performed (Haslbeck & Waldorp, 2020). For further information and sampling distributions of the edge-weights, see Supplementary Figures S1 and S2. Gaussian Graphical Model networks based on Spearman partial correlations were calculated as further robustness control analyses (Supplementary Figures S3 – S5).

For illustration of the complete sample network, the node positions were set using the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991), a data-driven approach to illustrate a network graph in a way such that highly connected nodes cluster together, all the edges are of comparable length, and there are as few crossing edges as possible (Epskamp & Fried, 2018). To allow for an easy visual comparison of the networks, the spatial node positions of the complete sample network were also used in the visualization of both subsample networks. Additionally, for visualization of edge weights, $w = .674$ (i.e., the highest edge weight across all networks) was used consistently as the maximum value to ensure a homogenous scaling of edge depictions across all networks.

To further allow for more convenient visual comparison of the subsample networks (patient vs. community), an additional difference network was created based on the difference weights matrix. The difference matrix was obtained by subtracting the community subsample weight matrix from the patient subsample weight matrix. Statistical comparison of the subsample networks were performed with the non-parametrical permutation-based Network Comparison Test (1000 Permutations, van Borkulo et al., 2017). Multiple comparison

correction (i.e., as multiple edges were compared between networks) was performed with Bonferroni, whereby statistical significance was defined by $p < .05$ (Burger et al., 2020).

Finally, we also explored the possibility of gaining insights into the relative importance of each node within the network by using the graph-theoretical metric degree centrality (k , sometimes also called node strength; Valente, 2012; van den Bergh et al., 2021). This metric was calculated for each node. Specifically, degree centrality is defined as the sum of the absolute weights connecting a given node to all other nodes in a network.

Network analyses and all visualizations were conducted in R (version 1.3.1056; R Core Team, 2014), using the packages *mgm* (Haslbeck & Waldorp, 2020), *qgraph* (Epskamp et al., 2012), *NetworkComparisonTest* (van Borkulo et al., 2017), and *bootnet* (Epskamp et al., 2018).

Results

In the cross-sectional whole-sample network, statistical modeling resulted in 15 non-zero edges (out of 66 possible edges; Figure 1; see Supplementary Figure S3 for the full weight matrix). Specifically, situational anxiety was positively associated with avoidance motivation ($w = .331$), risk group status ($w = .269$), perceived dangerousness ($w = .126$), avoidance frequency ($w = .102$), and with trait anxiety ($w = .071$). Furthermore, avoidance motivation was positively associated with avoidance frequency ($w = .611$) and perceived positive consequences ($w = .313$), and negatively associated with approach motivation ($w = .202$). Trait anxiety was positively associated with general symptoms of stress ($w = .236$) and DASS anxiety ($w = .145$).

Figure 1*Resulting psychological network for the complete sample*

Note. $N = 541$. Blue lines indicate positive associations, red lines indicate negative associations. The thickness and saturation of the lines reflect the strength of the associations (edge weights). Pre-defined node groups are highlighted in different colors. Nodes were placed using the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991). Anx = Symptoms of anxiety (DASS-21 subscale); AnxSit = Situational anxiety; App-M = Approach motivation; Avo-F = Avoidance frequency; Avo-M = Avoidance motivation; Danger = Perceived dangerousness of infection; Depr = Symptoms of depression (DASS-21 subscale); pInfect = Perceived probability of COVID-19 infection; PosC = Perceived positive consequences; Stress

= Symptoms of stress (DASS-21 subscale); RiskGr = Risk group status; TraitAnx = Trait anxiety (NEO-PI-R N1 scale).

Degree centrality (k) analyses suggest avoidance motivation as the descriptively most central node in the network ($k = 1.144$, see Figure 2). The nodes of the DASS node group ($k_{\text{Stress}} = 1.046$, $k_{\text{Anx}} = 0.815$, $k_{\text{Depress}} = 0.723$), and the situational anxiety node ($k = 0.979$) were also highly central. Medium centralities were found for the avoidance frequency node ($k = 0.713$), the trait anxiety node ($k = 0.452$), and the nodes of the approach node group ($k_{\text{Approach-M}} = 0.515$, $k_{\text{PosCons}} = 0.313$). The least central nodes in the network belonged to the COVID-19 node group ($k_{\text{Danger}} = 0.332$, $k_{\text{pInfect}} = 0.206$, $k_{\text{RiskGr}} = 0.269$).

Figure 2

Relative importance of the psychological network nodes in the complete sample

Note. $N = 541$. Relative importance was operationalized as degree centrality (k) and was computed as the sum of the absolute weights of each node's connections. A higher degree indicates that a node is more central within the psychological network. Anx = Symptoms of anxiety (DASS-21 subscale); AnxSit = Situational anxiety; App-M = Approach motivation; Avo-F = Avoidance frequency; Avo-M = Avoidance motivation; Danger = Perceived

dangerousness of infection; Depr = Symptoms of depression (DASS-21 subscale); pInfect = Perceived probability of COVID-19 infection; PosC = Perceived positive consequences; Stress = Symptoms of stress (DASS-21 subscale); RiskGr = Risk group status; TraitAnx = Trait anxiety (NEO-PI-R N1 scale).

Comparison between subsample networks

To explore potential network differences between the patient and the community subsamples, two separate subsample networks were computed and compared with each other. Network modeling resulted in 11 non-zero edges in the patient subsample network and 13 non-zero edges in the community subsample network (Figure 3, see Supplementary Figure S4 and S5 for the full weight matrices).

Figure 3

Resulting psychological networks for the patient subsample ($N = 218$) (A) and the matched community subsample ($N = 218$) (B)

Note. Blue lines indicate positive associations, red lines indicate negative associations. The thickness and saturation of the lines reflect the strength of the associations (edge weights). Pre-

defined node groups are highlighted in different colors. Nodes positions in both networks were fixed on the basis of the complete sample network. Anx = Symptoms of anxiety (DASS-21 subscale); AnxSit = Situational anxiety; App-M = Approach motivation; Avo-F = Avoidance frequency; Avo-M = Avoidance motivation; Danger = Perceived dangerousness of infection; Depr = Symptoms of depression (DASS-21 subscale); pInfect = Perceived probability of COVID-19 infection; PosC = Perceived positive consequences; Stress = Symptoms of stress (DASS-21 subscale); RiskGr = Risk group status; TraitAnx = Trait anxiety (NEO-PI-R N1 scale).

A visual comparison of the two networks revealed overall high similarity and that most of the topological properties observable in the whole-sample network are also evident in both subsample networks. However, descriptively, the network of psychotherapy patients was slightly less interconnected (11 vs. 13 non-zero edges in the community subsample). More specifically, the positive connections between situational anxiety and trait anxiety, between situational anxiety and perceived dangerousness, and between situational anxiety and risk group status, as well as the negative link between avoidance motivation and approach motivation, were only significantly above zero in the whole-sample network and the community subsample network but absent in the patient subsample network. In contrast, only in the patient sample network, risk group status was connected with perceived dangerousness.

For statistical comparison of the subsample networks, we used the Network Comparison Test (van Borkulo et al., 2017). The results revealed that neither the overall connectivity strength (patient sample network strength = 2.94; community sample network strength = 3.33, $p = .45$, 1000 permutations), nor the general network structure (max. difference in edge weights = .246; $p = .51$, 1000 permutations) differed significantly between the patient (density = .167) and community subsample (density = .197). Moreover, none of the descriptively observed differences between single network edges (see Figure 4) passed the significance threshold when

correcting for multiple comparisons with Bonferroni (all $p > .05$). This may at least partially result from relatively low power of the Network Comparison Test when applied to our sample of only 218 observations per group (small sample and small to medium density networks; see van Borkulo et al., 2017).

Figure 4

Difference network when directly comparing patient ($N = 218$) and community ($N = 218$) subsample networks

Note. Blue lines indicate stronger positive associations in the patient sample, red lines indicate stronger positive associations in the community sample. Associations which were initially negative in both samples are shown with dashed lines. The thickness and saturation of the lines

represent the strength of differences. Anx = Symptoms of anxiety (DASS-21 subscale); AnxSit = Situational anxiety; App-M = Approach motivation; Avo-F = Avoidance frequency; Avo-M = Avoidance motivation; Danger = Perceived dangerousness of infection; Depr = Symptoms of depression (DASS-21 subscale); pInfect = Perceived probability of COVID-19 infection; PosC = Perceived positive consequences; Stress = Symptoms of stress (DASS-21 subscale); RiskGr = Risk group status; TraitAnx = Trait anxiety (NEO-PI-R N1 scale).

Analyses of degree centrality revealed that, descriptively, avoidance motivation and general stress symptoms were the most central nodes, both in the patient and in the community subsample networks (see Figure 5 for the degree centralities in both subsamples). While the patient network showed descriptively higher centralities for avoidance frequency, anxiety symptoms, dangerousness of COVID-19, and the perceived likelihood of infection, the community subsample network showed descriptively higher centralities for situational anxiety, approach motivation and stress symptoms, and slightly higher centrality values for all other nodes. However, as revealed by the Network Comparison Test, these differences were not statistically significant (see above).

Figure 5

Relative importance of the psychological network nodes for the patient (N = 218) (top) and community subsample (N = 218) (bottom)

Note. Relative importance was operationalized as degree centrality and was computed as the sum of the absolute weights of each node's connections. A higher degree indicates that a node is more central within the psychological network. Anx = Symptoms of anxiety (DASS-21 subscale); AnxSit = Situational anxiety; App-M = Approach motivation; Avo-F = Avoidance frequency; Avo-M = Avoidance motivation; Danger = Perceived dangerousness of infection; Depr = Symptoms of depression (DASS-21 subscale); pInfect = Perceived probability of

COVID-19 infection; PosC = Perceived positive consequences; Stress = Symptoms of stress (DASS-21 subscale); RiskGr = Risk group status; TraitAnx = Trait anxiety (NEO-PI-R N1 scale).

To evaluate the stability of our findings to differences in the methodological graph analysis pipeline, all networks were again computed with Spearman partial correlations. These analyses resulted in very similar findings concerning the network structure, edge weights, and degree centrality values, suggesting relatively high robustness of our results despite the rather small sample size (see Supplementary Figures S3-S5, S7, S8).

Finally, to evaluate the stability of the network edge weights in our main analyses (using Mixed Graphical Models, MGM), bootstrapped distributions were estimated in accordance to Burger et al. (2020). As illustrated in Supplementary Figures S1 – S3, the results suggest appropriate weight stability.

Discussion

The present proof of concept study used graph-theoretical network analyses to study complex relations between individual variables, focusing on real world threat. Using the COVID-19 pandemic as a model of naturalistic threat, we exploratorily analyzed cross-sectional survey data on anxiety, stress, and approach-avoidance motivation from a psychotherapy patient and a community sample. The whole-sample network showed multiple expected associations. However, the descriptive differences between the patient and the community subsample networks were not significant. Yet, the descriptive differences between the two networks may inform future studies. Overall, our control analyses suggest a relatively high robustness of our findings despite the relatively small sample.

A network of multi-directional associations between psychological factors

In the whole-sample network, situational anxiety was associated with multiple individual psychological (i.e., trait anxiety) and physiological (i.e., risk group status) factors (see (Craske et al., 2017; Mineka & Zinbarg, 2006; Raymond et al., 2017)). This finding is in line with previous findings from bivariate analysis approaches (e.g., Kim & Laurence, 2020; Mertens et al., 2020; Spielberger, 1972, 1975). The association between situation-specific anxiety and threat evaluation facets (i.e., the perceived dangerousness of COVID-19) support theoretical models proposing a close relationship between threat evaluations and state anxiety (Lazarus & Folkman, 2006). Thus, overall, our network approach resulted in findings that support former empirical research.

Interestingly, the network approach may be used to generate hypotheses about potential multi-directional interactions. Three descriptive observations tentatively hint at a closer relationship of situation-specific anxiety levels and avoidance frequency with situation-specific factors than with trait factors. First, situational anxiety was, descriptively, more closely related to COVID-19 related physiological vulnerability and threat evaluation than to trait anxiety. Second, no avoidance measure was directly linked to trait anxiety. Third, threat evaluation (i.e., perceived dangerousness of COVID-19) was positively associated with situational anxiety but not with trait anxiety. This higher relevance of threat-related situation-specific factors in contrast to trait factors seems relevant and surprising, as several laboratory studies have reported biases toward more pronounced threat evaluations in individuals with high trait anxiety (Gazendam et al., 2013; Wong & Lovibond, 2018), and one COVID-19 specific survey study reported elevated threat evaluations in higher trait anxious individuals (Erceg et al., 2020). However, these previous studies investigated a smaller number of bivariate associations and did not consider the overall complex interaction pattern. Although our sample was comparatively small and our results require future replication, our analyses thus support the usefulness of network analyses to understand these complex patterns.

The psychological network we observed may also add knowledge to theories proposing that competing positive outcomes play an important role in regulating threat-related avoidance. The perceived positive consequences of approach were not directly associated with situational anxiety. However, they were positively associated with approach motivation, which, in turn, was negatively associated with avoidance motivation. These findings aligns with experimental studies showing a down-regulation of avoidance via positive outcomes, even when anxiety levels are high (Pittig, 2019). Importantly, our study's cross-sectional network data structure prohibits any causal interpretations and any conclusions about the directionality of the reported associations. In future research, network analyses of longitudinal data may, for instance, also allow testing the hypothesis that positive consequences indirectly attenuate avoidance via a reduction of avoidance motivation (e.g., Greene, 2021; Santos et al., 2018).

Network comparison: Insights into pathological mechanisms?

Besides the overall psychological network, we explored differences between a psychotherapy patient and a community subsample. Descriptively, many differences between these networks were observed. However, none of these differences reached the significance threshold when using the Network Comparison Test with Bonferroni correction. This was true for all network measures, i.e., the global strength, general structure, and single edge differences. However, it should be noted that the Network Comparison Test may have been statistically underpowered due to the relatively small subsample sizes in combination with the small to medium network densities (van Borkulo et al., 2017). Descriptive differences may, however, still add value to the field when being treated explicitly as hypothesis-generating. Specifically, avoidance motivation and approach motivation were negatively linked in the community subsample but not in the patient subsample. Also, situation-specific anxiety in the community subsample was, descriptively, more strongly related with perceived danger, risk group status, and trait anxiety than in the patient subsample. Future studies may, for example,

test whether avoidance motivation and situation-specific anxiety are less connected with situation-specific threat-related factors in patients than in healthy participants. This may allow to investigate theories that propose inflexible avoidance regulation as a central factor in anxiety disorders (e.g., Arnaudova et al., 2017; LeDoux et al., 2017). Relatedly, the most critical variable in the complete sample network was avoidance motivation, as indicated by its degree centrality, again indicating a central role of avoidance motivation in threat-related cognitions and behavior. Although no causal relations between the network variables can be inferred due to the cross-sectional structure of our data, our findings thus support an important role of avoidance motivation in the complex interactions between threat-related psychological states and traits and overt behavior. Node centrality measures, as reported in our study, can, however, be biased by the researchers' methodological decisions in the process of node selection (i.e., deciding which nodes are important and should be included in the network). Centrality values therefore always reflect a combination of "real" effects and the effects of node selection (i.e., the inclusion of multiple nodes that are likely linked to avoidance motivation will likely result in high node centrality for avoidance motivation). Future studies may develop methodologies, and preferably guidelines, to support more theory-driven node selection approaches and therefore to reduce the influence of potential biases.

Limitations

Further limitations should be noted. First, due to limited time (i.e., to hold the degree of COVID-19-related restrictions as comparable as possible), some items, including the items for situation-specific anxiety, approach and avoidance motivation, and the items for the avoidance frequency assessment, could not be validated in an independent sample. However, similar rating scales are frequently used in psychological research, and most assessed situations were part of established questionnaires (for more details, see Pittig et al., 2021). Second, while the patient subsample was characterized by a current mental health condition, individual diagnoses were

not assessed to protect the patients' rights of privacy and anonymity, thereby not allowing us to examine specific disorders. Third, all psychotherapy sample participants were undergoing psychotherapy at the time of the survey, which may have alleviated feelings of distress while also enhancing adaptive coping responses. Future studies may profit from including waiting list control participants. Finally, causal interpretations, and the directional relationships between anxiety, avoidance, and stress, may be fruitfully investigated using longitudinal data and dynamic network analyses (e.g., Greene, 2021; Santos et al., 2018).

Conclusion

In this proof of concept study, we tested the applicability of graph-theoretical network analysis to the investigation of multi-directional associations between anxiety, stress, and approach-avoidance motivation in real-life threat situations. The observed associations are mostly in support of existing theories and findings. Furthermore, our study extends the existing research by considering *multiple* associations between factors that are relevant for individual differences in anxiety and avoidance. This may help to guide new hypotheses about the impact of situation-specific threat factors in the emergence and maintenance of anxiety and avoidance behavior. To conclude, our study proposes network analysis as a promising tool for investigating complex relations of factors influencing threat-related responding. The extension of network analysis to longitudinal data (i.e., dynamic networks) may represent an especially fruitful future development in anxiety and avoidance research.

References

- Arnaudova, I., Kindt, M., Fanelow, M., & Beckers, T. (2017). Pathways towards the proliferation of avoidance in anxiety and implications for treatment. *Behaviour Research and Therapy*, 96, 3–13. <https://doi.org/10.1016/j.brat.2017.04.004>
- Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry : Official Journal of the World Psychiatric Association (WPA)*, 16(1), 5–13. <https://doi.org/10.1002/wps.20375>
- Bullmore, E., & Sporns, O. (2009). Complex brain networks: Graph theoretical analysis of structural and functional systems. *Nature Reviews. Neuroscience*, 10(3), 186–198. <https://doi.org/10.1038/nrn2575>
- Burger, J., Isvoranu, A.-M., Lunansky, G., Haslbeck, J. M. B., Epskamp, S., Hoekstra, R. H. A., Fried, E. I., Borsboom, D., & Blanken, T. (2020). *Reporting Standards for Psychological Network Analyses in Cross-sectional Data*. <https://doi.org/10.31234/osf.io/4y9nz>
- Chambers, J. A., Power, K. G., & Durham, R. C. (2004). The relationship between trait vulnerability and anxiety and depressive diagnoses at long-term follow-up of Generalized Anxiety Disorder. *Journal of Anxiety Disorders*, 18(5), 587–607. <https://doi.org/10.1016/j.janxdis.2003.09.001>
- Costa, P., & McCrae, R. (1992). Neo PI-R professional manual. *Psychological Assessment Resources*, 396.
- Craske, M. G., Stein, M. B., Eley, T. C., Milad, M. R., Holmes, A., Rapee, R. M., & Wittchen, H.-U. (2017). Anxiety disorders. *Nature Reviews. Disease Primers*, 3, 17024. <https://doi.org/10.1038/nrdp.2017.24>
- 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>
- Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph : Network Visualizations of Relationships in Psychometric Data. *Journal of Statistical Software*, 48(4). <https://doi.org/10.18637/jss.v048.i04>
- Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, 23(4), 617–634. <https://doi.org/10.1037/met0000167>
- Erceg, N., Ružojčić, M., & Galic, Z. (2020). Misbehaving in the Corona Crisis: The Role of Anxiety and Unfounded Beliefs. Advance online publication. <https://doi.org/10.31234/osf.io/cgjlw8>
- Foygel, R., & Drton, M. (2010). Extended Bayesian Information Criteria for Gaussian Graphical Models. *Advances in Neural Information Processing Systems* 23 (. <https://arxiv.org/pdf/1011.6640>
- Fried, E. I., van Borkulo, C. D., Cramer, A. O. J., Boschloo, L., Schoevers, R. A., & Borsboom, D. (2017). Mental disorders as networks of problems: A review of recent insights. *Social Psychiatry and Psychiatric Epidemiology*, 52(1), 1–10. <https://doi.org/10.1007/s00127-016-1319-z>
- Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience*, 21(11), 1129–1164. <https://doi.org/10.1002/spe.4380211102>
- Gazendam, F. J., Kamphuis, J. H., & Kindt, M. (2013). Deficient safety learning characterizes high trait anxious individuals. *Biological Psychology*, 92(2), 342–352. <https://doi.org/10.1016/j.biopsycho.2012.11.006>
- Greene, T. (2021). The dynamic interactions of PTSD symptoms in daily life. *European Journal of Psychotraumatology*, 12(sup1), 1866413. <https://doi.org/10.1080/20008198.2020.1866413>
- 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). <https://doi.org/10.18637/jss.v093.i08>

- Heeren, A., & McNally, R. J. (2016). An integrative network approach to social anxiety disorder: The complex dynamic interplay among attentional bias for threat, attentional control, and symptoms. *Journal of Anxiety Disorders*, 42, 95–104.
<https://doi.org/10.1016/j.janxdis.2016.06.009>
- Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2011). MatchIt : Nonparametric Preprocessing for Parametric Causal Inference. *Journal of Statistical Software*, 42(8).
<https://doi.org/10.18637/jss.v042.i08>
- Kim, H. H.-S., & Laurence, J. (2020). Covid-19 restrictions and mental distress among American adults: Evidence from Corona Impact Survey (W1 and W2). *Journal of Public Health (Oxford, England)*. Advance online publication. <https://doi.org/10.1093/pubmed/fdaa148>
- Lazarus, R. S., & Folkman, S. (2006). *Stress, appraisal, and coping* [Nachdr.]. Springer.
- LeDoux, J. E., Moscarello, J., Sears, R., & Campese, V. (2017). The birth, death and resurrection of avoidance: A reconceptualization of a troubled paradigm. *Molecular Psychiatry*, 22(1), 24–36.
<https://doi.org/10.1038/mp.2016.166>
- Leiner, D. J. (2018). *SoSciSurvey*. (Version 2.3.00) [Computer Software]. <http://www.sosicisurvey.com>
- Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. *Behaviour Research and Therapy*, 33(3), 335–343. [https://doi.org/10.1016/0005-7967\(94\)00075-U](https://doi.org/10.1016/0005-7967(94)00075-U)
- Lovibond, S. H., & Lovibond, P. F. (1996). *Manual for the depression anxiety stress scales* (2nd ed.). Psychology Foundation of Australia.
- Mertens, G., Gerritsen, L., Duijndam, S., Salemink, E., & Engelhard, I. M. (2020). Fear of the coronavirus (COVID-19): Predictors in an online study conducted in March 2020. *Journal of Anxiety Disorders*, 74, 102258. <https://doi.org/10.1016/j.janxdis.2020.102258>
- Mineka, S., & Zinbarg, R. (2006). A contemporary learning theory perspective on the etiology of anxiety disorders: It's not what you thought it was. *The American Psychologist*, 61(1), 10–26.
<https://doi.org/10.1037/0003-066X.61.1.10>
- Mogg, K., & Bradley, B. P. (2009). A cognitive-motivational perspective on the processing of threat information and anxiety. In J. Yiend (Ed.), *Cognition, Emotion and Psychopathology* (pp. 68–85). Cambridge University Press. <https://doi.org/10.1017/CBO9780511521263.005>
- Nilges, P., & Essau, C. (2015). Die Depressions-Angst-Stress-Skalen: Der DASS--ein Screeningverfahren nicht nur für Schmerzpatienten [Depression, anxiety and stress scales: DASS--A screening procedure not only for pain patients]. *Schmerz (Berlin, Germany)*, 29(6), 649–657.
<https://doi.org/10.1007/s00482-015-0019-z>
- Ostendorf, F., & Angleitner, A. (2004). *NEO-Persönlichkeitsinventar nach Costa und McCrae: NEO-PI-R ; Manual*. Revidierte Fassung. Hogrefe.
- Pittig, A. (2019). Incentive-based extinction of safety behaviors: Positive outcomes competing with aversive outcomes trigger fear-opposite action to prevent protection from fear extinction. *Behaviour Research and Therapy*, 121, 103463. <https://doi.org/10.1016/j.brat.2019.103463>
- Pittig, A., Boschet, J. M., Glück, V. M., & Schneider, K. (2020). Elevated costly avoidance in anxiety disorders: Patients show little downregulation of acquired avoidance in face of competing rewards for approach. *Depression and Anxiety*. Advance online publication.
<https://doi.org/10.1002/da.23119>
- Pittig, A., Glück, V. M., Boschet, J. M., Wong, A. H. K., & Engelke, P. (2021). Increased anxiety of public situations during the COVID-19 pandemic: Evidence from a community and a clinical sample. Manuscript submitted for publication.
- Pittig, A., & Scherbaum, S. (2020). Costly avoidance in anxious individuals: Elevated threat avoidance in anxious individuals under high, but not low competing rewards. *Journal of Behavior*

- Therapy and Experimental Psychiatry*, 66, 101524.
<https://doi.org/10.1016/j.jbtep.2019.101524>.
- Pittig, A., Wong, A. H. K., Glück, V. M., & Boschet, J. M. (2020). Avoidance and its bi-directional relationship with conditioned fear: Mechanisms, moderators, and clinical implications. *Behaviour Research and Therapy*, 126, 103550. <https://doi.org/10.1016/j.brat.2020.103550>
- R Core Team. (2014). *R: A language and environment for statistical computing*. (Version 1.3.1056) [Computer Software]. R Foundation for Statistical Computing, Vienna, Austria. <http://www.R-project.org/>
- Raymond, J. G., Steele, J. D., & Seriès, P. (2017). Modeling Trait Anxiety: From Computational Processes to Personality. *Frontiers in Psychiatry*, 8, 1.
<https://doi.org/10.3389/fpsy.2017.00001>
- Robert Koch Institute. (2020a). *Coronavirus Disease 2019 (COVID-19). Daily Situation Report of the Robert Koch Institute: 08/09/2020 -Updated Status for Germany* [Press release].
- Robert Koch Institute. (2020b). *Epidemiologischer Steckbrief zu SARS-CoV-2 und COVID-19*.
https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Steckbrief.html
- Robert Koch Institute. (2021). *Covid-19-Trends in Deutschland im Überblick*.
https://www.rki.de/EN/Content/infections/epidemiology/outbreaks/COVID-19/Situationsberichte_Tab.html;jsessionid=EE68D43AA287131BF4332922E480BC1F.internet102?cms_gtp=14466884_list%253D10
- Robinaugh, D., Haslbeck, J. M. B., Waldorp, L., Kossakowski, J. J., Fried, E. I., Millner, A., McNally, R. J., van Nes, E. H., Scheffer, M., Kendler, K. S., & Borsboom, D. (2019). Advancing the Network Theory of Mental Disorders: A Computational Model of Panic Disorder. Advance online publication. <https://doi.org/10.31234/osf.io/km37w>
- Santos, H. P., Kossakowski, J. J., Schwartz, T. A., Beeber, L., & Fried, E. I. (2018). Longitudinal network structure of depression symptoms and self-efficacy in low-income mothers. *PloS One*, 13(1), e0191675. <https://doi.org/10.1371/journal.pone.0191675>
- Spielberger, C. D. (1972). Conceptual and methodological issues in anxiety research. In C. D. Spielberger (Ed.), *Anxiety. Current Trends in Theory and Research, Volume 2* (pp. 481–493). Academic Press.
- Spielberger, C. D. (1975). The measurement of state and trait anxiety: Conceptual and methodological issues. In L. Levi (Ed.), *Emotions - Their parameters and measurement* (pp. 713–725). Raven Press.
- Steinmetz, H., Batzdorfer, V., & Bosnjak, M. (2020). *The ZPID lockdown measures dataset for Germany*. <https://doi.org/10.23668/PSYCHARCHIVES.3019>
- Taylor, S., Landry, C. A., Paluszek, M. M., Fergus, T. A., McKay, D., & Asmundson, G. J. G. (2020). Covid stress syndrome: Concept, structure, and correlates. *Depression and Anxiety*, 37(8), 706–714. <https://doi.org/10.1002/da.23071>
- Valente, T. W. (2012). Network interventions. *Science (New York, N.Y.)*, 337(6090), 49–53.
<https://doi.org/10.1126/science.1217330>
- van Borkulo, C., Boschloo, L., Kossakowski, J., Tio, P., Schoevers, R., Borsboom, D., & Waldorp, L. (2017). *Comparing network structures on three aspects: A permutation test*.
<https://doi.org/10.13140/RG.2.2.29455.38569>
- van Borkulo, C. D., Borsboom, D., Epskamp, S., Blanken, T. F., Boschloo, L., Schoevers, R. A., & Waldorp, L. J. (2014). A new method for constructing networks from binary data. *Scientific Reports*, 4, 5918. <https://doi.org/10.1038/srep05918>
- van den Bergh, N., Marchetti, I., & Koster, E. H. W. (2021). Bridges over Troubled Waters: Mapping the Interplay Between Anxiety, Depression and Stress Through Network Analysis of the DASS-21. *Cognitive Therapy and Research*, 45(1), 46–60. <https://doi.org/10.1007/s10608-020-10153-w>

Wong, A. H. K., & Lovibond, P. F. (2018). Excessive generalisation of conditioned fear in trait anxious individuals under ambiguity. *Behaviour Research and Therapy*, 107, 53–63.
<https://doi.org/10.1016/j.brat.2018.05.012>