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

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Abstract

Background: 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.

Methods: A total of 436 participants who were matched on age and gender (218 psychotherapy patients, 218 online-recruited nonpatients) completed an online survey assessing these factors in response to the COVID-19 pandemic.

Results and Discussion: 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 online subsample networks did not differ

Valentina M. Glück, Paula Engelke, and Kirsten Hilger share first authorship.

significantly, however, descriptive differences may inform future research.

KEYWORDS
anxiety, approach, avoidance, graph analysis, network analysis, threat

1 | 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 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 personality factors may be relevant for these behavioral adaptations. For example, high trait anxiety has been associated with stronger negative responses in threatening situations (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, contributing 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 downregulation through competing positive outcomes is reduced in individuals with anxiety disorders and even in healthy individuals with high trait anxiety (Pittig & Scherbaum, 2020; Pittig, Boschet, et al., 2021). Such findings highlight the role of appetitive factors in the regulation of avoidance behavior, such as competing goals, rewards, and approach motivation.

The development of anxiety and avoidance in interactions with a variety of factors obviously goes beyond bivariate associations. Thus, a comprehensive approach to capture the complexity of these psychological interactions is required. Graph-theoretical network analysis provides tools 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 subsample and a matched online subsample to gain insights into potential aberrations in psychologically vulnerable individuals concerning their response pattern in threatening environments.

2 | METHODS

2.1 | Participants

The sample consisted of 541 participants who were recruited in Germany from mid of May 2020 until the beginning of August 2020, that is, during the first months of the COVID-19 pandemic (see Table 1). The sample size was based on a trade-off between higher statistical power (i.e., 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) an online subsample ($N = 323$) 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 subsample ($N = 218$) that was recruited from the outpatient clinic for psychotherapy at the University of Würzburg. Of note, both subsamples filled in the questionnaires online, but the participants in the patient subsample received specific invitations, while participation in the online sample was open for the general population. 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 subsample 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 patients' privacy, we refrained from collecting any psychological diagnoses of individual patients. Concerning the online subsample, 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 before data analysis, resulting in a final total sample size of $N = 541$ (i.e., before matching; see Table 1). The survey was implemented using the platform SoSci Survey (Leiner, 2018, www.soscisurvey.de).

TABLE 1 Demographic and questionnaire data.

	Complete sample		Matched online subsample		Matched patient subsample		t^{a}	*p*	*d*
N	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	0.186	0.13
Trait anxiety (NEO-PI-R N1)	17.70	(5.69)	15.84	(5.80)	19.87	(5.02)	7.75	**<0.001**	0.74
DASS symptoms									
Anxiety (0–42)	6.39	(7.43)	4.59	(6.26)	9.00	(8.24)	6.30	**<0.001**	0.60
Depression (0–42)	10.33	(10.10)	8.52	(9.47)	12.93	(10.88)	4.51	**<0.001**	0.43
Stress (0–42)	12.88	(9.95)	10.51	(9.39)	16.22	(10.06)	6.13	**<0.001**	0.59
COVID-19 ratings									
Risk group (*n*)	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	**0.003**	0.29
Likelihood of infection (1–5)	2.72	(0.98)	2.62	(0.97)	2.75	(1.00)	1.41	0.159	0.14
Anxiety, approach-avoidance									
Situational anxiety (0–4)	1.13	(0.90)	1.04	(0.88)	1.21	(0.95)	1.94	0.054	0.19
Avoidance frequency (0–4)	1.81	(1.01)	1.77	(1.07)	1.80	(1.00)	0.27	0.790	0.03
Avoidance motivation (0–4)	1.74	(0.97)	1.72	(0.94)	1.73	(1.05)	0.07	0.943	0.01
Approach motivation (0–4)	1.52	(0.65)	1.60	(0.69)	1.47	(0.62)	1.97	0.050	0.19
Positive consequences (0–4)	1.52	(0.67)	1.48	(0.64)	1.58	(0.73)	1.58	0.115	0.15

Note: Means (and standard deviations). Significant differences between subsamples ($p < .05$) 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 $t(434)$.

2.2 | Study procedure

All study procedures were conducted in accordance with the declaration of Helsinki (1975, revised in 2008; World Medical Association, 2009), 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 received 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).

2.3 | Measures

The online survey (for a detailed description see Pittig, Glück, 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 anxiety, depression, and stress symptoms 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 (like the NEO-PI-R N1), 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 the 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 in respect to 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, Glück, et al., 2021). For each of these four situations, the participants rated (a) their situational anxiety in the previous 2 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 2 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 2 weeks. The average individual ratings of these four situations were used for the five situation-specific variables 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, that is, (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. All analyses with the perceived positive consequences variable were carried out with the individual average of the six life domains (Cronbach's $\alpha = 0.93$).

2.4 | Network analyses

The complex patterns of associations between the psychological trait variables and the situational state factors were exploratively modelled as a psychological network using graph theory. 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). Note that 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 the patient subsample with the network of the online subsample. To reduce sampling bias, we created two matched subsamples using nearest-neighbor matching (Ho et al., 2011). Specifically, the closest neighbors to the smaller subsample were selected, resulting in two equally sized subsamples (each $n = 218$) matched on age, sex, risk group status, and employment status (see Table 1).

The 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, least absolute shrinkage and selection operator (LASSO)-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 nonzero. 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, that is, 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 Supporting Information: Figures S1 and S2. Gaussian Graphical Model networks based on Spearman partial correlations were calculated as further robustness control analyses (Supporting Information: Figures S3–S5).

For the illustration of the complete sample network, the node positions were set using the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991). This algorithm is 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, $w = 0.674$ (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 allow for a more convenient visual comparison of the subsample networks (patient vs. online), we created an additional difference network based on the difference weights matrix. The difference matrix was obtained by subtracting the online subsample weight matrix from the patient subsample weight matrix. The statistical comparison of the subsample networks was performed with the nonparametrical permutation-based Network Comparison Test (1000 Permutations, van Borkulo et al., 2022). Multiple comparison correction (i.e., as multiple edges were compared between networks) was performed with the Bonferroni method, whereby statistical significance was defined by $p < .05$ (Burger et al., 2022).

Finally, we also explored the relative importance of each node within the networks 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., 2022), and *bootnet* (Epskamp et al., 2018).

3 | RESULTS

In the cross-sectional whole-sample network, the statistical modeling revealed 15 nonzero 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 ($w = 0.331$), risk group status ($w = 0.269$), perceived dangerousness

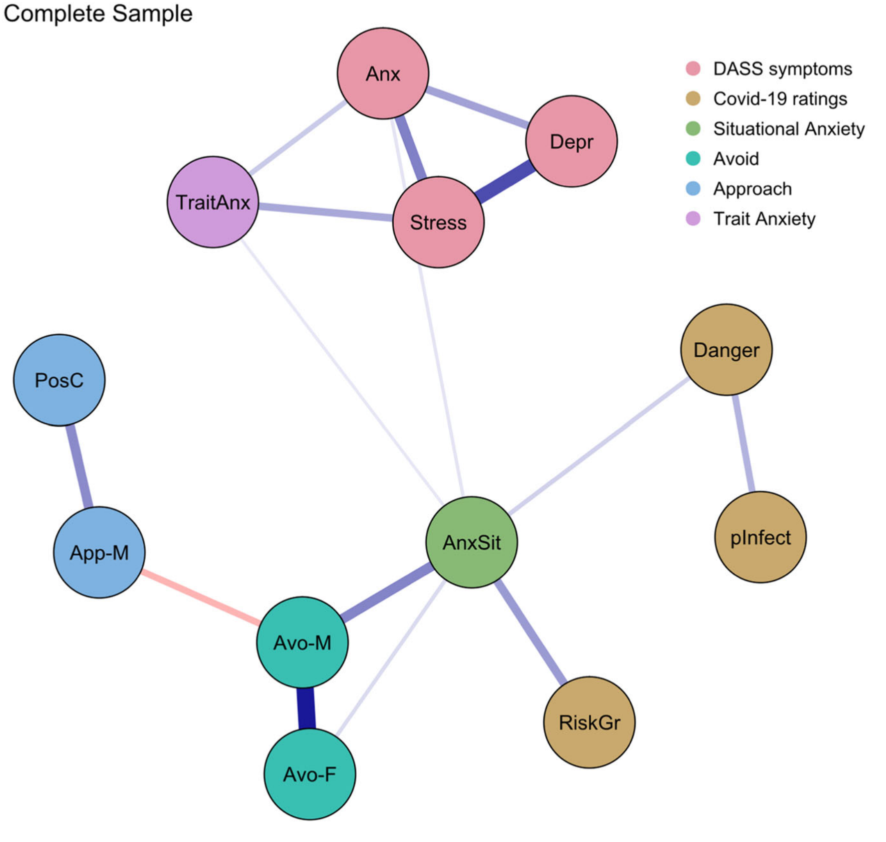

FIGURE 1 Psychological network for the complete sample. $N = 541$. Blue lines indicate positive associations, red lines indicate negative associations. The thickness and saturation of the lines reflect the strength of the associations (edge weights). Predefined node groups are highlighted in different 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).

($w = 0.126$), avoidance frequency ($w = 0.102$), and with trait anxiety ($w = 0.071$). Furthermore, avoidance motivation was positively associated with avoidance frequency ($w = 0.611$) and perceived positive consequences ($w = 0.313$), and negatively associated with approach motivation ($w = 0.202$). Trait anxiety was positively associated with general symptoms of stress ($w = 0.236$) and DASS anxiety ($w = 0.145$).

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 ($k_{Stress} = 1.046$, $k_{Anx} = 0.815$, $k_{Depress} = 0.723$), 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 ($k_{Approach\text{-}M} = 0.515$, $k_{PosCons} = 0.313$). The least central nodes in the network belonged to the COVID-19 node group ($k_{Danger} = 0.332$, $k_{pInfect} = 0.206$, $k_{RiskGr} = 0.269$).

3.1 | Comparison between subsample networks

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

A visual comparison of the two networks revealed an overall high similarity. Most of the topological properties of the whole-sample network were also evident in both subsample networks. However, descriptively, the network of psychotherapy patients was slightly less interconnected (11 vs. 13 nonzero edges in the online 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 in the online subsample network. In contrast, risk group status was connected with perceived dangerousness in the patient subsample network only.

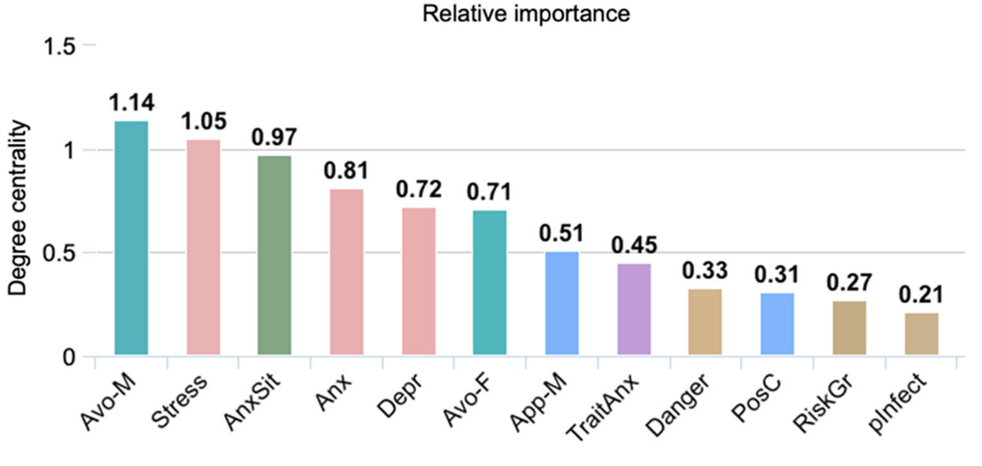

FIGURE 2 Relative importance of the psychological network nodes in the complete sample. $N = 541$. Relative importance was operationalized as degree centrality (k) and was computed as the sum of the absolute weights of each node's connections. A higher degree indicates that a node is more central within 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).

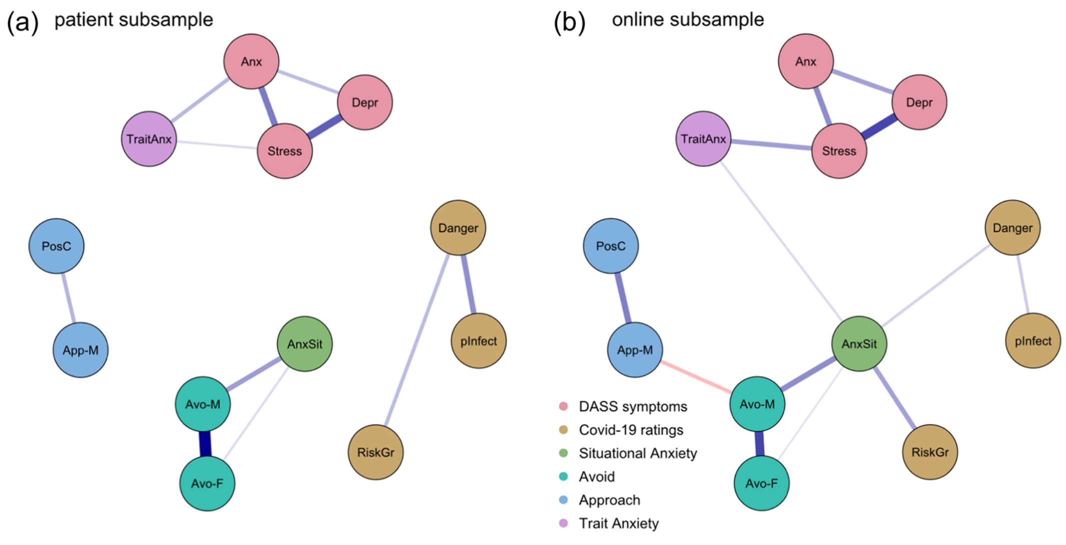

FIGURE 3 Psychological networks for the patient subsample ($N = 218$) (a) and the matched online subsample ($N = 218$) (b). Blue lines indicate positive associations, red lines indicate negative associations. The thickness and saturation of the lines reflect the strength of the associations (edge weights). Predefined 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).

For the statistical comparison of the subsample networks, we used the Network Comparison Test (van Borkulo et al., 2022). The results revealed that neither the overall connectivity strength (patient subsample network strength = 2.94; online subsample network strength = 3.33, $p = 0.45$, 1000 permutations), nor the general network structure (max. difference in edge weights = 0.246; $p = 0.51$, 1000 permutations) differed significantly between the patient (density = 0.167) and online subsample (density = 0.197). 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 $p > 0.05$). Note that this lack of significance 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., 2022).

The analysis of degree centralities revealed that, descriptively, avoidance motivation and general stress symptoms were the most central nodes, both in the patient and in the online subsample networks (see Figure 5 for the degree centralities in both subsamples). The patient network showed descriptively higher centralities for avoidance frequency, anxiety symptoms, dangerousness of COVID-19, and perceived risk of infection, while the online 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 centrality differences were not statistically significant (see above).

To evaluate the stability of our findings regarding different graph analysis pipelines, all networks were also computed based on 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 Supporting Information: 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

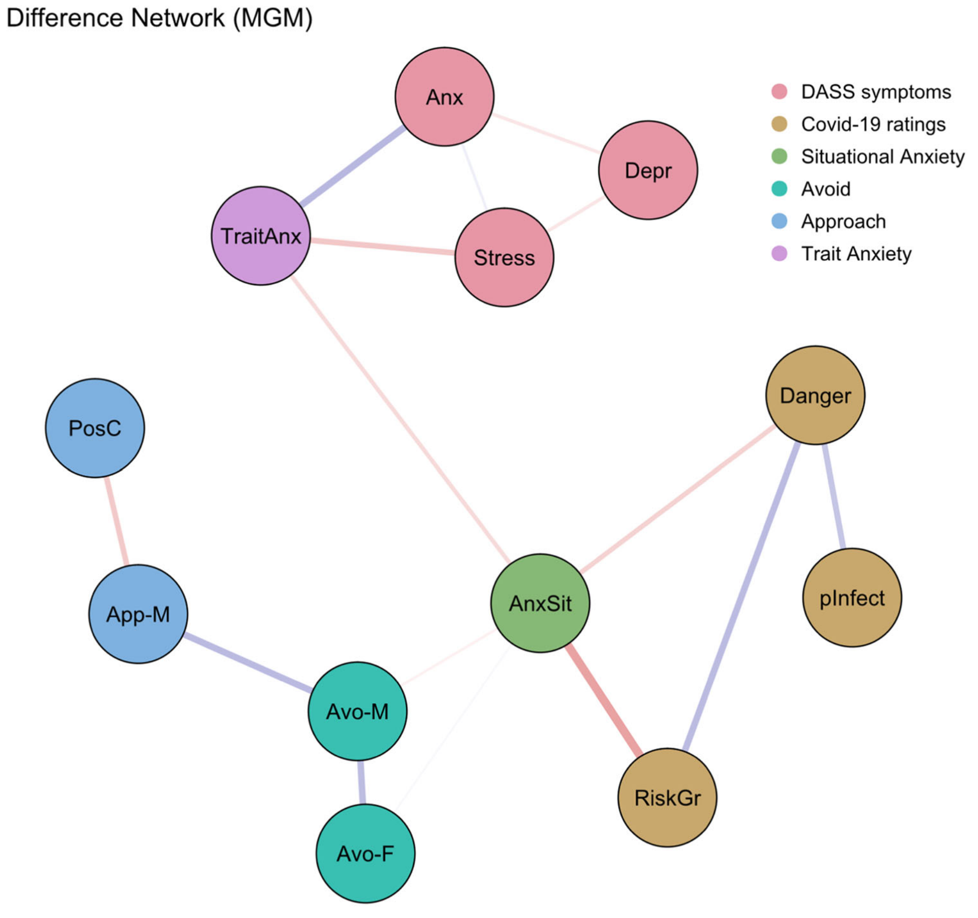

FIGURE 4 Difference network when directly comparing patient (*N* = 218) and online (*N* = 218) subsample networks. Blue lines indicate stronger positive associations in the patient subsample, red lines indicate stronger positive associations in the online subsample. The thickness and saturation of the 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).

distributions were estimated in accordance to Burger et al. (2022). As illustrated in Supporting Information: Figures S1–S3, the results suggest appropriate weight stability.

4 | DISCUSSION

Using the COVID-19 pandemic as a model of naturalistic threat, this proof-of-concept study explored complex associations between trait- and situational anxiety, stress, and approach-avoidance motivation with graph-theoretical network analyses. Psychological networks were computed from cross-sectional survey data of an online subsample and of a psychotherapy patient subsample. Multiple expected associations were revealed and despite the rather limited subsample sizes of *N* = 218 appropriate robustness of networks was supported by multiple

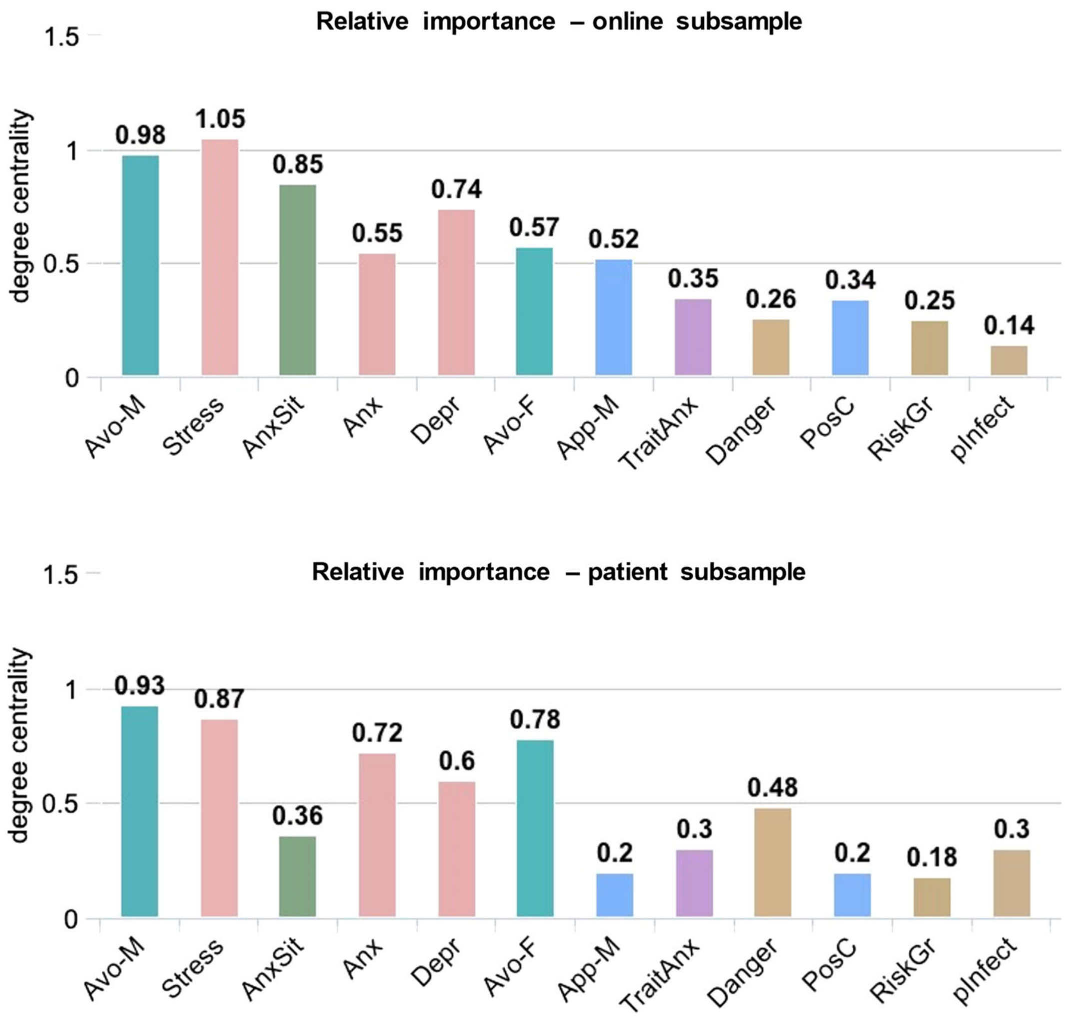

FIGURE 5 Relative importance of the psychological network nodes for the patient (*N* = 218, top) and online subsample (*N* = 218, bottom). Relative importance was operationalized as degree centrality and was computed as the sum of the absolute weights of each node's connections. A higher degree indicates 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).

control analyses, that is, calculating the edge weights with two different algorithms and with bootstrapping. Although network differences between the two subsamples did not reach statistical significance, descriptive contrasts may inform future research and generate new hypotheses.

4.1 | Support for existing evidence on threat processing by new methods

One of the most prominent findings of our analyses on the whole sample is that situation-specific anxiety is 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)—a result that aligns well with previous findings from bivariate analysis approaches (e.g., Kim & Laurence, 2020; Mertens et al., 2020; Spielberger, 1972, 1975). Second, the here observed associations between situation-specific anxiety and threat evaluation facets (i.e., the perceived dangerousness of COVID-19) also support established theoretical models proposing a close relationship between threat evaluations and state anxiety (Lazarus & Folkman, 2006). Finally, the observation that perceived positive consequences of approach were not directly associated with situational anxiety strength, but instead with approach motivation, which, in turn, was negatively associated with avoidance motivation, is well in line with research on the role of competing positive outcomes in regulating threat-related avoidance, specifically with experimental evidence about the downregulation of avoidance via positive outcomes, even when high anxiety levels are present (Pittig, 2019). However, it is important to be aware of the fact that due to the cross-sectional data structure, our study prohibits any causal interpretations and conclusions about the directionality of the reported associations. Thus, further research is required to more directly link our results to the previously reported experimental investigations. In future research, network analyses of longitudinal data may also allow testing further hypotheses, such as the hypothesis that positive consequences indirectly attenuate avoidance via a reduction of avoidance motivation (e.g., Greene, 2021; Santos et al., 2018), and compare laboratory findings to more naturalistic data.

In contrast to the above-outlined observations fitting quite well into existing empirical evidence, a rather surprising finding of the whole sample network is that situational anxiety is more strongly interconnected with avoidance motivation and threat evaluation (i.e., perceived dangerousness of COVID-19) than with trait anxiety. This contradicts multiple laboratory studies suggesting more pronounced threat evaluations in individuals with high-trait anxiety (Gazendam et al., 2013; Wong & Lovibond, 2018), and one COVID-19-specific survey study that reported elevated threat evaluations in higher-trait anxious individuals (Erceg et al., 2020). The arbitrariness of the node selection procedure, which is inherent to most network analysis approaches, may be one factor contributing to this discrepancy as it could impact nodes' centralities (see Neal et al., 2022).

4.2 | Network comparison: Generating new hypotheses about avoidance regulation?

The comparison between the psychotherapy patient subsample and the general online subsample revealed many descriptive differences, none of which reached the significance threshold when correcting for multiple comparisons. This was true for all network measures (i.e., the global strength, general structure) as well as for all single-edge differences. However, it should be noted that the Network Comparison Test may have been statistically underpowered to detect network differences in our study due to the relatively small subsample sizes in combination with small to medium network densities (van Borkulo et al., 2022). The observed descriptive network differences may, nevertheless, add value to the field in proposing new foci for hypotheses to-be-tested in future research. For instance, we observed avoidance motivation and approach motivation to be strongly negatively linked in the online subsample but not in the patient subsample, while the situation-specific anxiety in the online subsample was, descriptively, more strongly related with perceived danger, risk group status, and trait anxiety than in the patient subsample. A potential hypothesis motivated by these results may, for example, state that avoidance motivation and situation-specific anxiety are less dependent on situation-specific threat-related factors in anxious psychotherapy patients than in less anxious individuals, which may mirror inflexible avoidance regulation as a central factor in anxiety disorders (e.g., Arnaudova et al., 2017; LeDoux et al., 2017). However, again we could not exclude the possibility that the node selection procedure adopted here may have biased our results in unintended ways, thus that future research using network analyses may strive for standardised and thus more comparable node definitions.

4.3 | Limitations

As the most important limitation, the node centrality measures, as reported in our study, can be biased by methodological decisions in the process of node definition (i.e., deciding which nodes are important and should be included in the network, see also Neal et al., 2022). Centrality values 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 to reduce the influence of such potential biases. Another limitation is the cross-sectional nature of the study, which does not allow for causally interpreting the associations between the nodes, restricting the use of the data to the comparison with existing research and to the generation of new hypotheses. Several further limitations must also be considered. First, some items, including the items for situation-specific anxiety, approach and avoidance motivation, and the items assessing avoidance frequency were not validated in an independent sample due to limited time (i.e., to hold the degree of COVID-19-related restrictions as comparable as possible). Similar rating scales are, however, frequently used in psychological research, and most assessed situations were part of established questionnaires (for more details, see Pittig, Glück et al., 2021). Second, the patient subsample was characterized by a current mental health condition, but specific diagnoses were not assessed to protect the patients' rights of privacy and anonymity, thereby not allowing us to examine specific disorders. Third, all psychotherapy subsample participants were undergoing psychotherapy at the time of data collection, which may have alleviated feelings of distress while also enhancing adaptive coping responses. Future studies may profit from including waiting list control participants. Fourth, the generalizability of the findings may be limited due to potential regional idiosyncracies and potential effects of the recruitment strategy on the characteristics of the online subsample. Therefore, future studies may aim to reproduce these findings in other contexts. Additionally, causal interpretations, and directionality of the 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).

5 | CONCLUSION

In this proof-of-concept study, we evaluated the applicability of graph-theoretical network analysis for the investigation of complex associations between situation-specific anxiety, trait anxiety, stress, and approach-avoidance motivation in real-life threat situations. Most of the observed associations align well with existing theories and findings, while others were rather unexpected and provide new foci of hypotheses to be tested in future research about complex, situation-specific factors in the emergence and maintenance of anxiety and avoidance. To conclude, our study proposes network analysis as promising tool for investigating complex relations of factors influencing naturalistic threat-related responding. Especially when the limitations of network analysis are appropriately addressed in future studies, for example by analysing longitudinal data (i.e., dynamic networks), network approaches may represent a fruitful future development in anxiety and avoidance research.

AUTHOR CONTRIBUTIONS STATEMENT

Valentina M. Glück, Andre Pittig, Kirsten Hilger, Alex H. K. Wong, Paula Engelke, and Juliane M. Boschet conceived of the study. Valentina M. Glück, Juliane M. Boschet and Andre Pittig collected the data. Kirsten Hilger, Juliane M. Boschet, Andre Pittig, and Paula Engelke analyzed the data. Paula Engelke and Kirsten Hilger prepared figures and tables. All authors were involved in interpreting results and writing the manuscript.

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CONFLICT OF INTEREST STATEMENT

The author declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in OSF at https://osf.io/k273s/.

ETHICS STATEMENT

Approval was granted by the Ethics Committee at the University of Würzburg (Referral GZEK 2020-31).

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