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# Network analyses of ecological momentary emotion and avoidance assessments before and after cognitive behavioral therapy for anxiety disorders

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A R T I C L E I N F O

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A B S T R A C T

Negative emotions and associated avoidance behaviors are core symptoms of anxiety. Current treatments aim to resolve dysfunctional coupling between them. However, precise interactions between emotions and avoidance in patients' everyday lives and changes from pre- to post-treatment remain unclear. We analyzed data from a randomized controlled trial where patients with anxiety disorders underwent 16 sessions of cognitive behavioral therapy (CBT). Fifty-six patients (68 % female, age: $M = 33.31$, $SD = 12.45$) completed ecological momentary assessments five times a day on 14 consecutive days before and after treatment, rating negative emotions and avoidance behaviors experienced within the past 30 min. We computed multilevel vector autoregressive models to investigate contemporaneous and time-lagged associations between anxiety, depression, anger, and avoidance behaviors within patients, separately at pre- and post-treatment. We examined pre-post changes in network density and avoidance centrality, and related these metrics to changes in symptom severity. Network density significantly decreased from pre- to post-treatment, indicating that after therapy, mutual interactions between negative emotions and avoidance were attenuated. Specifically, contemporaneous associations between anxiety and avoidance observed before CBT were no longer significant at post-treatment. Effects of negative emotions on avoidance assessed at a later time point (avoidance instrength) decreased, but not significantly. Reduction in avoidance instrength positively correlated with reduction in depressive symptom severity, meaning that as patients improved, they were less likely to avoid situations after experiencing negative emotions. Our results elucidate mechanisms of successful CBT observed in patients' daily lives and may help improve and personalize CBT to increase its effectiveness.

## 1. Introduction

Negative emotions are a core symptom of anxiety disorders and associated with avoidance behaviors (World Health Organization, 2019). Emotion-motivated avoidant coping contributes to the maintenance of psychopathology (Barlow et al., 2021; Salters-Pedneault et al., 2004; Sauer-Zavala & Barlow, 2021) and therefore constitutes a key target in cognitive behavioral therapy (CBT; Asnaani et al., 2020; Bullis

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et al., 2019; Espejo et al., 2017; Yasinski et al., 2020; see Sønderland et al., 2023 for a review). Through emotional awareness training, reappraisal, or exposure, current treatment approaches aim to weaken the link between negative emotions and avoidance and resolve dysfunctional patterns (Barlow et al., 2017). However, the precise interactions between patients' emotional experience and behavioral response patterns, as well as changes underlying effective treatment have not been well characterized at the process level.

In order to capture how clinically relevant symptoms unfold in the "here and now" in patients' everyday lives, ecological momentary assessments (EMA) provide process-oriented information of excellent internal and external validity (Bolger et al., 2003; Scott et al., 2020; Shiffman et al., 2008). Typical indices derived from EMA studies comprise mean, standard deviation, Root Mean Sum of Squared Distance (RMSSD) – a measure of instability, and autocorrelations – a measure of inertia. In EMA studies, high mean negative affect has been associated with psychopathology (Heller et al., 2019), while altered emotion dynamics such as high variability and instability in negative affect have been linked with mood disorders (Lamers et al., 2018; Sperry et al., 2020), anxiety (Lamers et al., 2018), decreased well-being (Houben et al., 2015), dysfunctional emotion regulation styles (Sperry & Eckland, 2021), and neuroticism (Mader et al., 2023). In contrast, for healthy individuals, greater maintenance and more frequent return to a set of emotional states over time was associated with lower neuroticism and better occupational outcomes and mental health (D'Mello & Gruber, 2021).

In addition to these indices, information on symptom interactions can be derived from statistical models that estimate not only parameters for single variables, but also quantify the relationship between different variables over time. One promising approach is multilevel vector autoregressive (mlVAR) modeling (Bringmann et al., 2016) within a network analysis framework (Borsboom et al., 2021; Bringmann et al., 2013). This approach estimates the dynamic structure of a specific set of variables, which are commonly visualized as *nodes* in a network connected by lines or *edges*, depicting the strength and direction of associations. From this perspective, mental disorders are conceptualized as networks where nodes representing different symptoms may reinforce each other, forming stable symptom-syndromes (Borsboom & Cramer, 2013). It thus allows for a syndrome-centered perspective, and – if based on longitudinal data – can elucidate mechanistic associations (Fisher & Bosley, 2020; Schumacher et al., 2023). For example, temporal networks such as mlVAR can identify symptoms exerting the greatest relative effects (Bringmann et al., 2013) and inform about temporal precedence of one symptom over another (Fisher et al., 2017). Such information is central to clarifying mechanistic associations and may even be valuable for therapeutic decision-making in the future (Fernandez et al., 2017; Fisher et al., 2019; Rubel et al., 2018).

Clinical research has commonly focused on network metrics that quantify how dense a network is or how central a particular node (Beard et al., 2016; Robinaugh et al., 2020b). In a dense network, symptoms are tightly connected, e.g., reinforcing each other, whereas in a sparse network, symptoms are less dependent on each other. A symptom that is very central to a network has many connections and may thus influence many other symptoms or be easily triggered by other symptoms.

Conditions such as mood disorders (Pe et al., 2015), anxiety (Shin et al., 2022), burn-out symptom severity (Spiller et al., 2021), or general risk factors, such as neuroticism (Bringmann et al., 2013), have been associated with dense negative emotion networks. Such high network density can be interpreted as a system that is inflexible and resistant to change, thus providing an alternative explanation model beyond theory-based conceptualisations of single risk factors. There is also evidence on temporal dynamics, showing that increasing autocorrelations within emotions and elevated correlations between emotions are positively related with the emergence of psychopathology (van de Leemput et al., 2014).

Unfortunately, while there is an increasing number of clinical EMA studies investigating affect dynamics (e.g., Scott et al., 2020), few integrate behavioral responses such as avoidance. Given the importance of emotion-driven behaviors for the maintenance of psychopathology (Hershenberg et al., 2017; Robinaugh et al., 2020a), a better understanding of these associations and their putative change during therapy appears crucial (Eustis et al., 2020; Sønderland et al., 2023). Moreover, despite the promise of network analysis, only a few studies have so far applied this approach to elucidate change mechanisms active in psychotherapy. Curtiss et al. (2021) investigated networks estimated based on cross-sectional data before and after therapy, reporting changes in symptom co-occurrence. Furthermore, they showed that different types of treatment corresponded with different network structures, suggesting that mechanisms of change may differ.

Findings on temporal networks, which better capture mechanistic relationships between symptoms, also offer promising first results. A case study by Robinaugh et al. (2020a) described changes in temporal networks of disorder-related symptoms in two patients before and after therapy, demonstrating the potential of this method. A recent feasibility case study examined autocorrelations in heart rate variability (HRV) of seven patients assessed by fitness tracker over two-weeks during therapy (Hehlmann et al., 2021). Changes in the temporal dynamics of HRV varied considerably between patients, and results indicated associations between HRV inertia and anxiety, however, no pre-post comparisons were conducted in this study. In two other clinical studies on emotional disorders, symptom networks were established based on questionnaire data from therapy sessions. In the study of O'Driscoll et al. (2021), these networks of anxiety and depression items showed a high degree of connectedness among most symptoms, which was stable across sessions. Although their sample was large and highly representative, the data comprised only three to six assessments per patient. In contrast, in the study of Schumacher et al. (2023), data from 32 therapy sessions for depression were analyzed. They observed marked changes in lagged symptom associations (though no overall decrease in density) which differed depending on treatment (disorder-specific vs non-specific psychotherapy). In both studies, assessments were separated by long time intervals ($\geq$1 week or longer), thus networks were not informative regarding dynamics on a shorter time scale (e.g. processes that unfold within a single day). Therefore, it remains unclear whether decreases in network density can be found when taking into account more immediate symptom associations.

Epskamp et al. (2018) highlighted the importance of timing. For example, a patient with panic disorder may start sweating and experience heart palpitations which are immediately followed by increased anxiety, possibly prompting them to leave the situation quickly. If this patient reports on their symptoms only every few hours (a common EMA interval), such fast-paced relations could not be captured in a temporal network, where symptoms at one time point predict symptoms at a later time point. According to Epskamp et al. (2018), these associations between somatic arousal, anxiety, and avoidance might rather be reflected in significant connections in a contemporaneous network, which estimates associations within the same time point. A recent review discusses the advantages and disadvantages of different temporal design parameters in EMA studies (Seizer et al., 2024).

The present study used intensive longitudinal data collected in patients with anxiety to study potential changes in the coupling between negative emotions and avoidance behaviors observed before and after CBT, employing a network approach. Specifically, patients underwent transdiagnostic CBT focused on changing emotion-triggered reactive behavioral patterns (Barlow et al., 2017). Thus, we hypothesized sparser emotion-avoidance networks at post-treatment, indicating effective decoupling between negative emotions and avoidance as a putative mechanism of change. Our aims were threefold: 1) to assess concurrent and time-lagged associations between negative emotions (anxiety, depression, anger) and avoidance behaviors, 2) to investigate whether these resolved from pre- to post-treatment, reflected in a decrease in network density and, more specifically, avoidance centrality, and 3) to examine whether greater reductions in density and avoidance centrality were related to greater reductions in symptom severity (i.e., anxiety, depression, and mobility in everyday life). In addition, we tested whether we could replicate previous findings showing positive correlations between network density and avoidance centrality with symptom severity at baseline and explored moderation effects of baseline network metrics on symptom improvement.

## 2. Material and methods

### 2.1. Transparency and openness

We report all data exclusions, all measures used in this study, and we follow Journal Article Reporting Standards (JARS; Appelbaum et al., 2018). Data and analysis code are available on the Open Science Framework: https://osf.io/8my6x/. We analyzed data from a randomized controlled trial, which was pre-registered (https://clinicaltrials.gov/ct2/show/NCT03945617), and for which a study protocol with analysis plan was published (Müller-Bardorff et al., 2024). Data were processed and analyzed in R, version 4.3.2 (R Core Team, 2023). We used the R package 'mlVAR' (Epskamp et al., 2021) to set up mlVARs, 'qgraph' to visualize the observed associations as networks and to extract specific network metrics (Epskamp et al., 2012), and 'lme4' to construct linear mixed-effects models (LMEMs; Bates et al., 2015).

### 2.2. Participants

Patients were recruited from the public through a study website, newspaper articles, online platforms, mailing lists from public institutions, and flyers. Inclusion criteria were a primary diagnosis of DSM-5 anxiety disorder (Mini International Neuropsychiatric Interview; Sheehan et al., 1997; i.e., panic disorder with or without agoraphobia, generalized anxiety disorder, social anxiety disorder, anxiety disorder not otherwise specified, adjustment disorder with anxiety, adjustment disorder with mixed anxiety and depressed mood, specific phobia with severe impairment), age between 18 and 65 years, and fluency in German. Patients were excluded if they were currently undergoing concomitant psychotherapy, had a current or past diagnosis of a schizophrenia spectrum disorder or bipolar disorder, current suicidal ideation or acute suicidality, current substance or alcohol dependence or

**Table 1**
Sample characteristics ($N = 56$).

| Variable | | *n* | *M* | *SD* | *Range* |
|---|---|---|---|---|---|
| Sex | | | | | |
| | Female | 38 | | | |
| | Male | 17 | | | |
| | missing | 1 | | | |
| Age at admission | | | 33.31 | 12.45 | 18–60 |
| Diagnosis | | | | | |
| | SAD | 26 | | | |
| | GAD | 14 | | | |
| | PD/AG | 11 | | | |
| | SP | 4 | | | |
| | PD | 1 | | | |
| Comorbidity | | | | | |
| | yes | 44 | | | |
| | no | 12 | | | |
| Medication | | | | | |
| | none | 35 | | | |
| | somatic (+contraceptives) | 10 (+5) | | | |
| | AD | 4 | | | |
| | stimulants | 1 | | | |
| | benzodiazepines | 1 | | | |
| Education | | | | | |
| | Obligatory School | 1 | | | |
| | High School | 15 | | | |
| | Apprenticeship | 17 | | | |
| | University of applied sciences | 5 | | | |
| | University | 17 | | | |
| | missing | 1 | | | |
| Nationality | | | | | |
| | Swiss | 42 | | | |
| | European | 12 | | | |
| | Other | 1 | | | |
| | missing | 1 | | | |

| **Symptom severity** | **Baseline** | | | **Post** | | |
|---|---|---|---|---|---|---|
| | ***n (%)*** | ***M*** | ***SD*** | ***n (%)*** | ***M*** | ***SD*** |
| OASIS | 56 (100) | 9.04 | 3.39 | 56 (100) | 4.80 | 2.55 |
| ODSIS | 56 (100) | 4.20 | 4.70 | 56 (100) | 3.86 | 3.83 |
| BDI | 55 (98) | 16.45 | 10.91 | 56 (100) | 9.88 | 8.44 |
| MI (accompanied) | 46 (82) | 1.56 | 0.52 | 55 (98) | 1.37 | 0.44 |
| MI (alone) | 46 (82) | 2.07 | 0.71 | 55 (98) | 1.68 | 0.57 |
| **Ecological Momentary Assessments** | **Baseline** | | | **Post** | | |
| | ***n (%)*** | ***M*** | ***SD*** | ***n (%)*** | ***M*** | ***SD*** |
| Anxiety | 56 (100) | 20.69 | 13.64 | 56 (100) | 13.81 | 12.17 |
| Depression | 56 (100) | 27.26 | 18.16 | 56 (100) | 20.42 | 14.55 |
| Anger | 56 (100) | 11.87 | 9.68 | 56 (100) | 10.16 | 9.94 |
| Avoidance | 56 (100) | 13.83 | 10.67 | 56 (100) | 7.85 | 7.99 |

*Note.* SAD = social anxiety disorder; GAD = generalized anxiety disorder; PD/AG = panic disorder with agoraphobia; SP = specific phobia, PD = panic disorder; AD = antidepressants; OASIS = Overall Anxiety Severity and Impairment Scale; ODSIS = Overall Depression Severity and Impairment Scale; BDI = Beck Depression Inventory; MI = Mobility Inventory.

abuse, Cluster A or B personality disorder, or if there were any medical contraindications impeding thorough exposure (e.g., cardiovascular diseases or autoimmune diseases). A total of 95 patients participated in the study, however, the present analysis focused on data from the CBT group (n = 71) of which 56 provided EMA data at baseline and post-treatment. Simulations of power and sample size for paired comparisons with EMA data have shown that 45 participants should be sufficient to detect a small effect with above 80 % probability given at least 35 completed surveys at an alpha level of $\alpha = 0.05$ (Oleson et al., 2022). Details on demographic and clinical characteristics of our final sample are presented in Table 1. All patients who participated were remunerated with 120 Swiss Francs upon completing the final assessment.

### 2.3. Procedure

Initially, patients received information about study goals and procedures (Fig. 1). If interested, they underwent a telephone screening for inclusion and exclusion criteria. If eligible, they were invited to an in-lab assessment, which included a clinical interview to verify diagnostic status. Interviews were conducted by trained psychology graduate students under the supervision of psychological psychotherapists. Patients completed a battery of clinical questionnaires and other baseline assessments (for details see Müller-Bardorff et al., 2024). At the end, a smartphone application was installed on their mobile devices. Patients were instructed to use the application during 14 consecutive days to collect EMA on emotion and avoidance in this time period (see section below).

After baseline assessment, patients were randomly assigned to either CBT or waitlist group using the DatInf Randlist tool (Version 1.2). Data from the latter group are not presented here. Neither study therapists nor the study team had access to the randomization list. Patients who were randomized to CBT started treatment immediately following baseline assessment (including EMA). CBT treatment was conducted according to the Unified Protocol for Transdiagnostic Treatment of Anxiety Disorders (UP; Barlow et al., 2017) and comprised, on average, 16 sessions. The UP is a transdiagnostic CBT approach for emotional disorders that utilizes different modules such as emotional awareness training, cognitive reappraisal, identification of emotion-motivated avoidance, and exposures to reduce dysfunctional reactivity to emotions and emotion-motivated avoidant coping.

After treatment completion, participants were re-assessed with the same clinical questionnaires from the baseline assessment and completed another EMA for 14 days. All procedures were approved by the cantonal ethics committee of Zurich (BASEC-No. 2017–01443) and the study was carried out in accordance with the Declaration of Helsinki and the Good Clinical Practice (GCP) guideline.

### 2.4. Measures

#### 2.4.1. Ecological momentary assessments of negative emotions and avoidance

During the 14 days of assessments, patients received five prompts per day at block-randomized intervals between 10 am and 8 pm. Patients rated emotions and avoidance behaviors experienced within the past 30 min on a visual analogue scale, ranging from 0 (“*not at all*”) to 100 (“*as much as possible*”). By focusing on the past half-hour, we ensure more accurate ratings of emotions, which constitute transient states that may not be accurately captured if, e.g., participants are asked about the entire time since the last assessment. Each EMA self-report comprised 22 items in total. The present study specifically focuses on avoidance and three facets of negative affect. These comprise *anxiety* (“anxious”, “panicked”), *depression* (“depressed”, “joyless”, “exhausted”), and *anger* (“angry”, “irritable”). *Avoidance* was indexed by three behavioral items, “avoided activities”, “left situation due to anxiety”, and “avoided social contact”. Items for each construct were selected based on conceptual considerations, and composite scores were calculated as the mean across the respective items. The proposed factor structure was statistically validated through inspection of intercorrelations between items and multilevel confirmatory factor analysis based on pre-treatment data from the CBT group. The model was then tested on post-treatment data to verify measurement invariance across both time points. McDonald’s omega was calculated as a measure of internal consistency at the within- and between-person levels (Hayes & Coutts, 2020). Results for pre-treatment scores showed good internal consistencies with McDonald’s omega ranging between 0.90–0.91 at the between-person level and 0.65–0.77 at the within-person level (see Supplement 1 for details).

The smartphone application was based on MobileCoach (www.mobile-coach.eu), an open-source software platform for behavioral health interventions and data collection purposes (Filler et al., 2015; Kowatsch et al., 2017).

#### 2.4.2. Anxiety, depression, and avoidance severity

Before and after treatment, patients completed self-reports on symptom severity, as well as anxiety-related avoidance behaviors. We used the 5-item Overall Anxiety Severity and Impairment Scale (OASIS; Norman et al., 2006) to measure anxiety symptom severity, and the OASIS-derived 5-item Overall Depression Severity and Impairment Scale (ODSIS; Bentley et al., 2014) to measure depressive symptom severity. These scales assess the frequency and intensity of anxiety (OASIS) or depression (ODSIS), avoidance due to anxiety (OASIS) or depression (ODSIS), and impairment due to anxiety (OASIS) or depression (ODSIS). Both have been shown to have good to excellent internal consistency (ODSIS: $\alpha = .93$; Mira et al., 2019; OASIS: $\alpha = .86$ Norman et al., 2006) and good test–retest reliability (Ito et al., 2015; Norman et al., 2006). Internal consistency in our study was good to excellent (OASIS: $\alpha = .83$;

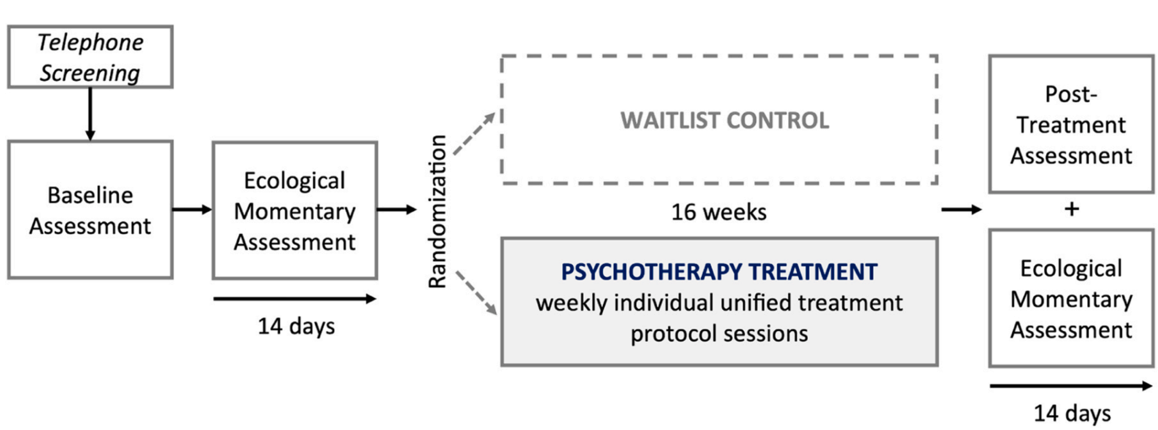


**Fig. 1.** Study procedure.

ODSIS: $\alpha = .95$). Both questionnaires instruct participants to rate each item on a scale ranging from 0 to 4 considering the last week, where higher sum scores indicate greater symptom severity and impairment.

Avoidance severity was assessed with the 27-item mobility inventory (MI; Ehlers et al., 2001), which focuses on avoidance of places (e.g., supermarket), modes of transport (e.g., bus), and situations (e.g., being at a party) due to anxiety or discomfort. Ratings are made on a scale from 1 (*never avoid*) to 5 (*always avoid*), with participants reporting both for when they are accompanied (MI-accompanied) and when they are alone (MI-alone). Mean scores are calculated separately for both scenarios. Internal consistency in our study was excellent (MI-accompanied: $\alpha = .93$; MI-alone: $\alpha = .92$).

### 2.5. Data analysis

First, we set up mlVARs to examine associations between EMA-derived negative emotions and avoidance behaviors within time points (contemporaneous associations) and from one time point to the next (temporal associations), separately at baseline and post-treatment. Due to its multilevel framework, the standard mlVAR model allows for investigations at the level of the group (fixed effects) and at the level of the individual (random effects). In our lag-1 model, each variable is regressed on the directly preceding values, both those of the other variables (cross-lagged effects) as well as its own (auto-lagged effects). In other words, the resulting estimates provide information about the extent to which one variable is predicted from all variables, including itself, at the previous assessment. Estimates of contemporaneous associations are obtained after controlling for all temporal effects. MlVARs generally assume that the mean and variance of the data is stable within the assessment period. We therefore conducted the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for stationarity (Kwiatkowski et al., 1992), implemented in the 'urca' package (Pfaff, 2008), for each variable and each individual separately, for both baseline and post-treatment data. Since the results indicated non-stationarity for some variables in some individuals (14.73 % on average at baseline and 12.05 % on average at post-treatment; see Supplement 2 for results per composite score), we decided to remove any trends in the data before running our mlVAR model to prevent biased parameter estimation (Rovine & Walls, 2006). We also constructed mlVARs without detrending to gauge its effects.

Second, for each participant, we extracted metrics of pre- and post-treatment network density and avoidance node centrality to quantify aspects of network structure. Density was calculated by summing the absolute values of the auto- and cross-lagged effects and dividing by the number of possible effects in the network (16 in our case). Density is useful to characterize a network as a whole but does not provide information about specific effects between selected variables (Bringmann et al., 2016). To examine effects of negative emotions on avoidance and vice versa, we extracted different centrality metrics specifically for the avoidance node. In particular, we calculated the sum of the absolute values of the incoming and outgoing edges, termed *instrength* and *outstrength*, respectively (Bringmann et al., 2016). While instrength provides information about the extent to which avoidance can be predicted by negative emotions (and avoidance) at the previous time point, outstrength reflects the effect avoidance has on negative emotions (and avoidance) at the next time point. We investigated whether the magnitude of negative emotion-avoidance associations decreased after therapy by analyzing change in network metrics from pre- to post-treatment. To this end, we constructed LMEMs with density, avoidance instrength, or avoidance outstrength as the dependent variable and time (with two levels – pre and post) as fixed effect.

Third, we analyzed pre-post changes in symptom severity and tested whether improvements in symptom severity were positively correlated with reduced emotion-avoidance associations. To assess whether patients showed significant reductions in symptom severity from before to after therapy, we set up four LMEMs, one each with the outcome of interest (OASIS, ODSIS, MI-accompanied, or MI-alone) as the dependent variable and with time as fixed effect. To explore whether greater reductions in symptom severity were linked to greater reductions in network metrics, we calculated pre-post change scores for each questionnaire (OASIS, ODSIS, MI) and for relevant network metrics (density, avoidance instrength, and avoidance outstrength). Change scores of symptom severity were then correlated with change scores of network metrics.

To determine whether we could replicate previous findings positively linking negative emotion network structure with symptom severity (Pe et al., 2015; Shin et al., 2022; Spiller et al., 2021), we examined correlations between baseline network metrics (density, avoidance instrength and avoidance outstrength) and baseline symptom severity scores (OASIS, ODSIS, MI-accompanied, MI-alone).

Finally, because so many studies have reported a positive association between negative emotion network density and symptom severity, and because emotion-motivated avoidance constitutes a central maintenance mechanism of psychopathology (Teachman et al., 2014), we conducted an additional exploratory moderation analysis. Specifically, we investigated whether network density and avoidance instrength at baseline would be predictive of the magnitude of reductions in symptom severity from before to after therapy. We set up separate LMEMs for each outcome (OASIS, ODSIS, or MI scores). Fixed effects included time, network metrics (density or avoidance instrength) assessed at baseline, and an interaction term for time with baseline network metric.

In all LMEMs, we included by-participant random intercepts and age and sex as covariates. Continuous predictors were z-standardized prior to their inclusion in any model. We generally checked for outliers, removed cases with extreme values (above the third quartile plus three times the interquartile range (IQR) or below the first quartile minus three times the IQR; Kassambara, 2023) and reported this in the results section.

## 3. Results

### 3.1. Ecological momentary negative emotion and avoidance behavior assessments

Overall, EMA completion rates were acceptable with well over half of the 70 surveys completed at baseline ($M = 46.61$, $SD = 12.44$, total data points: 2610) and post-treatment ($M = 41.00$, $SD = 13.45$, total data points: 2296 data points). One participant responded only four times at baseline and was therefore excluded from analyses. Table 1 shows descriptive statistics for anxiety, depression, anger, and avoidance reported at baseline and post-treatment. The individual time series for these variables at baseline and post-treatment are provided in the supplement (Supplementary Figure 1 and 2).

### 3.2. Associations between negative emotions and avoidance behaviors

We set up mlVARs to model contemporaneous and temporal relations between EMAs of negative emotions and avoidance behaviors at baseline and post-treatment. The group level results are visualized as networks in Fig. 2. The analysis revealed significant positive contemporaneous associations between negative emotions (anxiety, depression, anger) and between depression and avoidance both at baseline and post-treatment, albeit attenuated at the latter time point. There was a significant positive association between anxiety and avoidance at baseline, but not at post-treatment. Anger and avoidance were not associated within time point in either network. No significant edges emerged between anxiety and avoidance in the temporal networks, indicating that neither variable was predictive of the other. There were significant positive temporal relations between avoidance and depression at baseline, with edge weights showing a stronger prediction of avoidance by depression than vice versa. This bidirectional association was not found at post-treatment. No significant temporal associations were observed

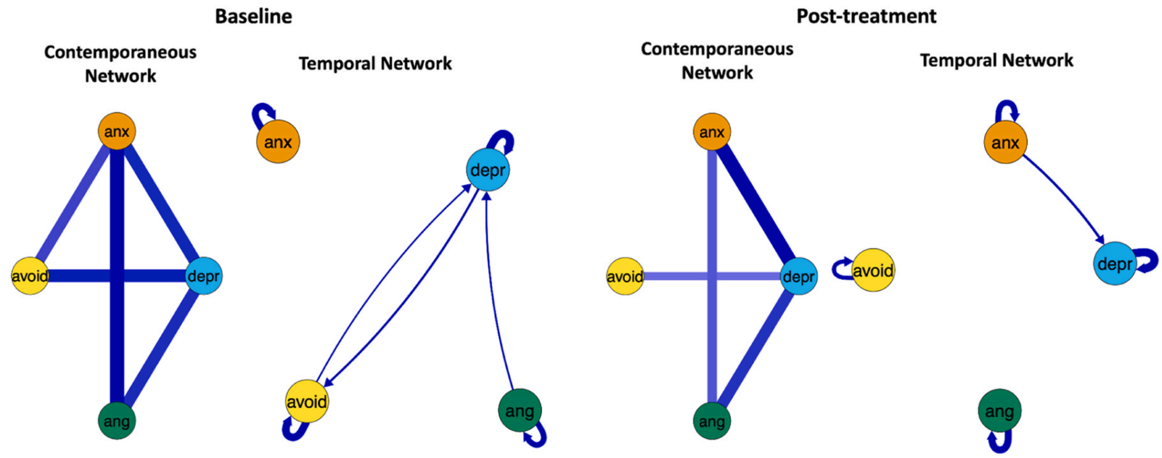


**Fig. 2.** Contemporaneous and temporal networks. *Note*. Significant group level associations between negative emotions and avoidance behaviors, visualized as networks, where variables are depicted as nodes connected by edges (blue = positive connections; red = negative connections). Associations between negative emotions and avoidance behaviors within time point (contemporaneous networks) are visualized as undirected edges. Time-lagged associations are shown in the temporal networks, where the cross-lagged effects are depicted as directed edges (arrows) from one node to the other and the auto-lagged effects as self-loops. The strength of the effect, the edge weight, is reflected in the thickness of the lines. Avoid = avoidance; anx = anxiety; depr = depression; ang = anger.

for the anxiety node at baseline; however, at post-treatment, anxiety positively predicted depression. Auto-lagged effects were smaller at post-treatment, especially for avoidance. The post-treatment temporal network was generally sparser compared to the baseline network. An analysis without detrending revealed the same networks.

### 3.3. Pre-post changes in network structure

We extracted network density as well as instrength and outstrength of the avoidance node from the estimated networks. A check for outliers by time point revealed a few extreme values, which were excluded from subsequent analyses (two in avoidance instrength at baseline, one in avoidance outstrength at baseline, and two in outstrength at post-

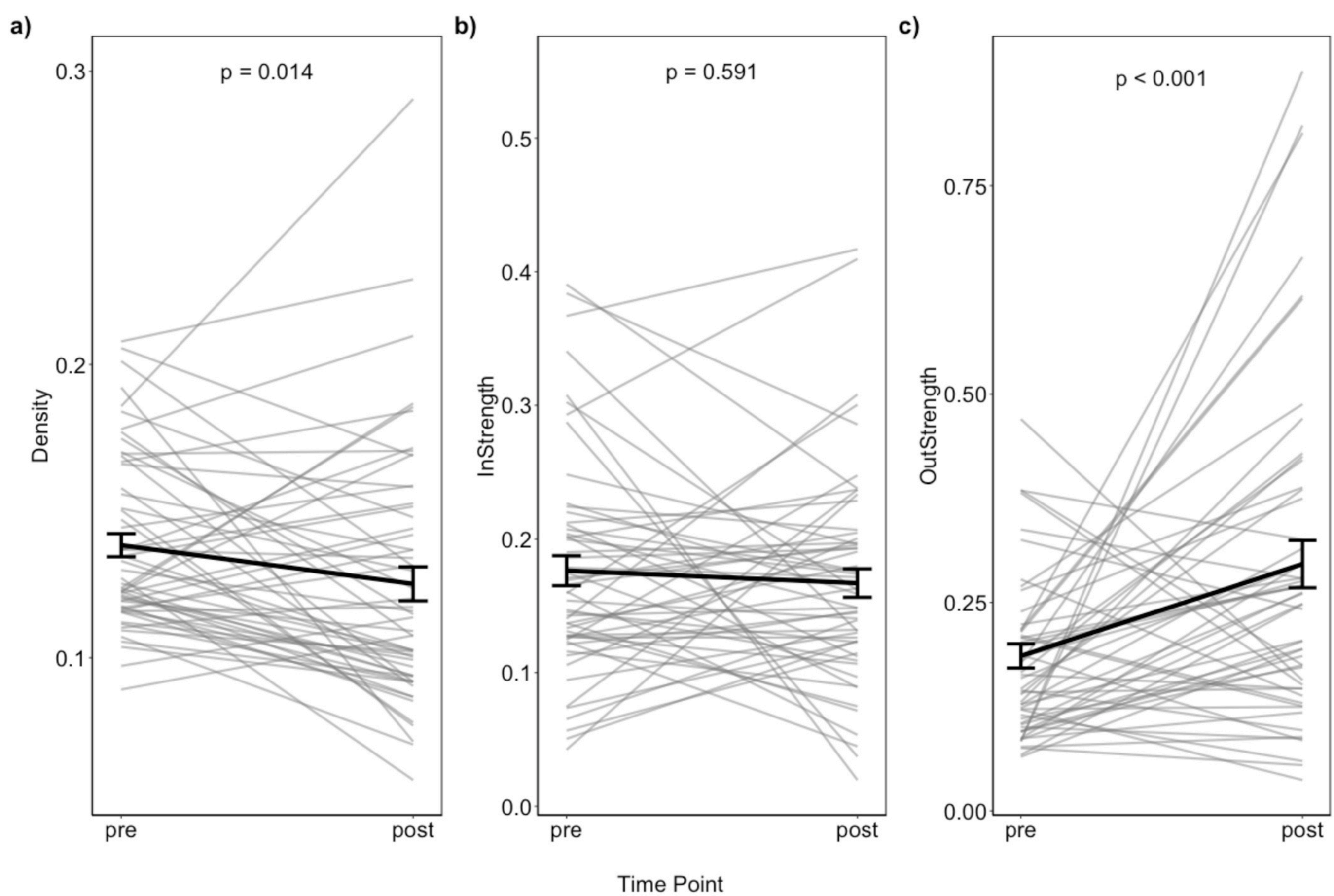


**Fig. 3.** Pre-post changes in network structure metrics. *Note*. Changes in network metrics from pre- to post-treatment: a) shows network density, b) avoidance instrength, c) avoidance outstrength. The sample mean is shown in black with error bars denoting standard error. Individual participant data are shown in gray.

treatment). As indicated in the network visualization, density was significantly reduced from pre- to post-treatment ($\beta = -0.01$, $t = -2.54$, $p = 0.014$). The average reduction in avoidance instrength was not statistically significant ($\beta = -0.01$, $t = -0.54$, $p = 0.591$). However, we observed a significant increase in avoidance outstrength from before to after therapy ($\beta = 0.11$, $t = 3.43$, $p < 0.001$). No significant effects of age or sex were found in any of these models. Changes in network structure metrics are shown in Fig. 3. Detailed model results are reported in Supplementary Tables 1–3.

### 3.4. Pre-post changes in symptom severity

A significant effect of time emerged in models assessing change in anxiety symptom severity ($\beta = -4.16$, $t = -9.01$, $p < 0.001$) and avoidance severity (MI-accompanied: $\beta = -0.20$, $t = -3.52$, $p < 0.001$; MI-alone: $\beta = -0.37$, $t = -4.38$, $p < 0.001$). As expected, participants reported significantly reduced anxiety and avoidance severity post-treatment, while change in depressive symptoms was not significant ($\beta = -0.18$, $t = -0.41$, $p = 0.686$), see Fig. 4 and the Supplementary Tables 4–7 for model details. We also conducted an additional analysis of the waitlist control group, confirming no change in symptom severity and avoidance severity in these patients (Supplementary Figure 5).

### 3.5. Associations Between Changes in Network Metrics and Changes in Symptom Severity

We examined whether the observed changes in network structure metrics were related to the changes in symptom severity in a correlation analysis using pre-post change scores (Fig. 5). Data checks revealed a few extreme values (one in MI-accompanied change scores, two in MI-alone change scores) which we removed before running the analyses. We used Spearman's rank correlation due to non-normally distributed data. Results showed that reductions in avoidance instrength were positively correlated with reductions in ODSIS scores ($r_s(54) = 0.31$, $p = 0.022$). This means that at the same time as negative emotions became less predictive of avoidance at the next time point, patients reported greater improvement in depressive symptoms. For decreases in OASIS scores, the finding was similar, though not statistically significant ($r_s(54) = 0.22$, $p = 0.112$). We observed a trend for a negative association between reduction in ODSIS scores and an increase in avoidance outstrength ($r_s(53) = -0.26$, $p = 0.059$), indicating a link between improvement in depressive symptoms and avoidance becoming more predictive of negative emotions. No significant correlations between change in network density and change in symptom severity were evident.

### 3.6. Correlations between network metrics and anxiety, depression and avoidance symptom severity at baseline

Because most scores were non-normally distributed, we employed Spearman's rank correlation, testing the strength and direction of monotonic associations between network metrics and symptom severity at baseline. Density correlated positively with OASIS ($r_s(56) = 0.28$, $p = 0.033$) and MI-alone scores ($r_s(46) = 0.30$, $p = 0.044$). There was also a positive, albeit statistically non-significant association between density and ODSIS scores ($r_s(56) = 0.26$, $p = 0.057$). Avoidance instrength was positively associated with OASIS ($r_s(54) = 0.37$, $p = 0.006$) and ODSIS scores ($r_s(54) = 0.41$, $p = 0.002$). Finally, avoidance outstrength correlated positively with OASIS ($r_s(55) = 0.33$, $p = 0.014$) and MI-alone scores ($r_s(45) = 0.39$, $p = 0.008$). There were no significant associations between network metrics and MI-accompanied scores (all $p > 0.05$). Supplementary Figure 3 visualizes correlations between network metrics and OASIS, ODSIS, and MI-alone scores at pre-treatment. Additionally, we show correlations at post-treatment in Supplementary Figure 4.

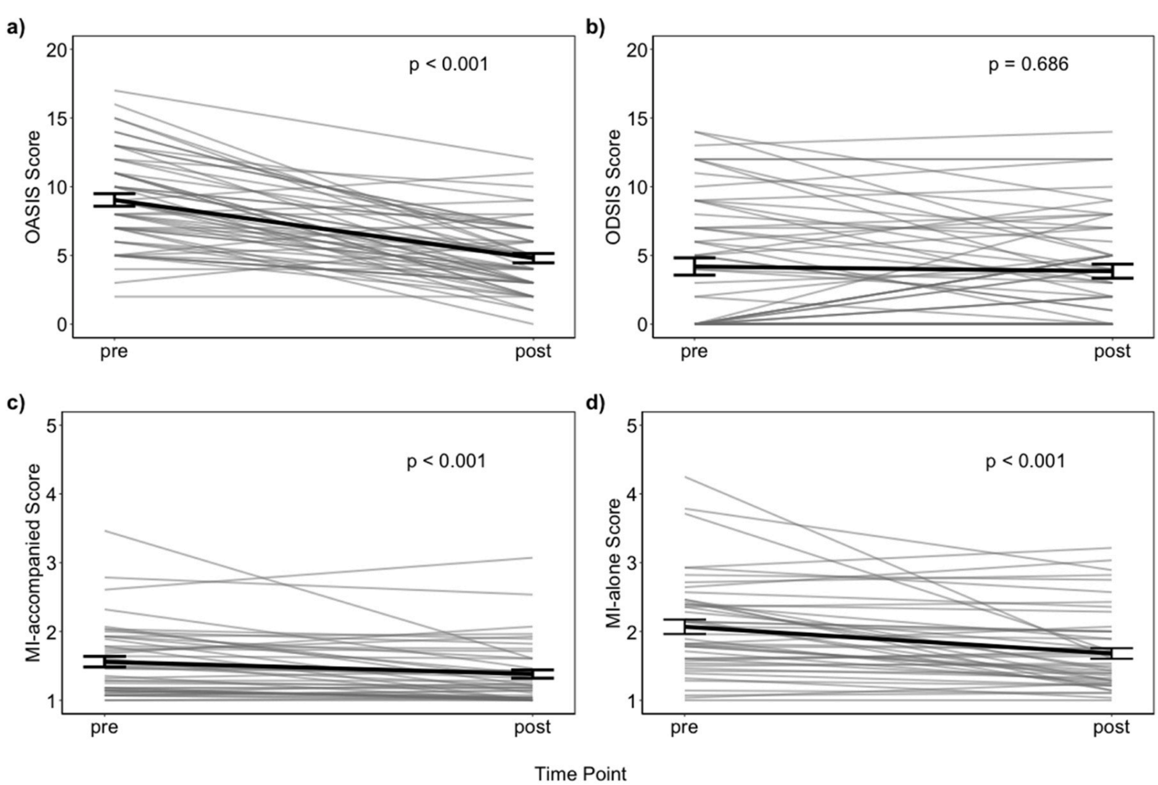


**Fig. 4.** Pre-post changes in symptom severity. *Note*. Changes in symptom severity from pre- to post-treatment for a) anxiety symptom severity (OASIS scores), b) depressive symptom severity (ODSIS scores), c) avoidance severity (MI-accompanied scores), d) avoidance severity (MI-alone scores). The group mean is shown in black with individual participant data shown in gray.

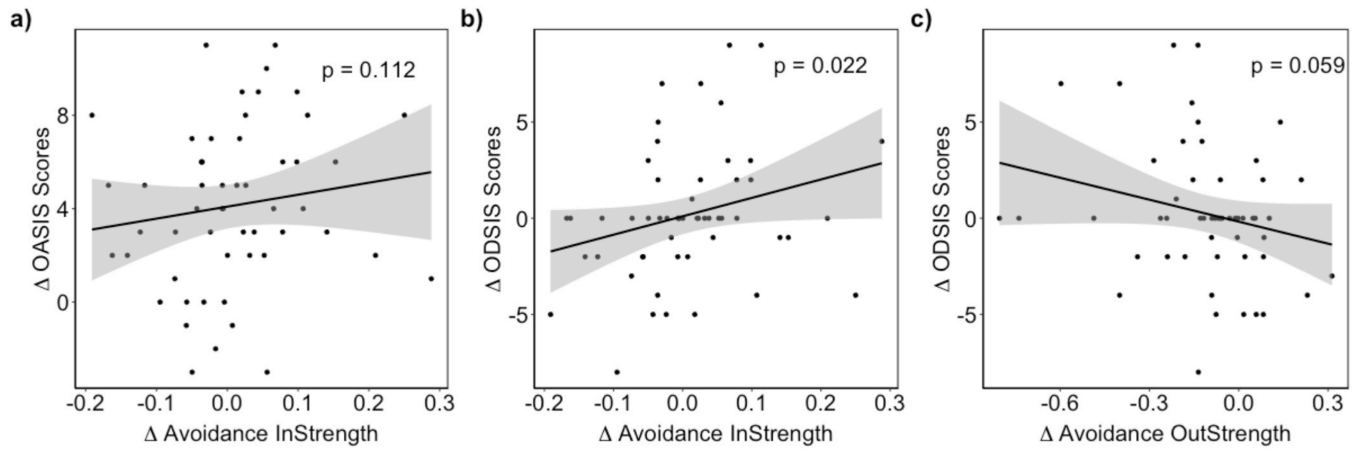


**Fig. 5.** Correlations between reduction in avoidance centrality and reduction in symptom severity. *Note.* a) change in avoidance instrength and OASIS scores, b) change in avoidance intstrength and ODSIS scores, c) change in avoidance outstrength and ODSIS scores. Change scores were calculated by subtracting post-treatment scores from baseline scores, a higher change score therefore reflects a greater decrease.

### 3.7. Network metrics as moderators of pre-post changes in symptom severity

In an exploratory analysis, we investigated whether baseline network density and avoidance instrength moderated pre-post change in symptom severity. There was a significant interaction effect of time and avoidance instrength on OASIS scores ($\beta = -0.92, t = -2.06, p = 0.044$; Supplementary Figure 6). When negative emotions were more predictive of avoidance behavior at baseline, patients showed greater symptom improvement. With regard to density, we observed only marginally significant interaction effects with time on OASIS scores ($\beta = -0.87$, $t = -1.94$, $p = 0.058$) and MI-alone scores ($\beta = -0.15$, $t = -1.88$, $p = 0.067$). See Supplementary Tables 8–10 for model details.

## 4. Discussion

The present study investigated putative mechanisms of change during CBT in anxiety patients by examining changes in emotion-avoidance networks based on EMA before and after therapy and potential associations with symptom improvement due to therapy.

As expected, network analyses of baseline assessments revealed significant positive contemporaneous associations between anxiety and avoidance as well as depression and avoidance. Results on temporal associations were less clear, however. Although we found a significant effect of depression on avoidance at the next time point, and vice versa, anxiety and anger did not appear to trigger or be predicted by avoidance at pre-treatment. The timing of assessments may at least partly explain non-significant associations (Epskamp et al., 2018). Possibly, anxiety exerted its effect on avoidance rather quickly, whereas effects of depression unfolded at later time points. Anxiety is primarily a state of heightened arousal and fear in response to perceived threats. It activates the "fight or flight" response, leading to swift behavioral changes aimed at avoiding danger (e.g., Barlow, 2002). Intervals between EMA prompts spanned roughly two hours. If patients' anxiety led them to avoid situations immediately, these effects would rather have been captured in the contemporaneous than the temporal network. Depression, on the other hand, is characterized by a state of low energy, lack of motivation, and anhedonia (American Psychiatric Association, 2013). Its effects on avoidance may occur more slowly, relating to withdrawal and inactivity due to feelings of hopelessness and low energy. Partly in line with our findings, Piccirillo and Rodebaugh (2022) also report temporal associations between depressed mood and avoidance, but not anxiety and avoidance, using three-hour intervals. Overall, more research is needed to better understand the timing of these symptom dynamics. Significant temporal auto-correlations for avoidance indicated the persistence of avoidant behavioral tendencies.

Given the lack of significant edges at either time point, it seems anger was not associated with avoidance behaviors in this sample. A previous study on experiential avoidance found no relations with outward or inward anger expressions (Kashdan et al., 2010). Anger is unique among emotions in that it can trigger both avoidance and approach motivation (Aarts et al., 2010). Many have rather linked it with approach behavior (Carver & Harmon-Jones, 2009; Robinson et al., 2016), which may explain the lack of connections. Although anger shares commonalities with fear, e.g., negative valence, it qualitatively differs from the other negative emotions studied here.

In line with our main hypothesis, but in contrast to previous studies that did not report clear reductions in symptom interactions (O'Driscoll et al., 2021; Schumacher et al., 2023), both contemporaneous and temporal networks were sparser at post-treatment. Significant reductions in network density suggested that negative emotions and avoidance behaviors were less interconnected after treatment. In accordance with our expectations, contemporaneous associations between anxiety and avoidance observed before treatment were no longer significant in the post-treatment network, while associations between depressive symptoms and avoidance had considerably weakened. Thus, after CBT, negative emotions had become decoupled from avoidance behaviors, perhaps indicating that patients had learned to tolerate negative emotions, and these no longer triggered avoidance. To confirm weakened effects of negative emotions on avoidance at the next time point and vice versa, we examined avoidance instrength and outstrength. Although instrength was on average lower at post-treatment, there was no statistically significant change in the effect of negative emotions on avoidance. Again, it is possible that the timing of assessments was not optimal to detect such effects. After therapy, avoidance outstrength was increased, indicating that avoidance more strongly predicted negative emotions. This was unexpected yet might be explained by patients' increased self-awareness of avoidance in their everyday life and knowledge of its negative long-term consequences. While, before therapy, many patients do not realize how many areas of their life are affected by avoidance, they likely acquire greater awareness through CBT. They may more critically evaluate their own behaviors so that reverting to old patterns at post-treatment and avoiding a situation perhaps triggers negative affect. The observed increase in avoidance outstrength may therefore reflect that patients are actively working towards resolving dysfunctional patterns. In support of this notion - and in line with recent evidence (Schaeuffele et al., 2024), results confirmed the effectiveness of the treatment. Patients' anxiety levels and their tendency to engage in avoidance when feeling anxious or uncomfortable decreased significantly from pre- to post-treatment (as did the EMA reports of avoidance behaviors).

As expected, network characteristics were related to psychopathology. At baseline, patients with denser negative emotion-avoidance networks reported higher levels of anxiety, depression, and avoidance severity. This is consistent with reports that more strongly connected negative emotion networks are positively linked with depressive symptoms (Lydon-Staley et al., 2019; Pe et al., 2015), burn-out symptom severity (Spiller et al., 2021), anxiety (Shin et al., 2022) and neuroticism (Bringmann et al., 2016). Going beyond these previous findings, we observed converging results for avoidance instrength which was positively associated with anxiety and depression. The more consistently negative emotions led to avoidance in patients' everyday lives the more anxious and depressed they felt before treatment. While the observed reduction in network density did not appear significantly correlated with improvement in symptoms, we could show that decreases in avoidance instrength were positively associated with decreases in depression severity. Concerning improvements in anxiety, results went in the same direction. These findings corroborate the assumption that CBT treatment reduces the reliance on avoidant emotion regulation in patients' everyday lives, thereby interfering with the central maintenance mechanism for psychopathology and improving symptoms (Barlow et al., 2021; Eustis et al., 2020; Teachman et al., 2014). Therapeutic interventions such as cognitive flexibilization and exposure might have contributed to loosening the coupling between symptoms, since they specifically aim at modifying dysfunctional reactivity to anxiety, sadness or anger (e.g., Wilamowska et al., 2010). Our sample consisted of patients with anxiety disorders, but many of them had comorbid depressive disorders and they underwent treatment according to the UP which has been shown to be efficacious in reducing both symptoms of anxiety and depression (Schaeuffele et al., 2024).

The exploratory moderation analysis showed that patients with the highest avoidance instrength scores at the outset showed the steepest reductions in anxiety. We did not have a specific a priori hypothesis regarding the direction of interactions, as either patients with the highest deficits at baseline (compensation model) or those with the least deficits (capitalisation model) might benefit most from treatment (Cheavens et al., 2012). Previous research with depressed individuals indicated that treatment approaches matched to individual strengths, not deficits, are more effective (Cheavens et al., 2012). Our findings in patients with anxiety are more in line with the compensation model, suggesting that treatment is most effective for patients with stronger initial impairment in emotion regulation. This may reflect a good match of treatment target (e.g., counteracting dysfunctional anxiety) to the difficulties these patients showed (e.g., emotion-motivated avoidance behaviors).

We acknowledge limitations of this work. First, our analysis did not include patients from the waitlist condition, therefore we cannot state with certainty that the observed pre-post changes in network structure are indeed caused by CBT treatment. Due to 3:1 randomisation into the treatment and control group, patients in the waitlist condition were too few to estimate stable networks for comparison with the treatment group. Future studies should include larger control groups to show that pre-post changes in network structure and their correlation with changes in symptom severity are specific to the treatment group. Such evidence would support the notion that the observed changes reflect a mechanism of recovery.

Second, timing factors critically impact temporal associations (Shin et al., 2022). In line with other EMA studies (e.g., Pe et al., 2015, 90 min; Shin et al., 2022, 90 min; Spiller et al., 2021, 120 min), the interval between two prompts spanned roughly two hours, and only emotions and avoidance experienced within 30 min before a prompt were reported. Thus, depending on the pace with which, e.g., avoidance followed negative emotions, associations might not have been captured in an optimal manner (e.g., captured as contemporaneous or not captured at all). Therefore, the temporal network analysis might have underestimated the full extent of time-lagged associations. This could explain why we did not find some of the expected effects, in particular a significant pre-post decrease in avoidance instrength. Nonetheless, with regard to the other pre-post comparisons, we did observe significant effects, indicating overall appropriate timing parameters.

Third, sample size and number of assessments would ideally have been larger for this type of analysis. Unfortunately, the onset of the COVID-19 pandemic hampered recruitment and data collection. Regarding the number of prompts, we considered the trade-off between sampling frequency and feasibility for the participants. However, some patients missed quite a few surveys and it could have helped to extend the assessment period, if not increase the number of prompts per day. A lower number of available consecutive assessments could also have affected estimation of temporal associations.

Finally, it must be noted that the strategy of how symptom nodes are formed and how the networks are estimated does affect the final results and to date there are no structured guidelines (Bringmann et al., 2022; Schumacher et al., 2022). Thus, the present study shares this limitation with other studies in this still growing research field.

Future studies should test whether our findings replicate in independent clinical samples. They may also assess cognitive forms of avoidance such as distraction, suppression and rumination (Eustis et al., 2020; Vanzhula et al., 2020), which we did not investigate, but which are common in mood disorders. We focused on behavioral avoidance, a primary target in CBT where exposure is a key component, as it can be readily observed and reported in EMA. To not overburden patients, we refrained from assessing cognitive aspects, but cognitions and appraisals should ideally be included to better understand their contribution to symptom dynamics. Moreover, research should consider idiosyncratic patterns in temporal networks to capture mechanisms of change at the level of the individual to help personalize and optimize treatment (Fisher et al., 2017; Robinaugh et al., 2020a). Since there is great variation in symptoms between patients (Piccirillo & Rodebaugh, 2022), person-specific networks might be useful to match treatment options according to individual needs. This could improve treatment and further clarify the interconnections between network dynamics, symptom improvement, and specific therapeutic interventions.

## 5. Conclusion

Our results underscore the potential of investigating change mechanisms active during therapy from the perspective of system theory, using intensive longitudinal data and network analyses. EMA data is useful for capturing processes in patients' everyday lives, beyond those that unfold during treatment sessions. By focusing not only on dynamic relations between different emotions but also on the associations between negative emotions and avoidance behaviors, we can advance research on symptom development in anxiety disorders. Our findings indicate that a loosening of negative emotion-avoidance networks may constitute a mechanism of change in psychotherapy that is related to improvement in clinical symptoms.

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## CRediT authorship contribution statement

**Birgit Kleim:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Aaron Fisher:** Writing – review & editing, Conceptualization. **Tobias Kowatsch:** Writing – review & editing, Software, Methodology, Conceptualization. **Isaac Galatzer-Levy:** Writing – review & editing, Conceptualization. **Tobias Spiller:** Writing – review & editing. **Ava**

**Schulz:** Writing – review & editing, Investigation. **Christina Paersch:** Writing – review & editing, Investigation. **Dominique Recher:** Writing – review & editing, Investigation, Data curation. **Miriam Müller-Bardorff:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation. **Laura E. Meine:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation.

## Declaration of Competing Interest

TK is affiliated with the Centre for Digital Health Interventions, a joint initiative of the Institute for Implementation Science in Health Care, University of Zurich, the Department of Management, Technology, and Economics at ETH Zurich, and the Institute of Technology Management and School of Medicine at the University of St. Gallen. Centre for Digital Health Interventions is funded in part by CSS, a Swiss health insurer. TK is also a cofounder of Pathmate Technologies, a university spin-off company that creates and delivers digital clinical pathways. However, neither CSS nor Pathmate Technologies was involved in this research. All other authors declare no conflict of interest.

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.janxdis.2024.102914.

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