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Emotion dynamics of clients with test anxiety before and after an imagery-based treatment☆,☆☆

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ABSTRACT

Background and objectives: Imagery-based techniques have become a promising means in the treatment of test anxiety (TA). Although previous studies have demonstrated the effectiveness of imagery-based treatment, not all clients seem to benefit from it. The present study compares clients' pre- as well as post-treatment emotion dynamics between responders and non-responders. Furthermore, it examines treatment-related changes in emotion dynamics in both subgroups.
Methods: The results are based on 44 clients suffering from TA who underwent a six-session imagery-based treatment and include Ecological Momentary Assessment (EMA). Emotions were assessed with the Profile of Mood States four times a day over the course of two weeks before and after the treatment. Temporal networks were computed to index emotion dynamics.
Results: Pre-treatment emotion dynamics differed between responders and non-responders. Similarly, post-treatment emotion dynamics differed as well between both groups. Some changes were also observed between pre-treatment and post-treatment networks: for responders, fatigue no longer predicted anger, and depression predicted itself; for non-responders, calmness predicted fatigue, anger, depression, contentment, and anxiety. In addition, fatigue no longer predicted itself and anxiety predicted vigor.
Limitations: The investigation is marked by several limitations: a liberal inclusion threshold of at least a 50% response to EMA prompts, and a relatively homogenous sample.
Conclusion: These results provide first evidence for the idea that emotion dynamics may be associated with response to treatment for TA. Furthermore, effective imagery-based treatments may be tied to changes within these dynamics.

Exams are an essential part of today's meritocracy, and often influence individuals' future success and career opportunities. It is therefore not surprising that test anxiety (TA) is a widespread phenomenon, especially among students. About 55% of students have experienced TA and roughly one quarter are affected by severe TA (see Hill & Wigfield, 1984; Holm-Hadulla et al., 2009). TA is characterized by negative thoughts about consequences of failure in exams or other evaluation-related situations. Its symptoms manifest in phenomenological (e.g., intense fear), physiological (e.g., hyper-activation of the hypothalamic-pituitary-adrenal axis), and behavioral (e.g., sleep disturbances) responses (Fehm & Fydrich, 2011; Morris & Liebert, 1970; Zeidner, 1998; Zeidner & Matthews, 2010).

Various approaches addressing TA have been developed. Evidence shows that it can be effectively reduced by treatments that include skill-focused and cognitive components. However, several researchers have noted the limitations of the existing approaches (e.g., Brown et al., 2011; Prinz et al., 2019). First, some of these techniques may be too time-consuming and therefore not feasible in an exam situation. Second, negative thoughts about consequences or failure can be a product of underlying negative emotional beliefs and dysfunctional schemas (e.g., defectiveness and shame).

One promising approach to overcome maladaptive emotional beliefs

☆ The protocol of this study was published in Prinz et al. (2016, 2019). Part of the data analyzed in this study were published in Prinz et al. (2021).☆☆ The datasets analyzed in the current study are available from the corresponding author on reasonable request.

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involve the emotion-focused technique of imagery. Imagery-based techniques, especially Imagery Rescripting (IR), reach the core of dysfunctional schemas. In this context, Reiss et al. (2017) provided first evidence for the utility of integrating imagery work with traditional cognitive-behavioral techniques for treating TA. Their results demonstrated a significant reduction in TA symptoms after students participated in a group intervention combining CBT and IR.

Motivated in part by the reviews showing greater efficacy for individual therapy over group programs in the treatment of TA (Ergene, 2003), Prinz et al. (2019) tested the effectiveness of an imagery-based 6-session treatment protocol addressing TA in individual therapy. The results of their multiple-baseline pilot study demonstrated that the protocol was well-accepted by clients, with TA levels dropping significantly from recruitment or baseline to delayed follow up.

Despite these promising results, imagery-based treatments (like most forms of psychotherapy) may be effective on average but are not necessarily equally effective for all clients. It is therefore important to try and isolate factors which could help identify individuals who are likely to respond well or poorly to these interventions. Indeed, the field of data-informed and measurement-based treatments (e.g., Lutz et al., 2021), which has emerged over the past decades, has sought to find predictors or decision-support tools that could go beyond mere clinical judgement. Data-informed and measurement-based treatments represent new methods for example based on network analyses to map contemporaneous and temporal associations of emotional experiences such as anxiety. This methodology is designed for person-specific associations (Fisher et al., 2017) and help to inform personalized recommendations which factors may be most therapeutically beneficial for a given client (Webb et al., 2022). Given the centrality of emotions to psychotherapy in general (and possibly even more so to imagery-based treatments in which emotional processing is key; Prinz et al., 2021; 2022), emotional factors may serve as likely candidates.

The rationale for using imagery as a therapeutic technique essentially lies in its powerful impact on emotions. Imagery has been found capable to activate the same emotional reactions as if the imagined scenario would be an actual experience (for reviews, see Holmes & Mathews, 2010; Ji et al., 2016). Importantly, emotions are dynamic, and fuller understanding of emotions requires attending to their dynamic and fluctuating nature using repeated measures over time (Kuppens et al., 2010). One way of investigating real-time emotional dynamics is Ecological Momentary Assessment (EMA). Notably, studies in the broader field of psychotherapy research have demonstrated that pre-treatment EMA data could be used to predict treatment response (e.g., Husen et al., 2016), generate idiographic treatment plans (e.g., Fisher et al., 2019), and explore clients' ability to differentiate between their emotions (e.g., Lazarus & Fisher, 2021).

To our knowledge, no study to date has explored emotion dynamics in TA, and doing so could prove quite fruitful. Contrary to its name, the syndrome of TA involves more than the single and isolated emotion of anxiety; rather, it appears to be a mixture of different emotions, both prospective and retrospective (Pekrun et al., 2004): fear of the consequences of failure, anger at educators, peers, or oneself; feelings of inferiority tied to failure experiences; shame at admitting poor performance to others; guilt over poor study habits or behaviors; but at times, also interest in one's chosen topic of studies, and hope for further development or immersion in a particular discipline. All these emotions are not active at the same time or with the same intensity; instead, they interact with each other and fluctuate in their intensity over time. Unique aspects of individuals' emotion dynamics may play some role in differential treatment responses among clients with TA, and acknowledging these may help with the early identification of likely responders and non-responders. Thus, the present is focused on the exploratory investigation of emotion dynamics in TA. More specifically, one aim of the present study is to test whether clients who responded or did not respond to imagery-based treatment addressing TA differ in their pre-treatment emotion dynamics.

A second aim of the present study is to examine changes in clients' emotion dynamics from pre- to post-treatment. Important hints about changes in emotion dynamics come from two recent studies. In one of these studies (van der Gucht et al., 2019), 61 stress clinic patients underwent a mindfulness-based intervention, reporting their current emotions using an EMA design with 40 prompts across four consecutive days before and after the intervention. Patients improved in positive as well as negative emotion differentiation from pre- to post-intervention. In another study, Houtveen et al. (2022) provided self-compassion training and analyzed dynamic symptom networks of eleven patients with somatic symptom disorder; patient-specific changes were observed after the training.

Though the present study differed in its treatment approach, we expected its imagery-based treatment to affect certain changes in emotion dynamics as well. Specifically, the treatment focuses, at least in part, on aversive memories, early learning experiences in which a child's subjectivity (incl. emotions, thoughts, and needs) were invalidated, trivialized, or dismissed by significant others. Such experiences leave memory traces of the events themselves but also affect a person's self-representation, and thus lead to self-concept and emotion regulation difficulties. Invalidation is likely to strengthen a self-critical voice which perceives certain emotions or needs as unacceptable, and which then generates subsequent (secondary) negative emotions whose objects are the primary emotions or needs. We expect that TA may be one result of such experiences and that these invalidations lead to specific emotion dynamics that still plague the client. Since imagery-based techniques directly focus on activating emotions and aims to change the balance of power between different aspects of the self, we would expect them to lead to significant changes in emotional experiences and dynamics after treatment.

One way of in which imagery-based treatments may exert their effect is by creating opportunities for corrective meta-emotional processing which strengthens the client's emotional self-acceptance (which echoes a point made by clinical theorists from a variety of approaches: e.g., Ellis, 1980, 2003; Gilbert, 2009; Hayes et al., 2006; for review, see Mancini & Mancini, 2018). Some evidence for the efficacy of addressing meta-emotional processing comes from an experimental study conducted with phobic individuals (Couyoumdjian et al., 2016), in which participants were asked to evaluate their own phobic reactions (e.g., How childish do you evaluate yourself?) and then rate their belief in this their evaluation. During the procedure the participants were exposed to the phobic target before and after undergoing an intervention tailored to reduce negative meta-emotional evaluations. Following this intervention, individuals showed reduced physiological fear responses to the feared stimuli in a follow-up exposure; a control condition showed no such reduction following mere re-exposure. In other words, changes in meta-emotional beliefs bring about changes in the emotions themselves.

In sum, though imagery-based treatments have been shown to be an effective treatment for test anxiety (e.g., Prinz et al., 2019; Reiss et al., 2017), not all clients benefit from them. The present study explores the idea that pre-treatment emotion dynamics – as well as changes in such dynamics over the course of treatment – may be associated with treatment response. It employs repeated multilevel vector autoregressive network analyses to index emotion dynamics, and is guided by the following research questions:

1. Are the average pre-treatment within-person emotion networks of clients about to receive imagery-based treatment for TA different for those who respond well and those who do not respond well to the treatment?
2. Do the two groups differ in their average *post*-treatment within-person emotion networks?
3. Finally, within each group, will we observe changes between the pre- and the post-treatment average within-person emotion networks?

1. Material and methods

1.1. Study overview

The sample consisted of students suffering from TA who had participated in an open-trial study between 2017 and 2020 at a university outpatient clinic in southwest Germany. The study investigated the effectiveness and underlying mechanisms of imagery-based techniques with an evidence-based six-session treatment protocol (Bar-Kalifa et al., 2019; Prinz et al., 2016, 2019). The treatment protocol is freely available at www.osf.io/hraqd. Previous analyses based the present sample (Prinz et al., 2021, 2022) had focused on psychophysiological data, and particularly on client-therapist physiological synchrony, rather than on clients' emotions.

Written informed consent was obtained. Clients were informed about the general aims of the study but were naïve regarding the specific hypothesis of this study. All clients were aware that completing the EMA questionnaires might bring aversive everyday events into focus and possibly lead to temporary increases in distress. They were aware that participation is voluntary and that they can stop treatment at any time for any reason and without negative consequences. Receiving the treatment was at no costs, and participation was not compensated in any way. This study was approved by the local research ethics committee.

Clients who consented to take part in the study underwent the first EMA burst which took place in the two weeks prior to treatment. The EMA burst consisted of emotional experience ratings four times a day (i.e., every 4 waking hours). Treatment started one day after the last EMA prompt, and included six weekly sessions. The second two-week EMA burst started at the beginning of the week following the last session. The follow-up assessment took place seven weeks after the second EMA burst.

1.2. Clients

Clients were included in the analyses when they (1) had a *Test Anxiety Inventory* (TAI; Spielberger, 1980) score higher than 54 (i.e., one standard deviation above the norming sample's average); (2) had no imminent risk for suicide; (3) were currently not in any other form of psychological treatment targeting test anxiety; and (4) responded to at least 50% of the EMA prompts both pre- and post-treatment. Ninety-two potential clients were screened for eligibility. Of these, seven were excluded because of TAI scores below threshold, and nine did not start treatment because of scheduling issues. Twelve additional clients dropped out during the treatment period. Thus, 64 clients completed the entire treatment. Of these, an additional 20 had to be excluded because of insufficient responses (i.e., <50%) to the EMA prompts either pre-partum or post-partum. Thus, our analyses were based on a sample of 44 clients (84% female). For more client information, see Table 1. The sub-group excluded for insufficient responses did not differ significantly from the remainder of the sample in terms of TAI intake scores ($t = 0.32$, $df = 62$, $p = .75$) though they do differ in follow up scores ($t = -2.62$, $df = 62$, $p = .01$). This is discussed below as a limitation.

1.3. Therapists, training, and supervision

Twenty-four therapists treated between one and four clients each ($M = 1.8$, $SD = 0.9$). Therapists were either psychotherapy trainees ($n = 6$) with an average experience of two years or masters' students in clinical psychology ($n = 18$), with no prior therapy experience. All therapists received intensive training in using the six-session protocol and were supervised by an experienced clinical psychologist.

1.4. Measures

1.4.1. Test anxiety

At recruitment and follow up, clients completed the TAI (Spielberger, 1980), a 20-item self-report measure. The items are answered on a 4-point Likert scale ranging from 1 (almost never) to 4 (almost always). All items can be aggregated to a total score. The TAI showed good internal consistency in our sample of $N = 44$ clients (pre-treatment: $\alpha = 0.79$; post-treatment: $\alpha = 0.93$). Pre-post scores were used to test for symptomatic change.

Table 1
Sample characteristics: Demographic and clinical variables.

Variables	Mean	Range
Client age (in years)	26.1	20–57
Academic year	5.2	1–16
	N	%
Marital status		
single	31	70.5
in relationship	11	25.0
married	2	4.5
Academic field		
Psychology	14	31.8
Law	7	15.9
Education	6	13.6
Business	4	9.1
Computer science	4	9.1
Other	9	20.5
Degree being pursued		
Bachelor	31	70.5
Masters	3	6.8
PhD	1	2.3
Other	9	20.5

1.4.2. Emotional experience

The adapted and shortened daily diary version (Cranford et al., 2006) of McNair et al. (1971) Profile of Mood States (POMS) is a self-report questionnaire consisting of 21 items, assigning seven subscales: Vigor, Anxiety, Depression, Anger, Fatigue, Content, and Calm. In two 2-week bursts (before and after treatment), clients were asked to rate the extent to which they had felt these feelings during the last 4 h, four times a day. They rated the intensity of each mood item on a five-point Likert scale (1 = "not at all", 5 = "extremely"). Clients received a reminder link via their email address, which was active for 2 h. The instruction and items are available at *https://osf.io/asqr9/*. As several authors have pointed out, there is no golden standard for the optimal EMA design (Hall et al., 2021; Janssens et al., 2018). To find a balance between high temporal resolution and response burden, we opted for emotional experience ratings 4 times a day, every 4 h (8 am, 12 pm, 4 pm, and 8 pm). This design is in line with previous studies on emotional experience (e.g., Husen et al., 2016). The between-person and within-person reliabilities for the subscales were computed using procedures outlined by Shrout and Lane (2012) and are presented in Table 2.

1.5. Analytic approach

1.5.1. Reliable change

To divide clients into responders and non-responders, we used the reliable change index (RCI; Jacobson & Truax, 1992) computed for the TAI. We used the standard deviation and the test-retest reliability reported for the norming sample (Spielberger, 1980) of college undergraduate students (women: SD = 13.7; men: SD = 12.43; $r_{tt} = 0.80$). Based on these figures, we obtained RCIs of 16.98 for women and 15.41 for men.

1.5.2. Network analysis

Temporal networks were used to investigate emotion dynamics. While contemporaneous networks solely show which emotions are associated at the same time, temporal networks allow to identify certain emotions which predict one another over time.

Table 2
Within-person and between-person reliabilities for each subscale pre- and post-treatment.

	Reliability index	Vigor	Anxiety	Depression	Anger	Fatigue	Content	Calm
Pre	Within	0.84	0.79	0.87	0.84	0.82	0.90	0.81
	Between	0.85	0.82	0.87	0.76	0.87	0.90	0.80
Post	Within	0.79	0.71	0.78	0.79	0.73	0.84	0.73
	Between	0.77	0.73	0.75	0.68	0.77	0.80	0.79

Analyses were done using R 4.1.0 (R Core Team, 2021). The R package mlVAR (v0.4.4; Epskamp et al., 2021) was used to estimate the networks for responders and non-responders before (pre) and after (post) imagery-based treatment. The seven subscales of the POMS (i.e., Vigor, Anxiety, Depression, Anger, Fatigue, Content, and Calm) were set as the variables (i.e., nodes) in the network models. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were performed for each client and variable to check for stationarity. For all four networks (responders/non-responders x pre/post), the model settings were identical. Correlated random effects were estimated. To address the nested structure of the data with assessments nested within days and within clients, the multilevel models ensured that the last measurement of a day did not predict the first measurement of the next day and that non-consecutive assessments were treated as missing. A stability check was performed following the procedure by Blanchard et al. (2023) and Jongeneel et al. (2020). A description of the procedure can be found in the supplemental materials.

We used the R package mnet (v 0.1.0; Haslbeck, 2023; Haslbeck et al., 2023) to investigate whether the networks differ significantly in four comparisons (2 responses: responders vs. non-responders × 2 time points: before vs. after treatment). The package allows modeling group differences in longitudinal network models and uses a permutation test to compare two multilevel VAR models estimated on two nested datasets. The permutation test estimates the null distribution of a test statistic by permuting the observations and calculating the test statistic for each permuted dataset. In our study, the test statistic was the difference between the edge weights of the multilevel VAR models for the two nested datasets (e.g., responders vs. non-responders before treatment). We used 1000 permutations per comparison. The package randomly assigns each observation to one of the two groups for each permutation and estimates the multilevel VAR models on the permuted data sets. The difference between the estimated parameters of the models for the two permuted data sets is then calculated and stored. After performing all permutations, the function compares the observed difference in edge weights to the distribution of differences calculated from the permuted data sets. The p-value is calculated as the proportion of permuted differences greater than or equal to the observed difference.

2. Results

Overall, 3853 data points out of the 4926 possible data points (44 clients × 14 days × 4 times a day × 2 EMA bursts) were available. Clients answered an average of 46.7 (range: 31 to 55) pre-treatment and 41.0 (range: 29 to 55) post-treatment EMA prompts. Because the last measurement of a day did not predict the first measurement of the next day and nonconsecutive assessments were treated as missing, the regressions in the temporal network models from one time point to the next were based on 2370 data points with an average of 30.1 (range: 16 to 41) pre-treatment and 23.8 (range: 8 to 41) post-treatment EMA prompts per client. The descriptive statistics of the emotion measures for responders and non-responders at pre- and post-treatment can be found in the supplemental materials (Table S5). Applying the criterion of ±1 for skewness and kurtosis (Meyer et al., 2016) indicating a non-normal distribution, 3 of 7 emotion items (i.e., anger, depression, anxiety) were not normally distributed. The results of the stability check can be found in the supplemental materials (Table S6) and were in support of the stability of the network edge weights.

2.1. Reliable change

Based on the RCI indices, 20 clients remained unchanged (effect size from recruitment to follow-up: $d = 0.45$), and 24 clients experienced positive reliable change from recruitment to follow-up (effect size: $d = 0.86$). No clients deteriorated.

Hypothesis 1. Pre-Treatment Temporal Emotion Dynamics in Responders versus Non-Responders

Fig. 1 (panels A and B) presents the pre-treatment temporal networks for responders and non-responders, respectively. Responders who were more anxious at time t−1 were less calm and more depressed at time t; those who were more fatigued at time t−1 were more anxious and angry at time t; and a negative association was found between calmness at time t−1 and fatigue at time t. Furthermore, six auto-regressive associations were found for fatigue, anger, contentment, anxiety, vigor, and calmness. Non-responders, who were more anxious at time t−1 were less calm at time t; those who were more fatigued at time t−1 were less vigorous at time t; and those who were angrier at time t−1 were more depressed at time t. In addition, a positive association was found between depression at time t−1 and anxiety at time t, as well as seven auto-regressive associations for fatigue, anger, depression, contentment, anxiety, vigor, and calmness.

While the networks of both groups appear different at first sight, only one edge differed significantly (see Table 3, which compares edges from the temporal emotion networks of responders and non-responders at pre-treatment; only edges that were found to be significant in at least one group are shown). Non-responders who were more fatigued at time t−1 were less vigorous at time t.

Hypothesis 2. Post-Treatment Temporal Emotion Dynamics in Responders versus non-Responders

Fig. 1(panels C and D) presents the post-treatment temporal networks for responders and non-responders, respectively. Responders who were calmer at time t−1 were less fatigued and more content and vigorous at time t. In addition, six auto-regressive associations were found for fatigue, depression, contentment, anxiety, vigor, and calmness. Non-responders, who were more anxious at time t−1 were less fatigued and more vigorous at time t; those who were calmer at time t−1 were less depressed, anxious, and fatigued and more content at time t. In addition, three auto-regressive associations were found for fatigue, anger, and calmness.

Again, though the networks of both groups appear quite different at first sight, only one edge differed significantly (see Table 4). Although for both responders and non-responders the association between fatigue and anxious was not significant, non-responders were significantly less anxious at time t, when they were more fatigued at time t−1 and vice versa.

Hypothesis 3a. Pre- versus Post-Treatment Temporal Emotion Dynamics in Responders

Among responders, the pre-treatment association between time t−1 fatigue and time t anger was no longer significant at post-treatment. Instead, at post-treatment, responders show an auto-regressive association for depression (see Table 5).

Hypothesis 3b. Pre- versus Post-Treatment Temporal Emotion Dynamics in Non-Responders

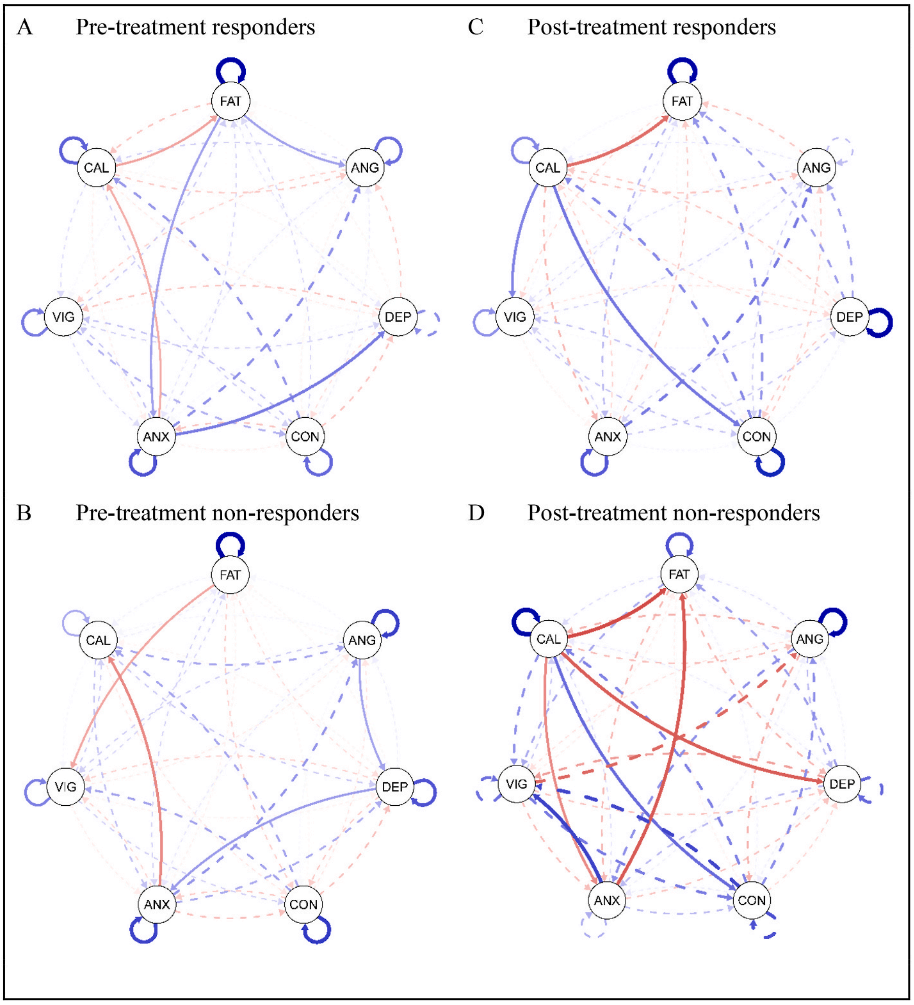

Fig. 1. Responders' and Non-Responders' Temporal Emotional Networks Pre- and Post-Treatment. Blue paths indicate positive and red paths indicate negative edges. Only significant edges are displayed, with thicker edges indicating stronger associations. All edge weights are provided in the online supplement and are available at *https://osf.io/asqr9/*. FAT = fatigue, ANG = anger, DEP = depression, CON = content, ANX = anxiety, VIG = vigor, CAL = calm.

Table 3
Difference Edge Weights and p-Values from the Permutation Test Comparing Temporal Emotion Networks of Responders and Non-Responders at Pre-Treatment.

	Vigor $_{t-1}$	Anxiety $_{t-1}$	Depression $_{t-1}$	Anger $_{t-1}$	Fatigue $_{t-1}$	Content $_{t-1}$	Calm $_{t-1}$
Vigor $_t$	−0.01	−0.13	0.02	0.12	**−0.13**	0.05	−0.03
	(p = .924)	(p = .229)	(p = .874)	(p = .084)	**(p = .040)**	(p = .626)	(p = .604)
Anxiety $_t$	−0.07	0.02	0.13	0.00	−0.07	0.01	0.10
	(p = .303)	(p = .876)	(p = .286)	(p = .984)	(p = .292)	(p = .894)	(p = .090)
Depression $_t$	−0.07	−0.07	0.08	0.12	−0.07	−0.01	0.09
	(p = .382)	(p = .474)	(p = .494)	(p = .237)	.313	(p = .956)	(p = .166)
Anger $_t$	−0.02	−0.01	0.09	0.06	−0.13	−0.06	0.19
	(p = .812)	(p = .940)	(p = .509)	(p = .521)	(p = .070)	(p = .670)	(p = .098)
Fatigue $_t$	−0.01	−0.07	0.00	0.01	0.00	−0.05	0.16
	(p = .906)	(p = .499)	(p = .981)	(p = .869)	(p = .973)	(p = .601)	(p = .076)
Content $_t$	−0.05	−0.07	−0.02	0.02	−0.06	0.06	−0.09
	(p = .614)	(p = .529)	(p = .800)	(p = .772)	(p = .396)	(p = .596)	(p = .183)
Calm $_t$	0.06	−0.05	0.00	−0.05	0.10	−0.02	−0.10
	(p = .510)	(p = .620)	(p = .983)	(p = .472)	(p = .215)	(p = .839)	(p = .187)

Note. The variables in the columns at time t−1 predict the variables in the rows at time point t. Significant differences between both groups appear in **bold**.

Pre-treatment, a negative association was found between t−1 anxiety and t calmness. In addition, time t−1 fatigue was predictive of time t vigor. These associations were no longer significant at post-treatment. At post-treatment, non-responders who were calm at time t−1 were less fatigued, less depressed, and more content at time t. Again, a difference was significant, although the association was not significant in either the pre or post-treatment network. While calmness at time t−1 tended to be positively associated with anger at time t at pre-treatment, at post-treatment, the trend was reversed. Additionally, at post-treatment, those who were more anxious at time t−1 were more vigorous at time t. Finally, the positive pre-treatment auto-regressive association for fatigue became weaker at post-treatment (see Table 6).

Table 4
Difference Edge Weights and p-Values from the Permutation Test Comparing Temporal Emotion Networks of Responders and Non-Responders at Post-Treatment.

	Vigor $_{t-1}$	Anxiety $_{t-1}$	Depression $_{t-1}$	Anger $_{t-1}$	Fatigue $_{t-1}$	Content $_{t-1}$	Calm $_{t-1}$
Vigor $_t$	0.00 (p = .993)	0.13 (p = .242)	−0.07 (p = .493)	−0.06 (p = .520)	0.13 (p = .078)	0.11 (p = .415)	−0.05 (p = .596)
Anxiety $_t$	−0.05 (p = .618)	−0.13 (p = .269)	0.02 (p = .827)	0.10 (p = .300)	**−0.16** **(p = .031)**	0.02 (p = .844)	−0.03 (p = .734)
Depression $_t$	−0.06 (p = .639)	−0.12 (p = .364)	−0.18 (p = .124)	0.07 (p = .532)	−0.06 (p = .487)	−0.05 (p = .604)	−0.12 (p = .294)
Anger $_t$	−0.20 (p = .113)	−0.15 (p = .224)	−0.10 (p = .410)	0.17 (p = .160)	0.01 (p = .876)	0.17 (p = .144)	0.01 (p = .927)
Fatigue $_t$	−0.06 (p = .596)	−0.10 (p = .303)	−0.02 (p = .823)	0.10 (p = .262)	−0.16 (p = .091)	−0.12 (p = .344)	0.01 (p = .904)
Content $_t$	0.06 (p = .565)	0.05 (p = .635)	0.08 (p = .359)	−0.13 (p = .124)	0.00 (p = .955)	−0.11 (p = .383)	−0.03 (p = .771)
Calm $_t$	0.04 (p = .626)	0.08 (p = .467)	0.09 (p = .406)	−0.11 (p = .181)	0.02 (p = .766)	−0.03 (p = .790)	0.09 (p = .356)

Note. The variables in the columns at time t−1 predict the variables in the rows at time point t. Significant differences between both groups appear in **bold**.

Table 5
Difference Edge Weights and p-Values from the Permutation Test Comparing Pre- and Post-Treatment Temporal Emotion Networks within Responders.

	Vigor $_{t-1}$	Anxiety $_{t-1}$	Depression $_{t-1}$	Anger $_{t-1}$	Fatigue $_{t-1}$	Content $_{t-1}$	Calm $_{t-1}$
Vigor $_t$	−0.04 (p = .631)	−0.02 (p = .857)	0.05 (p = .638)	0.09 (p = .158)	−0.06 (p = .523)	0.00 (p = .968)	0.11 (p = .169)
Anxiety $_t$	−0.06 (p = .498)	−0.02 (p = .858)	0.04 (p = .722)	−0.02 (p = .796)	−0.04 (p = .417)	0.08 (p = .611)	−0.07 (p = .493)
Depression $_t$	−0.05 (p = .600)	−0.12 (p = .080)	**0.17** **(p = .021)**	−0.01 (p = .913)	−0.04 (p = .605)	0.10 (p = .427)	−0.02 (p = .860)
Anger $_t$	0.05 (p = .747)	0.01 (p = .854)	0.18 (p = .158)	−0.12 (p = .157)	**−0.13** **(p = .018)**	−0.08 (p = .622)	0.00 (p = .984)
Fatigue $_t$	−0.02 (p = .787)	−0.11 (p = .262)	0.13 (p = .085)	−0.07 (p = .313)	−0.03 (p = .767)	0.09 (p = .385)	−0.06 (p = .409)
Content $_t$	−0.04 (p = .699)	0.03 (p = .778)	−0.02 (p = .853)	0.07 (p = .277)	−0.01 (p = .933)	0.07 (p = .596)	0.11 (p = .129)
Calm $_t$	0.01 (p = .940)	0.06 (p = .517)	−0.06 (p = .472)	−0.03 (p = .648)	0.09 (p = .417)	0.01 (p = .933)	−0.06 (p = .548)

Note. The variables in the columns at time t−1 predict the variables in the rows at time point t. Significant differences between both groups appear in **bold**.

Table 6
T- and P-Values from the Permutation Test comparing Pre- and Post-Treatment Temporal Emotion Networks within Non-Responders.

	Vigor $_{t-1}$	Anxiety $_{t-1}$	Depression $_{t-1}$	Anger $_{t-1}$	Fatigue $_{t-1}$	Content $_{t-1}$	Calm $_{t-1}$
Vigor $_t$	−0.04 (p = .804)	**0.24** **(p = .016)**	−0.04 (p = .635)	−0.09 (p = .334)	**0.21** **(p = .028)**	0.06 (p = .541)	0.10 (p = .102)
Anxiety $_t$	−0.04 (p = .695)	−0.18 (p = .098)	−0.07 (p = .497)	0.08 (p = .375)	−0.12 (p = .184)	0.09 (p = .363)	**−0.20** **(p < .001)**
Depression $_t$	−0.04 (p = .754)	−0.17 (p = .097)	−0.09 (p = .385)	−0.06 (p = .561)	−0.03 (p = .664)	0.05 (p = .701)	**−0.23** **(p < .001)**
Anger $_t$	−0.13 (p = .113)	−0.13 (p = .279)	−0.01 (p = .894)	−0.01 (p = .949)	0.02 (p = .822)	0.15 (p = .076)	**−0.18** **(p = .009)**
Fatigue $_t$	−0.07 (p = .526)	−0.15 (p = .061)	0.11 (p = .192)	0.02 (p = .789)	**−0.18** **(p = .049)**	0.02 (p = .841)	**−0.20** **(p < .001)**
Content $_t$	0.07 (p = .515)	0.15 (p = .160)	0.08 (p = .460)	−0.09 (p = .183)	0.05 (p = .606)	−0.10 (p = .297)	**0.18** **(p = .001)**
Calm $_t$	−0.01 (p = .918)	0.20 (p = .144)	0.03 (p = .742)	−0.09 (p = .516)	0.01 (p = .888)	0.00 (p = .989)	0.13 (p = .196)

Note. The variables in the columns at time t−1 predict the variables in the rows at time point t. Significant differences between both groups appear in **bold**.

2.2. Additional analyses

To interpret responders' and non-responders' pre and post-treatment network associations, all edge weights are listed in the online supplement https://osf.io/asqr9/. The significant non-autoregressive edges range between 0.12 and −0.19, indicating small effect sizes. The significant autoregressive edges range between and 0.20 and 0.36.

3. Discussion

The present study examined emotion dynamics of clients suffering from TA before and after a six-session imagery-based treatment. We aimed to investigate whether the temporal emotion networks of responders differed from those of non-responders either pre- or post-treatment. We also sought to determine whether either group's post-treatment networks differed from their respective pre-treatment networks. Emotion dynamics were assessed using high frequency data collection (four times a day, every 4 h, over the course of two 2-week bursts). Due to the exploratory nature of the study and the preliminary results, the findings must be interpreted with caution and require further elaboration. However, we would like to discuss some possible interpretations.

Our first research question was whether the average pre-treatment within-person emotion network of clients about to receive imagery-based treatment for TA differs between those who respond well and those who do not respond well to the treatment. As expected, responders showed different pre-treatment emotion dynamics compared to non-responders. Surprisingly, however, this difference was only significant for one association. Non-responders who were more fatigued at time t−1 were less vigorous at time t, a pattern not present among responders. This finding that non-responders report less vigor after feeling fatigue might indicate that they tend to deal differently with the experience of fatigue, possibly ignoring the feeling (or their need), not taking a break and are therefore less vigorous at the next time point.

Our second research question was whether the two groups differ in their average *post*-treatment within-person emotion networks. Again, only one significant difference was found and surprisingly for the association between fatigue and anxiety, which was neither significant for responders nor non-responders. Non-responders who were more fatigued at time t−1 were less anxious at time t. This pattern was significantly different compared to responders. It is possible that non-responders tend to ignore or suppress their anxiety in association with fatigue. However, no conclusions about the frequency of emotions can be drawn from the networks themselves. The fatigue-anxiety link might not be found in responders, because their test anxiety was reduced by the treatment. Low ratings with little variability make the detection of significant effects nearly impossible.

Our third research question was whether within-group changes in emotion dynamics occur between pre- and post-treatment. Among responders, the temporal association between fatigue and anger was no longer significant at post-treatment, and those who were more depressed at time t−1 sustained this feeling at time t. We believe this differentiation between fatigue and anger is adaptive and may reflect improved emotion regulation in treatment responders following treatment. Improved emotion regulation may also be indicated by the emergence of a positive auto-regressive association for depression. A positive response to the treatment provided is characterized by an increase in the acceptability and flexibility of certain emotions – particularly, depression. As a result of effective validation and/or emotion processing, responders may be better able to distinguish between emotions, not ignoring them but accepting them. Methodologically, the findings regarding negative emotions (e.g., anger) may be attributable to low ratings that lacked variability. The lack of variability might be due to floor effects where the scale prevents differentiation among observations at its lower end. However, it is plausible that participants may not frequently experience these negative emotions, leading to a skewed distribution. Therefore, the results should be interpreted cautiously, as skewed items could impact the entire network.

Surprisingly, the differences between the pre-treatment and post-treatment emotion networks of non-responders were quite considerable. The negative temporal association between anxiety and calmness as well as the one between fatigue and vigor at pre-treatment was no longer significant at post-treatment. Additionally, the strong auto-regressive association for fatigue became weaker at post-treatment. Instead, negative temporal associations emerged between calmness and fatigue, depression, and anxiety. Furthermore, positive temporal associations between calmness and contentment as well was anxiety and vigor emerged. We speculate that non-responders were less stable in their emotional experience and therefore show more emotional dynamics. Although non-responders did not show a reliable change in their test anxiety at the end of treatment, they may still have implemented techniques from the treatment. The findings that more calmness at time t−1 was associated with less fatigue, anger, depression, and anxiety as well as more contentment at time t may result from the effective use of some of the treatment techniques taught and practiced in the therapy (e.g., safe-place imagery).

3.1. Implications and future directions

To our knowledge, this is one of only a handful of studies to investigate emotion dynamics before and after treatment, and the first to do so in the context of test anxiety. Given the exploratory nature of the study, the results must be interpreted with caution. Adopting this design may help improve the effectiveness of treatments by highlighting particular inter-affect associations that may call for targeted interventions and support treatment personalization (Lutz et al., 2021), and also by identifying potential non-responders before treatment.

With respect to the goal of finding specific targets for intervention, the positive association between fatigue and anger at pre-treatment for responders, which was no longer significant at post-treatment, might suggest that our treatment somehow targets the fatigue-anger link. In contrast, the positive association observed among non-responders between fatigue and vigor at pre-treatment might serve as a worthwhile target for more effective interventions.

With respect to the early and reliable identification of potential non-responders, analyses such as those reported here may make it possible to adapt treatments to the specific client's needs, or to alert both the clinician and the client that other courses of treatment may be more appropriate. We suggest that the network approach is highly suitable for addressing these aims. Additionally, network approaches help consider psychological phenomena (e.g., emotions) as a set of interacting and reinforcing constructs, thus providing an alternative to monocausal approaches to mental disorders (Bringmann et al., 2022). Indeed, several authors have demonstrated the potential of drawing personalized intervention recommendations (Rubel et al., 2018; Howe et al., 2020), and predicting dropout (Lutz et al., 2018) from network analyses.

Alongside its strengths, this investigation is also marked by several noteworthy limitations. First, the inclusion threshold (of at least a 50% response rate to EMA prompts) is quite liberal, but still led to considerable data loss. In particular, clients were less likely to respond to post-treatment EMA prompts, presumably because they had little incentive to do so now that treatment was over. Because we wanted full pre- and post-treatment data for all, this meant much pre-treatment data was lost as well. Had we set the threshold at even higher rate, we would have lost even more data, but more importantly, may have biased the sample to include only the most conscientious or perfectionistic participants. Future studies should include incentive structures that increase post-treatment response.

A second limitation of the study is its reliance on a relatively homogenous sample, treated with a specific imagery-based treatment protocol. This limits the generalization of the results to other treatments. Replication and extension studies are needed.

Finally, even though VAR-based networks offer the potential of mapping individual network structure, their reliability and validity remain uncertain and they have to be interpreted with caution (for more limitations of VAR-based networks, see Bringmann, 2021). Furthermore, the use of temporal networks (in this study) must be discussed critically. Even though significant associations were found, the additional analyses show that most of the identified effect sizes are small (average within-person non-autoregressive associations range between 0.12 and −0.19), and therefore explain less variance. This might be a result of temporal networks and highlights the challenges of drawing meaningful insights about emotion dynamics using discrete emotion items collected at comparatively long intervals (each 4 h). Future studies could benefit from more frequent measurements, idiographic analyses, or the inclusion of contextual factors. The analysis of affect dynamics and of within-client change in these dynamics from pre- to post-treatment may contribute to understanding of the emotion dynamics at work in TA and/or in imagery-based treatments such as the one utilized here. For example, one finding emerging from this analysis – a finding which may have considerable clinical relevance – is the interesting role played by anger within TA. The importance of anger may be tied, at least in part, to the nature of the treatment provided here, which utilized imagery (e.g., imagery with rescripting) methods. When working with individuals suffering from test anxiety, we find that the situations re-imagined are often ones in which some figure (e.g., a teacher or a parent) had been very harsh or critical. Successful imagery often involves the mobilization of the client's observer ego (or "healthy adult" mode; Lazarus & Rafaeli, 2021) to recognize and express anger towards this figure. This opportunity to validate and enact anger may help the client change their meta-emotional beliefs, so that they no longer condemn their anger but rather accept it. In other words, effective processing of anger within this treatment is not aimed at eliminating post-treatment anger; instead, it is aimed at learning to accept it and make use of it through assertiveness or through "changing emotion with emotion" (Greenberg, 2021).

4. Conclusions

This study adds to the growing body of research on TA and on imagery-based treatment of this disorder. Its results offer an intriguing perspective on emotional dynamics within TA, and provide preliminary evidence that certain emotional dynamics may predict better or worse response to this imagery-based treatment. They also suggest that emotion dynamics may change following effective (and intriguingly, also ineffective) treatment. Nevertheless, due to the challenges in investigating emotion dynamics, the results must be interpreted with caution and require further elaboration.

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CRediT authorship contribution statement

Jessica Uhl: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Steffen Eberhardt:** Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing – review & editing. **Brian Schwartz:** Formal analysis, Supervision. **Eshkol Rafaeli:** Writing – original draft, Methodology, Project administration, Supervision. **Wolfgang Lutz:** Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they had no conflicts of interest with respect to their authorship or the publication of this article.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbtep.2023.101909.

References

Bar-Kalifa, E., Prinz, J., Atzil-Slonim, D., Rubel, J. A., Lutz, W., & Rafaeli, E. (2019). Physiological synchrony and therapeutic alliance in an imagery-based treatment. *Journal of Counseling Psychology, 66*(4), 508–517. https://doi.org/10.1037/cou0000358

Blanchard, M. A., Hoebeke, Y., & Heeren, A. (2023). Parental burnout features and the family context: A temporal network approach in mothers. *Journal of Family Psychology*. https://doi.org/10.1037/fam0001070

Bringmann, L. F. (2021). Person-specific networks in psychopathology: Past, present and future. *Current Opinion in Psychology*. https://doi.org/10.1016/j.copsyc.2021.03.004

Bringmann, L. F., Albers, C., Bockting, C., Borsboom, D., Ceulemans, E., Cramer, A., … Wichers, M. (2022). Psychopathological networks: Theory, methods and practice. *Behaviour Research and Therapy*, Article 104011.

Brown, L. A., Forman, E. M., Herbert, J. D., Hoffman, K. L., Yuen, E. K., & Goetter, E. M. (2011). A randomized controlled trial of acceptance-based behavior therapy and cognitive therapy for test anxiety: A pilot study. *Behavior Modification, 35*(1), 31–53.

Couyoumdjian, A., Ottaviani, C., Petrocchi, N., Trincas, R., Tenore, K., Buonanno, C., & Mancini, F. (2016). Reducing the meta-emotional problem decreases physiological fear response during exposure in phobics. *Frontiers in Psychology, 7*, 1105. https://doi.org/10.3389/fpsyg.2016.01105

Cranford, J. A., Shrout, P. E., Iida, M., Rafaeli, E., Yip, T., & Bolger, N. (2006). A procedure for evaluating sensitivity to within-person change: Can mood measures in diary studies detect change reliably? *Personality and Social Psychology Bulletin, 32*(7), 917–929. https://doi.org/10.1177/0146167206287721

Ellis, A. (1980). Rational-emotive therapy and cognitive behavior therapy: Similarities and differences. *Cognitive Therapy and Research, 4*(4), 325–340. https://doi.org/10.1007/BF01178210

Ellis, A. (2003). Early theories and practices of rational emotive behavior therapy and how they have been augmented and revised during the last three decades. *Journal of Rational-Emotive and Cognitive-Behavior Therapy, 21*(3/4), 219–243. https://doi.org/10.1023/A:1025890112319

Epskamp, S., Deserno, M. K., Bringmann, L. F., & Veenman, M. (2021). *mlVAR*.

Ergene, T. (2003). Effective interventions on test anxiety reduction. *School Psychology International, 24*(3), 313–328. https://doi.org/10.1177/01430343030243004

Fehm, L., & Fydrich, T. (2011). Prüfungsangst. In *Fortschritte der Psychotherapie* (Vol. 44). Hogrefe.

Fisher, A. J., Bosley, H. G., Fernandez, K. C., Reeves, J. W., Soyster, P. D., Diamond, A. E., et al. (2019). Open trial of a personalized modular treatment for mood and anxiety. *Behaviour Research and Therapy, 116*, 69–79. https://doi.org/10.1016/j.brat.2019.01.010

Fisher, A. J., Reeves, J. W., Lawyer, G., Medaglia, J. D., & Rubel, J. A. (2017). Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of Abnormal Psychology, 126*(8), 1044. https://doi.org/10.1037/abn0000311

Gilbert, P. (2009). Introducing compassion-focused therapy. *Advances in Psychiatric Treatment, 15*(3), 199–208. https://doi.org/10.1192/apt.bp.107.005264

Greenberg, L. S. (2021). In L. S. Greenberg (Ed.), *Changing emotion with emotion: A practitioner's guideChanging emotion with emotion* (pp. 59–90). American Psychological Association. https://doi.org/10.1037/0000248-004.

Hall, M., Scherner, P. V., Kreidel, Y., & Rubel, J. A. (2021). A systematic review of momentary assessment designs for mood and anxiety symptoms. *Frontiers in Psychology, 12*, Article 642044. https://doi.org/10.3389/fpsyg.2021.642044

Haslbeck, J. M. B. (2023). *Mnet: Modeling group differences and moderation effects in statistical network models [R package]*. https://cran.r-project.org/web/packages/mnet/index.html.

Haslbeck, J. M. B., Epskamp, S., & Waldorp, L. (2023). *Testing for group differences in multilevel vector autoregressive models*. Retrieved from psyarxiv.com/dhp8s.

Hayes, S. C., Luoma, J. B., Bond, F. W., Masuda, A., & Lillis, J. (2006). Acceptance and commitment therapy: Model, processes and outcomes. *Behaviour Research and Therapy, 44*(1), 1–25. https://doi.org/10.1016/j.brat.2005.06.006

Hill, K. T., & Wigfield, A. (1984). Test anxiety: A major educational problem and what can Be done about it. *The Elementary School Journal, 85*(1), 105–126. https://doi.org/10.1086/461395

Holm-Hadulla, R. M., Hofmann, F.-H., Sperth, M., & Funke, J. (2009). Psychische Beschwerden und Störungen von Studierenden. *Psychotherapeut, 54*(5), 346–356. https://doi.org/10.1007/s00278-009-0693-3

Holmes, E. A., & Mathews, A. (2010). Mental imagery in emotion and emotional disorders. *Clinical Psychology Review, 30*(3), 349–362. https://doi.org/10.1016/j.cpr.2010.01.001

Houtveen, J., van der Sluijs, J. V. E., Thorsell, S., van Broeckhuysen-Kloth, S. S., & Geenen, R. R. (2022). Changed dynamic symptom networks after a self-compassion training in patients with somatic symptom disorder: A multiple single-case pilot project. *Journal of Psychosomatic Research*, Article 110724.

Howe, E., Bosley, H. G., & Fisher, A. J. (2020). Idiographic network analysis of discrete mood states prior to treatment. *Counselling and Psychotherapy Research, 20*(3), 470–478.

Husen, K., Rafaeli, E., Rubel, J. A., Bar-Kalifa, E., & Lutz, W. (2016). Daily affect dynamics predict early response in CBT: Feasibility and predictive validity of EMA for outpatient psychotherapy. *Journal of Affective Disorders, 206*, 305–314.

Jacobson, N. S., & Truax, P. (1992). Clinical significance : A statistical approach to defining meaningful change in psychotherapy research. In *Methodological issues & strategies in clinical research* (pp. 631–648). American Psychological Association. https://doi.org/10.1037/10109-042

Janssens, K. A., Bos, E. H., Rosmalen, J. G., Wichers, M. C., & Riese, H. (2018). A qualitative approach to guide choices for designing a diary study. *BMC Medical Research Methodology, 18*(1), 1–12. https://doi.org/10.1186/s12874-018-0579-6

Ji, J. L., Heyes, S. B., MacLeod, C., & Holmes, E. A. (2016). Emotional mental imagery as simulation of reality: Fear and beyond-A tribute to Peter Lang. *Behavior Therapy, 47*(5), 702–719. https://doi.org/10.1016/j.beth.2015.11.004

Jongeneel, A., Aalbers, G., Bell, I., Fried, E. I., Delespaul, P., Riper, H., … Van Den Berg, D. (2020). A time-series network approach to auditory verbal hallucinations: Examining dynamic interactions using experience sampling methodology. *Schizophrenia Research, 215*, 148–156. https://doi.org/10.1016/j.schres.2019.10.0

Kuppens, P., Oravecz, Z., & Tuerlinckx, F. (2010). Feelings change: Accounting for individual differences in the temporal dynamics of affect. *Journal of Personality and Social Psychology, 99*(6), 1042–1060. https://doi.org/10.1037/a0020962

Lazarus, G., & Fisher, A. J. (2021). Negative emotion differentiation predicts psychotherapy outcome: Preliminary findings. *Frontiers in Psychology, 3144*. https://doi.org/10.3389/fpsyg.2021.689407

Lazarus, G., & Rafaeli, E. (2021). Modes: Cohesive personality states and their interrelationships as organizing concepts in psychopathology. *Journal of Abnormal Psychology, 2021*. https://doi.org/10.31234/osf.io/9yqr6

Lutz, W., Schwartz, B., & Delgadillo, J. (2021). Measurement-based and data-informed psychological therapy. *Annual Review of Clinical Psychology, 18*. https://doi.org/10.1146/annurev-clinpsy-071720-014821

Lutz, W., Schwartz, B., Hofmann, S. G., Fisher, A. J., Husen, K., & Rubel, J. A. (2018). Using network analysis for the prediction of treatment dropout in patients with mood and anxiety disorders: A methodological proof-of-concept study. *Scientific Reports, 8*(1), 1–9.

Mancini, A., & Mancini, F. (2018). Rescripting memory, redefining the self: A meta-emotional perspective on the hypothesized mechanism(s) of imagery rescripting. *Frontiers in Psychology, 9*, 581. https://doi.org/10.3389/fpsyg.2018.00581

McNair, D. M., Lorr, M., & Droppleman, L. F. (1971). *Manual for the profile of mood States*. San Diego: Educational & Industrial Testing Service.

Meyer, L. S., Gamst, G., & Guarino, A. J. (2016). *Applied multivariate research: Design and interpretation* (3rd ed.). Sage Publications.

Morris, L. W., & Liebert, R. M. (1970). Relationship of cognitive and emotional components of test anxiety to physiological arousal and academic performance. *Journal of Consulting and Clinical Psychology, 35*(3), 332–337. https://doi.org/10.1037/h0030132

Pekrun, R., Goetz, T., Perry, R. P., Kramer, K., Hochstadt, M., & Molfenter, S. (2004). Beyond test anxiety: Development and validation of the test emotions questionnaire (TEQ). *Anxiety, Stress & Coping, 17*(3), 287–316. https://doi.org/10.1080/10615800412331303847

Prinz, J., Bar-Kalifa, E., Rafaeli, E., Sened, H., & Lutz, W. (2019). Imagery-based treatment for test anxiety: A multiple-baseline open trial. *Journal of Affective Disorders, 244*, 187–195. https://doi.org/10.1016/j.jad.2018.10.091

Prinz, J., Lutz, W., Bar-Kalifa, E., & Rafaeli, E. (2016). Imagery Rescripting und psychophysiologische Zusammenhänge anhand eines ImRs-Behandlungskonzepts für Prüfungsangst: Überblick und erste Erfahrungen [Imagery Rescripting and Psychophysical Relations Based on the ImRs-Therapy Concept Used for Test Anxiety: Review and First Experience]. *PPmP - Psychotherapie · Psychosomatik · Medizinische Psychologie, 66*(12), 481–485. https://doi.org/10.1055/s-0042-113606

Prinz, J., Rafaeli, E., Reuter, J. K., Bar-Kalifa, E., & Lutz, W. (2022). Physiological activation and co-activation in an imagery-based treatment for test anxiety. *Psychotherapy Research, 32*(2), 238–248. https://doi.org/10.1080/10503307.2021.1918353

Prinz, J., Rafaeli, E., Wasserheß, J., & Lutz, W. (2021). Clients' emotional experiences tied to therapist-led (but not client-led) physiological synchrony during imagery rescripting. *Entropy, 23*(12), 1556. https://doi.org/10.3390/e23121556

Reiss, N., Warnecke, I., Tolgou, T., Krampen, D., Luka-Krausgrill, U., & Rohrmann, S. (2017). Effects of cognitive behavioral therapy with relaxation vs. Imagery rescripting on test anxiety: A randomized controlled trial. *Journal of Affective Disorders, 208*, 483–489. https://doi.org/10.1016/j.jad.2016.10.039

Rubel, J. A., Fisher, A. J., Husen, K., & Lutz, W. (2018). Translating person-specific network models into personalized treatments: Development and demonstration of the dynamic assessment treatment algorithm for individual networks (DATA-IN). *Psychotherapy and Psychosomatics, 87*(4), 249–251.

Shrout, P., & Lane, S. P. (2012). *Psychometrics. Handbook of research methods for studying. Daily life.* Guilford Press.

Spielberger, C. D. (1980). *Test anxiety inventory: Sampler set, manual, test, scoring.* Mind Garden.

Van der Gucht, K., Dejonckheere, E., Erbas, Y., Takano, K., Vandemoortele, M., Maex, E., … Kuppens, P. (2019). An experience sampling study examining the potential impact of a mindfulness-based intervention on emotion differentiation. *Emotion, 19*(1), 123.

Webb, C. A., Forgeard, M., Israel, E. S., Lovell-Smith, N., Beard, C., & Björgvinsson, T. (2022). Personalized prescriptions of therapeutic skills from patient characteristics: An ecological momentary assessment approach. *Journal of Consulting and Clinical Psychology, 90*(1), 51–60. https://doi.org/10.1037/ccp0000555

Zeidner, M. (1998). *Test anxiety: The state of the art. Perspectives on individual differences.* Plenum Press.

Zeidner, M., & Matthews, G. (2010). *Anxiety 101. Psych 101*. Springer. http://site.ebrary.com/lib/alltitles/docDetail.action?docID=10430932.

R Core Team (2021). R: A language and environment for statistical ## computing. R Foundation for Statistical Computing, Vienna, Austria. ## URL https://www.R-project.org/.