



Process-symptom-bridges in psychotherapy: An idiographic network approach

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Abstract

Aim: real-time monitoring of psychotherapeutic processes was recently described as a promising, new way of tracking periods of change in ongoing treatments. This approach generates complex, multivariate datasets that have to be presented in an intuitive way for clinicians to aid their clinical decision-making. Using network modeling and new approaches in centrality analyses, we examine “bridge nodes” between symptom stress and aspects of the psychotherapeutic process between therapy session (intersession processes, ISP).

Method: we recorded intersession processes as well as depressive and anxiety symptoms using daily questionnaires in ten cases. Regularized, thresholded intraindividual dynamic networks were estimated. We applied bridge centrality analysis to identify individual bridges between psychotherapeutic processes and symptoms in the resulting models. Case-wise interpretations of bridge centrality values are offered.

Results: bridge centrality analysis revealed individual bridge nodes between intersession processes and symptom severity. Strength and direction of bridges varied substantially across individuals.

Conclusion: given current methodological challenges, idiographic network studies are feasible and offer important insights for psychotherapy process research. In this case, we demonstrated how patients deal with periods of increased symptom stress. In this case we have described how patients deal with their therapy under increased symptom load. Bridges between psychotherapeutic processes and symptom stress are a promising target for monitoring systems based on ISP. Future studies should examine the clinical utility of network-based monitoring and feedback in ongoing therapies. In the near future, process feedback systems based on idiographic models could serve clinicians to improve treatments.

Keywords: depression, anxiety, intersession processes, ecological momentary assessment, network analysis

Introduction

Intersession Processes in Psychotherapy

The effect of a session of psychotherapy should extend beyond the duration of the session. This basic statement is independent of the theoretical orientation of the therapist, the treatment goal or the individual problems of the patient. If one compares the time a patient spends in the sessions with the remaining waking time, it quickly becomes clear

how important the processes indicating therapeutic change between the sessions should be. Thus, the terms “Intersession process” (ISP) or “Intersession experience” (IE) were proposed for the description of these phenomena (Orlinsky, Geller, Tarragona, & Farber, 1993; Schröder, Wiseman, & Orlinsky, 2009).

The psychometric structure of ISP was studied in two independent samples (Hartmann, Orlinsky, & Zeeck, 2011) using the “Intersession Experience Questionnaire” (IEQ, Orlinsky & Tarragona, 1986). The IEQ makes it possible to

describe and measure ISP in a comprehensive form. ISP covers a wide range of cognitive, behavioral and emotional processes related to current psychotherapy. For example, patients can recall the contents of their last session or reflect on possible contents of the next session. At the behavioral level, ISPs include attempts to implement therapy content in practice. On the relationship level, a desire for contact with the therapist can develop between sessions. These dimensions of content can in turn be of different emotional valence and occur in different situations.

ISP has been shown to predict treatment outcome in studies using weekly pre-session IEQ measures (Hartmann, Orlinsky, Weber, Sandholz, & Zeeck, 2010; Zeeck et al., 2016; Zeeck & Hartmann, 2005). Because at least some aspects of ISP are reported by more than 90% of patients (Orlinsky et al., 1993), they may be well suited to monitoring the course of therapy not only in terms of expectations of success. In ongoing therapies, they could also be an appropriate goal to adapt interventions without relying on symptom-focused techniques. Currently, there are no empirical studies on the complete absence of ISP. Although it is rare, there may be patients who do not report any form of ISP. The reasons for this may vary depending on the stage of therapy and the method but are probably related to the patient's detachment from their therapy.

New approaches in modeling individual data

Proponents of psychology as an idiographic science argue that a large proportion of phenomena – processes – studied in psychology cannot be examined on the group level (Molenaar, 2013). These processes have been shown to be not homogenous, meaning that their correlational structure is not uniform across individuals. Processes also show changes in mean and variance over time, further complicating group-level study designs (Molenaar, 2004). These properties violate the assumptions of group-level study designs. Instead, small-N designs or case studies were proposed (Fisher, Medaglia, & Jeronimus, 2018; Molenaar, 2013; Smith & Little, 2018) including statistical methods that adequately model intraindividual variation.

The treatment of mental disorders, including psychotherapy, psychiatry or clinical psychology, can profit from this person-based approach as well. Statistical methods can be applied to individual psychometric data, like questionnaires administered via mobile devices (ecological momentary assessment, EMA) daily, or even several times a day (Fisher, 2017; Molenaar, 1985). This way, insights with high ecological validity about an individual's psychopathology can be gained and used for treatment. Time-series models can reveal which symptoms influence other symptoms, so that the "root cause" of a disorder can be targeted directly using personalized interventions. Although the utility of various parameters of network models for targeting interventions has been disputed from a methodological point of view (Fried, 2017), a small number of studies in-

vestigated the use of individual time-series models, including network models, in interventions (Epskamp, van Borkulo, et al., 2017; Kroeze et al., 2017). One possible application would be the assessment of symptoms before treatment onset, so that information from individual time-series models can be used for tailoring treatments, as proposed under the name "dynamic assessment treatment algorithm" (DATA; Fernandez, Fisher, & Chi, 2017; Fisher & Boswell, 2016). This approach works by grouping symptoms by using factor analysis and then modeling their temporal dynamics with multivariate time-series analysis. Using coefficients from these models, information about how symptoms influence one another can be derived, offering possible information on which symptom to target first.

Another method of analyzing complex data is network analysis. It has been used to study mental disorders as network structures of interacting symptoms. First proposed and later refined and extended by Borsboom (2008, 2017), the "network theory of mental disorders" proposes that mental disorders are best understood as networks of interaction between different components (i.e. symptoms) that are linked through direct causal connections. The theory also states that certain symptoms have stronger connections in the network and that some symptoms can be grouped together into communities. Various applications in psychopathology were reported, like a network analysis of depressive symptoms measured by the Beck Depression Inventory (Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015), social anxiety disorder (Heeren & McNally, 2017) or post-traumatic stress disorder (McNally, 2017). When applied to large, cross-sectional datasets, network models of DSM-IV symptoms provide insights into comorbidity between psychiatric disorders on the population level (Boschloo et al., 2015).

However, as other methods that have been introduced here, network analysis is not limited to cross-sectional data. If applied to individual time series, network analysis can offer insights into the dynamic structure of psychopathology. In ongoing treatments, personal network models have been studied as a means of psychoeducation and as a feedback tool for clinicians. One case study by Kroeze et al. (2017) reported that a personalized network motivated a treatment-resistant patient suffering from anxiety and depression to undergo an exposure intervention. A graphical representation of the model was used to educate the person about body discomfort being the probable root cause of her problems. David, Marshall, Evanovich and Mumma (2017) derived a network structure for a patient suffering from major depressive disorder and social anxiety disorder, which revealed the underlying functional relations of the client's disorder. The authors showed that tension, worry and trouble in concentrating were important in this network, leading them to suggest muscle relaxation and mindfulness exercises.

Recently, a new interpretation method called "bridge expected influence" (BEI, Jones, Ma, & McNally, 2017) has

been proposed for network models. It was developed to identify “bridges” linking communities of nodes in networks. For example, a study on complicated grief symptoms and posttraumatic growth identified the item indicating a “change of worldview due to loss” as a bridge node between both communities (Bellet, Jones, Neimeyer, & McNally, 2018). In this study, BEI will be used to identify aspects of ISP that are linked to symptom stress.

This offers a convenient method to interpret patients’ intersession engagement with session content. A positive process-symptom BEI indicates that increased symptom stress and ISP co-occur. For example, a positive BEI for *remembering events from last session* would indicate that higher scores for this item positively influence symptom stress. Conversely, a negative BEI for *imagining a dialogue with the therapist* means that this item scores lower on days with higher symptom stress.

Current issues in process monitoring

Human change processes are non-ergodic. This means that intraindividual variation of these processes over time is different from interindividual variation across persons (Molenaar & Campbell, 2009). In non-ergodic psychological processes, the underlying models are not homogeneous: they vary greatly from person to person. Moreover, they are not stationary, so their statistical characteristics change over time. In non-ergodic psychological phenomena, traditional statistical research methods working at the group level often reach their limits.

It has also been argued that human change processes are characterized by non-linearity (Schiepek et al., 2017). Input and output in a non-linear system are not proportional to each other. The future behavior of a non-linear system cannot be predicted with high accuracy. New idiographic methods and modeling approaches therefore continue to face the challenge of sudden changes in system dynamics (Schiepek, Heinzel, Karch, Plöderl, & Strunk, 2016). In EMA-based monitoring, one main advance has been made by Schiepek and colleagues by offering clinicians a comprehensive software solution called “Synergetic Navigation System” (SNS) (Maurer, Aichhorn, Leeb, Matschi, & Schiepek, 2010). In inpatient settings, this method reached good compliance values for patients (Schiepek et al., 2016). The SNS enables researchers to administer web-based questionnaires on a regular basis. The questionnaires are automatically scored and the results displayed graphically so that the clinician can evaluate them conveniently.

Regular feedback discussions with the patient are an integral part of SNS-based monitoring. The data from the daily surveys are interpreted by the patient himself, while the therapist is mainly involved in assisting the patient in structuring their interpretation. SNS-based feedback and the accompanying treatment procedure proposed by the authors (Schiepek, Eckert, Kravanja, Wallot, & Haussmann, 2014) is greatly based on the theory of synergetics. Thus, it offers various ways to analyze the recorded time-series

using non-linear methods. However, it is unclear whether therapists who work with SNS use the synergy-based functions (recurrence plots, dynamic complexity) of SNS in their daily clinical practice, or use the daily records rather “atheoretically”, like a therapy diary.

One methodological challenge in the application of these methods in everyday clinical methods is how to enable clinicians to utilize these feedback tools. A recent assessment of attitudes towards process monitoring (Kaiser, Schmutzhart, & Laireiter, 2018) showed that only roughly one third of psychotherapists are willing to use process monitoring in their clinical practice. Therapists were particularly concerned about the workload for patients, as daily questionnaires could burden them. Most often, however, it was stated that the interpretation of process data was too complex to be introduced into everyday clinical practice. This objection is not unjustified: therapy process data are multivariate, non-linear time series. Their analysis requires complex statistical procedures. The use of process monitoring could probably be facilitated if monitoring systems process the complex data in such a way that clinicians can understand it independently of their theoretical orientation. This should be done without the system making too strong specifications, which render the clinical experience of the practitioner a secondary matter.

Network models could be a promising candidate, as they are relatively easy to interpret visually, interpretation aids like centrality are readily available and they can be used independent of a clinician’s theoretical approach to psychotherapy. The theory of intersession processes was directly derived from ambulatory clinical practice and is well-established through decades of theoretical and empirical work (Stewart & Schroder, 2015).

In this study, we combine new methods of intraindividual dynamic network analysis and a theoretical framework that can be used to describe the degree to which patients are engaging in therapy between their sessions. According to the theory behind ISP, patients form mental representations of their therapy over time. Recurrent activation of these representations between sessions can occur due to a variety of reasons, but were reported to occur most frequently during periods of painful affect and conflict (Geller & Farber, 1993). Thus, it can be expected that ISP and symptom stress covary to some degree. However, this finding was reported based on cross-sectional data that is unfit to represent individual cases.

Goals and Aims

In this paper, we try to validate the classic, cross-sectional finding that ISP and increased psychological distress covary. For this purpose, we will conduct idiographic assessments of short symptom scales and intersession process scales with high (i.e. daily) temporal frequency. Second, we examine the utility of combining high-frequency assessment of ISP and symptom stress with current methods of network modeling as a means of intraindividual data analy-

sis that is fruitful for psychotherapy process research. In this study we will explore the dynamics between inter-session processes and symptom load in order to take the first step for future monitoring applications. To achieve this, we demonstrate a method of moving-window network analysis that focuses on the within-person correlations between inter-session process and symptom stress. Monitoring of networks that change over the course of therapies has already been suggested by David, Marshall, Evanovich and Mumma (2017). As a first demonstration of possible monitoring applications, we will demonstrate a moving-window technique of idiographic network analysis to show the change of process- symptom- connections over time.

Design and Methods

Recruitment and participants

All patients were treated in the outpatient clinic of the University of Salzburg. During admission, they received information about the planned study. Treatment was delivered in a manualized form of transdiagnostic cognitive-behavioral therapy of emotional disorders (“Unified Protocol for Transdiagnostic Treatment of Emotional Disorders”, Barlow, 2011).

The diagnostic instruments at admission and termination included the structured clinical interview MINI-DIPS (Margraf, 2013) and the Hamilton rating scales for anxiety and depression (HAM-A, HAM-D, Hamilton, 1959, 1960). All participants fulfilled diagnostic criteria for either major depression, social anxiety disorder, generalized anxiety disorder, or combinations of those. The exclusion criteria were current substance dependency, bipolar disorder, acute suicidality or psychosis. Treatment length was between eleven and 35 weeks with variations due to number of treatment sessions, vacations or rescheduled sessions. Raw scores for HAM-A and HAM-D at intake and after treatment are reported.

We calculated reliable change index (RCI) scores using coefficient alpha and standard deviations reported for German samples (Maier, Buller, Philipp, & Heuser, 1988; Maier, Philipp, & Gerken, 1985). For HAM-D, a coefficient alpha of .73 and a standard deviation of 6.95 was used, resulting in a change of 9 points or more to be considered reliable. For HAM-A, an ICC of .74 and a standard deviation of 16.08 was reported, so that a change of 17 points or more will be considered reliable.

Daily assessments

Network models were fit to item-level time series. Depending on the diagnosis of the patient (depression, generalized anxiety disorder and/or social anxiety disorder), patients received one or more brief symptom scales. Additionally, a short inter-session process scale was used to measure therapeutic processes.

PHQ-9. For daily measurement of symptom stress, we

decided to use a well-validated measure of major depression (Kroenke, Spitzer, & Williams, 2001). This nine-item questionnaire was used successfully in previous studies with similar settings (Burns et al., 2011; Torous et al., 2015). The PHQ-9 was scored according to the two-factor structure reported by Guo et al. (2017), who found an affective and a somatic component to be of ideal fit.

GAD-7. For daily assessment of anxiety symptoms, we used another short measure, the GAD-7 (Spitzer, Kroenke, Williams, & Löwe, 2006). Just like the PHQ-9, the GAD-7 was shown to be of good psychometric quality regarding its reliability and validity. It consists of seven items that follow the DSM-IV criteria for Generalized Anxiety Disorder, even though it has successfully been used with other anxiety disorders as well (Kroenke, Spitzer, Williams, Monahan, & Löwe, 2007).

SAD-D. For social anxiety symptoms, we used a ten-item severity measure based on DSM-5 criteria (Knappe et al., 2014). This scale assesses cognitive, behavioral and affective symptoms of social anxiety disorder.

Short Inter-session Process Scale (SIPS). The SIPS is a short scale with ten items for assessing various aspects of inter-session processes in psychotherapy (Kaiser & Laireiter, 2018). The SIPS was developed specifically for ambulatory assessment studies on inter-session processes. The items of the SIPS were selected so that they convey enough meaning in single-item interpretation.

Procedure

All daily assessments were conducted using the assessment module of the DynAMo software package (Kaiser & Laireiter, 2017). Data was transmitted over a secure connection and saved to an online storage only accessible to the authors. All items in daily measures were assessed on a 0 to 100 visual analog scale. Patients received text messages including a personalized URL every 24 hours. Messages were sent out between 5 and 10 pm. The exact time was the patients’ choice.

Network modeling

Data preparation. All time series were tested for linear trend components using the KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). The KPSS test is used for testing the null hypothesis that a time series has a linear trend component. Time series that have trend components violate the assumptions of the statistical approaches used in this study. Thus, linear detrending was applied in the case of a significant test result before calculating the correlation matrix. If a patient missed their daily assessment or the delay was so large that they filled out the questionnaire after midnight, this resulted in unequally spaced time series. To correct for this, we applied cubic spline interpolation. If the delay was larger than 24 hours, this day was treated as missing.

Network estimation. We used the R-package qgraph (Epskamp, 2018) to estimate contemporaneous network

structures of intersession process and symptom scores. We estimated regularized partial correlation networks using the EBICglasso procedure (Epskamp, Borsboom, & Fried, 2017). Partial correlation networks indicate how strong the relationship between two variables is after the influence of all other variables has been controlled for. The least absolute shrinkage and selection operator (LASSO) was applied to reduce the false-positive rate. This procedure reduces small edge weights to zero. Shrinkage parameters are chosen so that the extended Bayesian Information Criterion (EBIC) is minimized. In simulation studies this method was shown to reduce the false-positive rate of connections in networks (Epskamp, Waldorp, Möttus, & Borsboom, 2016). Thus, EBICglasso can be seen as a conservative approach to model estimation when data are sparse. To further minimize the false-positive rate, we employed a thresholding rule recommended by Jankova and van de Geer (2018). Under this rule, weak edges in the network are set to zero, enforcing high specificity. We computed a network density coefficient for every patient's network. Network density is the fraction of the number of edges in a patient's network divided by the total number of edges that would theoretically be possible in the network.

Graphical representation. Networks contain nodes (symptom and intersession process items) and edges (contemporaneous correlations between scores). In the network graphs, nodes are connected by edges of varying thickness. The thicker an edge, the higher the partial correlation coefficient between two items. Blue edges indicate positive correlations while red edges indicate negative correlations. Nodes are placed using the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991). This algorithm places more strongly connected nodes closer to each other and nodes with stronger connections more to the center of the graph. This allows easy visual interpretation.

Centrality. Interpretation of network models is facilitated by various measures of centrality. These measures are good indicators for determining the relative importance or influence of specific nodes (Epskamp, Borsboom, et al., 2017; Epskamp & Fried, 2016). This is helpful for interpretation, as they summarize multiple connections of a node into one measure. In non-directed networks, three main indicators of centrality are generally used: betweenness, closeness, and strength. Betweenness indicates the number of times a node lies on the shortest path between two other nodes, thus “re-laying information” between those nodes. Strength is the sum of absolute edge weights of a node, which shows how strong the influence of this node in its network is. Closeness is the reciprocal of the sum of shortest path lengths between a node and all other nodes. Bridge expected influence will be estimated to get quantitative indicators for the strength of connection between intersession processes and symptom stress.

Moving window centrality analysis. Since a large amount of data was available for one patient, we chose this for the illustration of the moving-window technique. Using the methods described above, a series of network models for windows of analysis with the size of 100 time points will be calculated for this patient's data set. This means that we estimate network models for time point 1 to 100, point 2 to 101, 3 to 102, and so on. Average BEI values will be calculated for each of the models, resulting in a series of BEI values. This way we can demonstrate how the strength of the bridges between process and symptoms changes over time.

Results

Table 1 summarizes demographic data and diagnoses for all patients, including the individual sample size and symptom ratings before and after treatment.

Table 1. *Description of subjects, individual sample sizes and Hamilton scores for anxiety and depression before and after treatment.*

No.	Age	Gender	Diagnosis	N	Missing	HAM-A pre	HAM-A post	HAM-D pre	HAM-D post
P01	23	F	DEP, GAD	113	15	24	11	15	3*
P02	48	M	DEP, GAD	83	7	23	3*	15	2*
P03	21	F	SAD	106	15	25	8*	18	5*
P04	19	F	DEP	122	17	13	19	17	11
P05	18	F	SAD, DEP	185	0	29	9*	14	5*
P06	29	F	DEP	248	5	9	8	18	17
P07	21	F	DEP, GAD	120	18	19	13	18	7*
P08	25	M	DEP, GAD	103	7	24	7*	16	6*
P09	33	F	SAD	177	22	21	8	10	7
P10	53	M	GAD	116	15	16	7	10	10

Note. DEP = depression, GAD = generalized anxiety disorder, SAD = social anxiety disorder. HAM-A = Hamilton rating scale for anxiety score. HAM-D = Hamilton rating scale for depression score. *: reliable pre-post change; the value is equal to or below the reliable change threshold. N = number of time points sampled. Missing = number of missing time points.

Table 2. Node names and content descriptions of all items used in individual network models.

Node name	Symptom/Aspect
Phq1	Little interest, pleasure in doing things
Phq2	Feeling down, depressed, hopeless
Phq3	Sleep problems
Phq4	Tired, little energy
Phq5	Poor appetite or overeating
Phq6	Feeling bad about yourself
Phq7	Trouble concentrating
Phq8	Slowing down or restlessness
Phq9	Suicidal thoughts
Gad1	Nervous, anxious, on edge
Gad2	Unable to stop worrying
Gad3	Worrying too much
Gad4	Trouble relaxing
Gad5	Being restless
Gad6	Annoyed, irritable
Gad7	Afraid as if something awful might happen
Sad1	Terror, fear, fright in social situations
Sad2	Anxious, worried, nervous
Sad3	Thoughts of being rejected, humiliated
Sad4	Racing heart, sweat, trouble breathing
Sad5	Muscle tension, restlessness in social situations
Sad6	Avoidance of social situations
Sad7	Left social situations early
Sad8	Excess time preparing for social situations
Sad9	Distraction
Sad10	Help coping with social situations
Isp1	Thought about things that you could not express freely last session
Isp2	Thought about basic conditions (costs, appointments)
Isp3	Thought about topics for next session
Isp4	Thought about therapist
Isp5	Imagined dialogue with therapist
Isp6	Remembered events from last session
Isp7	Solving problems as discussed in sessions
Isp8	New ideas on topics discussed
Isp9	Positive treatment-related emotions
Isp10	Negative treatment-related emotions

Note. Content descriptions represent item content, not the complete item text. For full item text, refer to the scales' respective publications.

Individual network model results

Contemporaneous partial correlation networks were successfully estimated for all patients. Network models will be presented as graphs using the following color scheme: symptom stress item nodes are colored blue, ISP items are

colored yellow. Positive associations between nodes are blue, negative associations are red. Table 2 provides a key of node names for all network models.

Intercommunity analysis. Bridge expected influence scores for ISP items are listed in table 3. Additionally, within-patient average BEI scores were calculated. Brief summaries of the most prominent process-symptom bridge nodes for all ten patients will be provided here. Bridge nodes are considered "prominent" if their absolute values surpass the within-person average BEI value ($|BEI_p|$). Complete centrality measures for all models are provided in the supplementary material.

P01. The patient reported more frequent thoughts about topics (isp3) for her next session. When inspecting the network graph, thoughts about the next session's content (isp3) were strongly linked to being "annoyed and irritable" (gad6), suggesting that this is currently a core problem the patient would like to discuss. Conversely, thoughts about "things that she could not express freely" in the last session (isp1) was negatively connected to this item. The relatively high bridge centrality of these items ($BEI_{isp3} = 0.34$; $BEI_{isp1} = -0.25$) could also indicate that the patient expresses her intention to use her therapy sessions for addressing her problems with irritability.

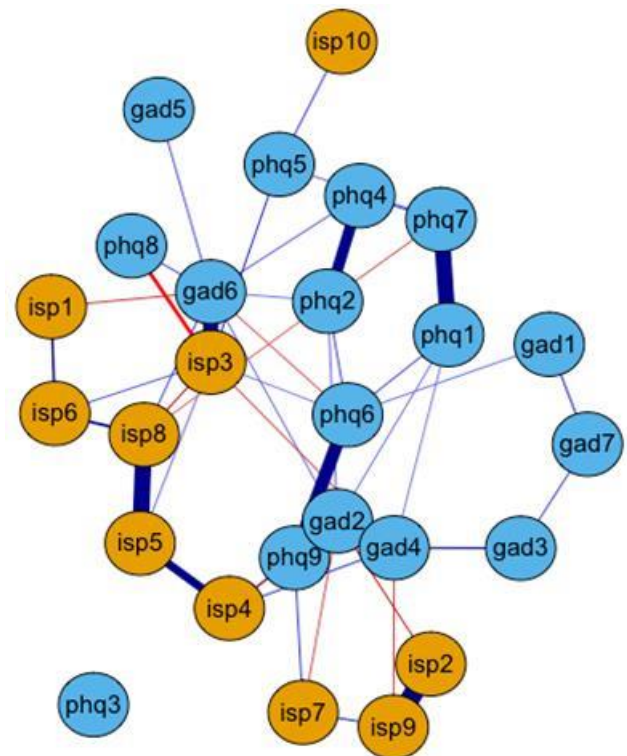


Figure 1. Network model of patient P01.

Table 3. Individual raw bridge expected influence scores for ten ISP items and their patient and item-wise averages.

	P01	P02	P03	P04	P05	P06	P07	P08	P09	P10
Isp1	-0.25	0.30	-0.19	0.02	0.32	0.19	0.16	-0.34	0.61	0.06
Isp2	-0.30	-0.16	0.48	-0.13	0.15	0.04	0.41			
Isp3	0.34	0.09	0.26	0.11	0.20		-0.41	0.26		-0.47
Isp4	0.16	-0.11	0.16		-0.33		-0.18	0.33		0.24
Isp5		0.21	-0.17	0.23	-0.17		-0.06		0.54	0.3
Isp6			*	-0.32	0.30		0.31	0.63	-0.36	-0.19
Isp7	0.04	0.25	-0.23	0.19	-0.01		0.35		-0.66	-0.35
Isp8	0.04						0.14	-0.33	0.08	-0.01
Isp9	-0.25		0.30				-0.13			0.19
Isp10	0.24				0.16	0.16	0.20	-0.25	0.76	0.07
BEI _p	0.12	0.11	0.20	0.10	0.16	0.04	0.24	0.21	0.30	0.19
Density	0.14	0.14	0.19	0.23	0.24	0.13	0.26	0.14	0.14	0.29

Note. *: item had to be excluded from the analysis due to all-zero scores. BEI values of zero are omitted. Higher BEI scores indicate that the item scored higher on days with increased symptom stress, while negative scores show the opposite. |BEI_p|, mean of absolute BEI values for patients. Density: fraction of the number of non-zero edges in a patient’s network divided by the maximum possible number of edges.

Thoughts about her therapist (isp4) were also positively linked to symptom stress via the “trouble relaxing” item (gad4), while positive treatment-related emotions (isp9) were negatively connected. This indicates that the patient evaluates her treatment more positively on days with low symptom stress.

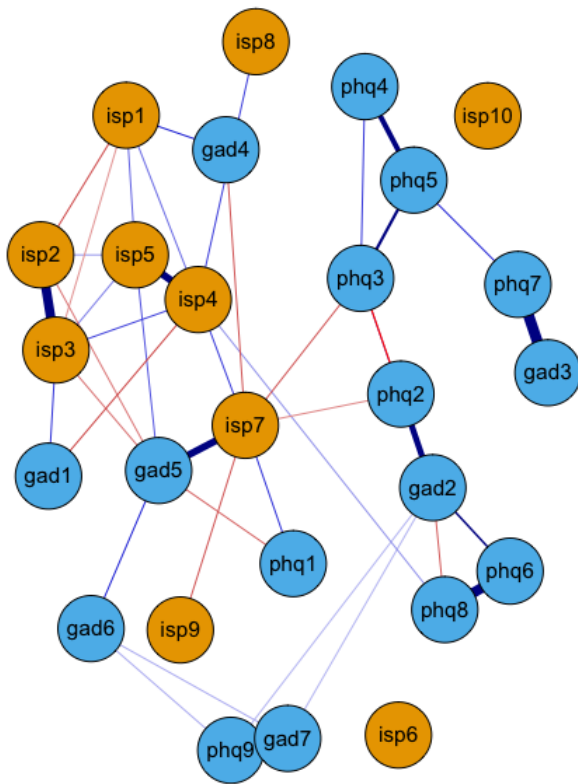


Figure 2. Network model of patient P02.

P02. This patient showed increased levels of problem solving (isp7) under increased symptom stress (BEI_{isp7} = .25), which suggests that he uses skills he learned in therapy sessions outside of the therapy room. The strong connection of this item to “being restless” (gad5) could indicate that this patient successfully implements relaxation techniques learned in treatment. Solving problems was less likely on days with higher depressive affect (phq2) or sleep problems (phq3). Additionally, he is more likely to recreate the therapeutic dialogue (isp5) under this condition.

P03. Under increased symptom stress, this patient reported more positive, treatment-related emotions (isp9) and more reflection on the next session’s content (isp3). This could mean that the patient starts to represent her treatment as something positive and is actively involved in the treatment process. Solving problems as discussed in sessions (isp7) was less likely under increased symptom load, especially when feeling “anxious, worried or nervous about social situations”. This indicates that the patient still shows some avoidance when attempting to deal with aversive situations.

P04. This patient reported more problem solving under increased symptom stress (BEI_{isp7} = 0.19) and also seemed to reflect on session content more frequently (BEI_{isp3} = 0.11). She also reported more imagined dialogues on days with increased symptom stress (BEI_{isp5} = 0.23). Still, the patient did not achieve reliable change after termination.

P05. In this case, both items referring to the past therapy session were positively linked to increased symptom stress (BEI_{isp1} = 0.32, BEI_{isp6} = 0.30), while both items involving the therapist were less likely to be reported on days with increased symptom stress (BEI_{isp4} = -0.33; BEI_{isp5} = -0.17).

P06. For this patient, only three bridge nodes were observed, all of which are positively linked to symptom stress: thinking about things that she could not express freely last session ($BEI_{isp1} = 0.19$), and negative treatment-related emotions ($BEI_{isp10} = 0.16$) and thoughts about basic conditions ($BEI_{isp2} = 0.04$). These links indicate a mainly negative treatment evaluation with little to no helpful representations the patient has access to. Interestingly, this patient also did not achieve reliable change in her treatment.

P07. The network model of this patient is densely interconnected, and all ISP items have connections to her symptoms. The ISP items isp2 (thoughts about basic conditions, $BEI_{isp2} = 0.41$), isp6 (remembered events from last session, $BEI_{isp6} = 0.31$) and isp7 (solving problems as discussed in therapy, $BEI_{isp7} = 0.35$) were especially high when symptom stress increased, while item isp3 (thinking about possible contents of the next session) was low under increased symptom stress ($BEI_{isp3} = -0.41$).

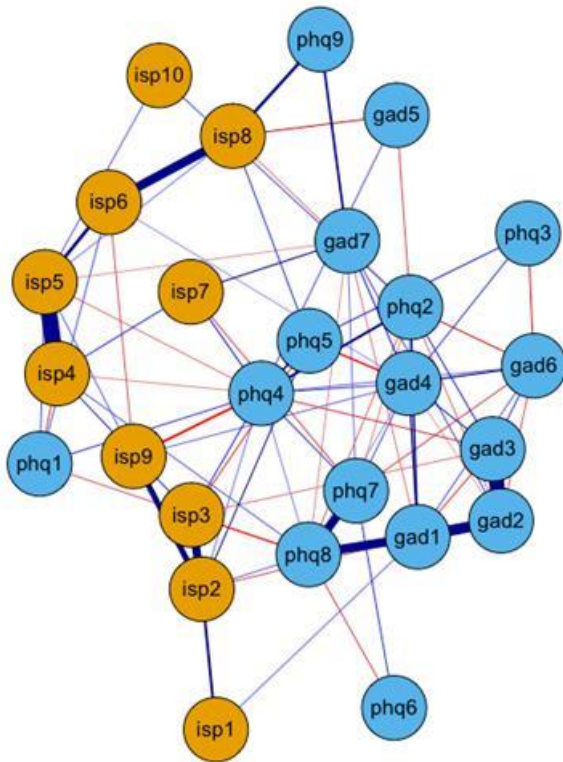


Figure 7. Network model of patient P07.

P08. This patient's network is less densely connected but contains a number of links between symptoms and ISP. Items 3 (thought about topics for next session, $BEI_{isp3} = 0.26$), 4 (thought about therapist, $BEI_{isp4} = 0.33$) and 6 (remembered events from last session, $BEI_{isp6} = 0.63$) are most strongly linked to symptom stress. This indicates that the patient at least began to form a representation of his therapy that he can use to engage with symptom stress. Items 1 (thought about things that the patient could not express freely last session, $BEI_{isp1} = -0.34$), 8 (new ideas for topics discussed in sessions, $BEI_{isp8} = -0.33$) and 10 (negative treatment-related emotions, $BEI_{isp10} = -0.25$) were less

likely under increased symptom stress.

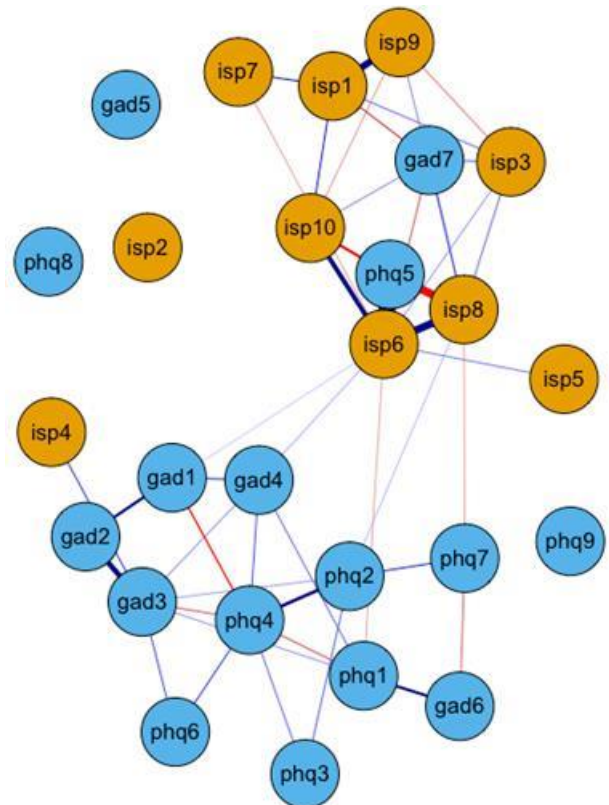


Figure 8. Network model of patient P08.

P09. In this graph, the relationships between ISP and SAD symptom items become apparent. The item isp1 (Thought about things that you could not express freely last session) has a strong bridge connectivity ($BEI = .61$), which is likely to result from the strong connection to sad6 (Avoidance of social situations). The item isp7 (Solving problems as discussed in sessions) is a strong negative bridge, which is negatively linked to two SAD items (sad5: Muscle tension, restlessness in social situations; sad8: Excess time preparing for social situations).

P10. For this patient, items isp4 (thought about therapist, $BEI_{isp4} = 0.24$), isp5 (imagined dialogue with therapist, $BEI_{isp5} = 0.30$) and isp9 (positive treatment-related emotions, $BEI_{isp9} = 0.19$) were positively connected to symptom stress. This means that the recall of his representation of the therapist including positive emotions was more likely under this condition. This patient seems to activate his representation of her relationship with the therapist, which is accompanied by a positive evaluation of his therapy. Items isp3 (thought about topics for next session, $BEI_{isp3} = -0.47$), isp6 (remembered events from last session, $BEI_{isp6} = -0.19$) and isp7 (solving problems as discussed in sessions, $BEI_{isp7} = -0.35$) were negatively connected. This patient had more thoughts involving the therapist or dialogues with him under higher symptom stress, while he reflected more on the content of past and future sessions and engaged in more problem solving under lower symptom stress.

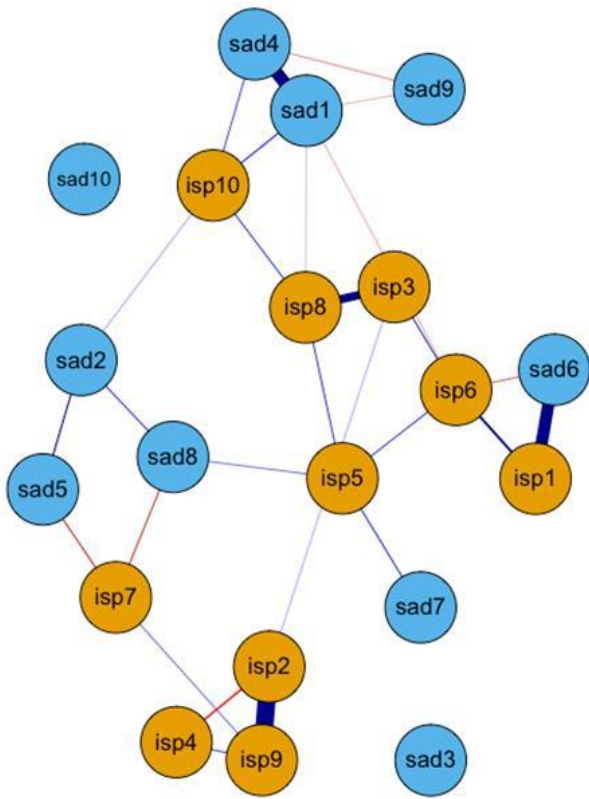


Figure 9. Network model of patient P09.

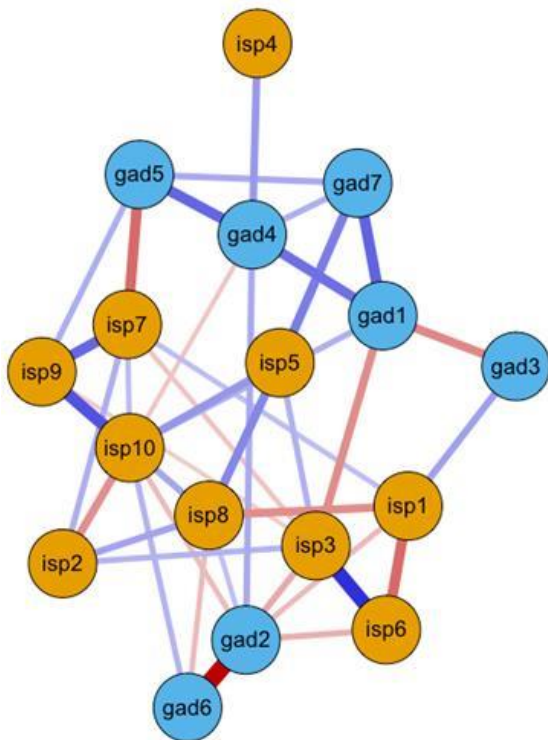


Figure 10. Network model of patient P10.

Moving-window network analysis. Due to the large amount of data available for patient P06, she was selected for demonstrating the concept of moving-window network analysis. We obtained a series of 148 network models. For each of these models, we calculated the average bridge expected influence. As illustrated in figure 11, the strength of connections between ISP and symptom stress peak after day 50 and substantially dropped over time. We provided a video animation showing the change in network models over time in the supplementary material.

Discussion

Using data courses from ten psychotherapies, we explored and demonstrated an approach to modeling psychotherapeutic processes and symptom stress in ongoing psychotherapies. To the authors' knowledge, this is the first study that explores how intersession processes and symptoms interact on a daily basis on an idiographic level. Although the available data come from a relatively homogeneous sample, it was shown that the intraindividual relationships of relevant variables vary greatly. Network models are a valuable method in providing detailed insights into idiographic dynamics in psychotherapy. We discovered individual bridges between ISP and symptom stress for every patient, but also discovered a high interindividual variability. These bridges can provide important insights for psychotherapy process research, as they can describe patients' treatment and problems on a temporally high-resolution level.

Our study validates the finding by Geller and Farber (1993) that predicted a covariation of ISP and symptom stress. Additionally, our findings indicate that there is substantial variation in how exactly symptom stress and ISP interact. This could show that the representation of the therapy has a different function for each patient. Patient P06, for example, showed little ISP activation under increased symptom stress and did not achieve reliable change in her treatment. The few process-symptom bridges were rather negatively colored. In the moving-window network analysis, we showed that the process-symptom bridge strength dropped over the course of treatment. It is possible that this patient could not establish a stable working relationship or found the therapy unsuitable for her own problem so that, over time, the patient increasingly detached herself from the therapeutic process. Earlier studies on ISP and treatment outcome (Hartmann et al., 2010; Zeeck et al., 2016) reported that a composite variable of negative treatment-related emotions and recreation of the therapeutic dialogue was predictive of treatment failure. With our approach, we provide further insights into this finding. If the retrieval of the representation of psychotherapy is associated with negative emotions, this could be an aversive stimulus. The patient tries to avoid this aversive stimulus, which is likely to reduce the frequency and intensity of recall. However, if the representation is activated too infrequently, it also means that it

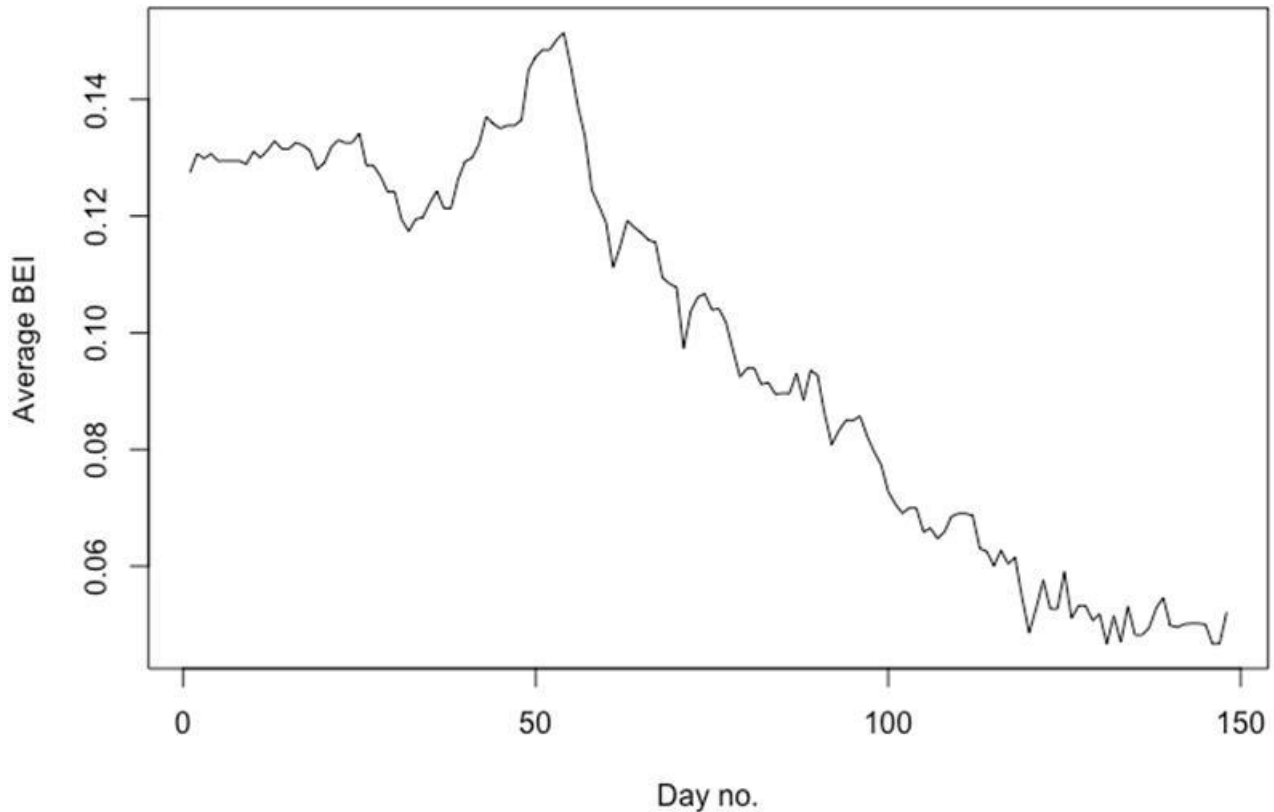


Figure 11. Bridge expected influence values for network models estimated in moving windows of 100 time points obtained from patient P06.

is not retrieved at decisive moments - for example, when the symptoms are more severe. Especially in such situations, representations could be useful either by leading to the application of therapeutic skills or by recalling a supportive, caring therapeutic relationship. This also aligns with the finding that negative treatment-related emotions suppress ISP activity on subsequent days reported by Kaiser and Laireiter (2018).

Limitations

Because we used daily sampling, we decided to estimate only contemporaneous (intra-day) networks. All items set “today” as the time frame, so patients were instructed to judge a whole day retrospectively. Intraday fluctuations of symptoms are common, as many EMA studies have demonstrated (Ebner-Priemer & Trull, 2009). The same is likely to be true for intersession processes. For example, an early survey study on ISP has shown that individual ISP events generally last for about one minute to a few seconds (Farber & Geller, 1994). Thus, temporal dynamics of process and symptom variables are probably much more fine-grained than daily assessment could capture. Modeling temporal associations would have been likely to result in mostly autoregressive associations under these conditions. For this

reason, the exact causal direction of associations in networks remains unclear. This is partly compensated by the fact that we can use bridge expected influence to estimate the influence of individual items on node communities.

The statistical power of the network models is limited by a low number of observations. Because we used regularized, thresholded partial correlation networks to estimate sparse, conservative models, it is likely that some of the weaker connections were set to zero and thus do not occur in our models. This can be resolved by increasing the sample size in future studies, possibly by including patients from long-term interventions in the measurement process. Due to the low sample size, the estimation of spurious edges cannot be ruled out completely. In order not to put too much strain on patients, we selected very short scales for daily assessments. Thus, certain aspects of both the patients’ disorders and intersession processes might not occur in our models.

Generally, dense networks lead to higher values of bridge centrality for all items. Thus, bridge centrality values should be interpreted relative to the overall network density or the average value of bridge centrality for one patient.

Outlook

Future work should study the utility for high-frequency monitoring of these processes more thoroughly. Especially for providing feedback to therapists, network models can be promising, but much more work is needed before possible implementations are ready for clinical practice. The approach demonstrated here is promising because even with a relatively low number of variables, network models convey additional meaning by putting the focus on associations. For example, a cognitive-behavioral therapist might be interested if their patient applies new behaviors on days with increased symptom stress. In more relationship-focused approaches like psychodynamic or interpersonal therapy, associations between positive, treatment-related emotions and relationship processes could indicate the development of a positive therapeutic alliance.

On the client side, daily questionnaires over the whole course of psychotherapy can be straining. Unlike inpatient settings, ambulatory psychotherapy does not provide a fully controlled environment, so everyday tasks could reduce compliance when completing questionnaires. The clinical utility of network-based monitoring and feedback applications have to justify the additional strain put on patients.

Methodologically, the approach proposed in this article could be extended to dynamic networks that model both time-lagged associations and contemporaneous correlations after partialling out time-lagged influences. One way to perform such analyses is graphical VAR (Epskamp, 2018).

Conclusion. Taken together, the results provided in this study present a fine-grained examination of intersession processes in psychotherapy. As predicted, ISPs and symptom severity showed covariation in most patients. The application of bridge expected influence provided further details on how this covariance looks like when studied with greater detail. This represents another step in psychotherapy process research, as we have shown that these processes interact with symptom stress on an intraindividual level and that this interaction varies over time. While causality cannot be established in such networks, the idiographic approach we proposed can be seen as a new direction in this field. Future studies should test the clinical utility of these findings with larger samples, possibly examining the predictive utility of network model data for treatment outcome or dropout.

Author contributions

TK designed the study, organized data collection, performed statistical analysis and drafted the first version of the manuscript and revised the manuscript after the first round of peer review. AL participated in the data collection and was actively involved in revising the manuscript. Both

authors read and approved the final manuscript.

Declaration of Interests

The authors declare no conflicting interests.

Ethical statement

The ethics committee of the University of Salzburg has reviewed and approved of the study (EK-GZ 23/2017). Written informed consent was obtained from all participants.

Supplemental materials

The video of time-window network analysis is available online: <https://osf.io/wqcrk>

A file containing data from centrality analysis for every patient is available online: <https://osf.io/j3y7x/>

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