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MONITORING CHANGE DYNAMICS – A NONLINEAR APPROACH TO PSYCHOTHERAPY FEEDBACK

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ABSTRACT

Innovations in information technology opened the way to monitor the nonlinear features of human change dynamics in real time. Especially the internet-based Synergetic Navigation System (SNS) was optimized for high-frequency assessment in real-world settings and for the nonlinear analysis of the collected time series data. The technology also has an impact on the conceptualization of psychotherapy feedback, e.g., concerning measurement frequencies and sampling rates, the variables to be assessed, the methods of time series analysis, the way how to practically use the technology, and how to do feedback-based interviews. One important aim is to identify order transitions and their precursors in psychotherapy and counseling. The options available in the SNS for analyzing and visualizing non-stationarities and related precursors are described and illustrated by Figures. The paper is completed by two perspectives on practice and theory – one on the individualization of measurement procedures and process-sensitive treatment designs, the other on the mathematization of models for understanding the complexity of change processes (computational systems psychology).

Keywords: change dynamics, psychotherapy feedback, ecological ambulatory assessment, order transitions, Synergetic Navigation System (SNS), precursors, personalization of measures and treatments

1. THE GAP BETWEEN OUTCOME MONITORING AND THE NONLINEAR DYNAMIC SYSTEMS APPROACH

The history of psychotherapy is characterized by a great variety of different approaches and confessions, in treatment as well as in research. There are hundreds of therapy schools (the exact number depends – beside other criteria – on the definition of what is a “psychotherapy school”), but there are also diverging and conflicting lines in research, e.g. between qualitative and quantitative approaches or between evidence-based practice (practice should apply treatments which are validated by Randomized Controlled Trials) and practice-based evidence. Also the reaction to this tradition of heterogeneity is at least twofold: enjoying the creative diversity or missing integration and synergy effects.

Two actual developments in psychotherapy seem to reproduce again a gap instead of an integration which could make both development lines more powerful. One is the increasing interest in outcome monitoring and feedback on therapeutic progress which has been adopted by many mental health providers all over the world (e.g., Evans et al., 2002; Kraus et al., 2005; Lambert et al., 2005; Miller et al., 2005; Trauer, 2010). Lambert (2007, 2010) or Newnham and Page (2010) describe it as an important feature of good clinical practice and ask for an integration of monitoring procedures into routines of mental health care. Another field of emerging interest is the nonlinear dynamic systems approach, which refers to Synergetics, chaos theory, and other theoretical and methodological concepts in complexity science (Orsucci, 2006, 2015; Gelo & Salvatore, 2016; Haken & Schiepek, 2006; Strunk & Schiepek, 2006; Tschacher et al., 1992). Empirical studies produced evidence for chaotic dynamics and cascades of self-organized order transitions in human change processes – with far reaching theoretical and practical consequences (Haken & Schiepek, 2006; Schiepek et al., 2014a; Strunk & Schiepek, 2006). Both development lines have created social networks and scientific cooperations all over the world. E.g., the Society for Nonlinear Dynamics in Psychology and the Life Sciences was founded in 1991, and in the Society for Psychotherapy Research an Interest Group for complexity science was initiated by Franco Orsucci in 2016.

The usual practice in psychotherapy feedback is to assess outcome at therapy sessions and to compare it to an expected treatment course of reference clients (so called "standard track"; Lambert et al., 2005). In contrast to this, the message of nonlinear dynamics is that there is no standard track or expected treatment response of human change dynamics because of the limited predictability of chaotic dynamics, the highly individualized and complex patterns of change, and the occurring order transitions between quasi-attractors. For practical purposes of successful interventions it is more important to know when the system shifts into a critical instability than if the trajectory is "on track" or not. In a strict sense, a chaotic, self-organizing system will never be "on track". From the point of view of complex dynamic systems, standard tracks (expected change trajectories) are more likely an artefact of low frequency and non-equidistant data collection and widely used linear assumptions than of the actual linearity of the phenomena under consideration. In consequence, therapy feedback can and should be fitted to the requirements of nonlinear dynamic systems by some methodological adaptations. New technological developments like the Synergetic Navigation system (SNS) allow for the identification of precursors and correlates of non-equilibrium order transitions in human change processes.

2. Bridging the Gap

If psychotherapy is basically the adaptive realization of conditions for self-organization, that is, for cascades of order to order transitions (Haken & Schiepek, 2006; Schiepek et al., 2015), a monitoring instrument for this kind of dynamics is needed. On this way we have to go some methodological steps which are outlined in the following.

In Session vs. Ecological Momentary Assessment

The majority of practitioners who use feedback routines ask clients for outcome ratings during therapy sessions (e.g., de Jong et al., 2014; Delgadillo et al., 2017; Lambert et al., 2002, 2005; Lutz et al., 2013). The consequence is long and varying periods of time between measures – in outpatient settings, but also in day treatment or inpatient settings (Newnham et al., 2010 a,b). Therapy feedback then loses the advantages of ecological momentary assessment, because experiences of every-day life aren't reported in close timely proximity to their actual occurrence. In contrast, daily assessment can reduce memory biases, distortions by state-dependent memory effects in distal settings, and the urge for implicit averaging over many events or days, resulting in enhanced ecological validity of the data (Ebner-Priemer & Trull, 2009; Fahrenberg et al., 2007; Wenze & Miller, 2010). For data collection in everyday settings, web-based devices such as smartphones, tablets, or laptops yield easy access to questionnaires whenever and wherever needed.

Outcome vs. Common Factors Monitoring

Feedback procedures focus almost exclusively on outcome measures (e.g., the Outcome Questionnaire (OQ-45; Lambert et al., 2004) and many others, see Delgadillo et al., 2017; Evans et al., 2002; Newnham et al., 2010a,b; Trauer, 2010). Focusing entirely on – albeit important – outcome excludes process-mediating aspects and general therapeutic ingredients. In order to grasp these aspects of therapy, the monitoring should also cover factors as resources, motivation for change, engagement, emotions, self-relatedness, expectancies, self-esteem, self-efficacy, or working alliance and ward atmosphere (Duncan et al., 2010; Norcross & Lambert, 2011). Besides outcome, therapy feedback should be sensitive to features of change processes like early rapid responses, sudden gains or losses (Lutz et al., 2013; Stiles et al., 2003), or rupture-repair sequences in the working alliance (Gumz et al., 2012; Stiles et al., 2004). Combining the common factors approach with therapy monitoring could result in a real-time assessment of common factor dynamics – which may be nonlinear and chaotic (Schiepek et al., 2014 a,b; Schiepek et al., 2017).

Irregular vs. Frequent and Equidistant Time Sampling

As stated above, it is often the sequence of therapy sessions that defines when patients give survey-based feedback. De Jong et al., (2014) report on a feedback study in outpatient settings with about 50% OQ administrations out of 32.3 (SD: 41.4) therapy sessions. De Beurs et al., (2011) administered the Brief Symptom Inventory four times during a sequence of more than 50 sessions. Such sampling rates represent outcome states at a certain time, but do not allow for the identification of dynamic patterns and pattern transitions. Figure 1 illustrates how the dynamics of a time series (daily ratings of self-esteem from a patient with Borderline Personality Disorder) is distorted and the information on the dynamic pattern is lost if measurement points are successively omitted. The rapid cycling during the first weeks of a treatment vanishes if ratings are only made on every fourth day (Figure 1c), weekly (Figure 1d), or at mixed weekly and fortnightly intervals, which is the most common periodicity of therapy sessions (Figure 1 e,f). Corresponding to the loss of information, the presented time series appear more and more linear with the shape of the curve depending on the chosen measurement points.

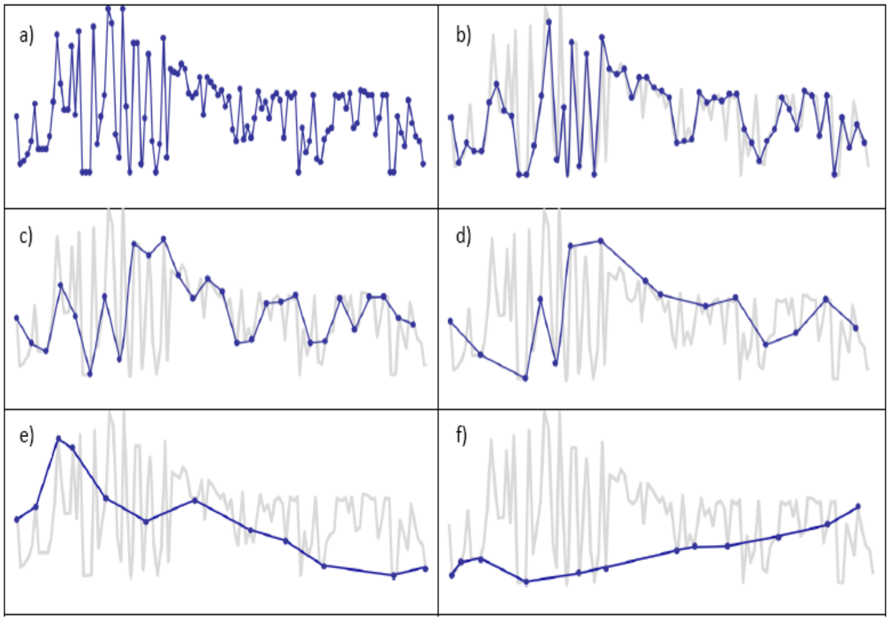

Figure 1. Illustration on how dynamic patterns depend on sampling rates and can be deformed by the arbitrariness of measurement time. (a) Empirical time series of "self-esteem" based on daily ratings of a client diagnosed as "Borderline Personality Disorder" (112 measurement points = days). (b) Only each second measurement point is taken. The pattern is less differentiated, but the curve has still a similar shape compared to the original one. It should be considered that analysis methods (e.g., on dynamic complexity, degree of synchronization) implemented in the SNS are based on running windows. For applying dynamic complexity (Schiepek & Strunk, 2010) or inter-item correlation a window width of 7 points reveals valid results. Reducing the measurement density by 2 would require a proportional enlargement of the window width with consequences for the actuality of analysis results. Actuality is crucial if treatment decisions should be based on such results. (c) Each forth measurement is taken from the original time series. The fluctuations dominating the first third of the process now are eliminated. (d) The time series corresponds to an assessment once per week, with a slight randomness (± 2 days) around a rhythm of exactly 7 days. (e, f) Varying measurement distances from 7 to 14 days correspond to a realistic session by session rhythm in outpatient settings. Depending on the exact day of the assessment, the shape of the curve and the resulting judgement on success or deterioration is drastically changed. Conclusion: Given a solid data base in time series the outcome of a therapy could not only be judged by pre-post measures but also by changing dynamic patterns. There is no "real" or "true" dynamics of psychotherapy since it depends on the selected theoretical constructs and measures, the sampling rate, and the system levels under consideration.

In order to get deeper insight into human change processes, it is important to perform frequent, continuous, and equidistant measurements (regular time sampling). Only regular and frequent assessments through process questionnaires allow for meaningful application of time series analysis methods in the domains of frequency (e.g., Fast Fourier Transformations, Time-Frequency Distributions, Cohen, 1989) and of nonlinear dynamics (Haken & Schiepek, 2006; Heath, 2000; Kantz & Schreiber, 1997). In consequence, there should be just as much emphasis placed on standardizing the sampling rates as there is currently on standardizing the instruments used for measurement (e.g., questionnaires). When aiming at (a) a complete recording of therapies (not only as an irregular event sampling), (b) frequent and (c) continuous measurements, and (d) considering practicalities of data collection, daily measurements appear to be a good and achievable way.

Linear vs. Nonlinear Dynamics

Most therapy feedback applications utilize linear models of psychological change. However, there are accumulating findings supporting nonlinearity and chaoticity of psychotherapy and change dynamics (e.g., Granic et al., 2007; Haken & Schiepek, 2006; Halfon et al., 2016; Hayes et al., 2007a,b; Heinzel et al., 2014; Kowalik et al., 1997; Schiepek et al., 1997; Schiepek et al., 2014a,b, 2017; Tschacher et al., 1998). Chaos implies different degrees of irregularity and complexity of the dynamics, including its sensitive dependency on initial conditions, on minimal input onto the system, or on micro-fluctuations (Schuster, 1989; Strunk & Schiepek, 2006). This so called "butterfly effect" restricts the predictability of systems' behavior dramatically.

Another well-known feature of human change processes is phase-transition-like behavior as modelled by theories of self-organization (especially Synergetics, Haken, 2004; Haken & Schiepek, 2006; Schiepek et al., 2014 a,b). Sudden changes (gains or losses) during psychotherapies may directly correspond to such phase transitions. Both critical fluctuations at instability points of the system dynamics and the deterministic chaos of the process – confounded with stochasticity in real-world systems – result in high complexity and inter-individual diversity of the dynamics. Synergetics predicts the occurrence of critical fluctuations and the increase of data-variability just before transitions from one pattern to another take place (Haken, 2004; Haken & Schiepek, 2006; Kelso, 1995; Schiepek et al., 2014 a,b).

Focus on Cases at Risk of Deterioration vs. Continuous Cooperative Process Control by Applying Decision Rules to All Cases

There is increasing evidence that feedback not only supports therapy in cases of threatening deterioration (Lambert et al., 2002) but also in prosperous therapies (Anker et al., 2009; de Jong et al., 2014; Lambert et al., 2005), or at least reduces average treatment duration and costs (Delgadillo et al., 2017). It appears to be especially beneficial if both - client(s) and therapist - exploit feedback (de Jong et al., 2014). In consequence, feedback tools should become part of everyday routine practice in different psychotherapeutic settings and the information produced should be shared by clients and therapists. A diversity of dynamic features shift into focus, and, as predicted by the theory of self-organization, critical instabilities and crises are utilized as common and necessary transients on the way to therapy effects. Therapists should be able to read these markers of self-organizing processes and encourage the client to communicate his/her experiences corresponding to the feedback results. As a result, clients will be accompanied towards further therapeutic steps and strengthened for (micro-)decisions on the way to therapeutic success. Herein the therapist continuously realizes a threefold reference: (i) to the information given by the client, (ii) to the theory (e.g., the theory of self-organization), and (iii) to the process data and analysis results. An important background are the decision criteria or heuristics given by the so called "generic principles" which are derived from Synergetics (Haken & Schiepek, 2006; Schiepek et al., 2015). They cover eight important conditions for successful self-organizing processes of a client: 1 create stable boundary conditions, 2 identification of relevant systemic patterns, 3 sense of significance, 4 control parameters and motivation for change, 5 destabilization and amplification of fluctuations, 6 kairos, resonance, and synchronization between client and therapist, 7 purposeful symmetry breaking, 8 stabilization of new patterns.

3. The Identification of Order Transitions – Converging Evidence from Different Methods Implemented in the Synergetic Navigation System (SNS)

From the perspective of self-organization, one of the most important aims of therapy feedback is to get early warning signals on upcoming order transitions. Periods of critical instability preceding such transitions are often sensitive to minor interventions, personal decisions, or new and encouraging activities. These periods are critical moments which in the ancient Greek mythology are called "Kairos" (see the 6th generic principle). However, critical instabilities can also be decisive moments for a development to the worse, e.g., to suicidal states (Fartacek et al., 2016).

The first and most simple way to identify precursors of order transitions is the inspection of raw data time series by the naked eye. This is by no means an objective method but given some experience in pattern recognition it provides a good first visual impression which can be consensually validated by the reports and electronic diaries of the client. Figure 2 shows some examples of order transitions as presented by the diagrams of the Synergetic Navigation System (SNS). In many cases critical instabilities can be identified before an order transitions takes place (Figure 2a), in other cases a transient deterioration may be a precursor (Figure 2 b,c). A next step is the presentation of the factor dynamics. Factors are subscales of a process questionnaire combining the information from several items. In the SNS, the items contributing to a factor are averaged and z-transformed (Figure 3). The SNS also allows for the superposition of several time series in a diagram, which creates an optimized picture of critical instabilities and order transitions (Figure 3a). In many cases the z-transformed factor dynamics shows the shape of a process more pronounced than the time series of the items. Figure 4 shows an example of a client diagnosed by the label of "dissociative identity disorder" (for a detailed description of this case see Schiepek et al., 2016). The time series of the raw data are quite noisy and fluctuating (Figure 4a), whereas the factor dynamics shows a much clearer "Gestalt" with one dominating order transition (Figure 4b).

Colored raw data diagrams transform the values of all included time series as given by the items of a process questionnaire into rainbow color scales. These diagrams create a synopsis of the evolution pattern of multiple time series (Figure 5).

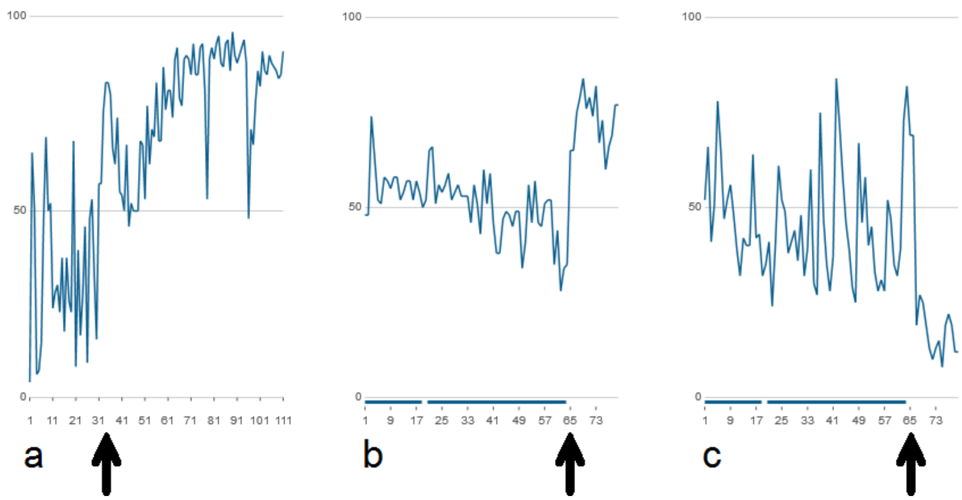

Figure 2. Time series of single items (raw data, Therapy Process Questionnaire-Revised, TPB-R). (a) “Today I felt joy,” (b) “Today I felt decided to change my problems,” (c) “Experienced intensity of problems and symptoms“ (time series (b) and (c) are taken from the same client, see also Figures 3b,c, 5a, 9, 13). (a) shows a critical instability before the transition (comp. Figures 3a, 5a, and 7), (b) and (c) show a transition after a short period of deterioration. The arrows indicate significant order transitions.

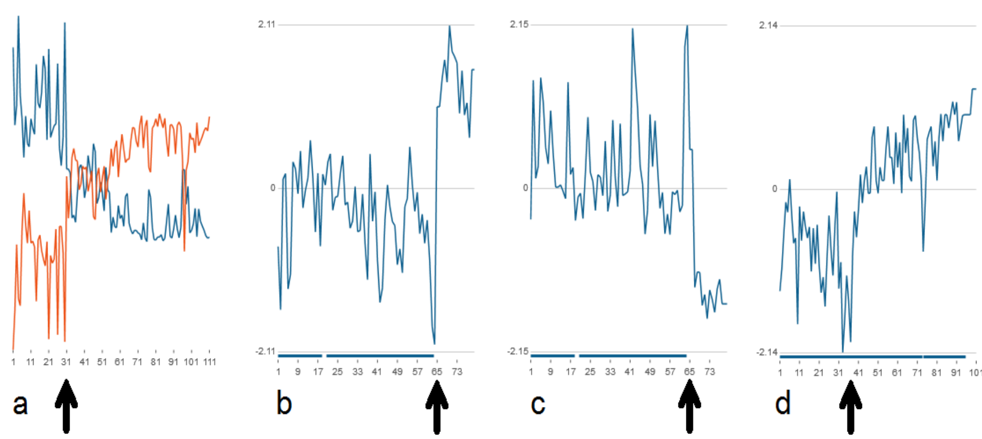

Figure 3. Time series of factors (Therapy Process Questionnaire, TPB-R). (a) Two factors superimposed: “Problem and symptom severity“ (blue) and “Self-awareness/body experience” (red; same client as in Figures 2a and 5b). (b) “Therapeutic progress / confidence / self-efficacy,” (c) “Problem and symptom severity.” (b) and (c) refer to the same client as Figures 2b,c, 5a, 9, 11, and 13), (d) “Therapeutic progress/confidence/self-efficacy” (another client). The arrows indicate significant order transitions.

Pattern transitions not only appear in changed mean levels of a time series, but also in their variability, rhythms, frequency distribution, complexity, or other dynamic features (see Figure 1a). The option of a superposition of time series in a diagram (Figure 3a) or the visualization of coloured raw data diagrams can show such synchronized or anti-synchronized rhythms in multiple time series (Figure 6a). In some cases, order transitions are characterized by the emergence or submergence of synchronized rhythms.

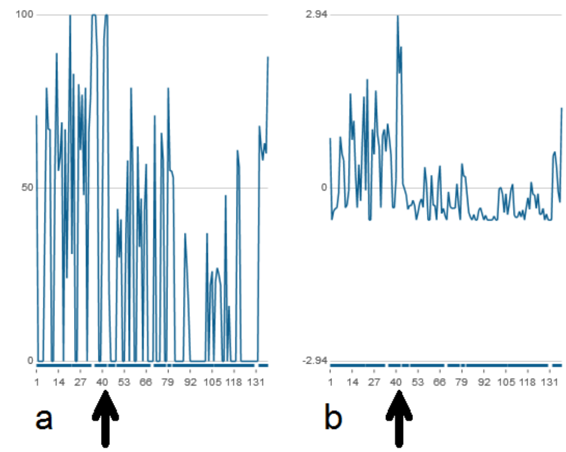

Figure 4. (a) Time series of the item “Today I experienced stress.” (b) Time series of the factor “Stress and coping with stress.” The items of this factor correspond to a child-related ego state of a client diagnosed as “dissociative identity disorder” (see also Figures 6, 10, 12, and 14, which refer to the same client). The arrows indicate the dominating order transition.

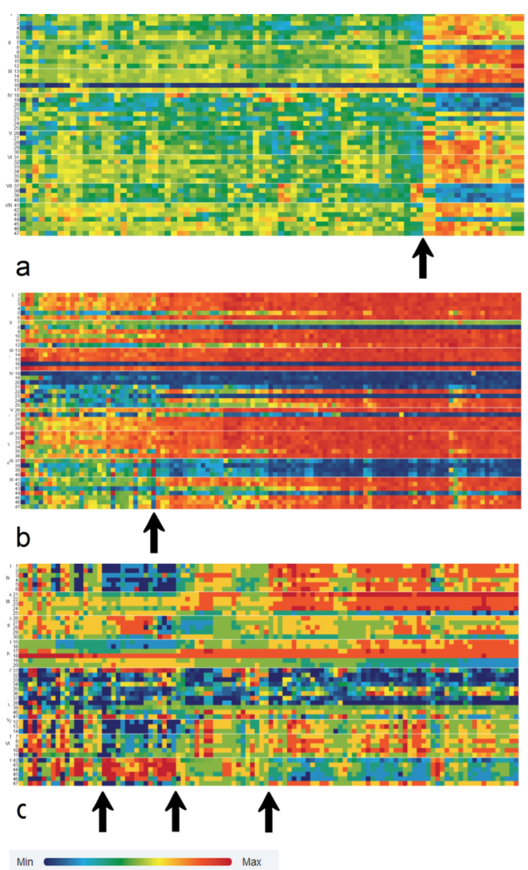

Figure 5. Colored raw data diagrams. The arrows indicate significant transitions. (a) Same client as in Figures 2b,c, 3b,c, 9, 11, and 13; (b) same client as in Figures 2a, 3a, and 7; (c) same client as in Fig. 3d.

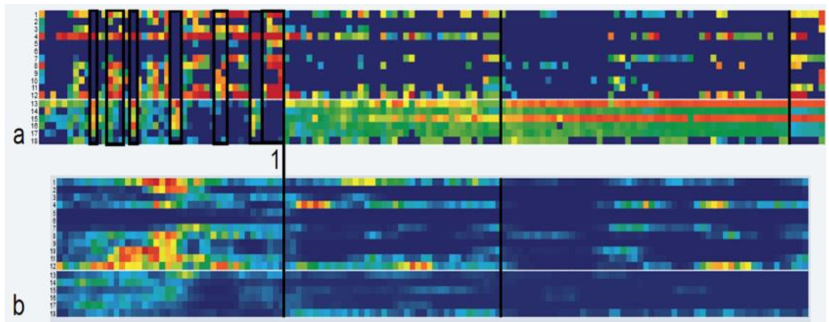

Figure 6. (a) Colored raw data diagram of a client diagnosed as “dissociative identity disorder.” Blue colors represent low intensities, yellow to red colors represent high intensities of the ratings. The vertical line (1) indicates the significant order transition of this therapy. Before this transition an alternating pattern between the items corresponding to two ego states can be identified. Black frames underline periods of alternating item scores and manifestations of states. Items 1 to 12 correspond to a “child” state, shown above the thin white line in the diagram; items 13 to 18 correspond to an “adult” state, shown under the thin white line. (b) Complexity resonance diagram of this client’s change process. The cluster of high dynamic complexity occurs especially in the items of the “child state” before the order transition, corresponding to the intensely fluctuating and mutually exclusive states.

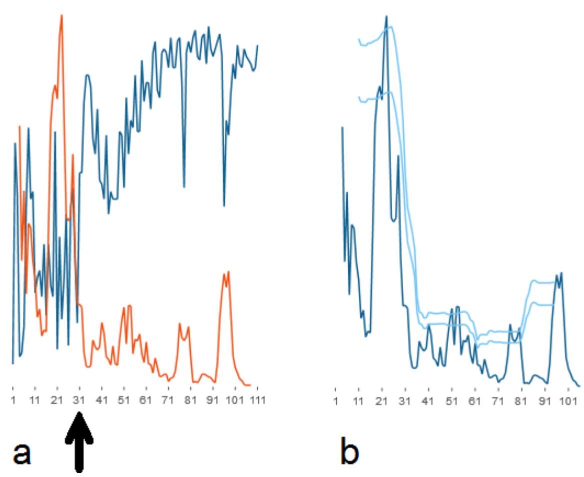

Figure 7. (a) The dynamic complexity (red) of the time series “Today I felt joy” (see Figure 2a). In the SNS diagrams, the dynamic complexity curve can be superimposed onto the time series of raw data or factors. The complexity peak precedes the order transition. (b) Over the dynamic complexity dynamic confidence intervals are calculated in a running window (95% [lower] and 99% [upper] thin blue line). Here the width of this running window is 21.

A common precursor of order transitions is critical instability (Haken, 2004; Haken & Schiepek, 2006). In the SNS this is represented by the measure of dynamic complexity, which combines the amplitude, the frequency, and the distribution of the values of a signal over the available range of a scale. All three features (amplitude, frequency and distribution) are calculated within a gliding window which runs over the complete time series (given daily measures the usual window width is 7 days) (Haken & Schiepek, 2006; Schiepek & Strunk, 2010). The evolution of dynamic complexity can be presented as time series (Figure 7) or as colored complexity resonance diagrams (Figure 8). In the resonance diagrams, vertical columns or sudden decreases of complexity over many items indicate order transitions. Another way of representing dynamic complexity is not to include all complexity values from all items and to transform them into colors, but to calibrate the complexity values within each time series. The 10 highest complexity values of an item's time series are transformed into grey steps (from black corresponding to the highest to a bright grey as the lowest complexity value, all others are white). This procedure is more sensitive for low complexity values and shows the synchronization of intra-item calibrated complexity in a grey-steps diagram (Figure 9).

In some cases, the weekly assessed symptom or stress intensity may indicate an upcoming transition. In the example presented in Figure 10a, the intensities of depression and stress are increased just before the order transition takes place. After this transition, the values are significantly reduced. In our routine practice, depression, anxiety, and stress are assessed once per week by the short form of the Depression-Anxiety-Stress Scales (DASS-21; Lovibond & Lovibond, 1995).

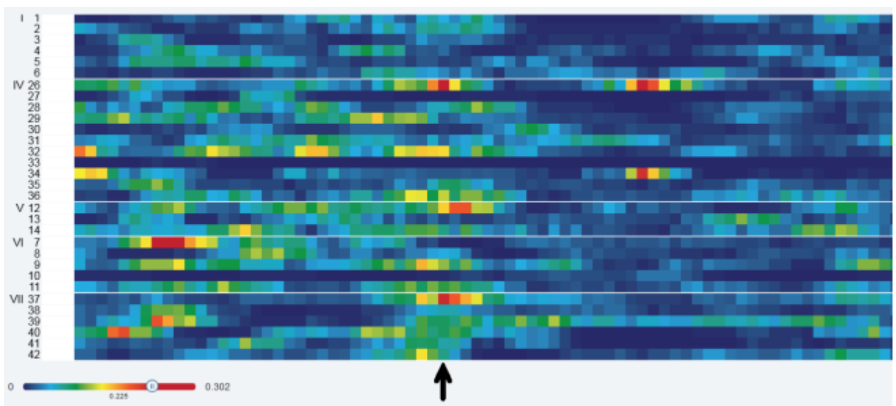

Figure 8. Complexity Resonance Diagram. The dynamic complexity is calculated in overlapping running windows (window width = 7 days). The maximum score of the dynamic complexity is depicted by a full red pixel, while all other values are graded according to that maximum (red = high, yellow = medium, blue = low complexity). The order transition is marked by the arrow.

Another precursor of order transitions is increased synchronization of the emotions and cognitions of a client, as represented by the items of a process questionnaire. In the SNS, the absolute (sign-independent) values of inter-item correlations of a questionnaire are averaged within a moving window and presented as averaged correlation strengths over time. This is a measure of coherence of the dynamics (Figure 10b, Figure 11). The changes of all inter-item correlations are presented in a sequence of correlation matrices with color-coded correlations (from –1 [dark red] over 0 [white] to +1 [dark green]). The correlation matrices are calculated within a running window (the window width is up to free choice, here: 7). A marker can be dragged along the time points to display the change in synchronization patterns over time. The local increase of the absolute inter-item synchronization together with a more pronounced correlation pattern corresponds in many cases to a qualitative change of the correlation pattern. Figure 12 illustrates this pattern transition in the case of the client diagnosed as "dissociative identity disorder." Before the first order transition, the correlation matrix represents the alternating ego states (high positive intra-state correlations of cognitions and emotions [green], high negative inter-state correlations [red]) which is dissolved after the order transition.

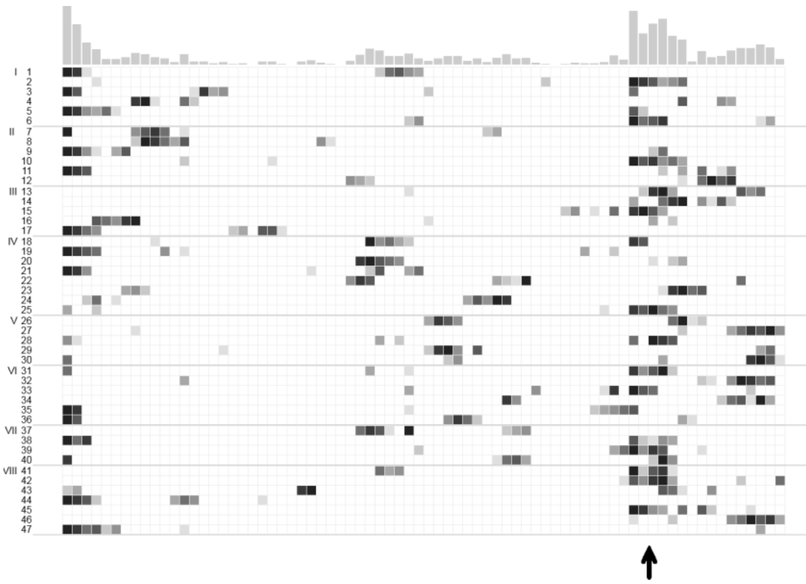

Figure 9. Complexity Resonance Diagram, based on an intra-item calibration of the dynamic complexity. The 10 highest complexity values of each item are coded by grey steps. The arrow indicates the order transition (same client as in Figures 2b,c, 3b,c, 11, 13).

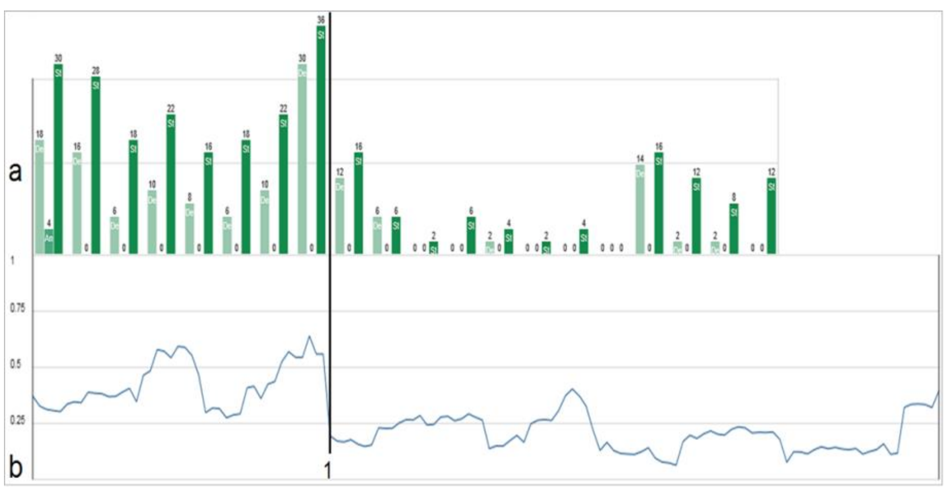

Figure 10. (a) Intensity of depression (light green), anxiety (except for the first week always at 0) and stress (dark green) (assessed once per week by the DASS-21, Lovibond & Lovibond, 1995). Just before the order transition (vertical line, comp. Fig. 6) the values are increased, after it the values decrease immediately to a lower level. (b) Averaged inter-item correlation calculated in a running window of 7 measurement points. The first part of the process is characterized by a pathological over-synchronization with the maximum just before the order transition (vertical line) (same client as in Figures 4, 6, 12, and 14).

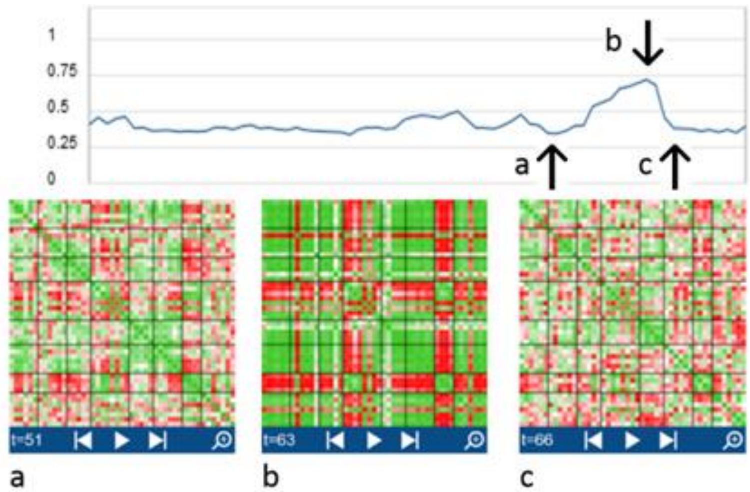

Figure 11. Locally increased inter-item synchronization during the period of an order transition (arrow b). The inter-item correlation matrices show an intensified and more pronounced pattern during the order transition compared to the matrices before and after the transition (a before, b during, c after). Each cell depicts the correlation of a respective item with another item on a gradual green (positive correlation values, $0 < r < 1$) or red (negative correlation values, $-1 < r < 0$) scale (white cells correspond to a correlation of 0) (same client as in Figures 2b,c, 3b,c, 5a).

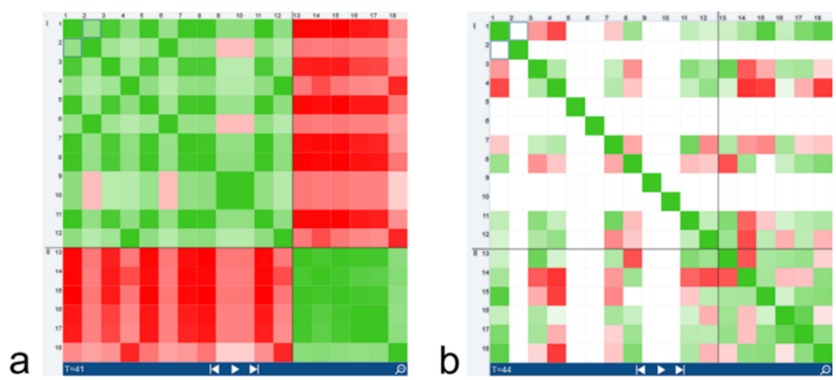

Figure 12. (a) Color-coded inter-item correlation pattern characterizing the first third of the monitoring period (before the vertical line (1) in Figures 6 and 10). The black lines differentiate the items of factor I and factor II. The left matrix (t = 41-47) is characterized by high positive within-factor item correlations (green colors) and negative between-factor item correlations (red colors). (b) Only some days later (t = 49-56), but after the main transition of the therapy (occurring at the vertical line in Figures 6 and 10), this pattern dissolved. The change of correlation patterns coincides with the client’s reports of increasing integration of her separate ego states throughout the therapeutic process.

A method which identifies recurrent patterns within a time series in a time×time diagram is Recurrence Plots (Eckmann et al., 1987; Webber & Zbilut, 1994). Snippets of a longer time series are embedded in a phase space defined by time-delay coordinates. Each snippet represents a vector point in the phase space (each measurement point is represented on an axis). The Euclidean distances between the vector points can be binary coded according to a selected threshold or, alternatively, the distances can be color coded. By this, recurrent patterns and their transients (periods of critical instability) become apparent. Usually, Recurrence Plots and CRDs show complementary patterns: transient periods (yellow to red colors; out-of-attractor dynamics) correspond to periods of critical instabilities, and hence, increased dynamic complexity, whereas recurrent periods (turquoise to blue) represent more or less stable quasi-attractors. Figure 13 illustrates the transition from one stable pattern to another (blue rectangles), with a short transient period in between (yellow to orange pixels).

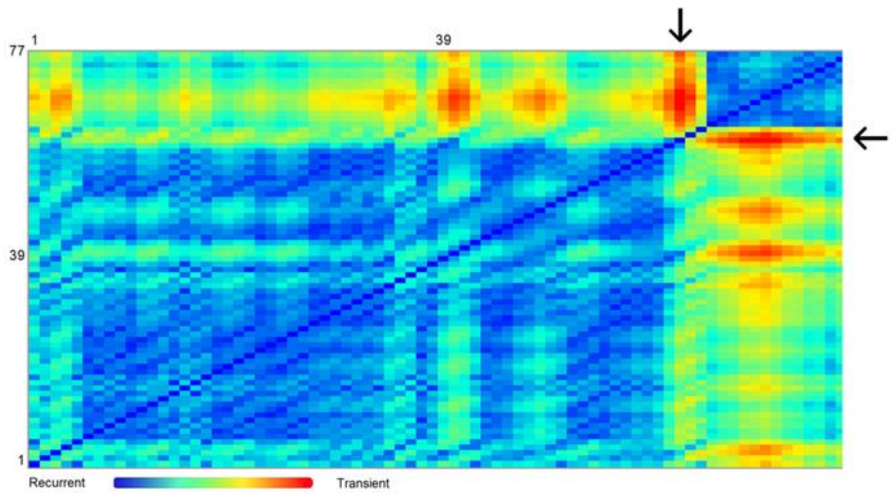

Figure 13. Recurrence Plot. The arrows refer to a short transient period (coded by yellow to red colors) between two more stable quasi-attractors (compare Figures 2b,c, 3b,c, 5a, and 9).

Beside the transition markers implemented in the SNS there are others, like increased local frequencies as identified by the wavelet-based method of Time Frequency Distributions (Cohen, 1989, see Haken & Schiepek, 2006, pp. 402ff.) or change points which can be identified by the method of Change Point Analysis (James & Matteson, 2014). It should be noted that the coincidence of more than one transition marker or precursor is needed to identify an order transition.

4. PERSPECTIVES ON PRACTICE AND THEORY

Feedback procedures are able to capture the nonlinear features of human dynamics. Ten years of experience with the Synergetic Navigation System allowed for a deep insight into these features in many cases (e.g., Heinzel et al., 2014; Schiepek al., 2014ab, 2015, 2016). Actually, a data set of 942 valid cases (average time series length: 73.5 daily measures (SD: 38.5), average missing data: < 3%) is available from different treatment centers. This continuously increasing data base opens the door to the investigation of many research questions and to a further validation of the mainly used process questionnaire (TPQ-R). In times of upcoming doubts on research results based on small samples it is important for psychotherapy science to go into the world of big data. Perhaps more important is the option to combine big data with the individualization of measures and treatment procedures (e.g., Fisher, 2015; Fisher & Bosley, 2015).

Individualization of Treatments and Measurement Procedures

After decades of focusing on therapy schools and on disease-related treatment programs it becomes evident that important challenges to psychotherapy and public health ask for new ways of problem solving which have to be focused on the unique client. These challenges concern the great interpersonal range of treatment outcomes, including non-responders and deteriorations, missing sustainability and stability of treatment effects, or treatments which are not sufficiently fitted to the complexity of client's problem configurations, living conditions, treatments goals, co-morbidities, and also to the dynamics of change processes (e.g., Lambert, 2013; Newman et al., 2010). The hope exists that personalized and tailored treatments can meet these challenges by optimized case formulations, personalized procedures, the dynamic adaptation of therapeutic procedures to the process, specific after-care programs, and also by using personalized measures. An advanced approach in personalized psychotherapy is the Synergetic Process Management (Haken & Schiepek, 2010) which uses individualized process monitoring based on a specific method of case formulation – the idiographic system modelling (Schiepek, 2003).

The method of idiographic system modelling starts by a semi-structured interview which produces a list of important psychological and social variables constituting the cognitive, emotional, and social system of the client. Starting off at a general picture of the client's life in the last couple of months, the therapist takes notes throughout the interview on important factors such as psychological problems, problem-solving methods, coping strategies, and impact on social life. These notes will form the basic components of the idiographic model (Schiepek et al., 2015). Therefore, practically any topic of importance to the client can be part of the interview and enter the system. It is advisable to try to capture the actual terms of the client's language, in order for client and therapist to create mutual understanding and producing the client's very own individual model. After the interview, all variables are being checked for their terminology and content, to make sure that the client can find himself in these. It is important that the components are expressed as variables that can change throughout time. In a perfect case, therapist and client manage to capture all important bio-psycho-social aspects of the client's life, incorporating cognitions, emotions, motives, behavior, or physiological states, using the client's own language and terminology as well as by using psychological constructs.

Subsequently, the inter-connections of these variables are mapped, creating a personal landscape of relevant aspects of the client's mental functioning – the idiographic system model (ISM). Using a flipchart, a variable A is written down and the list is being checked for other variables that are connected to it. Writing down a second connected variable B, both are linked with an arrow and a "+" or "–" symbol, indicating whether there is a positive relation (same directedness: increase in A leads to increase in B and decrease in A leads to decrease in B) or a negative relation (opposite directedness: increase in A leads to decrease in B and decrease in A leads to increase in B). An example is given by Figure 14. The client described that an increase in "dissociation" is accompanied with a decrease of the distraction through "disturbing voices", indicated by a "–" between the two variables. In contrast and symbolized by a "+," the more "rage/aggression" she experiences, the more she needs to toggle her "movie in the head (head-cinema)," and a decrease in aggression makes that coping-mechanism less necessary.

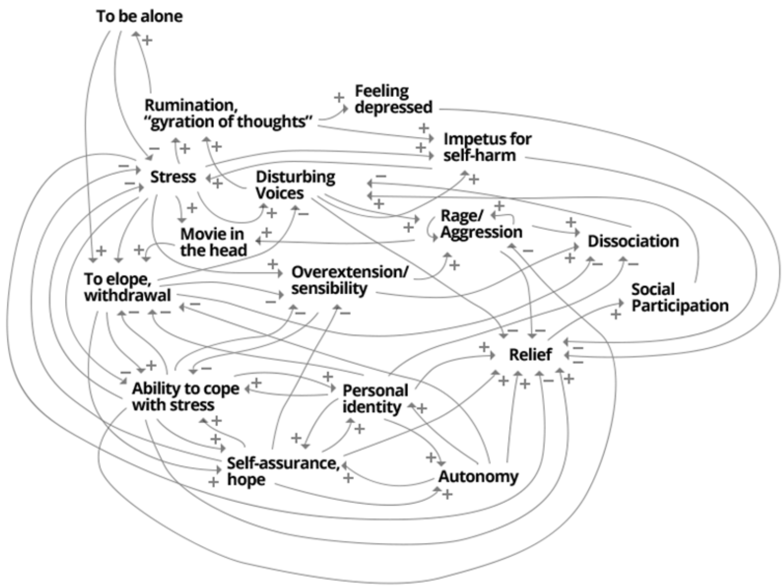

Figure 14. The idiographic system model of the client diagnosed as "dissociative identity disorder" (comp. Figures 6, 10, and 12). The items of her personalized process questionnaire correspond to the variables of this model. The client attributed many of the variables to be differentially prominent in separate ego states. The understanding of the model was the basis of seeing patterns, what before was experienced as volatile and erratic alternations of ego states. In contrast to her everyday life experience, the ISM represented a systemic synopsis of her psychological and social life, making amnestic separations of ego states visible. Consequently, this understanding allowed trauma-focused therapy and intensive work directed towards the ego states.

Most clients achieve to create a complete ISM in a session of about three hours, being in a "focused flow." They report to find themselves represented by their own model referring to it as "the map of their soul." ISMs help clients to better understand patterns of their behavior, and how in a systemic fashion, cognitions, emotions, and behaviors trigger each other. If it makes sense to the client, the variables and also the relations between them can be taken as targets of interventions and new experiences. The questionnaire editor of the SNS can be used to create a personalized process questionnaire, with usually one variable of the ISM corresponding to one item (comp. Fig. 6). Given the procedure of creating an ISM, clients have an optimized understanding of these personalized items. In consequence, the data produced by this kind of questionnaires are perhaps more valid than that produced by standardized questionnaires. The teamwork of client and therapist continuously refers to the ISM as well as to the time series produced by the personalized questionnaire (cooperative continuous process control).

Theoretical Modelling Psychotherapeutic Processes

The conceptual framework of self-organizing systems and the new data base given by nonlinear feedback technologies also have consequences on theoretical modelling. Efforts have intensified to understand how psychotherapy works, taking seriously that the "explanandum" is the change process and that an important key to understanding change lies within the change process itself rather than in the input onto it. During the last years our research group worked on a theoretical model which is able to simulate the nonlinear dynamics of change processes including important features of deterministic chaos: irregularity of the dynamics, sensitive dependency of the process on initial conditions and on small but well-timed interventions, global stability of the system's behavior within its (more or less stable) attractors, and the dependency of the actually realized attractor on the control parameters of the system, resulting in attractor shifts during the change process (Schiepek et al., 2017).

The model includes four variables or order parameters: (E) emotions; (I) insight, new perspectives; (M) motivation to change; (P) problem intensity; symptom severity; (S) success, therapeutic progress, goal attainment. Four control parameters mediate the interactions between the variables: (*a*) working alliance, capability to enter a trustful cooperation with the therapist, quality of the therapeutic relationship; (*c*) cognitive competencies, capacities for mentalization and emotion regulation; (*r*) behavioral resources or skills that are available for problem solving; (*m*) motivation to change as a trait, self-efficacy, positive expectations in one's development. Depending on their values, the effect of one variable on another is intensified or reduced, activated or inhibited (Figure 15).

A property of the model is the circular causality between states and traits (Figure 16). Traits are competencies or dispositions which modify the shapes of the nonlinear functions describing the effects of one state (variable) to another. In terms of personality psychology, traits are qualities of a person which influence states (cognitions, emotions, or behavior varying from moment to moment). In terms of Synergetics, states correspond to the order parameters of the model and traits correspond to its control parameters. Control parameters change at a slower time scale than the variables or states (separation of the time scales). In self-organizing systems the change of control parameters drives the phase transitions of the system (Haken, 2004; Haken & Schiepek, 2006).

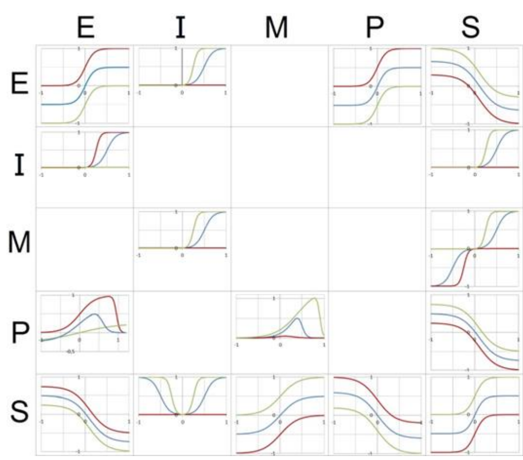

Figure 15. The 16 functions of the model (for a detailed description see Schiepek et al., 2017). The variables noted on the left of the matrix (lines) represent the input, the variables noted at the top (columns) represent the output. Each function is represented by a graph in a coordinate system (x-axis: input, y-axis: output). Green function graphs correspond to the maximum of the respective control parameter(s) (= 1), red graphs to the minimum of the parameter(s) (= 0). Blue graphs represent an in-between state (0 < parameter value < 1).

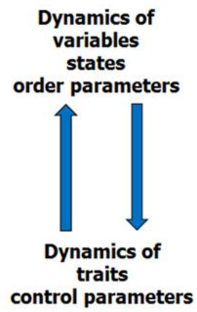

Figure 16. Circular causality between states (order parameters) and traits (control parameters).

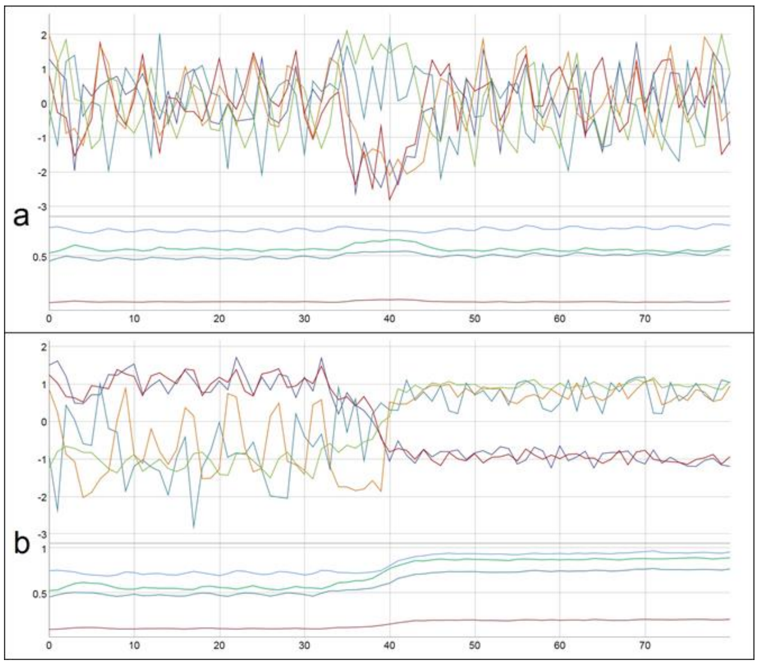

Figure 17. Two simulation runs of the model at the same levels of dynamic noise (a, b). Upper part of both diagrams: Dynamics of the variables or states (order parameters): E (dark blue), I (yellow), M (light blue), P (red), S (green). Lower part: Dynamics of the traits (control parameters): *a* (red), *m* (green), *c* (bright blue), *r* (dark blue). In both cases, the initial values of variables and parameters are identical. The added dynamic noise is 10% on E and P, 5% on M, I, and S, continuously. (a) A transient instability, but no order transition occurs. (b) The dynamic noise triggers an order transition.

Technically the model is realized by nine coupled nonlinear difference equations. Five represent the state or order parameter dynamics (E, I, M, P, S) and four represent the trait or control parameter dynamics (*a, c, r, m*) (Schöller et al., under review). The model explains how the circular interaction between control and order parameters can create stable effects at the personality level, or why in some cases dynamic noise can have important consequences whereas in other cases it has no impact (Figure 17). Other results of the model concern the different impact of punctual interventions vs. continuous interventions, or the significant time-dependency of interventions during the process.

The conclusion is that new methods of process monitoring and feedback are part of a new paradigm in psychotherapy. The Synergetic Navigation System opens the black box of human change processes and their nonlinear features, and in consequence, it also requires the individualization of treatments and measurement procedures. Finally, the design of theories on how psychotherapy works has to be developed according to the paradigm shift towards computational systems psychology and nonlinear complexity science.

REFERENCES

Anker, M., Duncan, B. & Sparks, J. (2009). Using client feedback to improve couples therapy outcomes: a randomized clinical trial in a naturalistic setting. *Journal of Consulting and Clinical Psychology, 77,* 693-704.

Cohen, L. (1989). Time-frequency distributions – A review. *Proc IEEE, 77,* 941-981.

de Beurs, E., den Hollander-Gijsman, M. E., van Rood, Y. R., van der Wee, N. J. A., Giltay, E. J., van Noorden, M. S., van der Lem, R., van Fenema, E. & Zitman, F. G. (2011). Routine outcome monitoring in the Netherlands: practical experiences with a web-based strategy for the assessment of treatment outcome in clinical practice. *Clinical Psychology and Psychotherapy, 18,* 1-12.

de Jong, K., Timman, R., Hakkaart-van Roijen, L., Vermeulen, P., Kooiman, K., Passchier, J. & van Busschbach, J. (2014). The effect of outcome monitoring feedback to clinicians and patients in short and long-term psychotherapy: a randomized controlled trial. *Psychotherapy Research, 24,* 629-639.

Delgadillo, J., Overend, K., Lucock, M., Groom, M., Kirby, N. McMillan, D., Gilbody, S., Lutz, W., Rubel, J. A. & de Jong, K. (2017). Improving the efficiency of psychological treatment using outcome feedback technology. *Behaviour Reserach and Therapy, 99,* 89-97.

Duncan, B., Miller, S., Wampold, B. & Hubble, M. (2010). *The Heart and Soul of Change.* 2nd ed. Washington: APA.

Ebner-Priemer, U. & Trull, T. (2009). Ecological momentary assessment of mood disorders and mood dysregulation. *Psychological Assessment, 21*, 463-475.

Eckmann, J. P., Oliffson Kamphorst, S. & Ruelle, D. (1987). Recurrence plots of dynamical systems. *Europhysics Letters, 4,* 973-977.

Evans, C., Connell, J., Barkham, M., Margison, F., McGrath, G. & Mellor-Clark, J. (2002). Towards a standardized brief outcome measure: psychometric properties and utility of the CORE-OM. *The British Journal of Psychiatry, 180,* 51-60.

Fahrenberg, J., Myrtek, M., Pawlik, K. & Perrez, M. (2007). Ambulatory assessment – monitoring behavior in daily life settings. *European Journal of Psychological Assessment, 23,* 206-213.

Fartacek, C., Schiepek, G., Kunrath, S., Fartacek, R. & Plöderl, M. (2016). Real-time monitoring of nonlinear suicidal dynamics: methodology and a demonstrative case report. *Frontiers in Psychology for Clinical Settings,* 7: 130 (1-14). doi: 10.3389/fpsyg.2016.00 130.

Fisher, A. J. (2015). Toward a dynamic model of psychological assessment: implications for personalized care. *Journal of Consulting and Clinical Psychology, 83,* 825-836.

Fisher, A. J. & Bosley, H. G. (2015). Personalized assessment and treatment of depression. *Current Opinion in Psychology, 4,* 67-74.

Gelo, O. C. G. & Salvatore, S. (2016). A dynamic systems approach to psychotherapy: A meta-theoretical framework for explaining psychotherapy change processes. *Journal of Counseling Psychology, 63,* 379-395.

Granic, I., O'Hara, A., Pepler, D. & Lewis, M. (2007). A dynamic systems analysis of parent child changes associated with successful real-world interventions for aggressive children. *Journal of Abnormal Child Psychology, 35*, 845-857.

Gumz, A., Brähler, E., Geyer, M. & Erices, R. (2012). Crisis-repair-sequences – Considerations on the assessment and classification of breaches in the therapeutic relationship. *BMC Medical Research Methodology, 12,* 10.

Haken, H. (2004). *Synergetics. Introduction and Advanced Topics.* Berlin: Springer.

Haken, H. & Schiepek, G. (2006). *Synergetik in der Psychologie (Synergetics in Psychology).* Göttingen: Hogrefe (2nd. Ed. 2010).

Halfon, S., Cavdar, A., Orsucci, F., Schiepek, G., Andreassi, S., Giuliani, A. & de Felice, G. (2016). A non-linear trajectory of change in play profiles of three children in psychodynamic play therapy. *Frontiers in Psychology for Clinical Settings, 7:1494*. doi: 10.3389/fpsyg.2016.01494.

Hayes, A. M., Feldman, G. C., Beevers, C. G., Laurenceau, J. P., Cardaciotto, L. A. & Lewis-Smith, J. (2007a). Discontinuities and cognitive changes in an exposure-based cognitive therapy for depression. *Journal of Consulting and Clinical Psychology, 75,* 409-421.

Hayes, A. M., Laurenceau, J. P., Feldman, G. C., Strauss, J. L. & Cardaciotto, L. A. (2007b). Change is not always linear: the study of nonlinear and discontinuous patterns of change in psychotherapy. *Clinical Psychology Review, 27,* 715-723.

Heath, R. A. (2000). *Nonlinear Dynamics: Techniques and Applications in Psychology.* Mahwah, NJ: Lawrence Earlbaum Associates.

Heinzel, S., Tominschek, I. & Schiepek, G. (2014). Dynamic patterns in psychotherapy - discontinuous changes and critical instabilities during the treatment of obsessive compulsive disorder. *Nonlinear Dynamics, Psychology, and Life Sciences, 18,* 155–176.

James, N. A. & Matteson, D. S. (2014). ecp: an R package for nonparametric multiple change point analysis of multivariate data. *Journal of Statistical Software, 62(7).*

Kantz, H. & Schreiber, T. (1997). *Nonlinear Time Series Analysis.* Cambridge, UK: Cambridge University Press.

Kelso, J. A. S. (1995). *Dynamic Patterns. The Self-Organization of* B*rain and Behavior.* Cambridge, MA: MIT Press.

Kowalik, Z. J., Schiepek, G., Kumpf, K., Roberts, L. E. & Elbert, T. (1997). Psychotherapy as a Chaotic Process II: The Application of Nonlinear Analysis Methods on Quasi Time Series of the Client-Therapist-Interaction: A Nonstationary Approach. *Psychotherapy Research, 7,* 197-218.

Kraus, D. R., Seligman, D. A. & Jordan, J. R. (2005). Validation of a behavioral health treatment outcome and assessment tool designed for naturalistic settings: the Treatment Outcome Package. *Journal of Clinical Psychology, 61,* 285-314.

Lambert, M. J. (2007). Presidential address: what we have learned from a decade of research aimed at improving psychotherapy outcome in routine care. *Psychotherapy Research, 17,* 1-14.

Lambert, M. J. (2010). “Yes, it is time for clinicians to routinely monitor treatment outcome.” In: B. Duncan, S. Miller, B. Wampold & M. Hubble (Eds.), *The Heart and Soul of Change* (pp. 237-266) (2nd. Ed.). Washington DC: American Psychological Association.

Lambert, M. J. (2013). Outcome in psychotherapy: The past and important advances. *Psychotherapy, 50*, 42-51.

Lambert, M. J., Whipple, J. L., Vermeersch, D. A., Smart, D. W., Hawkins, E. J., Nielsen, S. L. & Goates, M. (2002). Enhancing psychotherapy outcomes via providing feedback on client progress: a replication. *Clinical Psychology and Psychotherapy, 9,* 91-103.

Lambert, M. J., Morton, J. J., Hatfield, D. R., Harmon, C., Hamilton, S. & Shimokawa, K. (2004). *Administration ans Scoring Manual for the OQ-45.2 (Outcome Questionnaire)* (3rd. Ed.). Wilmington, DE: American Professional Credentialling Services.

Lambert, M. J., Harmon, C., Slade, K., Whipple, J. L. & Hawkins, E. J. (2005). Providing feedback to psychotherapists on their patient’s progress: Clinical results and practice suggestions. *Journal of Clinical Psychology, 61*, 165–174.

Lovibond, S. H. & Lovibond, P. F. (1995). *Manual for the Depression Anxiety Stress Scales.* Sydney: Psychology Foundation.

Lutz, W., Ehrlich, T., Rubel, J., Hallwachs, N., Röttger, M. A., Jorasz, C., Mocanu, S., Vocks, S., Schulte, D. & Tschitsaz-Stucki, A. (2013). The ups and downs of psychotherapy: Sudden gains and sudden losses identified with session reports. *Psychotherapy Research, 23,* 14-24.

Miller, S. D., Duncan, B. L., Sorrell, R. & Brown, G. S. (2005). The partners for change outcome management system. *Journal of Clinical Psychology, 61,* 199-208.

Newman, M. G., Przeworski, A., Fisher, A. J. & Borkovec, T. D. (2010). Diagnostic comorbidity in adults with generalized anxiety disorder: impact of comorbidity on psychotherapy outcome and impact of psychotherapy on comorbid diagnoses. *Behavior Therapy, 41,* 59-72.

Newnham, E. A. & Page, A. C. (2010). Bridgig the gap between best evidence and best practice in mental health. *Clinical Psychology Review, 30*, 127-142.

Newnham, E. A., Hooke, G. R. & Page, A. C. (2010a). Monitoring treatment response and outcomes using the World Health Organization’s Wellbeing Index in psychiatric care. *Journal of Affective Disorders, 122,* 133-138.

Newnham, E. A., Hooke, G. R. & Page, A. C. (2010b). Progress monitoring and feedback in psychiatric care reduces depressive symptoms. *Journal of Affective Disorders, 127,* 139-146.

Norcross, J. C. & Lambert, M. J. (Eds.) (2011). Psychotherapy relationships that work II. *Psychotherapy, 48*(1).

Orsucci, F. (2006) The paradigm of complexity in clinical neuro-cognitive science, *The Neuroscientist, 12*, 390-397.

Orsucci, F. (2015) Towards a meta-model of human change, from singularity to event horizon. *Chaos and Complexity Letters, 9/1.*

Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter S. R., et al., (2009). Early-warning signals for critical transitions. *Nature, 461,* 53–59.

Schiepek, G. (2003). A dynamic systems approach to clinical case formulation. *European Journal of Psychological Assessment, 19,* 175-184.

Schiepek, G., Kowalik, Z. J., Schütz, A., Köhler, M., Richter, K., Strunk, G., Mühlnickel, W. & Elbert, T. (1997). Psychotherapy as a chaotic process I. Coding the client-therapist-interaction by means of sequential plan analysis and the search for chaos: a stationary approach. *Psychotherapy Research, 7,* 173-194.

Schiepek, G. & Strunk, G. (2010). The identification of critical fluctuations and phase transitions in short term and coarse-grained time series – a method for the real-time monitoring of human change processes. *Biological Cybernetics, 102,* 197-207.

Schiepek, G., Heinzel, S., Karch, S., Aas, B. & Strunk, G. (2014a). Chaos and self-organization in psychotherapy. *Chaos and Complexity Letters, 8*(2/3), 231-256.

Schiepek, G., Tominschek, I. & Heinzel, S. (2014b). Self-organization in psychotherapy - testing the synergetic model of change processes. *Frontiers in Psychology for Clinical Settings,* 5/1089. doi: 10.339/fpsyg.2014.01089.

Schiepek, G., Eckert, H., Aas, B., Wallot, S. & Wallot, A. (2015). *Integrative Psychotherapy. A Feedback-Driven Dynamic Systems Approach.* Boston, MA: Hogrefe International Publishing.

Schiepek, G., Stöger-Schmidinger, B., Aichhorn, W., Schöller, H. & Aas, B. (2016). Systemic case formulation, individualized process monitoring, and state dynamics in a case of dissociative identity disorder. *Frontiers in Psychology for Clinical Settings,* 7:1545. doi: 10.3389/fpsyg.2016.01545.

Schiepek, G., Viol, K., Aichhorn, W., Hütt, M. T., Sungler, K., Pincus, D. & Schöller, H. (2017). Psychotherapy is chaotic—(not only) in a computational world. *Frontiers in Psychology for Clinical Settings,* 8:379. doi: 10.3389/fpsyg.2017.00379.

Schöller, H., Viol, K., Aichhorn, W., Hütt, M. T., Aas, B. & Schiepek, G. (under review). Personality development in psychotherapy: a synergetic model of state-trait dynamics. *Cognitive Neurodynamics.*

Schuster, H. G. (1989). *Deterministic Chaos. An Introduction.* Weinheim: VCH.

Stiles, W., Leach, C., Barkham, M., Lucock, M., Iveson, S., Shapiro, D., Iveson, M. & Hardy, G. (2003). Early sudden gains in psychotherapy under routine clinic conditions: practice-based evidence. *Journal of Consulting and Clinical Psychology. 71,* 14-21.

Stiles, W. B., Glick, M. J., Osatuke, K., Hardy, G. E., Shapiro, D. A., Agnew-Davies, R., Rees, A. & Barkham, A. (2004). Patterns of alliance development and the rupture-repair hypothesis: are productive relationships U-shaped or V-shaped? *Journal of Counseling Psychology, 51,* 81-91.

Strunk, G. & Schiepek, G. (1996). *Systemische Psychologie. Einführung in die komplexen Grundlagen menschlichen Verhaltens.* [Systemic Psychology. An Introduction to Complexity in Human Behavior and Cognition]. München: Elsevier.

Trauer, T. (Ed.) (2010). *Outcome Measurement in Mental Health. Theory and Practice.* Cambridge: Cambridge University Press.

Tschacher, W., Schiepek, G. & Brunner, E. J. (Eds.) (1992). *Self-Organization and Clinical Psychology. Empirical Approaches to Synergetics in Psychology*. Springer Series in Synergetics, Vol. 58. Berlin: Springer.

Tschacher, W., Scheier, C. & Grawe, K. (1998). Order and pattern formation in psychotherapy. *Nonlinear Dynamics, Psychology, and Life Sciences, 2,* 195-215.

Webber, C. L. & Zbilut, J. P. (1994). Dynamical assessment of physiological systems and states using recurrence plot strategies. *Journal of Applied Physiology, 76,* 965–973.

Wenze, S. J. & Miller, I. W. (2010). Use of ecological momentary assessemnt in mood disorders research. *Clinical Psychology Review, 30,* 794-804.