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Dynamic Patterns in Psychotherapy – Discontinuous Changes and Critical Instabilities during the Treatment of Obsessive Compulsive Disorder

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Abstract: *In therapy processes of a variety of disorders, discontinuous trajectories of symptom changes have been identified. In this study, we are reporting on such "sudden gains" that occur in the treatment of clients with obsessive-compulsive disorder (OCD) following cognitive-behavioral group therapy. Time series analysis of data taken from 18 OCD clients revealed that a discontinuously shaped symptom reduction took place already before exposure/response prevention (ERP) in a large number of clients. Coincidently with the steepest gradient of symptom change an increased level of dynamic complexity in daily ratings of 47 items of a specific change questionnaire was observed. Our results support hypotheses from the theory of complex self-organizing systems, postulating nonstationarity and critical instabilities during order transitions. Our study underlines the usefulness of real-time monitoring procedures with high-frequency ratings (daily measurements) in therapeutic routine practice.*

Key Words: process-outcome research, sudden gains, obsessive-compulsive disorder, nonlinear dynamics, critical instability

THEORETICAL BACKGROUND

The human "brain-mind" system has been characterized as a highly complex, dynamical, and nonlinear system (Orsucci, 2006). Thus, theories of nonlinear dynamic systems have been applied to analysis and modeling of data in clinical psychology (e.g. in the characterization of mental disorders (Thomasson, Pezard, Allilaire, Renault, & Martinerie, 2000) and in psychotherapy (e.g. Tschacher, Scheier, & Grawe, 1998; Schiepek & Perlitz, 2009). Following a conceptualization of psychotherapy as a self-organizing

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process, one core hypothesis is focusing on discontinuous patterns of change. Mental and neural processes are based on nonlinear systems and will undergo non-equilibrium phase transitions when control parameters are driving attractors out of equilibrium states. Indeed, sudden changes were reported by an increasing number of studies, but until now, explanations of the results in the framework of complexity theory are rare (but see Hayes & Strauss, 1998). Self-organization theories as synergetics (Haken, 2004; Haken & Schiepek, 2010) would predict discontinuous changes and in addition the manifestation of critical instabilities just before the change of patterns.

During the last years a substantial number of studies replicated findings of discontinuous changes in psychotherapy (see first Ilardi & Craighead, 1994). Such patterns of change are called “early sudden changes”, “sudden gains” or “sudden losses”. A definition of sudden gains was given by Tang and DeRubeis (1999a) in relation to their study applying the Beck Depression Inventory (BDI; Beck, Ward, Mendelson, Mock, & Erbaugh, 1961) in randomized clinical trials (RCTs) of cognitive therapy (CT) for depression: The magnitude of a sudden gain should be large (a) in absolute terms, (b) relative to symptom severity before the gain, and (c) relative to symptom fluctuation preceding the following gain. Although most of the studies reporting on discontinuous symptom changes during psychotherapies were realized in the treatment of depression (Busch, Kanter, Landes, & Kohlenberg 2006; Hayes et al., 2007a; Ilardi & Craighead, 1994, 1999; Kelly, Roberts, & Ciesla, 2005; Kelly, Cyranowski, & Frank, 2007a; Tang & DeRubeis, 1999a, 1999b; Tang, DeRubeis, Beberman, & Pham, 2005; Tang, DeRubeis, Hollon, Amsterdam, & Shelton, 2007; Vittengl, Clark, & Jarrett, 2005), sudden gains are not restricted to depressed clients but occur in the treatment course of other disorders such as bulimia nervosa, alcohol abuse, or obsessive-compulsive disorder (OCD) (Wilson, 1999; Schiepek et al., 2009; Stiles et al., 2003). These changes are not limited to manualized cognitive therapies (Tang, Luborsky, & Andrusyna, 2002) or to standardized settings with randomized controlled trials. Stiles et al. (2003) found sudden gains among clients with a variety of disorders treated with a variety of approaches in routine clinical settings, Stulz, Lutz, Leach, Lucock and Barkham (2007) report on early changes in routine outpatient conditions, Kelly et al. (2005) treated their patients in a group setting. Sudden symptom changes were found even in form of spontaneous phenomena not related to any intervention at all (Kelly, Roberts, & Bottonari, 2007b). Consequently, quite different outcome and symptom measurements were used in the description of sudden changes. In a single-case study, the discontinuous reduction of symptom severity of a client with OCD corresponded to significant changes in the activation of OCD-related brain structures (Schiepek et al., 2009). In this study, the Yale-Brown Obsessive Compulsive Scale (Y-BOCS; Goodman et al., 1989) was applied once per week and functional Magnetic Resonance Imaging (fMRI) using an individualized symptom provocation paradigm was performed three times during eight weeks of in-patient treatment. The steepest gradient of symptom reduction as well as a qualitatively different brain activity pattern occurred before the main intervention, i.e., exposure with response prevention (ERP), was implemented.

Sudden changes seem to be a universal and robust phenomenon in psychotherapy. A substantial percentage of clients experience discontinuously shaped change curves. Sudden gains, especially if they occur early in the therapy process, hold until the end of treatment or seem to be a necessary prerequisite for successful treatment (Gumz, Bauer, & Brähler, 2012; Kelly et al., 2005; Stiles et al., 2003; Tang & DeRubeis, 1999a). However, the mechanisms underlying such discontinuous shapes of symptom severity and other change markers are still not well understood. In classical terms of linear input-output-functions or treatment and dose to effect and outcome relations, this phenomenon is quite astonishing and puzzling. In terms of philosophy of science, it is an anomaly of normal psychotherapy science which postulates that the specific factors of treatment cause the effect in a linear damped function related to the dose. Consequently, explanations tried to provide evidence for changes in relevant factors occurring before symptom changes, such as cognitive restructuring in the pre-gain sessions of cognitive therapy (Tang & DeRubeis, 1999a, 1999b). Others have disputed this interpretation and have argued on behalf of common factors such as positive expectations, induction of hope, or positive therapeutic relationships (Ilardi & Craighead, 1994, 1999). Kelly et al. (2005) did not find any factors such as changes in self-esteem, attribution style, concurrent psychology-cal treatment or psychotropic medication preceding sudden treatment gains.

Many of these proposals have the character of ex-post explanations. In contrast to this, it would be more adequate to look for theoretical models explaining discontinuously shaped transitions in a more fundamental way and not as being uniquely reactive to external input such as instructions, (minor) interventions, or therapeutic techniques. Such models are quite common in other areas of science such as physics or brain research (Meyers, 2009) and are based on the existence of complex, nonlinear, and thermodynamically open systems spontaneously producing dynamic patterns out of intra-systemic processes. The emergence of new patterns or pattern transitions occurs through even small changes of relevant parameters of systems functioning. In systems and complexity science there is a family of theories explaining self-organization, for example synergetics (Haken, 2004), chaos theory (Ott, 1993; Strunk & Schiepek, 2006) or the theory of self-organized criticality (Bak, Chen, & Creutz, 1989). All of these model the behavior of nonlinear, complex systems in relation to their environments. In many cases these environments consist of other dynamic systems such as neural networks (oscillators) coupled to other neural networks, human beings interacting with other human beings, etc. Particularly, the field of synergetics was successful in realizing quite different “intended applications”, for example laser physics (Haken, 2004), pattern formation in biology, brain dynamics (Haken, 2002), motor behavior (Kelso, 1995), perception, decision making, or social interaction (Haken & Schiepek, 2010). This theory begins with basic laws of nonlinear system component interaction and explains the emergence of temporospatial patterns and the phenomenon of discontinuous phase-transitions. Once system dynamics have reached an instability point, phase-transitions are likely to occur. There are specific prerequisites for such self-organized pattern transitions such as (a) the existence of a system with nonlinearly interacting components or subsystems, (b) the existence of one or several control parameters driving the system out of the actual stability state, and (c) relative stable boundary conditions. One of the predictions of the model is the occurrence of critical fluctuations just before a system undergoes qualitative changes of pattern formation. If the conditions for self-organized order transitions are given, they will occur with only small external driving forces or even without any additional input. Indeed, discontinuous transitions of dynamic patterns were found in psychotherapies as well. Using a coding frequency of 10 seconds, Kowalik, Schiepek, Kumpf, Roberts, and Elbert (1997) found synchronized jumps of Local Largest Lyapunov Exponents (measuring the degree of chaoticity in a time series) and pointwise fractal dimensionality in the time series of self-presentation categories of client and therapist. Self-presentation categories may be described as different modes of interactive behaviors of client and therapist such as "seeking for help", "showing your suffering", or "show competence". At this measuring frequency, a psychotherapy process of 13 sessions was represented by multiple time-series of about 3,800 measurement points and a therapy of 9 sessions by time series of about 2,900 points. The characteristics of change in the constellation of self-presentation categories was found to corroborate the hypothesis of (a) nonlinearity and deterministic chaos realized in therapeutic change dynamics and interaction, (b) spontaneous order transitions in those processes, and (c) synchronized order transitions between client and therapist. Other studies focused on the self-organized synchronization between client and therapist at different temporal resolution and with different methods (e.g., Gumz et al., 2012; Ramseyer & Tschacher, 2008; Rockstroh et al., 1997)

The present study intended firstly to examine the sudden gain phenomenon in clients with obsessive-compulsive disorder (OCD) and to investigate if sudden gains follow a specific pattern across subjects. Since we were following the theoretical frame of complex self-organizing systems, no assumption was made in terms of when in the course of psychotherapeutic treatment a sudden gain would appear. To be a manifestation of a self-organized process and not the result of an intervention-driven symptom change, sudden changes would have to appear before the main intervention was introduced – in this case, exposure with response prevention (ERP). Secondly, we tested the hypothesis that a phase-transition-like phenomenon is accompanied by critical instabilities resulting in a marked increase of dynamic complexity of the time series reflecting the change process. The degree of critical instability would contribute to the prediction of therapy outcome.

METHOD

Setting

Clients were recruited from a psychosomatic day treatment center in Munich, Germany, specialized in treating OCD. The therapy rationale followed cognitive-behavioral therapy (psychoeducation, behavioral analysis, analysis of obsession- and compulsion-related cognitions) with an intensive period of ERP as the main intervention. ERP was introduced after a phase of preparation like writing, signing an "ERP contract", training coping skills, and performing minor confrontation exercises. The confrontation and coping exercises clients underwent during the pre-ERP phase were focused on every-day and interpersonal situations (not on OCD-specific symptom-provoking situations) of minor intensity and difficulty. Especially, it was a gradual and not a flooding / high intensity exposition.

Therapy was primarily provided in a group setting, with one group session per day (Monday to Friday). The therapy group was "open" in the sense that clients could join the group at any point in time as soon as a spot became available.

The cognitive-behavioral group was guided by two experienced female therapists and two experienced female co-therapists. In addition, clients participated in individual therapy sessions, relaxation training, and mentalization-focused sessions.

A written informed consent was obtained from all participants after procedures had been fully explained. The daily ratings using the Synergetic Navigation System were an integrative part of the therapy routine of the day treatment center Munich.

Table 1. Characteristics of the sample (*N* = 18 clients).

Variable	*Mean*	*SD*	*Min*	*Max*
Age	32.17	9.55	20	52
Y-BOCS score (OCD symptoms) pre	21.89	8.11	10	38
Y-BOCS score (OCD symptoms) post	13.72	5.91	0	24
TPQ: OCD symptoms pre	4.66	1.22	1.95	6.64
TPQ: OCD symptoms post	3.68	1.14	1.00	5.33
duration of treatment (days)	61.22	12.52	37	88
complexity score	.12	.047	.054	.22

Note: The OCD symptom severity was obtained from Y-BOCS and TPQ before (pre) and after (post) therapy. A significant symptom reduction was reported in Y-BOCS scores ($T(17) = 6.06$, $p < .001$), and in TPQ symptom scores ($T(17) = 4.18$, $p = .001$).

Participants

The sample consisted of 18 Caucasian clients diagnosed as OCD (see Table 1), all of them underwent ERP. Clients were assessed by an experienced psychiatrist and classified in accordance with F42.0 as "OCD, primarily obsessions and ruminations", with F42.1 as "OCD, primarily compulsions", and with F42.2 as "OCD, obsessions and compulsions" in the International

Classification of Diseases (ICD10). Their average age was 32.2 (*SD* = 9.6, range from 20 to 52 years), 9 were women (= 50%), 9 men (= 50%). Mean duration of treatment was 61 days (*SD* = 12.5, range from 37 to 88). All clients completed the Y-BOCS biweekly and the Therapy Process Questionnaire (TPQ, see next section) once per day. By this, the mean duration of treatment in days corresponded to the mean number of measurement points (61; *SD* = 12.5).

Procedure and Measures

The symptom rating was completed according to the Y-BOCS (Goodman et al., 1989), twice per week (self-rating). For analysis, we used the total score of the Y-BOCS (*min*. = 0; *max*. = 40). In order to compare symptom changes, individual Y-BOCS scores were *z*-transformed with reference to the individual mean and the group mean was calculated for each measurement point.

Daily ratings on the therapy process were collected by an internet-based device (Synergetic Navigation System, SNS), which allows for data mining (like self-ratings or interpersonal ratings) at high frequencies (Schiepek, 2009). The SNS is an ambulatory and real-time monitoring system which holds for outcome and especially for process assessment, with integrated mathematical tools for the analysis of nonlinear and nonstationary time-series (dynamic complexity, see below; synchronization patterns, recurrence plots, permutation entropy; Schiepek & Perlitz, 2009). Here, we used a rating frequency of once per day and applied a questionnaire developed specifically for high-frequency (daily) self-ratings during psychotherapeutic change processes (Therapy Process Questionnaire, TPQ; Schiepek, Eckert, & Weihrauch, 2003). The 47 items of the questionnaire are related to important common factors in psychotherapy processes discussed in the literature (see Nischk, Grothe, & Schiepek, 2000 for a pre-study). The factor analysis of the TPQ was based on 149 in-patient therapy processes and resulted in a 5-factor solution. Total explained variance is 74.5%. A confirmatory factor analysis performed for testing factor-model quality confirmed the 5-factor solution (for details see Schiepek, Aichhorn, & Strunk, 2012).

The factorial structure of the TPQ is reported in Table 2; for specific items and statistical details see Schiepek et al. (2012), and Haken and Schiepek (2010). Since the SNS is internet-based, clients could enter their daily TPQ ratings at three personnel computers at the day treatment center or at any other internet-accessible device.

Table 2. Factors of the Therapy Process Questionnaire (TPQ), modified for the application to day treatment centers.

I Therapy progress (16.9% explained variance)
II Impairment by symptoms and problems (16.3% explained variance)
III : Relationship quality and trust in therapists (16.3% explained variance)
IV Dysphoric affect (13.0% explained variance)
V Relationship with fellow patients (12.0% explained variance)

Sudden Gains

In this study, we applied the definition of "sudden gains" by Tang and DeRubeis (1999a). A sudden gain occurred between session *n* and session *n* + 1 if (a) a gain was at least 1 *SD* of all session-to-session changes in YBOCS scores; (b) the gain represented at least 25% of the pregain session's YBOCS scores; and (c) the mean YBOCS score of the three measurements before the gain was significantly higher than the mean YBOCS scores of the three measurements after the gain

The Dynamic Complexity (C)

An algorithm of dynamic complexity was used in this article to identify non-stationary phenomena and critical instabilities in short and coarse-grained time series. Dynamic complexity is the multiplicative product of a fluctuation measure and a distribution measure. Both measures are used for the analysis of discrete time series data with known theoretical data ranges. Let x_t represent the value of a variable measured at time *t* on the basis of a constant and discrete time interval (scanning frequency, e.g., one observation per day). Values are represented on the basis of a constant unit with theoretical data range s between the theoretical minimum $x_{\min}$ and the theoretical maximum $x_{\max}$ of *x*. The fluctuation measure (*F*) is sensitive to the amplitude and frequency of changes in a time signal, and the distribution measure (*D*) scans the scattering of values or system states realised within the theoretical data range of possible values or system states (see Schiepek & Strunk, 2010). In order to identify non-stationarity, the two measures are calculated within a data-window moving over the time series. In the current study, we chose a window width of 7 measurement points (days).

Fluctuation Intensity

The fluctuation algorithm is applied to segments of discrete time series. These segments are defined by the width of a moving window that can be fixed arbitrarily. The window runs over the whole time series and results in a continuous fluctuation intensity measure *F*. All measurement points within the window are subdivided into periods with cut-off points defined by changes in slope (points of return *k*). Trends can be: "increasing", "decreasing", or "no change" (for an example, see Fig. 1). The difference between the values x_n at the points of return *k* is taken irrespective of the sign – in absolute terms: $y_i = \left| x_{n_{k+1}} - x_{n_k} \right|$ and is divided by the duration of the period (i.e., the number of data points within the period from one point of return *k* to the next one *k*+1). By this, the change rate is related to its duration, and *F* is sensitive to the frequency as well as to the amplitude of the fluctuation. Theses fractions are summed up within the window. In order to normalise the fluctuation intensity, the result is related to the greatest possible fluctuation which is given by the maximum amount of change within a minimum duration. This is the sum of the differences between the lowest and the highest value of the available range between one and the next measurement point. The formula results in a normalised fluctuation intensity: $0 \le F \le 1$

$$F = \frac{\sum_{i=1}^{I} \frac{y_i}{(n_{k+1} - n_k)}}{s(m-1)} \tag{1}$$

with

$$y_i = \left| x_{n_{k+1}} - x_{n_k} \right|,$$

x_n = nth value of the time series, k = points of return (number of changes in slope of the data sequence), i = periods between points of return, I = total number of such periods within the window, m = number of measurement points within a moving window, m–1 = number of intervals between all measurement points of a window, and $s = x_{max} - x_{min}$ with x_{min} smallest value of the scale and x_{max} largest value of the scale.

One can immediately derive that

$$\sum_{i=1}^{I} \frac{y_i}{n_{k+1} - n_k} \le s(m-1),$$

so $0 \le F \le 1$; see Fig. 1. Note that $s(m\text{-}1)$ is the window area expressed in units of t and x and that s is not the empirical data range but the theoretical range of the scale.

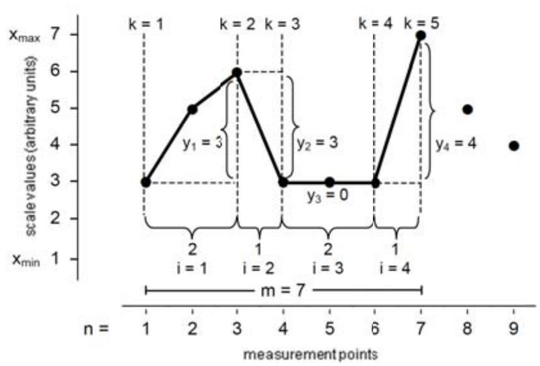

Fig. 1. Example for calculating the fluctuation intensity measure *F*.

In the example in Fig. 1, the *F*-value is calculated as follows: The first contributor is between k=1 and k=2 a difference of 3 (since x_1 = 3, x_3 = 6), divides by 2 (2 is the number of intervals between k=1 and k=2. The next contributor is between k=2 and k=3 a difference of 3, divided by only one interval. Next is a difference of 0 divided by 2 intervals (remains 0), and the last difference between k=4 and k=5 is 4, divided by 1. So we sum up 3/2 + 3/1 + 0/2 + 4/1 = 8.5. This sum is divided by the maximum of possible fluctuation, which is in this case (with the greatest number of points of return k = 1 to k = 7, and s = ($x_{max} - x_{min}$) = 7 – 1 = 6): 6/1 + 6/1 + 6/1+ 6/1 + 6/1 + 6/1 = 36. F = 8.5/36 = .23611.

Distribution

The degree of distribution D represents another aspect of critical instabilities. Whereas F is at its maximum when the dynamics jump between the minimum and maximum values with greatest and equal frequency, instabilities are often characterised by irregularities, resulting in quite different system states. In the extreme case, the values should be irregularly and chaotically distributed across the range of the measurement scale. As a result, the degree of distribution measures the deviance of the values from an ideal equal distribution of the values across the range or measurement scale. As for the calculation of F, we used a moving window running through the whole process and by doing this we consider the values over the full course of the process. For the distribution measure the order of values within the moving window is irrelevant, and in a first step values are sorted in ascending order. Let x_i be the values of a variable x at the sorting position i within the moving window X which is given by:

$$X = \{x_1, x_2, x_3, \ldots x_m\} \text{ with } x_1 \leq x_2 \leq x_3 \leq \ldots x_m$$

In the following calculation this sorted window is compared with an artificial data set of equally distributed values. This artificial data set consists of the same number m of values arranged in ascending order in equally spaced intervals between the theoretical scale minimum and maximum. The interval I is given by $I = s / (m\text{-}1)$, $s = x_{\max} - x_{\min}$ and the artificial data set Y is given by:

$$Y = \{y_1{=}I{*}1, y_2{=}I{*}2, y_3{=}I{*}3, \ldots y_m{=}I{*}m\}$$

If the data set in X is equally distributed within the data range, then differences between values at different positions in X must be equal to the differences in Y at the same positions. To give an example, if X is perfectly equally distributed within the data range, then $\delta_{Y.2\text{-}1} = y_2\text{-}y_1 = \delta_{X.2\text{-}1} = x_2\text{-}x_1$. Generally the aberration Δ_{ba} of X from the ideal given in Y can be calculated for the positions a and b as follows:

$$\Delta_{ba}{=}\delta_{Y.b\text{-}a} - \delta_{X.b\text{-}a} \text{ with } \delta_{Y.b\text{-}a} = y_b\text{-}y_a \text{ and } \delta_{X.b\text{-}a} = x_b\text{-}x_a$$

In total the aberration Δ^* is given by the following permutation of a and b.

$$\Delta^* = \sum_{c=1}^{m-1} \sum_{d=c+1}^{m} \sum_{a=c}^{d-1} \sum_{b=a+1}^{d} \Delta_{ba} \Theta(\Delta_{ba})$$

The two outer sums are permutations of all combinations of c and d within the window. The inner sums of a and b are representing all combinations of positions within the interval given by c and d.

$\Theta(\Delta_{ba})$ is the Heaviside step function resulting in 1 if Δ_{ba} is a positive number; otherwise the function results in 0. Therefore, only positive aberrations are considered, because negative aberrations have the consequence of resulting in positive ones in other positions. Hence, the distribution measurement D is given by:

$$D = 1 - \sum_{c=1}^{m-1} \sum_{d=c+1}^{m} \sum_{a=c}^{d-1} \sum_{b=a+1}^{d} \frac{\Delta_{ba} \Theta(\Delta_{ba})}{\delta_{Y.ba}} \tag{2}$$

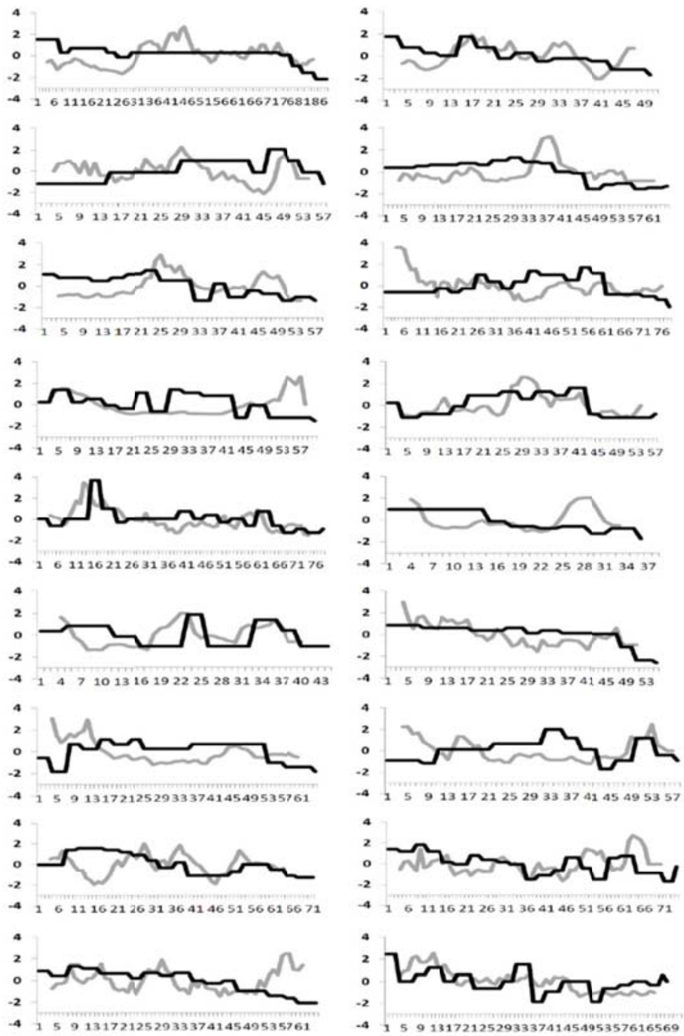

Fig. 2. Individual Y-BOCS and TPQ complexity trajectories of all 18 OCD clients. Each graph depicts the psychotherapy process of one client. The days of therapy are shown on the *x*-axes. Black lines: trajectory of the *z*-transformed Y-BOCS scores. Grey lines: trajectories of the *z*-transformed dynamic complexity based on 47 items of the TPQ.

One can see that D is normalized so that $0 \leq D \leq 1$, and a high value of D are the result of equally distributed measures of x within the moving window.

The multiplication of F and D values leads to a time series of values of the dynamic complexity (C) for each item. In the current study, each value of this time series includes the information of 7 days in the raw data time series (3 days before and 3 days after the current data point). Therefore, no values can be calculated for the first and last 3 days of each therapy process. To obtain a single measure for the instability of the system for each day of therapy, the complexity values of all items of the TPQ were averaged, resulting in one time series of the dynamic complexity for each client. The individual time series of dynamic complexity and Y-BOCS scores of all clients are shown in Fig. 2.

Phases of Critical Instability

One of the major applications of obtaining item-wise complexity time series for each client was to identify phases of elevated complexity (i.e. a phase of "critical instability"). A phase of critical instability was defined as a sequence of days that contributes to a significant increase in dynamic complexity across all items within one client, and therefore, referring to synchronized increases in within-subject dynamic complexity values in many items of the TPQ. In order to be sensitive to relative increases during the process a dynamic confidence interval was chosen that takes the data of 21 measurement points into account. Figure 4 shows the percentage of clients in a phase of critical instability within the sample for each day of therapy.

Complexity Score

For the prediction of symptom change with complexity values a single complexity score was calculated for each client. First, a mean complexity score was calculated by averaging complexity values across items and time points. Then, the difference between the maximum complexity value and the mean complexity score was computed. This measure was defined as "Complexity score". This score was used because the self-organization model underlying this study is primarily interested in local peaks of complexity indicating critical fluctuations and phase transitions during the process.

Therapy Outcome

Therapy outcome was identified by the pre-post-difference of the Y-BOCS (last measurement minus first measurement), and by the pre-post-difference of the factor II "impairment by symptoms and problems" of the TPQ. The mean of the items representing this factor was calculated for the first week of treatment and was then compared to the mean of the items during the last week of treatment (mean factor II last week minus mean factor II first week).

Time Series across Participants

In order to investigate patterns of change on a group level in the client sample of this study, we computed averaged time series of the Y-BOCS scores and the dynamic complexity (C). A problem with this procedure is that the length of time series differed between clients. We were especially interested in the relationship between ERP onset, change in complexity, and change in symptoms, therefore, we calibrated the time series at the ERP onset (= time point 0). To ensure a sufficient amount of data (at least 16 out of 18 clients) at all points in time, only the 35 days before ERP onset and the 10 days after ERP were taken into account for group analyses of pattern change depicted in Figs. 3 and 4.

RESULTS

Sudden Gains

According to the criteria for sudden gains defined by Tang and DeRubeis (1999a), session-to-session Y-BOCS changes greater than 3.6 points were regarded as “large” in absolute terms. In this study 8 out of 18 subjects met all three criteria for sudden gains. In 7 out of these 8 subjects, a sudden gain was found during the ERP preparation phase, in 1 subject the sudden gain was found during the first week of ERP.

Process-Outcome-Relations

The degree of dynamic complexity was found to be related to therapy results. If we take the pre-post-difference of the factor II “impairment by symptoms and problems” of the TPQ as an outcome criterion, the Complexity score correlates with $r = -.52$ ($p = .027$) to this outcome measure. Similarly, the Complexity score is related to symptom change measured by the Y-BOCS ($r = -.53$; $p = .025$). These results indicate that higher Complexity scores correspond to more reduced symptom severity and impairment at the end of therapy.

Patterns of Change

In the analyses on the group level, time series of individual symptom severity and dynamic complexity were calibrated to the onset of ERP. For each client, their individual ERP-onset was defined as $t = 0$ and the time series of the total Y-BOCS scores were related to this event. In 72.2% of the 18 cases, the steepest gradient of symptom change was located before ERP-onset. If we calculate the mean of all time series, the effect is not abolished. Figure 3a illustrates that the mean trajectory of the z-transformed individual total scores of the Y-BOCS has its steepest change gradient 4 days before ERP starts ($t = -4$ days), and symptom severity reaches a significantly reduced level at the day of ERP onset ($t = 0$) compared to the mean Y-BOCS level before the steepest change gradient ($T = 3.07$; $p = .007$). Before calculating the arithmetic mean per measurement point, all individual trajectories were normalized to $t = 0$ at (inter-individually different) ERP-onsets. Time points with a negative sign at the *x*-axis are located before the ERP of each client starts. In all of the examined therapy processes the ERP-phase was located in the last two or three weeks of their stay in the clinic and lasted 10 to 14 days. In all but two therapy processes, ERP was introduced 5 to 7 weeks after the beginning of the therapy. In these two subjects ERP was introduced after 10 weeks of therapy.

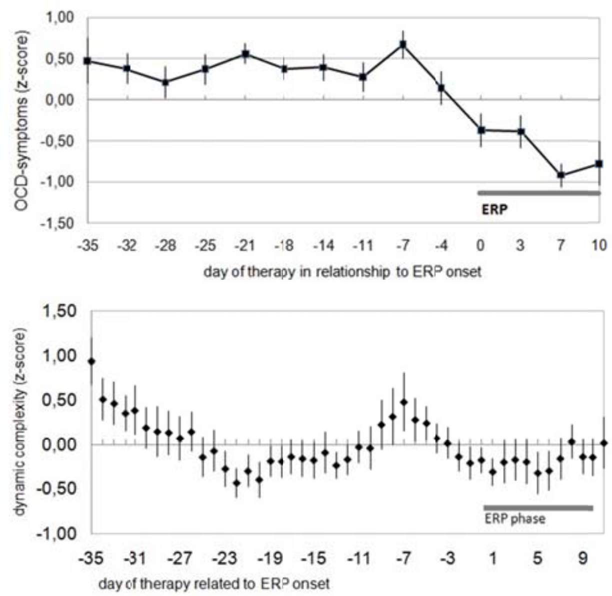

Fig. 3. (top) Group mean trajectory of the *z*-transformed total score of the Y-BOCS, completed twice per week. Vertical lines indicate +- 1 *SE* (standard error). (bottom) Arithmetic mean of the *z*-transformed complexity signals of all 18 change processes (average complexity over all 47 items of the TPB). Vertical lines indicate the standard error of the complexity signal. The dark grey bar indicates the ERP period. The graphs represent 35 days before ERP onset and 10 days after ERP onset.

Figure 3 (bottom) illustrates the mean z-transformed complexity signal of the change processes of the 18 subjects. When comparing the dynamic complexity at a specific day to the mean of dynamic complexity outside of critical instabilities (baseline complexity) on a group level, two peaks of dynamic complexity could be identified: One was found at the beginning of treatment ($T(17) = 3.61$, $p = .004$); the other complexity peak occurred three days before the steepest gradient of symptom reduction (see Fig. 3 (top)) and about 7 days before the ERP-onset ($T(17) = 2.48$, $p = .026$). The finding of complexity peaks on a group level, indicates that individual occurrences of complexity peaks (phases of critical instability) may not be randomly distributed, but show a certain “pattern”.

Another approach to the analysis of critical instabilities on a group level was to calculate frequencies of individual phases of critical instabilities across participants for each day of therapy (see Fig. 4). Then, comparisons between distinct time intervals could be made to indicate phases of a significantly higher probability for critical instabilities. In comparison to the mean relative frequency of critical instability over the whole process (M = 24.8%, SD = 13.5%), in the first observed days (day -35 to -28, M = 42.6%, SD = 6.1%, $T(60) = 3.66$, $p = .001$) and 11 to 4 days before the ERP onset (M = 41.7%, SD = 4.2%, $T(60) = 3.48$, $p = .001$) the probability (relative frequency) of critical instabilities increased significantly.

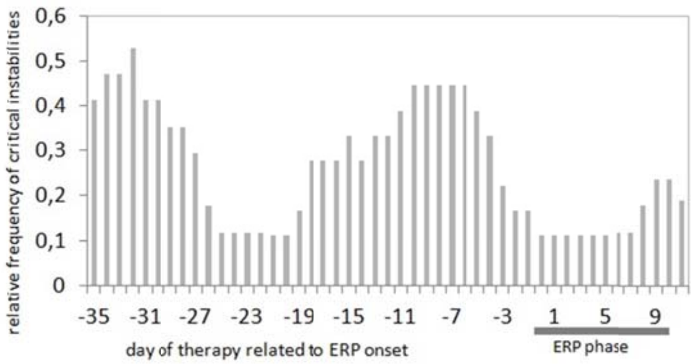

Fig. 4. Relative frequency of critical instability periods. Two phases can be identified where the relative frequencies of critical instabilities increases above 40%. This is at the beginning of the therapy and in the pre ERP phase.

DISCUSSION

In the current study, daily measures on psychotherapeutic processes of 18 OCD clients were collected and time series analyses were conducted to investigate the characteristics of change processes. It was found that symptom change occurred rather suddenly than gradually in many clients, replicating the "sudden-gain effect" (Tang & DeRubeis, 1999a) in a sample of OCD clients treated with cognitive-behavioral psychotherapy. By frequent Y-BOCS measurements we were able to reveal that the majority of these sudden changes took place already (directly) before ERP onset. Furthermore, we showed that an increase in dynamic complexity preceded the reduction in symptom severity and that the occurrence of critical instabilities (i.e. phases of elevated dynamic complexity across all items) was related to the magnitude of symptom improvements.

The replication of the sudden-gain effect in OCD patients, indicates that this observation is not unique to depressive patients as shown by Tang and collegues (Tang & DeRubeis,1999a, 1999b; Tang, DeRubeis, Hollon, Amsterdam, & Shelton, 2007), but is applicable to other psychiatric disorders as well. In this study, we wanted to take the analyses of change processes one step further to investigate characteristic patterns of change beyond the level of means and standard deviations. Therefore, the method of daily measurements was applied, which allowed for time series analyses including the calculation of dynamic complexity, a measure that contains information on the distribution and fluctuation of values within a moving time frame of 7 measurement points. The finding of a relationship between critical instabilities and psychotherapy outcome supports a hypothesis from Synergetics applied to psychotherapeutic change processes (Haken & Schiepek, 2010). Transitions from one stable system state to another stable state are thought to be mediated by a phase of critical instability, characterized by increased dynamic complexity. In the context of psychotherapy, it could be supposed that a destabilization of dysfunctional cognitive-behavioral patterns (i.e. obsessions and compulsions) facilitates the transition to more functional cognitive-behavioral patterns because a system is more prone to change processes in an instable phase. This view is supported by the results showing that symptom change is preceded by an increase in dynamic complexity.

The interesting findings of strong symptom change and increase in dynamic complexity preceding ERP can be interpreted in different ways. As shown in Figs. 3 and 4 two distinct phases of elevated dynamic complexity could be identified: the beginning of the period analyzed on the group level and the phase directly before ERP onset. The first phase of increased dynamic complexity was located in the beginning of the therapy process in the majority of clients; therefore, it might be interpreted as an initial instability period during the acclimatization process to the therapeutic setting, therapists, and other group members. Many clients reported feeling ambivalent about the intended therapy in the beginning, for example. Since another phase of increased complexity and decline in OCD symptoms occurred directly before ERP onset, it could not be caused or triggered by ERP directly. It seems that intended and specific results of ERP had already occurred before this presumably effective intervention in the treatment of OCD (Eddy, Dutra, Bradley, & Westen, 2004; Rosa-Alcazar, Sanchez-Meca, Gomez-Conesa, & Marin-Martinez, 2008) has started.

One possible explanation could include the effect of treatment expectation. While this effect may account for a certain amount of variance in symptom change, it may not explain why it would lead to symptom change at specific times across subjects. The accumulation of both critical instabilities and sudden gains directly before ERP, seems to imply distinctive features of this ERP-preparation phase that might have played a causal role in change dynamics observed in this study. It may be speculated that therapeutic tasks during the ERP-preparation phase, like writing and signing an ERP contract, presenting it to the group, performing minor confrontation exercises, and ambivalent feelings towards the feared major confrontation exercises during the ERP phase, have influenced both dynamic complexity and symptom change. According to the data of this sample, ERP itself seemed to have a rather stabilizing than destabilizing effect on the clients, which in turn might be due to the success in the confrontation exercises and experiences of self-efficacy and mastery. The experience of a profound reduction in arousal and anxiety during exposition to obsessive stimuli without having to perform compulsive behavior can lead to relief and a sense of gaining back control over one's feelings and actions.

However, other influences such as personal decisions, interpersonal crises or quality shifts in couple or familial relations, activation of personal resources or perspectives, cannot be ruled out as influencing factors on symptom changes. Referring to the body of research on influencing factors of psychotherapeutic change (for review see Orlinsky, Ronnestad, & Willutzki, 2004), our findings may add to the increasing amount of results suggesting a relatively small impact of specific intervention techniques on treatment outcome. Compared to common factors such as client variables (Bohart & Tallman, 2010; Clarkin & Levy, 2004), therapist variables (Beutler et al., 2004), quality of the therapeutic relationship and working alliance (Norcross, 2010), or other influence factors (Orlinsky, Ronnestad, & Willutzki, 2004), any specific intervention techniques can only account for a minor part of the outcome variance (Wampold, 2001, 2010). Therefore, it may be useful to look for integrative models taking discontinuous order transitions in psychotherapy processes into account – not as anomalies and marginal occurrences, but as core phenomena of evolving complex systems. Within this framework, psychotherapy could be understood as a dynamic facilitation of self-organizing processes in complex systems constituted by a client's biological, mental, and social structures. Such a nonlinear dynamic systems approach to the understanding of psychotherapy might be able to predict several phenomena such as symptom change through a pattern of instability (i.e. increase in dynamic complexity).

Building on work by Kelso (1995) and others, the nonlinear dynamic systems approach has recently been related to developments in neuroscience, conceptualizing the brain and its substructures as a network of complex, self-organizing systems with changing and function-dependent connectivity and patterns of synchronized neural activations (Haken, 2002; Haken & Schiepek, 2010; Schiepek & Perlitz, 2009; Tass & Hauptmann, 2007). One important distinction in nonlinear systems theory is between nonlinearity and nonstationarity. In a restricted sense, nonlinearity means the deviation from a straight line from one point to another (e.g., a change trajectory) or the non-proportionality of input and output (e.g., dose to effect relations). In this sense, sudden gain-studies and process research found that therapeutic change processes are not linear (e.g., Hayes et al., 2007a, 2007b). In a more generalized sense, nonlinearity characterizes the complex behavior of nonlinear systems, e.g., fractal dimensionality or chaoticity of attractors, even when these and other characteristics (such as mean, variance, and frequency spectrum) do not change over time. A test for nonlinearity in this sense has to be based on surrogate data testing, where the surrogates of a time series eliminate nonlinear features (for example, fractal dimensionality) by dividing a time series into pieces and recombining it in a random way, a procedure which leaves linear features (as mean, variance, or frequency spectrum) unchanged (Haken & Schiepek, 2010; Schreiber & Schmitz, 2000). If substantial dynamic characteristics of a process are changing, we not only speak of nonlinear qualities in the strict terminological sense of chaos theory, but of nonstationarity. Results from this and other studies (Kowalik et al., 1997; Schiepek & Perlitz, 2009) suggest that psychotherapy processes realize both, nonlinearity and nonstationarity.

Real-Time Monitoring

Another assumption of the nonlinear dynamics approach pertains to the existence of chaotic change trajectories, i.e., highly individualized dynamics combined with limited predictability of future dynamics in relation to the past. Where data allow for a closer inspection of change processes, the impression holds that different clients follow different change trajectories (e.g., Stulz et al., 2007). However, the shapes of change trajectories are not only client-specific, but also depend on the time resolution of the signal. Characteristics of nonlinearity, for example critical instabilities, dynamic or fractal complexity, and synchronization patterns of within-subject changes across items need signals with equidistant measures and a minimum of measurement frequency, resulting in sufficiently extended time series. Studying synchronization patterns between clients would additionally require that all clients can be measured on an identical time scale with a common starting point which could not be realized in the present study.

Our research has shown that it is possible to obtain such data by daily internet-assisted ratings, which can be established in routine practice and should become standard in the future. Here, the well- established process and process-outcome research in psychotherapy is joining the fast-growing movement of ambulatory assessment propagating new communication and real-time computing technologies (Bussmann, Ebner-Priemer, & Fahrenberg, 2009; Ebner-Priemer & Trull, 2009; Fahrenberg, Myrtek, Pawlik, & Perrez, 2007; Schiepek & Perlitz, 2009; Wenze & Miller, 2010). To quote Lambert (2010), “Yes, it is time for clinicians to routinely monitor treatment outcome”, and, as we would like to add, other change markers.

Using an ambulatory assessment device could be very useful for the monitoring as well as the data-based decisions and therapy control, but the device should be sensitive to nonlinear qualities and order transitions including their associated critical instabilities occurring in psychotherapy processes. Without shedding further light onto the therapy process, the mere reporting of treatment outcome as related to this study might have been interpreted once more as a causal effect of the applied intervention (ERP) on substantial pre-post-differences in symptom severity. But now, high-frequency real-time monitoring not only helps to get new insights into the mechanisms of how psychotherapy works, but also allows for repeated feedback and the control of a nonlinear process in a “cybernetic” partnership with the client.

Limitations and Future Research

One of the shortcomings of the current study is the relatively small number of clients (18 clients). Nevertheless, results were found to be statistically significant and in line with the sudden-gain literature as well as with results on process research motivated by the nonlinear dynamic systems approach (Gumz et al., 2012; Haken & Schiepek, 2010; Hayes & Strauss, 1998; Hayes et al., 2007a, 2007b; Kowalik et al., 1997; Schiepek & Perlitz, 2009; Tschacher, Baur,

& Grawe, 2000). Another limitation was that our definition of psychotherapy outcome was restricted to symptom reduction. Also, other definitions of critical instability would have been possible and not necessarily limited to the measure of dynamic complexity. Finally, the current results are related to a specific setting. Therefore, results may not be easily generalized to other settings, clients, or treatments. Since the clients were recruited from an "open therapy group" (i.e. a group allowing clients to enter at any time as soon as a spot becomes available) investigating synchronization of change processes between subjects is very limited. To obtain an identical time scale for all participants, a "closed therapy group" where all clients enter the group at the same time point would be required.

For future research, we would suggest further studies with larger sample sizes. If tools such as the Synergetic Navigation System which was used for data mining and data analysis in this study, could find a broader application in daily practice in psychotherapy, problems of limited sample sizes could be overcome. Also, other mathematical procedures (e.g. recurrence plots, permutation entropy) could be integrated in the analyses in order to validate the notion of mathematically defined phases of critical instabilities. Additionally, more and different outcome criteria should be used, including not only questionnaires, but also behavior measures and physiological markers, and these criteria should be recorded at several follow-up times in order to get an impression of outcome stability. Finally, constructs should be integrated in process research which could explain the hypothetical change trajectories or which could rule out alternative hypotheses (e.g., therapy expectations).

Conclusion

Specific indicators of psychotherapy-related change processes in 18 OCD clients were obtained by daily ratings using an internet-based device which allows for data collection, visualization of the resulting time-series and outcome-scores, and for a nonlinear time-series analysis with different algorithms. One of these algorithms used in the study measures the changing degree of dynamic complexity of the time series data. Dynamic complexity combines the degree of fluctuation intensity and the distribution of the values over the scale range. The method illustrated the coincidence of a distinguished peak in dynamic complexity of daily rated items in the TPQ with the steepest gradient of symptom severity reduction, represented by the total score of the Y-BOCS, as administered twice per week. Both the discontinuous decay of symptom severity (obsessions and compulsions) and a complexity peak across participants occurred shortly before exposure/response prevention started. A relationship between dynamic complexity and symptom reduction supports predictions from synergetics theory.

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