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Wolfgang Tschacher and Christian Scheier

Complex Psychological Systems: Synergetics and Chaos

12

Not even the Creator of the Universe knew what the man was going to say next.

K. Vonnegut, *Breakfast of Champions*

In this chapter we demonstrate that the approach of synergetics serves as a unifying research agenda for psychology and psychiatry. Psychological dynamics may continue the tradition of systems and Gestalt approaches in these disciplines and yet profit from the refined method developed in dynamical systems theory. Our premise is that in the complex psychosocial systems encountered in psychiatry, social psychology, and clinical psychology, low-dimensional nonlinear dynamics is an indication of pattern or Gestalt formation—in other words, deterministic chaos can be taken as evidence of synergetic effects.

We present time series data from diverse fields in order to discern signs of nonlinearity, chaos, and reduction of degrees of freedom. This approach provided evidence for deterministic chaos in paths of schizophrenic symptomatology, and sociophysiological pilot studies suggest that the process of social interaction may be described as increasing social synchronization. Moreover, extensive documentations of the courses of psychotherapies provided indications of pattern formation.

Basic Assumptions

The following statements are working hypotheses of a synergetic approach within psychology (Tschacher, Schiepek, & Brunner, 1992). We discuss these assumptions throughout this chapter. We also offer empirical findings and methods that may help to test the significance of this approach.

DYNAMICS AND PSYCHOLOGY

Within most domains of psychology, the development of systems in time is crucial. Cross-sectional methods become inadequate and even misleading when dynamics is concerned.

SYNERGETICS AND PSYCHOLOGY

Psychosocial and cognitive–emotional systems (PSS and CES, respectively) are complex. Thus, low-dimensional dynamics can only be expected to occur after self-organization has taken place. Only the macroscopic level of complex psychological systems is accessible to observation; macrodynamics constantly emerges from microscopic complexity.

DETERMINISM IN PSYCHOLOGY

Erratic dynamics of psychological systems is often mistaken for a sign of stochasticity (cf. Perna and Masterpasqua, chapter 1, this volume) in instances when it might have been produced by nonlinear deterministic dynamics. Thus, the dominant role of statistics in psychology should be complemented by deterministic models.

EXOVIEW OF PSYCHOLOGY

The dynamical approach to psychology is basically exopsychological in nature (i.e., the observer is implicitly regarded to be outside the system observed). Our methods apply to quantitative measures, so our studies are based on this exoview. However, another view "from within" may be taken. We address this endopsychological view in the general discussion.

Self-Organization

Synergetics deals with the phenomenon of self-organization in complex systems (Haken, 1983a, 1983b). *Complexity* can be defined as the amount of information required for a complete description of a system. Complex systems consist of many components that may act individually (i.e., they have many degrees of freedom). Thus, a brain is a complex system; a crystal (although composed of many components) or a driven pendulum (even if it produces chaotic dynamics) is not a complex system.

The central phenomenon of synergetics is a massive reduction of the effective degrees of freedom in a system. Some variables (the "order parameters") establish themselves throughout the system, so that the behavior of the components is synchronized by these collective ("macroscopic") variables. Thus, a highly complex system immensely reduces its complexity by organizing itself.

This can be modeled mathematically by stability analysis. In the vicinity of a critical point, one or few state variables of a system become unstable (i.e., the corresponding characteristic exponents become positive at a certain constellation of environmental control parameters). In nonlinear systems the unstable variables are coupled to the ones that remain stable. The amplitudes and refractory times of unstable variables are larger than those of the stable variables. Therefore, stable variables may tend to follow the behavior of unstable variables and can be expressed as a function of the unstable variables. The variables that are destabilized at a critical point in control parameter space gain the potential of becoming global order parameters of the system.

The emergence of order in complex systems is an impressive phenomenon observable throughout nature; examples range from regular cloud formations to the meandering of rivers, from chemical to biological "clocks" (Jantsch, 1980; Nicolis & Prigogine, 1977; Winfree, 1980). Spontaneous pattern formation looks like a violation of the second law of thermodynamics (which states that entropy must increase or remain constant in the course of time in a closed system), but actually is not: Self-organization is found only in open systems. If a self-organizing system is cut off from all fluxes (like energy, matter, information) that may permeate it, dynamical patterns eventually die out, that is, entropy increases again.

Are systems within psychology necessarily complex? We think they are not. Mainstream psychology tends to restrict problems to the interactions of a few independent and dependent variables (e.g., frustration, aggression), viewed in cross section. Hypotheses concerning such problems may well be complicated, but the problem chosen (the "system") is not complex.

Complexity enters whenever a *specific* psychological system (i.e., a CES or a PSS consisting of two or more CES) is considered. In a way, the complexity of the single case has the same source as the stochasticity of the common cross-sectional approach in psychology. With a dynamical view, however, one can adopt a different and, in our opinion, innovative focus on single systems.

We believe that the assumption that single CES and PSS are *complex* systems is of an axiomatic nature with considerable face validity. The unpredictability of individual behavior is only one case in point. Generally, in a cognitive system an overwhelming number of cognitive and emotional microevents, memory traces, learned reactions, and so on are activated or available for action at any given "psychological moment." They form a broad stream of conscious and subconscious components out of which only a few are "selected." The selected components shape the motor, cognitive, and emotional behavior of an individual CES in the sense of order parameters. They are selected because they are best fit to reduce the environmental tension (cf. affordances after Gibson, 1979) given by the (informational) fluxes that permeate an open CES. Instead of alluding to the concept of tension reduction we might formulate more generally: Components are selected because they adapt best to the valences of an individual's life space (Lewin, 1936).

The pattern of order parameters can be observed phenomenologically, but the microlevel "stream of (sub)consciousness" cannot, at least not in its entirety. The micro-level of a CES is therefore endowed with a hypothetical or virtual character (Schiepek & Tschacher, 1992; Tschacher, 1990).

How does chaos enter the picture (symbolized by the Gestalt phenomenon of Figure 1)? In each of the paradigmatic, complex systems of self-organization research there are regions in parameter (phase) space where a system exhibits chaotic dynamics. In other words, three or more order parameters must have emerged simultaneously from a system's microscopic modes resulting in a chaotic (or hyperchaotic; Rössler, 1979) macroscopic system of competing order parameters. It follows that finite-dimensional chaos in a complex system marks the presence of self-organization (Figure 2). In the same system, chaotic

FIGURE 1

Chaos and order are related.

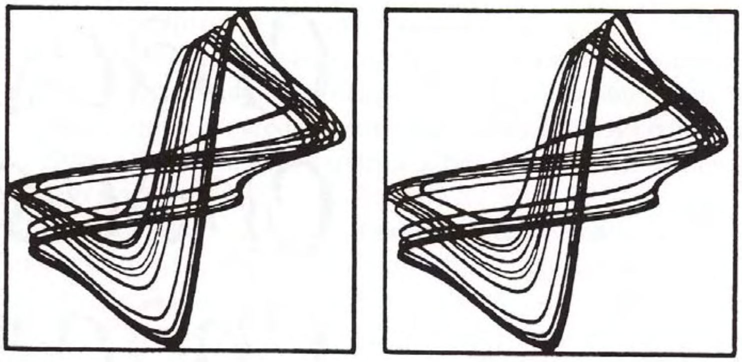
regimes commonly are found with parameter values that indicate larger distances from thermal equilibrium than regimes with simpler dynamics (like fixed points and limit cycles).

Signatures of Chaos

Chaotic dynamics is found in many systems. Historically, nonlinear science started with the study of mathematical structures in a computer (Lorenz, 1963); soon after, the behavior of recursive algorithms (maps, cellular automata, differential equations) suggested that there were randomlike dynamics in each of them which had several attributes in common. The same chaotic attributes later were found in real-world systems that were as disparate as classical reversible systems (e.g., the three-body system of Poincaré; coupled oscillators) and dissipative irreversible systems (the laser; chemical reaction systems). The attributes of chaos may be summed up in four points, which initially appear to be incompatible:

(a) Chaotic time courses become *unpredictable* after some (short) period of time. "Sensitivity to initial conditions" serves as a

FIGURE 2



Dynamics of the Belousov-Zhabotinski system (stereoscopic view of the attractor in phase space): An example of chaos as a hallmark of self-organization because finite-dimensional dynamics govern this complex chemical reaction system.

definition of chaos (Bergé, Pomeau, & Vidal, 1984, p. 104). The future development cannot be foreseen (i.e., appears randomlike).

(b) Chaos arises from *deterministic* systems as simple as iterative nonlinear maps (e.g., the logistic equation used to model population dynamics) or differential equations (like the well-known Lorenz system that describes the Bénard convection, i.e., self-organized patterns in driven fluid systems).

(c) Chaos is a kind of *homeostasis*—the volume of phase space is contracted under chaotic dynamics despite the rapid decline of predictability. The simplest prototype is a strange attractor that simultaneously contracts and expands phase space by a process of stretching and folding (Rössler, 1976).

(d) Chaos may result in self-similar, *fractal* structures of attractors and separatrices in phase space.

During the last decade the number of studies investigating chaos in all types of empirical systems has grown exponentially. The problem usually is to distinguish deterministic chaos from random noise in time series of a single system. The measure used most frequently is dimensionality computed with the algorithm of Grassberger and Procaccia (1983).

In psychology, however, data sets are characterized by relatively short time series lengths, few steps of the scales, and probably high measurement error. Therefore, methods that try to estimate the dimensionality of fractal attractors (the fourth attribute of chaos from the above list) are not applicable in most cases (Ruelle, 1991; Steitz, Tschacher, Ackermann, & Revenstorf, 1992), and so some of the enthusiasm chaos theory evokes from psychologists and social scientists is clearly premature. At present, available methods are inadequate to detect the occurrence of chaos in psychological data, even if the *Zeitgeist* of psychology states otherwise. In the following empirical example we exploit the dynamical rather than the structural (i.e., fractal) signature of chaos. We use a dynamical measure such as the predictability of the time series and thus refrain from estimating the fractal dimension of the system's attractor.

Empirical Examples

IS SCHIZOPHRENIA A CHAOTIC DYNAMICAL DISEASE?

The concept of dynamical diseases (Glass & Mackey, 1988; an der Heiden, 1992) is based on a systems view of psyche, body, and social world. It says that behind "symptoms" is a dynamical system at work. Whatever dynamics a specific system may exhibit under normal circumstances, a dysfunction in the sense of a dynamical disease is equivalent to a significant change of this dynamical regime. Pathological behavior evolves out of healthy behavior by way of a *bifurcation* (a phase transition between two different dynamical regimes). A bifurcation is also found if an unordered complex system spontaneously evolves into an ordered state; this indicates the emergent phenomenon of pattern formation studied by synergetics (Haken, 1983a).

The dynamical concept of disorder does not a priori distinguish between sick and healthy; rather, it views illness as merely a different way of functioning by the same system. In an individual with bipolar depression, for example, a limit cycle (governing the oscillations between manic and depressed states) represents the disorder, whereas normal functioning is characterized by a point attractor of an individual's mood regulation system.

Our hypothesis concerning schizophrenia is that psychotic episodes may be understood as manifestations of a chaotic system, that is, psychoses and schizophrenia are dynamical diseases. Clues to this point are given in studies of Ciompi, Ambühl, and Dünki (1992), who reported finding fractal values in schizophrenia data using the Grassberger–Procaccia algorithm. Schmid (1991) discussed scale invariance (an expression of fractality) in the context of a multilevel view of schizophrenia.

Formal notation deals with *stochastic dynamical systems.* They can be symbolized by a differential equation with a stochastic term $F(t)$ describing external fluctuations that act on the system.

$$dx/dt = N[x(t),\mu] + F(t) \qquad (1)$$

In Equation 1, $x(t)$ is a vector of the state variables of the system dependent on time t (state variables are all m phenomenological descriptors of the system, thus spanning a state space of dimension m). N is the (linear or nonlinear) function that determines the temporal change of state variables. The function itself depends on the environment of the system expressed by a set of control parameters.

Equation 1 lends itself to the following simple classification of qualitatively distinct dynamical systems:

(a) $F(t) >> N[x(t),\mu]$: If the noise or random term is much larger than the deterministic part of the equation, the system defined by Equation 1 becomes a more or less pure stochastic process. This means that the time series shows no evidence of a dynamical disease.

(b) $F(t) << N[x(t),\mu]$: This yields a deterministic system capable of producing equilibrium states ("attractors"). Point attractors can be realized by systems with linear or nonlinear N, whereas chaotic equilibria are necessarily derived from nonlinear systems.

(c)
$$\frac{\sigma^2\{N[x(t),\mu]\}}{\sigma^2[F(t)]} = R,$$

where R is the signal-to-noise ratio (the ratio of variances σ^2 of the deterministic and stochastic terms of Equation 1). A combination of the above cases is predominant in most empirical time series reflecting noisy deterministic systems. Here a further distinction can be made by using statistical tests:

(c_1) N is nonlinear. A useful technique for distinguishing chaotic from nonchaotic motions is the calculation of Lyapunov exponents, where possible. If one Lyapunov exponent is positive, the system is chaotic (with some degree of contamination by noise).

(c_2) N is linear. The time series should be modeled by an autoregressive process.

Method

Participants

We worked with patients treated at Soteria Bern, a small therapeutic residential community in Switzerland for persons experiencing a first psychotic manifestation (Aebi, Ciompi, & Hansen, 1993; Ciompi, 1991). The prerequisite for inclusion in our sample was that a patient's daily manifestations of psychotic symptomatology could be observed for a long enough period of time (at least 200 days). Thus, our group of patients constitutes a sample of Soteria residents with long hospitalizations.

The longitudinal course was mapped by daily ratings of a patient's psychoticity by staff members. The focus of our interest was the course of psychotic derealization measured with a 7-point scale (with 1 denoting normal functioning and a relaxed state and 7 denoting hallucinations or catatonia). The state vector $x(t)$ after Equation 1 therefore contains only one (global) variable (for details, see Tschacher, Scheier, & Hashimoto, 1997).

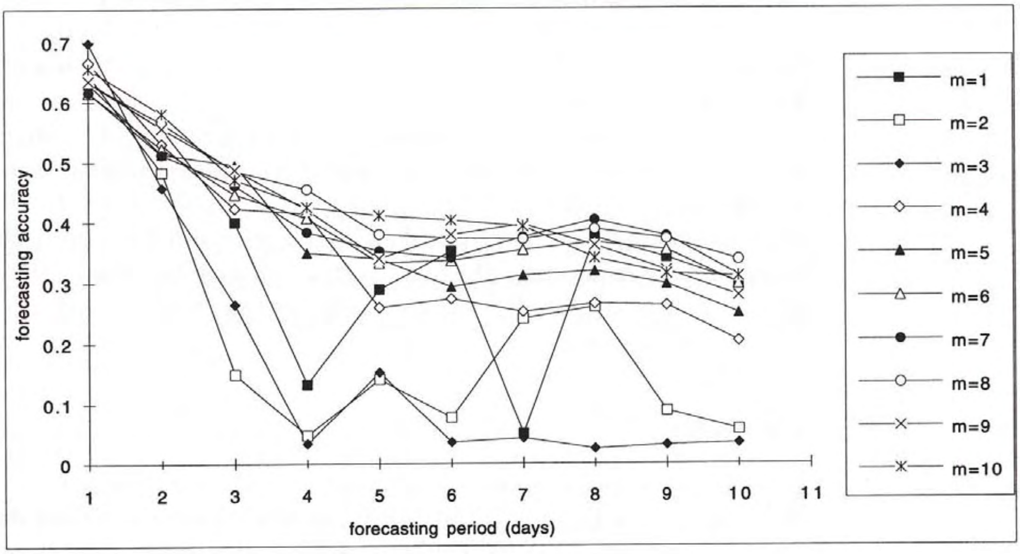
Algorithm

We implemented the nonlinear forecasting algorithm (NFA) proposed by Sugihara and May (1990), which we combined with surrogate data statistics. The NFA is robust concerning the restraints for data quality common in psychological research (Scheier & Tschacher, 1996). The procedure is as follows. The time series is divided into two halves; the first half is a "library" that can generate forecasts. To make forecasts, the m-dimensional phase space of the system must be reconstructed from the one-dimensional time series using the method of Takens (1981). In phase space, each state of the system is represented by one point. Thus, forecasting temporal development addresses the question of which point is next approached by the system. If the system is deterministic we may assume that adjacent points ("nearest neighbors") in phase space change in a similar way.

In this way we can forecast the future development of any given state documented in our patients. The accuracy of forecasting can be defined as the correlation of expected evolution of system states with the actual evolution of the system. The actual evolution of a system state A is realized in the second half of the time series. The expected evolution can be extrapolated on the basis of A's nearest neighbors in the "library" data. Figure 3 charts such correlations of actual versus expected evolutions which are derived using NFA from the data set of one patient. As can be seen, the correlation value for time Step 1 ("next day") is around .7. A forecasting period of 5 days, however, no longer yields a valid prognosis (the correlation has decreased to about .15 at an embedding dimension of $m = 3$).

The change of forecasting accuracy for increasing periods of time is characteristic for the kind of time series that has been mapped—one can derive a "signature" of the system's dynamics. For example, a linear autoregressive system yields no decrease of correlations, but a con-

FIGURE 3



Courses of forecasting accuracies computed with the Sugihara–May (1990) nonlinear forecasting algorithm, embedding dimensions *m* from 1 to 10; the figure is based on daily psychoticity data of a patient.

stant positive value of forecasting accuracy; a random generator in a computer (or a noisy system) shows no correlations deviating from zero; a deterministic–chaotic system acts according to sensitivity to initial conditions (the definition of chaos given above) by giving a trajectory of prognoses that resembles the one depicted in Figure 3: Short-term predictability together with nonpredictability in the longer run is a basic sign of deterministic chaos.

Surrogate Method Data

We used surrogate data to evaluate the statistical significance of our time series classification using forecasting accuracies. This method is described at length in Theiler, Galdrikian, Longtin, Eubank, and Farmer (1992) and Scheier and Tschacher (1994), and it is illustrated here by an example. First, we compute a discriminating statistic with the forecasting method NFA, for example, + for the forecasting accuracy for a 1-day period ($r = .70$ in Figure 3). Using the same method, we then determine the forecasting accuracies for a number of surrogate data sets (i.e., artificially generated "time series" that are identical with the measured data according to mean, variance, and length). In this way we gain a *distribution* of discriminating statistics, so we can test whether the empirical time series can be discriminated from a population of surrogate data.

We used tests in two ways: First, we tested whether empirical time series can be predicted better than random; second, we fitted autoregressive models to the original data, used the various realizations of models as surrogate data sets, and examined whether empirical data could still be forecasted better than their linear models. Thus, the surrogate data method allowed us to test two null hypotheses:

Null Hypothesis 1: The time series behaves like a string of random numbers as far as forecastability is concerned, that is, an a-system (stochastic system) according to the classification given above.

Null Hypothesis 2: The time series examined behaves like a linear autoregressive process (a c_2-system).

The rejection of both null hypotheses indicates that a certain time series contains nonrandom serial structure and is nonlinear. We also tested for the largest Lyapunov exponent (lambda, which indicates the rate of divergence of neighboring trajectories in phase space). Divergence points to entropy production and sensitive dependence from initial conditions—in other words, deterministic chaos. We used the algorithm as suggested by Wolf, Swift, Swinney, and Vastano (1985).

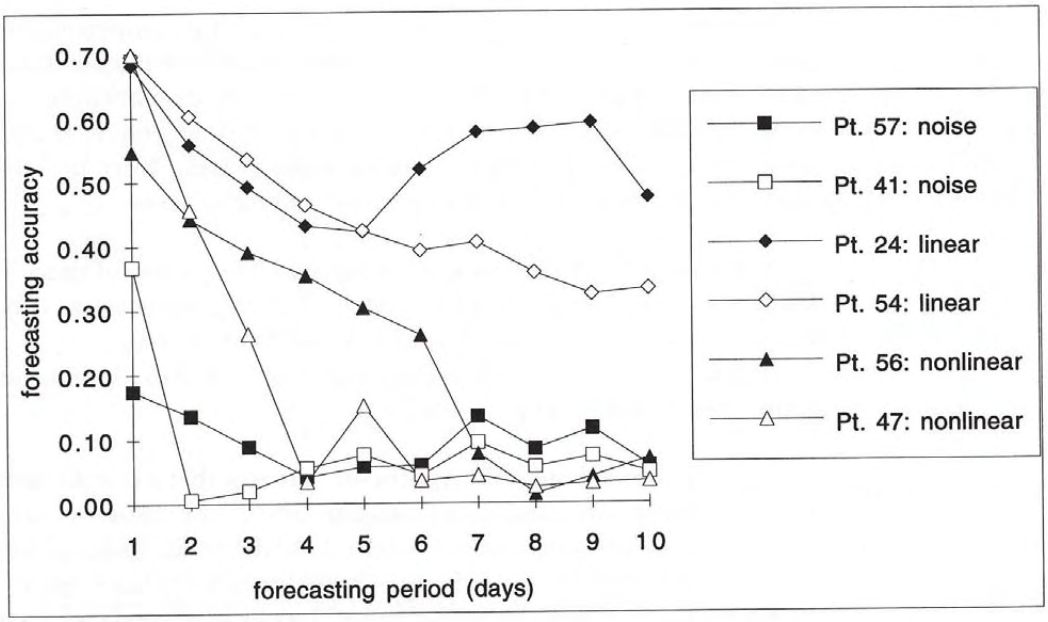
Results

Three groups of psychotic courses can be distinguished by inspection of forecasting accuracies and the significance tests. Two courses in each group, respectively, are presented in Figure 4. The first group of courses yields forecasting curves of the chaotic–deterministic type. These time series are likely to be c_1-systems: The discussion of the population dynamical time series in Sugihara and May (1990) corresponds to our finding of a variable amount of noise in our nonlinear time series, which reduces 1-day forecasts to values of between .92 (approximately 10% noise) and .4 (approximately 60% noise). Eight out of 14 patients (57%) have nonlinear dynamics. The Lyapunov exponents indicate that at least 6 patients showed signs of chaotic dynamics.

Another four time series are best modeled as autoregressive linear processes (c_2-systems), because they show no significant change in forecasting accuracies over time. Two further time series can be characterized as random data sets (a-systems).

Table 1 lists the forecasting accuracies according to Sugihara and May (1990) for the psychosis time series and the effect measures for

FIGURE 4



Courses of forecasting accuracies for six exemplary psychosis time series: (c_1)-systems (nonlinear), (a)-systems (noise), (c_2)-systems (linear).

both null hypotheses. Our interpretations of significance tests are summarized under the table heading Model.

Discussion

Our investigation offers evidence that a larger proportion of the psychoses we studied show nonlinear time courses. This is (to our knowledge) the first time that the validity of the concept of dynamical diseases has been established on statistical grounds in this important area of psychopathology. In addition, we succeeded in showing by the estimation of Lyapunov exponents that most of the nonlinear courses may be interpreted as expressions of low-dimensional chaos. This applies to at least six out of eight nonlinear cases. This interpretation is further supported by the fact that, in the linear and noisy cases of our sample, exponents do not deviate significantly from zero. This last result has to be treated with caution because the estimation of Lyapunov exponents rests on an insufficient data base.

In principle, the CES in which psychopathology occurs consist of many components; they are high-dimensional, complex systems.

TABLE 1

Results of the nonlinear forecasting algorithm (NFA) and related significance tests

Patient	Forecasting Accuracy	Forecasting Decline	λ	$H_0(1)$	$H_0(2)$	Model
62	.790	.422	.024	12.22**	0.98	Linear
54	.696	.229	.014	17.13**	1.23	Linear
24	.852	.408	.002	11.97**	0.87	Linear
13	.661	.269	.104	10.84**	1.72	Linear (nonlinear?)
34	.479	.325	.004	11.64**	2.28*	Nonlinear (linear?)
48	.472	.364	.020	4.70**	2.18*	Nonlinear (linear?)
51	.920	.288	.142	11.28**	1.90	Nonlinear
47	.698	.344	.270	15.27**	2.18*	Nonlinear
56	.578	.206	.372	9.26**	6.66**	Nonlinear
19	.671	.326	.243	5.13**	2.33**	Nonlinear
53	.757	.450	.214	4.59**	3.42**	Nonlinear
58	.358	.123	.117	2.72**	8.16**	Nonlinear
41	.477	.113	.002	1.66	4.91**	Noise (nonlinear?)
57	.174	.005	.021	0.80	5.26**	Noise

Note: Forecasting accuracy = degree of predictability of a time series (maximum NFA correlation between forecast 1 day ahead and actual data); forecasting decline = mean forecasting accuracy 1 day ahead minus mean forecasting accuracy 5 days ahead; λ = value of the largest Lyapunov exponent; $H_0(1)$ = noise effect measured from test of the first null hypothesis; $H_0(2)$ = linearity effect measure (effect measures are values under a standard normal distribution).

* $p = .05$. ** $p = .01$.

Nevertheless, we found evidence of nonlinear dynamics of low dimensionality which we interpret as reflecting the dynamical disease process of psychosis. This may be understood as an example of *self-organization,* by which a coherent longitudinal pattern emerges from a complex, potentially unordered and unpredictable system. In terms of Gestalt psychology, we observed a synergetic figure–ground effect: A nonlinear and probably chaotic process is contrasted against its environment in an emergent process of pattern formation. In other words, a dynamical Gestalt emerges from its multicausal environmental "ground." In summary, we found some indication that many schizophrenic psychoses may be dynamical diseases with chaotic courses.

SOCIAL PSYCHOLOGY: SYNCHRONIZATION OF OSCILLATORS

In the next study we investigated a PSS (which consists of two coupled individual CES). Our working hypothesis was that empathy and social coherence may lead to a synchronization of variables (Bandler & Grinder, 1982; Levenson & Ruef, 1992; Tschacher, 1990; Warner, 1992). At the level of motor behavior, such social phenomena are well known. Similarity of gestures, posture, and mimics often indicates how close and personal a relationship is (cf. therapeutic "pacing"). We studied whether this applies at the physiological level as well. We may interpret synchronization phenomena again as an expression of pattern formation in a social context, as psychosocial self-organization (Brunner & Tschacher, 1991; Tschacher & Brunner, 1995).

Method

Quantitative information on social interaction was recorded with the help of portable devices that measure and store physiological signals (Kölner Vitaport™ System, Ingenieurbüro Becker, Karlsruhe, Germany). In the pilot study reported here we mapped the physiological and motor behavior of two individuals during conversation. The conversation was about private topics chosen by the interviewee. The interviewer, a psychotherapist, was instructed to effect a state of mutual understanding and empathy followed by a disruption of this state. From each condition we extracted a 5-minute interval. Thus, we tried to establish two qualitatively distinct states of the PSS.

Four variables were acquired from each person: a three-point electrocardiogram (ECG) from the thorax; respirational activity (gathered by a strain-sensitive belt); and movements of the right and left hand (through acceleration sensors). The covariance of 4×4 variables therefore contains the information on social coupling and synchronicity during the conversation episodes.

Modeling of the time series was accomplished by state space representations (Priestley, 1988). This method allows for a compact description of multiple time series x_{t+1} (in principle convertible into a general autoregressive moving-average [ARMA] model):

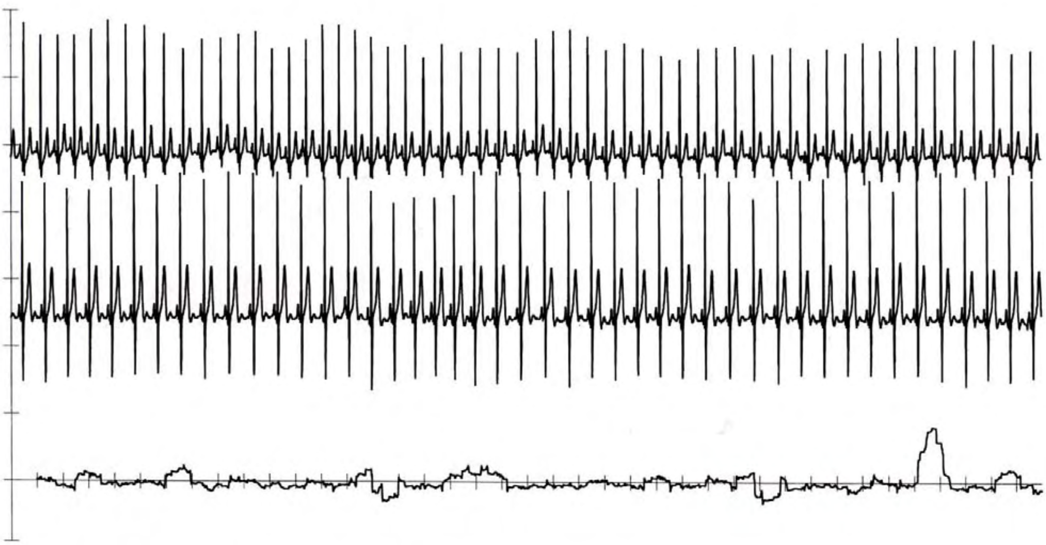
$$x_{t+1} = Fx_t + e_t. \tag{2}$$

The state vector x_{t+1} evolves from the state x_t by multiplication with the transition matrix F. Random shocks are added. The transition matrix consists of cross-regressions and autoregressions with lag 1 and of additional components caused by higher lags. If a convergent estimation of the matrix is possible on the basis of available data, we gain a linear model of the interactions of variables which may be interpreted causally (as a regression of a variable at time t to a variable at time $t + 1$). We used the SAS™ statistical package (SAS Institute Inc., Cary, NC) for data analysis.

Results

A complete synchronization of variables (in dynamical terms, phase coupling or entrainment of oscillators) is a striking event; we did not

FIGURE 5



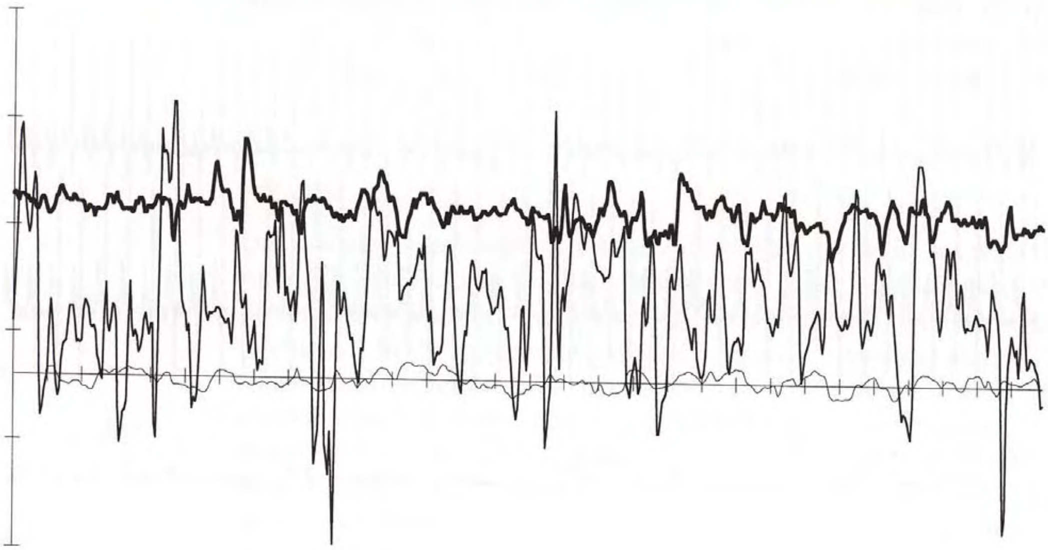
Electrocardiographs (ECGs) of interviewee (top) and interviewer (bottom) during empathy Phase 1. The bottom time series are moving correlations of both ECGs in 1-s windows.

observe it in our pilot study. The dual ECGs (Figure 5) show no phase coupling. The same applies to respiration cycles (Figure 6).

For a first overview on the degree of interactive coupling of the two persons, we looked at the correlation matrix. Table 2 shows Pearson correlations (Bonferroni-corrected significant values emphasized). For example, the movements of the left and right hand of the interviewee are highly correlated, whereas the interviewer does not coordinate movements bilaterally. In this case we were interested in interindividual coordination; 3 of 16 possible social correlations are significant in the empathy condition of Phase 1 (interviewee's respiration with the interviewer's left and right hand movements; interviewer's respiration with interviewee's left hand). All significances are lost in Phase 2.

The theory of time series analysis states that cross-correlations need not give an adequate reflection of the interactions; partial correlations have to be considered. Therefore we modeled the time series of all eight variables using the state space approach (separately for Phases 1 and 2). Both phases yield a model of the same form: respirational variables are included with lag 2, all others with lag 1; this is analogous to an ARMA(2,1) model. Here, we can only summarize the complicated state space models by the significant F cells. In phase 1 ("empathy"), 6 out of 46 socially relevant cells are significant at the 5% level; we found a mutual feedback system between the inter-

FIGURE 6



Respiration time series of interviewer (thick line) and interviewee (medium line) during Phase 1; the thin line shows moving correlations of both in 10-s windows.

viewee's respiration and the interviewer's ECG. In Phase 2 there are 7 significances, and they are almost exclusively caused by the effect of all interviewee's variables on the interviewer's respiration.

Discussion

At this time we cannot interpret the state space finding reliably, because the high number of the models' parameters casts doubt on the significances. The absolute values of the significant regressions are often small: Only a moderate part of covariance can be explained by interpersonal synchronization. Moreover, the Phase 1 versus Phase 2 conditions account for a qualitative but not quantitative difference. In summary, we think it is premature to speak of evidence for sociophysiological coupling in the case we examined. Nevertheless, our method seems adequate for micro-analyses of interaction. It is straightforward to test the hypothesis of synchronization in a future project where single case studies can be combined and tested statistically.

PSYCHOTHERAPY: REDUCTION IN DEGREES OF FREEDOM?

Our final example deals with therapy systems, that is, a special kind of PSS. We studied longitudinal data of the courses of 22 psychother-

TABLE 2

Correlations matrix of eight sociophysiological variables

	Interviewer				Interviewee			
	Resp.	**Act1**	**Act2**	**ECG**	**Resp.**	**Act1**	**Act2**	**ECG**
Interviewer								
Resp.		.005	−.031	**−.353**	.026	.016	−.089	−.007
Act1	**.216**		−.072	−.005	.046	.070	.088	.020
Act2	.035	.017		−.013	−.118	−.047	−.045	−.013
ECG	−.022	.046	−.015		.005	−.053	−.030	−.013
Interviewee								
Resp.	.056	**.136**	**.176**	.020		.067	**.166**	.013
Act1	−.123	−.063	−.081	.021	**−.143**		**.516**	.045
Act2	**−.180**	−.056	−.047	.016	**−.192**	**.710**		.030
ECG	.017	.036	.005	−.063	.020	.006	−.019	

Note: Resp. = respiration; Act1 and Act2 = movement–activity of right hand and left hand; ECG = electrocardiogram. Values below the diagonal are empathy data (Phase 1); values above the diagonal pertain to Phase 2. Bonferroni significant correlations appear in bold.

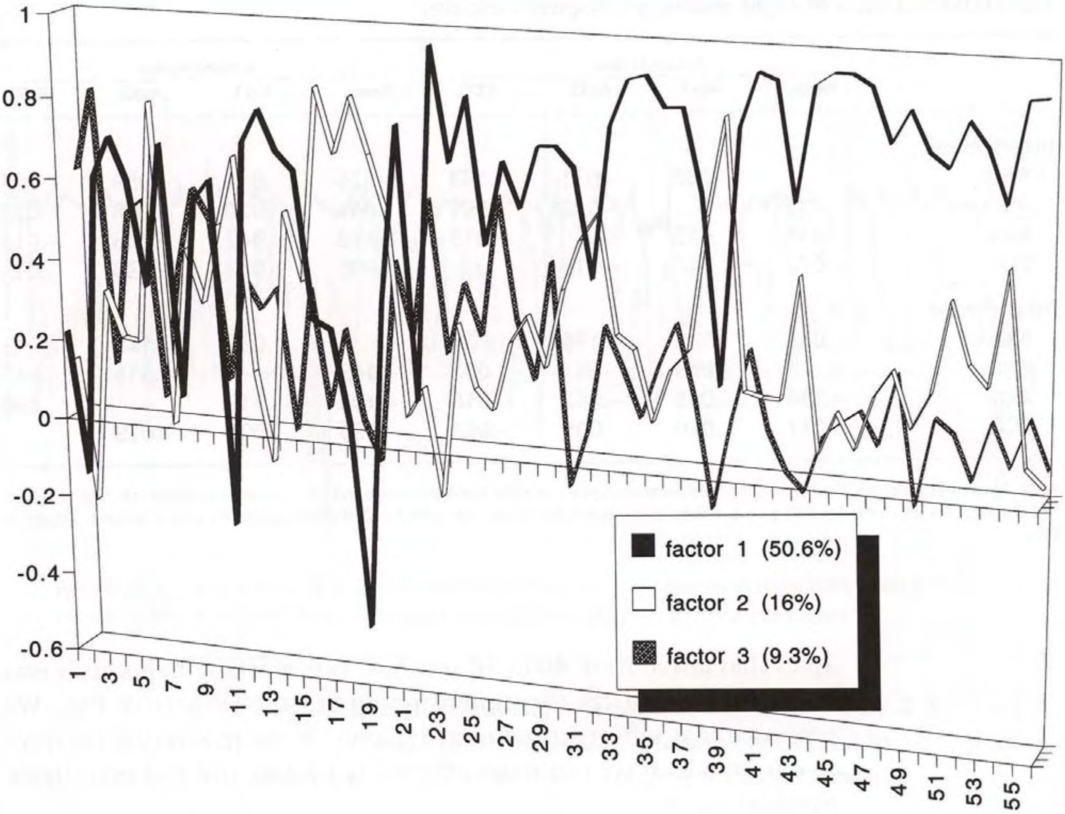
apies that lasted from 40 to 90 sessions. Our working hypothesis was that therapy reduces the dimensionality of the respective PSS. We proposed that self-organizational dynamics is the theoretical perspective from which we can more effectively understand and investigate psychotherapy.

Method

Therapies were conducted and documented at the psychotherapeutic center of Bern University by Grawe and coworkers (Grawe, Caspar, & Ambühl, 1990). Each session of each therapy was assessed by the therapist using a 14-item questionnaire (sample item: "I have the impression that the client did come up with what really bothers him/her.") and also by the client using a questionnaire of up to 29 items (sample item: "Today I felt comfortable with the therapist."). Thus, for each therapy course, data on 33 (in some therapies, 43) variables per weekly session were collected.

We used factor analysis for data reduction. We conducted principal component analyses of the correlation matrices of the time series variables (O-technique; Cattell, 1966); this method reduces the correlating variables to factors that mark special attributes of the therapy process. Factor analyses of this kind have been used in synergetics to extract order parameters in self-organizing complex systems (Friedrich & Uhl, 1992; Haken, 1988, labeled *Karhunen–Loeve expansion*). Figure 7

FIGURE 7



Time course of factor loadings of the three dominant O-technique factors of a 56-hr psychotherapy.

plots the time courses of the three largest order parameters (after varimax rotation) of a 56-session therapy of our sample.

In this therapy system, the factors may be interpreted as follows. Factor 1 loads especially in optimistic, solution-oriented therapy sessions of high rapport and insight into problems. Factor 2 signifies lack of clarity and initiative with a tendency toward avoidance. Factor 3 represents indifference or contentment with signs of resistance. In Figure 7 the course of therapy shows an unstable initial phase which—after several crises—eventually merges in the establishment of a clear therapeutic alliance.

In the following we used factor analyses as a tool to estimate the number of degrees of freedom (the dimensionality) of a therapy system (Tschacher & Grawe, 1996). The idea is to define a window (we chose 30 consecutive sessions) and compute the degrees of freedom as the number of unrotated factors with an eigenvalue larger than 1. We may then compare the degrees of freedom of the initial sessions with those of the final sessions of all therapies. By this procedure ("O-window-technique") we are in a position to put the central hypothesis to test, namely, that the emergent evolution of a system is accompanied by a marked reduction of degrees of freedom.

Results and Discussion

Table 3 presents the changes between each therapy's initial and final window of 30 sessions. We listed the degrees of freedom (the number of factors with eigenvalues greater than 1) and percentage of variance explained by the first unrotated factor. The reduction of degrees of freedom is significant ($t = 3.73$; $p = .0006$, one-tailed; for the Wilcoxon nonparametric statistic, $p = .0014$). This is consistent with the finding that the largest factors explain a larger portion of the system's variance in the final windows ($t = -3.07$; $p = .003$). This result supports—at least in the available sample of 22 therapy systems—the hypothesis of a reduction of degrees of freedom during the course of psychotherapy. We may interpret this finding as a consequence of self-organizing tendencies of the PSS evolving in a therapeutic relationship. We assume that the evolution of this system follows a nonlinear course as in Figure 7. There is a phase of critically fluctuating factor loadings in the first third of sessions, then a phase of relative stability and rapport during the second half of this therapy.

General Discussion

We think that there is growing evidence of nonlinear dynamics in the fields of psychology and psychiatry. In three exemplary data sets we found indications of chaotic dynamics and self-organization. If findings like ours can be replicated, there should be a shift toward a dynamical investigation and understanding of psychological systems.

There is still need for progress on the methodological side. Above all, methods must be well-behaved regarding noisy data. It seems that concentration on measuring fractal dimensions was only one possible way, and a doubtful one in some respects (cf. Ruelle, 1990). Forecasting methods use the dynamical properties of chaos (unpredictability) rather than structural properties of the attractors (fractal dimension). If these methods are combined with statistical hypothesis testings, positive findings of nonlinearity and chaos should become

TABLE 3

Comparison of initial and final phases in 22 psychotherapy courses of the Bern comparative study

Therapy No.	*n*	Degrees of freedom Initial	Degrees of freedom Final	Variance of Factor 1 Initial	Variance of Factor 1 Final
12	63	4	3	57.30	67.22
30	59	6	5	47.26	57.21
46	73	2	2	81.31	87.48
49	56	3	3	74.63	70.53
75	59	5	5	62.18	51.12
77	59	2	3	78.53	77.13
84	71	3	3	68.39	72.31
93	56	6	4	52.20	65.63
303	90	6	4	45.85	57.31
308	85	4	3	54.99	72.13
312	56	5	2	56.69	76.52
317	62	4	3	66.89	67.82
9	44	5	4	50.40	49.77
24	42	2	1	85.83	89.40
35	51	5	3	50.65	75.55
55	48	5	4	48.39	63.76
83	44	7	6	44.37	42.36
304	48	3	2	72.68	77.69
305	40	3	2	73.90	74.63
306	53	3	3	72.00	72.34
307	49	4	4	56.60	59.7
314	52	1	2	87.08	85.8
M		4.00	3.23	63.10	68.79

Note: Each psychotherapy course consists of 40 or more sessions.

increasingly hard to ignore by mainstream psychology. Another methodological improvement is overdue: Methods of nonlinear modeling should be developed to analyze multiple time series (cf. Tong, 1990).

The results of a dynamical view have practical consequences for issues of psychotherapy:

(a) Our results support the possibility that schizophrenia may be a chaotic dynamical disease. Thus, the question of how to influence chaotic systems arises. We should keep in mind that chaos does not mean total uncontrollability (as is suggested by colloquial language), but rather short-term determinism combined with long-term unpredictability. From this follows the paradoxical sounding notion of chaos control. Therapeutic interventions can control chaotic dynamics if the time span between intervention and evaluation (which guides new interventions) is chosen appropriately. This time span may be short because in chaos predictability tends to fade with the passing of time (see the data for Patients 47 and 56 in Figure 4). This has obvious implications for the frequency of therapy sessions.

According to nonlinear theory, there are different ways of restituting the dynamics to nonpsychotic regions of state space (or, respectively, of shaping degrees of freedom so that therapeutic alliance becomes possible). First, with gradual variation of the environment (control parameters) the attributes of attractors change in an often discontinuous manner. Second, if other "nonpathological" attractors continue to exist, there is an opportunity to drive the system into the basins of these attractors by single interventions or perturbations (i.e., even without changing control parameters). Functioning in these attractors then immediately has to be stabilized structurally in the sense of relapse prevention. Finally, chaotic behavior can be made oscillatory by small repeated inputs to control parameters when the contingency between input and effect is monitored (such feedback loops have been demonstrated to work in technical applications; see Pyragas, 1992).

(b) The gradual generation of order seems to play a role in the courses of psychotherapies, as is shown by the reduction of degrees of freedom found in our study. The hypothesis of social synchronization is consistent with this finding because synchronization reduces the complexity (i.e., the degrees of freedom) of a PSS. Thus, we may begin to speculate about the therapeutic implications opened up by these findings. The question of dealing with complex systems has been approached in the context of synergetics (applications to clinical psychology are discussed in, e.g., Kriz, 1990; Kruse & Stadler, 1990; Schiepek, Fricke, & Kaimer, 1992; Tschacher, 1990). Initial evaluations of the correlations of therapy outcome measures with the complexity of the therapeutic PSS suggest that there is a link of positive outcome (e.g., a patient's evaluation of therapy success) with low complexity. A therapeutic relationship rated as beneficial also corresponds to low PSS complexity. Again, this fits well with the social synchronization hypothesis stating that empathic states show more synchronization.

A theoretical project of the future will be to conceptualize endodynamics in psychology (cf. Atmanspacher & Dalenoort, 1994; Rössler, 1987, 1994). The dynamical and synergetic approach advertised throughout this chapter—like all forms of natural science except quantum theory—depends on the implicit exoposition of a godlike observer. Yet, if observers are so aloof that they do not change what they observe, then how can they intervene? The complementary question is just as difficult: What can we say about the dynamics of systems viewed only from inside? Considerations such as these are in danger of leading to paradoxes, but they are of obvious practical relevance as well, because as psychologists we usually deal with endo-systems (e.g., as therapists in psychosocial systems of which we are definitely parts or as introspectors of our own selves and consciousness; Tschacher & Rössler, 1996).

For the endo-project, we propose not to engage in the kind of metaphorical thinking used in the philosophy of self-reference and autopoiesis (Maturana & Varela, 1980). In our view, the efforts of radical constructivists resulted in solipsistic and relativistic attitudes which have proven counterproductive to the progress of systemic psychotherapy. We would not take an all-or-none position. A system may be more or less of an endo-system depending on how much self-reference is present, on how strongly observation influences the observed. So we think that even in this respect quantification is meaningful. For example, a therapeutic relationship with intense transference and countertransference activity is clearly an endo-system, whereas the relationship of, say, a behaviorally oriented therapist and a client who wishes to quit smoking should be less endo-systemic in nature.

Which effects are predicted by the endo-view? In principle, endo-systems differ in how time is characterized. In dynamical science, time is a directionless smooth variable. Not so in introspection—here time has varying velocity and an extended "psychological now" exists. Another aspect strikes us as also important: Endo-systems constantly produce new emergent variables (Kampis, 1994). Thus, the resulting dynamics would be nonstationary, yielding impossible traditional time series analysis. The therapy analyses presented above point to this fact of changing global variables. New, more encompassing order parameters emerge whereas old order disintegrates. This is obviously much more complicated than dynamics with one stable, if even chaotic, regime.

To conclude, we think there is much to be explored at both ends of the dynamical research spectrum. At one end we should try to translate *chaos, attractors,* and *self-organization* into a therapeutic and practical approach, which could then be labeled *systemic.* At the other end, constantly new questions deserving increasing theoretical and philosophical sophistication arise—which hallmarks dynamics as a science viewed from inside.

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