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A Quantitative Method for the Analysis of Nomothetic Relationships Between Idiographic Structures: Dynamic Patterns Create Attractor States for Sustained Posttreatment Change

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Abstract

Objective—The present article aimed to demonstrate that the establishment of dynamic patterns during the course of psychotherapy can create attractor states for continued adaptive change following the conclusion of treatment

Method—This study is a secondary analysis of T. D. Borkovec and E. Costello (1993). Of the 55 participants in the original study, 33 were retained for the present analysis due to the homogeneity of psychotherapy outcome among these participants. Of these 33, the majority were White (88%) and female (70%), and the average age was 35.44 years ($SD = 14.46$). Participants participated in 12 weeks of either cognitive behavioral therapy or applied relaxation. Daily diary entries from the treatment period were subjected to time series analyses in order to determine the degree of order versus disorder present within individual dynamic systems. These idiographic data were then aggregated for nomothetic analysis of treatment outcome via linear mixed effect models.

Results—Spectral power due to daily to intradaily oscillations in thrice-daily diary data significantly moderated reliable change over posttreatment follow-up such that lesser power predicted increases in reliable change over the 1-year follow-up period. Additionally, residual variance for dynamic factor models significantly moderated the slope for change over the follow-up period, such that lesser variance—and thus greater order in dynamic systems—predicted increases in reliable change.

Conclusions—The degree of order in dynamic systems established during therapy acted as an adaptive attractor state, promoting continued positive gains 1 year after the conclusion of therapy. The present study represents an important innovation in the study of dynamic systems in psychotherapy.

Keywords

ecological momentary assessment; dynamic systems; statistical methods; psychotherapy

The *Diagnostic and Statistical Manual of Mental Disorders*, 4th edition (*DSM-IV*; American Psychiatric Association, 1994) defines a mental disorder as “a clinically significant behavioral or psychological syndrome or pattern” (p. xxxi). Moreover, it is generally established that psychotherapeutic interventions are indicated when individuals develop maladaptive patterns in cognition, affect, and/or behavior that cause significant distress or impairment (Mahoney, 1991). It is the goal of psychotherapy to interrupt these patterns and replace them with more adaptive patterns of thought, affect, and action (Mahoney, 1991). Decades of psychotherapy outcome data have demonstrated that psychotherapy works, decreasing psychopathological symptomatology (Chambless & Ollendick, 2001; Newman & Stiles, 2006) and improving interpersonal functioning (Crits-Christoph, Gibbons, Narducci, Schamberger, & Gallop, 2005; Horowitz, Rosenberg, Baer, Ureño, & Vilasenor, 1988; Newman et al., 2011), among other beneficial outcomes. However, many have called for the investigation of the mechanisms of psychotherapeutic action in order to ascertain how and why psychotherapy works (e.g., Kazdin, 2005, 2007; Kraemer, Wilson, Fairburn, & Agras, 2002) and, in some cases, why it does not.

Patterns of cognition, affect, and behavior are potentially integral to the understanding of therapeutic successes and failures. Specifically, the strength and breadth of these patterns—both maladaptive patterns that precede and necessitate psychotherapy and more adaptive patterns established within psychotherapy—are likely to impact the adaptive versus maladaptive responses that an individual generates in response to their environment. Utilizing patterns as the level of description emphasizes the relationships *between* observable phenomena. More important, this is not limited to the relationship between one construct and another (e.g., cognitions and behaviors), but also includes relationships within a single construct from one moment to another (Kelso, 1995). Thus, we can conceptualize these patterns as dynamic, where the state of a given cognition (affect, behavior) at one moment in time is dependent—at minimum—on the state of that cognition in preceding moments. Within a dynamic systems perspective (Luenberger, 1979), patterns of cognition, affect, and behavior can be conceptualized as attractor states. These states are so named because they draw the system into coherence and give it structure, just as the force of gravity both draws objects toward a body of sufficient mass and gives structure to the physical laws that govern behavior on and around the body. The stronger an attractor state, the more energy is required to move a system from the preferred state.

Initially developed within mathematics and physical sciences, work in dynamic systems theory has begun to be applied to the field of psychology (Vallacher, Coleman, Nowak, & Bui-Wrzosinska, 2010; Vallacher & Nowak, 1997), with some recent attention to clinical psychology and psychotherapy (Hayes, Laurenceau, Feldman, Strauss, & Cardaciottto, 2007; Hayes & Strauss, 1998; Laurenceau, Hayes, & Feldman, 2007; Tschacher & Ramseyer, 2009; Tschacher, Scheier, & Grawe, 1998). Dynamic systems involve a tension between stability and variability wherein stability gives the system order and variability allows flexibility. The organization of a system over time leads to the establishment of patterns of stability (i.e., attractors). The presence of attractors in a dynamic system promotes convergence around a limited set of outcomes, even from widely divergent initial conditions (e.g., stimuli, environmental features).¹ In individuals seeking psychotherapy, maladaptive attractor states facilitate convergence around patterns of cognition, affect, and behavior that cause the individual distress (e.g., interpersonal dysfunction, worry, depressogenic schemas, etc.). Thus, across multiple domains, and despite the distressing or impairing consequences, these individuals find themselves operating within a limited range of thoughts, feelings, and

¹It should be noted that three types of attractors have been identified: fixed-point, periodic, and chaotic. The present article focuses exclusively on fixed-point attractors. For a discussion of the role of each of the three variations within psychological research, see Vallacher and Nowak (1997).

actions. The degree to which psychotherapy can effectively draw a system away from stable maladaptive attractor states and then replace them with stable *adaptive* attractors might therefore dictate the degree to which the therapy can have successful long-term effects.

The latter portion of this hypothesis was tested by Tschacher et al. (1998), who examined the relationship between increases in order during psychotherapy and beneficial outcomes (reduction of social anxiety symptoms, improvements in self-image and emotional well-being). These authors proposed that the establishment of patterns during psychotherapy bring adaptive order to dynamic systems involved in the therapeutic process and that these patterns are positively related to therapeutic gains. Tschacher et al. did not specify the nature of these patterns and noted that “pattern is a semantic concept which is realized differently in each single system” (p. 197). Increased order was quantified as a reduction in the number of factors needed to describe the therapy process in factor analyses of therapy variables. Indeed, reductions in the number of factors from the first 30 sessions of therapy to the final 30 sessions were significantly predictive of therapeutic gains. More important, these authors neither measured initial maladaptive attractors nor directly measured the dissolution of initial attractors. The examination of increased order during psychotherapy assumed the prerequisite deconstruction of preexisting maladaptive patterns and consequent increases in disorder. Ideally, the exploration of dynamic systems in psychotherapy would include measures of disorder and order as well as provide a meaningful way to examine the qualitative nature of the patterns established during the psychotherapy process.

Tschacher et al. (1998) demonstrated that the increase in order observed within their study was directly related to the establishment of adaptive patterns. However, it is possible that disorder could be generated during therapy, without necessarily leading to the reorganization of cognitive or affective systems into adaptive order. Within dynamic systems theory, destabilization of a system is required for change in that system, as energy is expended to draw the system away from attractor states. As noted above, stability and order are in direct opposition to variability and disorder. In psychotherapy, destabilization is analogous to disorder in cognitive, affective, and behavioral systems (Mahoney, 1991). If the disorder in destabilized systems is not replaced with new, adaptive patterns, individuals may face a greater likelihood of returning to previous maladaptive attractor states. It would follow that disordered systems would likely be predictive of negative therapeutic outcomes.

Dynamic analyses of therapeutic process and outcome should seek to assess levels of order versus disorder during psychotherapy as well as to describe the qualitative nature of patterns within dynamic systems. Specifically, patterns of relevant cognition, affect, or behavior should be examined for stability and variability, as these factors are likely to be predictive of long-term outcomes. However, a tension exists between the need to assess dynamic systems within individuals and the need to determine rank-order differences in outcome across individuals. Dynamic systems of cognition, affect, and behavior are inherently idiographic; that is, they occur within the individual. Psychotherapy as well is an inherently idiographic process. Whether through insight, behavioral modification, cognitive restructuring, or some other process, the vehicle of change lies within the psychic structures, behaviors, and cognitions of the individual. However, our quantitative approaches to assessing process and outcome in psychotherapy are almost exclusively nomothetic (i.e., aggregated across individuals). Such an approach assumes a level of homogeneity in dynamic processes that is rarely extant in our data. Surely, idiographic processes should be assessed via idiographic methodologies (Hayes et al., 2007; Krause, Howard, & Lutz, 1998). And yet, as behavioral scientists we endeavor to be able to generalize to a population.

Most psychological processes are nonergodic, so that the structure of intraindividual and interindividual variation are different and unrelated (Molenaar, 2004). Put simply, we should

not expect that a single individual, sampled 100 times, and 100 individuals, sampled once, will yield similar or correlated results. For instance, the Big Five personality traits have been replicated extensively in traditional nomothetic analyses across individuals (McCrae & John, 1992). However, Borkenau and Ostendorf (1998) found that when the individual time series of 22 participants sampled on 90 consecutive days were factor analyzed, the Big Five factor structure was not reliably reproduced.

By aggregating across individuals, nomothetic analyses of time-varying processes explicitly disregard important within-individual dynamics. The assumptions underlying such aggregations are that uncontrolled factors outside of the independent variables of interest will vary randomly across individuals, that these variations will effectively cancel each other out, and that they ultimately represent error or noise in the variability of the outcome (Sidman, 1960). However, Mischel (1973) has pointed out that both intra- and interindividual variability often contain meaningful information that can have substantial impact on measured outcomes. Specifically, the variability in patterns of behavior within individuals over repeated occasions is a powerful index of intrapersonal outcomes (Mischel, 1973; Mischel & Shoda, 1995).

We therefore propose an integration of idiographic and nomothetic methodologies for the analysis of psychotherapy process and outcome based on dynamic systems theory. Moreover, we present a quantitative approach that accommodates intraindividual variation in time-varying processes, while also allowing group comparisons in rank-order outcomes. The present article aims to demonstrate how intensive repeated measurement of therapy-relevant domains can be used to model dynamic systems within psychotherapy and to determine the degree of order versus disorder within these systems. Additionally, we demonstrate how to examine the qualitative nature of patterns generated during the psychotherapy period. The following paragraphs detail the type of data and analyses required for this approach and spell out the proposed hypotheses of the present study.

Data and Analyses

Ecological momentary assessment (EMA) data can provide a powerful tool for the assessment of dynamic systems (cf. Lichtwarck-Aschoff, Kunnen, & van Geert, 2009). However, these data have been underused in the study of dynamic processes in psychotherapy (Laurenceau et al., 2007). Moreover, the use of EMA data within the domains of health, coping, psychopathology, and psychotherapy have been almost exclusively limited to multilevel regression models (Schwartz & Stone, 1998; Shiffman, Stone, & Hufford, 2008) that both aggregate across individuals as well as constrain time-varying processes within continuous, linear trajectories. As noted by Hayes et al. (2007), the intensive repeated measurement of therapy variables over time can facilitate the examination of nonlinear change processes, including relative points of stability and variability in dynamic systems. However, longitudinal treatment of EMA data within multilevel or mixture models cannot adequately model intraindividual variation in time-varying processes (Molenaar, 2004; Sterba & Bauer, 2010). The present study presents a method by which intraindividual variation can be accommodated and differences in time-varying processes examined across individuals. Specifically, we propose the use of two idiographic time series methodologies—spectral analysis and dynamic factor analysis—in concert for the delineation of patterns in dynamic systems in order to demonstrate the degree of order versus disorder in dynamic systems, the qualitative nature of dynamic patterns, and the overall influence such patterns have on rank-order differences in psychotherapy outcome.

Spectral analysis is a method by which a time series of dependent observations can be decomposed into a spectrum of independent frequencies, where these frequencies

correspond to oscillatory patterns in the data. In the case of a hypothetical 100-day treatment for anxiety, an oscillation of .01 cycles per day corresponds to one cycle per treatment period, whereas an oscillation of 1 cycle per day corresponds to a daily pattern. Spectral analysis requires the removal of mean levels and trends, such that the resulting frequencies are unrelated to mean levels of anxiety at intercept or changes in mean levels of anxiety in response to treatment. Thus, these oscillatory patterns address the *structure* of anxious experience and not the *degree*. Spectral power is the degree to which a given frequency or oscillatory pattern accounts for the overall variability in the observed process. Here, we are interested in high-frequency oscillatory patterns (see below), and the amount of spectral power in these frequencies.

Whereas spectral analysis examines the presence and influence of oscillatory patterns, it cannot address the character of these patterns. Dynamic factor analysis (Molenaar, 1985) allows the articulation of specific relationships within a dynamic system using a structural equation modeling (SEM) framework. We propose that the degree of patterning in individual dynamic systems during psychotherapy can be modeled effectively via dynamic factor analysis and will likewise be positively related to treatment outcome. Thus, we sought to demonstrate in the present study that dynamic factor analysis and spectral analysis can work in concert to demonstrate the presence, nature, and influence of patterns in dynamic systems during psychotherapy.

Goals and Hypotheses

The goals of the present study were threefold and additive in nature. We propose that (a) dynamic systems within individuals can be modeled effectively via time series analysis of EMA data, specifically spectral analysis and dynamic factor modeling, (b) idiographic time series analyses will adequately accommodate heterogeneity in dynamic processes allowing the aggregation and analysis of data at the nomothetic level, and (c) analyses will reflect the degree of order within individual dynamic systems, and this order will in turn be reflected in adaptive attractor states which persist over time.

In the present article, the degree of order and dynamic patterning established during the psychotherapy period will be quantified via the spectral power in high-frequency domains and the degree of sequential structure in dynamic factor models. In regard to the former, stability is reflected in lower frequency oscillations, whereas variability is reflected in higher frequency oscillations. Patterns that are subject to change on a daily, or even intradaily, basis reflect high degrees of volatility and instability, whereas those that are more stable will be invariant across days, weeks, or even months. Therefore, greater spectral power in daily to intradaily oscillations reflects greater disorder in dynamic systems. Regarding the measurement of order within dynamic factor models, the term *sequential structure* refers to the degree to which the observations in a dynamic system are meaningfully predicted by other observations. Within the present study, sequential structure refers to the degree to which diary entries are predicted by preceding intra- or interdaily entries. We propose that diary entry periods—here, morning, midday, and evening—can be modeled via dynamic factor models in order to examine the sequential structure in the autocorrelations (relationships between successive sequential observations) and lagged relationships (relationships between nonsequential successive observations) between intra- and interdaily observations. The greater the number of significant patterns between daily observations, the greater the sequential structure and, ultimately, the greater the degree of order in the dynamic system.

In order to investigate the aims of the present study, we used psychotherapy process and outcome data from a previously published study in which cognitive behavioral therapy

(CBT) was compared with an applied relaxation (AR) behavioral therapy and a reflective listening nondirective (ND) therapy (Borkovec & Costello, 1993). All participants completed EMAs in the form of diary ratings of subjective anxiety thrice daily, in the morning, afternoon, and night.

Method

Participants

Of 508 potential participants referred from agencies and news advertisements, 442 (87%) were ruled out for not meeting criteria, leaving 55 (11%) clients who were randomized to receive psychotherapy. Eight clients (2%) dropped out at early stages of treatment, and three clients were removed because of a deteriorating condition (increasing depression). Clients were independently assessed by two interviewers. A client was admitted to the study if both interviewers agreed on the following points: Generalized anxiety disorder (GAD) was the principal diagnosis; panic disorder criteria were not met; clinician severity rating (see below) was rated 4 (moderate) or greater; no other psychosocial therapy was ongoing; the client had not previously received any of the methods of the study; no medical contributions to anxiety symptoms (e.g., hypoglycemia, thyroid problems) were present; no antidepressant medication was being taken; and there was an absence of severe depression, substance abuse, psychosis, and organic brain syndrome.

Borkovec and Costello (1993) reported significantly greater improvement in the AR and CBT conditions compared with ND at posttreatment and over the follow-up period. However, no significant differences were found at posttreatment or during follow-up between AR and CBT. Because the present study was interested in a homogenous sample of maximal size, ND participants were excluded and collapsed across AR and CBT clients. This provided 33 clients for the present study, who completed psychotherapy. In both the AR and CBT conditions, therapy was administered twice per week for 12 weeks. The initial four sessions were 90 min in length, and all following sessions were 1 hr in length.

The average age of the 33 remaining completers was 35.44 years ($SD = 11.93$). The average duration of the problem was 15.16 years ($SD = 14.46$). Ethnic composition was as follows: 29 participants were White, two were African American, one was Hispanic, and one was Indian. Twenty-three participants were women; 10 were men. Twenty-one were married, 11 were single, and one was divorced. Eight clients were on stabilized psychotropic medications. All of these characteristics were evenly distributed and nonsignificantly different among conditions. Multivariate analyses of variance (MANOVAS) indicated that agency referrals versus responders to advertisements and drug-taking versus nondrug-taking clients did not differ in severity on pretherapy measures or in outcome at any period and differed demographically only on age: The drug-taking group was older than the nondrug-taking group.

Outcome measures

Clinician's Severity Rating (CSR)—The CSR (Di Nardo, O'Brien, Barlow, Waddell, & Blanchard, 1983) is generally viewed as an important diagnostic indicator in clinical trials, nosology, and psychopathology studies (Borkovec & Costello, 1993; Brown, Chorpita, & Barlow, 1998). For each diagnosis, interviewers assigned a 0–8 rating indicating their judgment of the degree of distress and interference in functioning associated with the disorder (from 0 = *none* to 8 = *very severely disturbing/disabling*). Clients who met criteria for any diagnosis were assigned a CSR of 4 (*definitely disturbing/disabling*) or higher (clinical diagnoses). When key features of a disorder were present but were not judged to be extensive or severe enough to warrant a formal diagnosis (or for disorders in partial

remission), a CSR of 1–3 was assigned. When no features of a disorder were present, clinical severity ratings of 0 were given. Brown and colleagues (Brown, Di Nardo, Lehman, & Campbell, 2001) demonstrated good to excellent interrater reliability for CSRs for anxiety and mood disorders except dysthymia ($r = .36$), with correlations ranging from .65 to .84.

The Hamilton Anxiety Rating Scale (HARS; Hamilton, 1959)—This 14-item clinician administered scale provides a rating of severity of each overarching anxiety symptom cluster on a scale ranging from 0 (*not present*) to 4 (*very severe/incapacitating*). Estimates of internal consistency of the HARS range from adequate to good in one study ($\alpha = .77$ to $.81$) (Moras, Di Nardo, & Barlow, 1992) to excellent ($\alpha = .92$) in another (Kobak, Reynolds, & Greist, 1993). Retest reliability was ICC = .86 across 2 days, and interrater reliability ranged from an ICC of .74 to .96 (Bruss, Gruenberg, Goldstein, & Barber, 1994). HARS scores correlate significantly with self-report measures of anxiety in clinical samples (Beck & Steer, 1991; Maier, Buller, Philipp, & Heuser, 1988) and with patient and clinician ratings of anxiety severity (Snaith, Harrop, Newby, & Teale, 1986). The scale also discriminates people with and without anxiety disorders (Kobak et al., 1993) and is sensitive to treatment change (Maier et al., 1988). A version with less overlap between anxiety and depressive symptomatology (Riskind, Beck, Brown, & Steer, 1987) was used.

The Penn State Worry Questionnaire (PSWQ; Meyer, Miller, Metzger, & Borkovec, 1990)—The PSWQ is a 16-item self-report measure of the frequency and intensity of worry. Items are rated on a 5-point Likert scale regarding the degree to which a particular statement is typical of him or her. Item numbers 1, 3, 8, 10, and 11 are reverse scored, and all 16 items are summed. Sample items include “Many situations make me worry” and “I’ve been a worrier all my life.” Factor analysis indicated that the PSWQ assesses a unidimensional construct with an internal consistency coefficient of .91 (Meyer et al., 1990). High retest reliability (ranging from .74 to .93) was also demonstrated across periods ranging from 2 to 10 weeks (Molina & Borkovec, 1994). The PSWQ has also been shown to distinguish individuals with GAD from each of the other anxiety disorder groups (Brown, Antony, & Barlow, 1992). Correlations between the PSWQ and measures of anxiety, depression, and emotional control supported the convergent and discriminant validity of the measure (Brown et al., 1992). In addition, this measure discriminated samples that (a) met all, some, or no *DSM-III-R* diagnostic criteria for GAD and (b) met criteria for GAD versus posttraumatic stress disorder (Meyer et al., 1990). The PSWQ has also demonstrated sensitivity to change in response to psychotherapy (Meyer et al., 1990).

Ongoing measures

Client daily diary—Patients recorded anxiety levels three times a day (in the morning, afternoon, and night), rating their overall level of anxiety during the preceding period of the day on a 0–100 scale. The present study also had an average diary compliance rate of 94.4%. Percentage of missing data ranged from 0% to 23% ($M = 8.3\%$, $SD = 6.4\%$). Clients were asked to complete this measure daily throughout the entire treatment period.

Results

Approach to idiographic analyses

Univariate time series analysis (spectral analysis)—In the first step, daily diary ratings for each participant were treated as univariate stationary time series and assessed for oscillatory patterns via spectral analysis. All consecutive observations were contained within a single vector, and the total number of observations was equal to the number of individual diary entries (morning, afternoon, and night). Although methods for the spectral analysis of time series data available within standard statistical packages assume an even spacing of

observations, the present data do not meet this assumption (i.e., spacing between observations was 6, 6, and 12 hr per daily iteration). Therefore, we applied an adapted discrete Fourier transformation that can handle arbitrarily spaced data, yielding a power spectrum and corresponding raw periodogram. More important, this adaptation also accommodates the presence of missing data, which can be seen as a variant of unequal spacing in the time series. The Fourier implementation was written for Fortran by the third author and was based on algorithms by Mathias et al. (2004).² Within this implementation, the univariate time series with missing data for each individual was accompanied by a vector of cumulative time designations, allowing for the approximation of the underlying uniform time series.

The Fourier transformation decomposes a time series (measurements in the time domain) into patterns or oscillations (measurements in the frequency domain). The power spectrum indicates the contribution of specific frequencies to the overall power (i.e., variability in the data). We conceptualized the power spectrum as being composed of four windows of frequency power: very low (.001–.032 cycles/day), low (.033–.141 cycles/day), high (.142–.999 cycles/day), and very high (1–1.5 cycles/day). These windows correspond to oscillatory patterns of greater than 1 month, multiple weeks, multiple days, and daily to intradaily variability, respectively. We were interested in the very high-frequency power (VHFP), that is, the power attributed to oscillations of 1 day or less. Such oscillations correspond to patterns of daily and intradaily structure in each individual's experience of anxiety. Greater power in the very high-frequency range connotes the presence and influence of highly variable patterns of anxious experience, that is, patterns that are changing on a daily to intradaily basis. Total power was calculated for the specified window of interest. Because the fundamental frequency—the smallest measureable frequency unit within a power spectrum—differs as a function of the length of the time series, the number of discrete frequencies within each idiographic power spectrum differed as a function of the total number of observations. Therefore, we summed total power for each window of interest and then divided it by the number of discrete frequencies observed.

Multivariate time series analysis (dynamic factor models)—In the second step, we treated daily diary ratings for each participant as three-variate stationary time series. Thus, we treated morning, afternoon, and nighttime diary entries as separate dependent variables. Total observations within each factor were equal to the total number of consecutive days in treatment. A vector autoregressive (VAR) model with a lag of 1 day (1) was tested by creating a block-Toeplitz matrix.³ Thus, for each participant, we created a VAR(1) model wherein we examined the intra- and interdaily relationships between subjective anxiety ratings. All VAR analyses were carried out in LISREL (Version 8.80; Joreskog & Sorbom, 2006). Within LISREL, coefficients within the beta matrix denote the contemporaneous and lagged relationships of interest. For each of the 33 participants, we created an initial model in which afternoon was regressed on morning and nighttime on afternoon within both day ($t - 1$) and day (t). No other intra- or interdaily regression relationships were initially allowed. The lambda (λ) matrix was set to identity, and the theta (θ) matrix was fixed at zero. These restrictions are necessary in LISREL for modeling relationships between latent variables with single indicators. The beta matrix was then inspected for meaningful modification indices (MIs). In the event of a significant MI, this path was allowed and the analysis was rerun. In the event of multiple significant MIs, the largest MI was allowed, and the analysis was rerun. Final models were accepted when no further significant MIs were present within the beta matrix.

²Source code for this implementation can be made available upon request to Aaron J. Fisher.

³Missing data were handled via pairwise deletion in the estimation of the block-Toeplitz covariance matrix.

Integration of idiographic data into nomothetic analyses

Step 1—Once we calculated the VHFP for each individual, we entered these data into an aggregate, nomothetic data set for analysis of treatment outcome across individuals.

Step 2—After we found a dynamic factor solution for the three-variate VAR(1) data for each participant, we extracted the standardized zeta (ζ) value of the evening observation for day (t) and entered it into the aggregate data set. Technically, this value is the residual variance in the nighttime measurement at day (t), after accounting for the linear dependence of day (t) on day (t – 1), as well as the dependence of day (t) afternoon on day (t), morning and day (t), and nighttime on day (t) afternoon. However, it follows that it can be conceptualized as the residual variance for the entire VAR(1) model. The greater the total sequential structure in the VAR(1) model, the lesser the residual variance in the final observation of the model, and the lesser the degree of sequential structure in the model, the greater the degree of residual variance. Henceforth, the standardized ζ value of the evening observation for day (t) is referred to as *residual variance* and is considered to reflect the degree of sequential structure in each individual's daily experience of anxiety. It should be further emphasized that the relationship between residual variance and sequential structure is inverse; the larger the residual variance, the lesser the sequential structure.

Finally, after accounting for the differential lengths of individual time series (Steps 1 and 2), idiosyncratic oscillatory patterns (Step 1), and patterns of linear dependence and sequential structure (Step 2), it is possible to move to the aggregate level with confidence that the person-specific nature of the data has been adequately addressed.

Idiographic analyses

Spectral analysis—Across the 33 participants in the present study, VHFP ranged from 22.17 to 469.87 ($M = 163.06$, $SD = 98.04$), and accounted for a minimum of 14.33% and a maximum of 30.5% of total observed power ($M = 23.37\%$, $SD = 4.14\%$).

Dynamic factor models—Table 1 displays the participant identification number, number of observations, and fit statistics for each of the 33 dynamic factor models. Number of observations ranged from 66 to 136 days ($M = 90.67$, $SD = 17.42$). We assessed model fit for each dynamic factor model via the following indices: chi-square goodness-of-fit, root-mean-square error of approximation (RMSEA), standardized root-mean-square residual (SRMR), and comparative fit index (CFI). All models yielded nonsignificant chi-square values and alternative fit statistics likewise reflected excellent fitting models in all 33 cases. In addition, we conducted chi-square difference tests between the null model—containing only within-day autoregressive parameters—and the final model for each participant. All chi-square differences were significant with the exception of one participant (#131), wherein p was equal to .06. Thirty of the 33 chi-square difference tests yielded significance values of $p < .001$. Results for these tests are provided in Table 2.

All consecutive autoregressive relationships were significant. That is, morning significantly predicted afternoon, and afternoon significantly predicted nighttime for both day (t – 1) and day (t) across all 33 models. Three other types of relationships emerged: interdaily stabilities, intradaily lagged regressions, and interdaily lagged regressions. Stabilities refer to instances in which observations at a given time at day (t) were predicted by the equivalent time at day (t – 1) (morning to morning, afternoon to afternoon, nighttime to nighttime). Intradaily lagged relationships involved direct effects of morning on evening. Finally, interdaily lagged relationships involved any number of permutations wherein an observation at day (t – 1) predicted a subsequent observation at day (t).

Figures 1 and 2 depict examples of dynamic factor models for Participants 141 and 612, respectively. Figure 1 (Participant 141) portrays a dynamic factor model with relatively little sequential structure, whereas Figure 2 (Participant 612) portrays a dynamic factor model with high sequential structure, quantified by the relatively low residual variance (.37). Residual variance (standardized ζ s) ranged from .30 to .96 ($M = 0.69$, $SD = 0.18$). Figure 3 provides a scatterplot of the relationship between residual variance and high-frequency power.

Nomothetic analyses

To reduce the probability of Type I error, we created a GAD-change measure by calculating the average reliable change index (RCI; Jacobson & Truax, 1991) across three GAD outcome measures: the HARS, CSR, and PSWQ. RCI reflects the degree of change that occurred beyond the fluctuations of an imprecise measuring instrument, and values greater than 1.96 represent statistically significant change (McGlinchey, Atkins, & Jacobson, 2002). RCI is a commonly used measure of treatment gains and is favored over the use of categorical classification systems because of its greater statistical power as a continuous variable (Steketee & Chambless, 1992). The following values were used in the RCI formulae in the present study: GAD CSR: $SD = 0.91$, reliability = .72; PSWQ: $SD = 8.09$, reliability = .91; HARS: $SD = 6.9$, reliability = .80. The standard deviations represent the standard deviation of the pooled sample at pretherapy assessment, and the reliability estimates represent reported reliability coefficients for each measure (Bruss et al., 1994). We calculated mean RCIs for change immediately after treatment, at 6-month follow-up, and 12-month follow-up.

In all of the following analyses, we ran mixed-effect regressions in *R*. Random effects for intercept and slope were allowed in all models and found to be significant.

Interaction of time and residual variance on RCI over the follow-up period—In order to assess the impact of residual variance on the slope for RCI over the follow-up period, we ran a mixed-effect regression analysis examining the interaction between time and residual variance. Block-by-block results for this model are presented in Table 3.

We entered the main effect for time into the first block, which was significant. Consistent with results originally reported in Borkovec and Costello (1993), participants exhibited significant increases in reliable change over the follow-up period. We added residual variance to the model in the second block and found it to be a nonsignificant predictor of posttreatment RCI. We added the interaction between time and residual variance in the third block. Residual variance significantly moderated the slope for change in RCI over the follow-up period, such that greater residual variance predicted a significant decrease in reliable change over the follow-up period. Conversely, when controlling for the interaction between time and residual variance, the main effect for time remained positive and significant. Given the inverse relationship between residual variance and order, these results indicate that greater levels of daily to intradaily patterning over the course of treatment predicted greater gains in RCI over the follow-up period, whereas lesser patterning predicted decreases in RCI over this period.⁴ Figure 4 depicts the relative slopes for RCI over the follow-up period within the upper and lower quartiles for residual variance.

⁴Given the variability in number of observations per participant, we tested whether the number of observations predicted the amount of residual variance across participants and found that it did not. We likewise tested whether residual variance predicted outcomes above and beyond the number of observations and found that when adding a main effect for observations, and a Time $\times$ Observations interaction to the linear mixed effect model for Residual Variance $\times$ Time on RCI, the number of observations did not affect the slope for RCI, nor did it impact the coefficient for the Residual Variance $\times$ Time effect.

Interaction of time and VHFP on RCI over the follow-up period—In order to assess the impact of VHFP on the slope for RCI over the follow-up period, we ran a mixed-effect regression analysis examining the interaction between time and VHFP. Block-by-block results for this model are presented in Table 4.

We entered the main effect for time into the first block and found it to be significant. We added VHFP to the model in the second block and found it to be a nonsignificant predictor of posttreatment RCI. We added the interaction between time and VHFP in the third block. VHFP significantly moderated the slope for change in RCI over the follow-up period, such that greater VHFP predicted a significant decrease in reliable change over the follow-up period. Conversely, when controlling for the interaction between time and VHFP, the main effect for time remained positive and significant. Therefore, greater levels of VHFP over the course of treatment predicted decreases in RCI over the follow-up period, and lesser levels of VHFP predicted increases in RCI over this period. As noted above, VHFP reflects highly variable changes in daily to intradaily patterns. Thus, greater day-to-day variability during the treatment period predicted decreases in RCI over the follow-up period. Figure 5 depicts the relative slopes for RCI over the follow-up period within the upper and lower quartiles for VHFP.

Discussion

The present study aimed to demonstrate that the establishment of dynamic patterns during the course of psychotherapy can create attractor states for continued adaptive change following the conclusion of treatment. Because intraindividual change in dynamic systems during psychotherapy is an inherently idiographic and nonergodic process, we sought to demonstrate how idiographic and nomothetic methodologies could be effectively integrated by first accounting for intraindividual variability in time-varying processes within individuals before aggregating these data in order to examine group processes (i.e., rank-order differences in treatment outcome). We proposed that EMA data—specifically thrice-daily diary entries of subjective anxiety—could be modeled effectively at the idiographic level with univariate and multivariate time series methodologies. Finally, we proposed that data from these idiographic models—specifically, the VHFP of the spectral analyses and the residual variance of the VAR(1) dynamic factor models—effectively measure the level of order in dynamic systems and thereby the degree to which psychotherapy effectively establishes new adaptive attractor states for continued growth after the conclusion of treatment.

Univariate vectors of continuous diary observations were transformed from the time domain into the frequency domain via an adapted Fourier transformation for unequally spaced observations. Spectral power was assessed at very low, low, high, and very high frequencies. Power at the very high frequency (oscillations of 1–1.5 cycles/day) was calculated for each individual, and we entered these data into a standard nomothetic data set for analysis across individuals. The VHFP significantly moderated the slope for change in RCI over the follow-up period such that greater VHFP predicted significant decreases in RCI over the follow-up period. VHFP reflects the presence and influence of patterns of anxious experience that are varying (oscillating) at a daily to intradaily rate. Greater degrees of variability in day-to-day patterns are analogous to greater levels of instability and disorder in dynamic systems. Thus, higher levels of disorder and instability in daily patterns of anxious experience during treatment were predictive of greater reductions in RCI over the follow-up period. Conversely, higher levels of order during the treatment period predicted continued positive gains 1 year after the conclusion of therapy.

Additionally, three-variate VAR(1) models were constructed for each of the 33 participants in the present study. All models provided an excellent fit to the data, as indicated by chi-square tests and alternative fit indices. The standardized residual variance for the evening observation at day (t) was extracted from each model and aggregated across individuals. These residuals—the inverse of the sequential structure of the VAR(1) model—significantly moderated the slope for change in RCI over the follow-up period such that greater residual variance, and thus *lesser* day-to-day sequential structure, predicted significant decreases in RCI over the follow-up period, whereas greater sequential structure predicted increases in RCI over this period. These results demonstrate that patterning established during therapy acted as an adaptive attractor state, promoting continued positive gains 1 year after the conclusion of therapy.

Importantly, neither VHFP nor sequential structure was related to reliable change exhibited *during* therapy. Thus, the present data do not support the hypotheses that VHFP reflected negative therapeutic outcomes or structural dependence positive therapeutic outcomes. These findings therefore demonstrate the utility of the proposed methodology for augmenting and extending traditional assessments of therapeutic efficacy.

An important distinction should be made here between the highly variable daily patterns represented by measurements of VHFP, which reflect instability and disorder, and the stable daily patterns represented by structural dependence, which reflect order. Spectral power in the very high-frequency range is related to patterns oscillating at daily to intradaily rates, thereby yielding daily to intradaily changes in patterns of anxious experience. Conversely, patterning revealed by dynamic factor analyses reflects stable relationships between the thrice-daily diary entries. Thus, although patterns within a VAR(1) model represent relationships in a 2-day period, these relationships are assumed to be representative of the entire time series period—here a course of psychotherapy—and are not subject to change day-to-day.

Results of the present study demonstrate that both VHFP and structural dependence can therefore reflect the degree of order versus disorder in dynamic systems. Yet the mechanisms by which these reflections are made differ between the two approaches. The residual variance of each factor model represents the element of the time series that has no sequential dependency, as this has been partialled out via the structural relationships between observations. Thus, this process has a flat spectrum—it is the innovation process (Bode & Shannon, 1950). In contrast to this, the spectra calculated via the Fourier transformation, from which the VHFP is derived, are computed from the original time series and are a direct result of the sequential dependency therein. The amount of nonflatness of the spectrum (the differential power across the spectrum) is a reflection of the sequential dependency in the data. Restated, the degree to which observations within the time series are correlated directly relates to the degree of oscillatory patterning represented across the power spectrum.

The complementary nature of these models suggests that they are of equal and additive value. Whereas VHFP examines the tension between stability and variability, the residual variance of the dynamic factor model can directly measure the degree of adaptive, stable patterning within a system. Moreover, although the former is based on the predictable component of the time series, the latter reflects the innovation process. In addition, Figures 1 and 2 illustrate that dynamic factor models can elucidate the qualitative nature of the patterns exhibited during the treatment period. Future work might focus on the use of these structural models for real-time clinical interventions. Because both the degree and nature of patterns can be determined at an idiographic level, emphasis might be put on establishing more ordered systems by targeting points of particular disorder or instability.

Dynamic systems theory predicts that systems become self-organized into stable patterns of functioning. Such points of stability are known as attractor states, drawing the system into a limited range of functioning. When these stable patterns are psychological, emotional, or interpersonally maladaptive, it is necessary to disrupt the stability of the system in order to create stability around new, more adaptive patterns. Thus, maladaptive attractor states, which cause an individual to experience a limited range of socioemotional outcomes, are replaced by more adaptive attractors. These, in turn, promote more adaptive cognitions, affects, behaviors, and outcomes. Psychotherapy endeavors to facilitate such a process. In measuring the mechanisms of psychotherapy within the context of dynamic systems theory, it is important to delineate stability and variability in dynamic systems and the construction of new adaptive patterns. Demonstrating that meaningful differences between order and disorder can be identified and that greater order predicts increased gains after the conclusion of therapy strengthens the notion that patterns established during treatment act as adaptive attractor states for sustained positive gains after the conclusion of treatment. Thus, the present study represents an important innovation in the study of dynamic systems in psychotherapy. We have presented here two variables that successfully capture the degree of order versus disorder in dynamic systems. Moreover, we have shown that greater levels of order and patterning during therapy represent adaptive attractor states and that these attractor states draw individuals toward continued growth.

The present study is also consistent with recent calls to enrich nomothetic assessment of psychotherapy process and outcome with more idiographic methodology (Barlow & Nock, 2009; Hayes et al., 2007). Moreover, the separate treatment of time series data via spectral analysis and dynamic factor modeling for each of the 33 individuals in the present study accounts for the nonergodic nature of the time-varying phenomena during the treatment period. *Ergodicity* refers to a condition whereby a process tested n number of times within an individual can be expected to behave similarly to a process tested once across n individuals. Given the idiosyncrasies in repeated measurements of individuals over time (autocorrelations, differential number of observations, differential patterns of sequential structure), it cannot be reasonably assumed that psychotherapeutic change is an ergodic process. However, once the idiographic nature of the data has been accommodated, these models can be used to reflect meaningful differences *between* individuals. Thus, it can be said that we have examined nomothetic relationships between idiographic structures, looking at trends across subjects in intraindividual variation.

The present study has important implications for future studies, as well as the treatment of existing data. Future treatment studies should endeavor to use intensive repeated measurements of therapy-relevant domains such as cognition, affect, behavior, or interpersonal functioning. Assessment of dynamic systems within or between such domains will likely greatly enrich determinations of therapeutic success derived from pre- and posttherapy assessments. Additionally, extant EMA data previously assessed via random effects or latent growth models may be importantly complemented or augmented by the time series methodologies used within the present study.

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Participant 141

Figure 1.
Dynamic factor model for Participant 141.5

⁵Dynamic factor models facilitate the representation of time series data within an SEM framework. Here, relationships between a given day (t) and the preceding day (t – 1) are modeled for thrice-daily observations of self-reported anxiety over an entire psychotherapy treatment period.

Participant 612

Figure 2.
Dynamic factor model for Participant 612.

Figure 3.

Scatterplot of relationship between residual variance and very high-frequency power. VHFP = very high-frequency power (i.e., the contribution of daily to intradaily oscillations to the overall variability in the data).

Figure 4.
Interaction of very-high frequency power (VHFP) and time on reliable change over follow-up.

Figure 5.
Interaction of residual variance and time on reliable change over follow-up.

Table 1

Person-Specific Dynamic Factor Model Fit Indices

Participant	Obs.	χ^2	df	p	RMSEA	SRMR	CFI
101	81	7.56	6	.27	.057	.045	.99
105	88	5.90	6	.43	<.001	.029	1.00
109	69	5.90	11	.88	<.001	.064	1.00
110	83	4.75	7	.69	<.001	.038	1.00
125	136	3.54	6	.74	<.001	.041	1.00
128	88	8.18	10	.61	<.001	.058	1.00
131	76	6.44	10	.78	<.001	.058	1.00
132	81	5.84	8	.67	<.001	.060	1.00
134	80	4.74	8	.78	<.001	.058	1.00
137	109	6.63	7	.47	<.001	.035	1.00
141	85	6.09	9	.73	<.001	.046	1.00
142	121	5.61	8	.69	<.001	.047	1.00
144	80	5.54	8	.70	<.001	.057	1.00
145	80	5.17	8	.74	<.001	.053	1.00
152	83	3.53	5	.62	<.001	.031	1.00
154	110	9.71	7	.21	.060	.032	.99
204	97	6.54	7	.48	<.001	.043	1.00
205	66	4.58	5	.47	<.001	.049	1.00
213	77	3.17	6	.79	<.001	.035	1.00
221	67	4.56	5	.47	<.001	.044	1.00
306	118	3.77	6	.71	<.001	.036	1.00
315	69	3.15	9	.96	<.001	.045	1.00
319	92	6.48	7	.48	<.001	.049	1.00
324	103	11.25	10	.34	.025	.048	.98
420	70	4.76	7	.69	<.001	.047	1.00
422	112	6.18	8	.63	<.001	.038	1.00
426	75	2.43	7	.93	<.001	.021	1.00
432	105	4.39	8	.82	<.001	.038	1.00
434	99	11.91	7	.10	.085	.058	.99

Participant	Obs.	χ^2	df	p	RMSEA	SRMR	CFI
606	101	9.13	7	.24	.055	.044	.99
612	103	4.37	6	.63	<.001	.021	1.00
615	104	6.62	6	.36	.032	.046	.99
623	84	5.71	8	.68	<.001	.061	1.00

Note. Obs. = total days; RMSEA = root-mean-square error of approximation; SRMR = standardized root-mean-square residual; CFI = comparative fit index.

Table 2

Chi-Square Difference Tests for Person-Specific Dynamic Factor Models

Participant	χ^2_{null}	df_{null}	χ^2_{final}	df_{final}	χ^2_{diff}	df_{diff}	p
101	41.24	11	7.56	6	33.68	5	<.001
105	48.86	11	5.90	6	42.96	5	<.001
109	5.90	11	5.90	11	0	0	—
110	34.50	11	4.75	7	29.75	4	<.001
125	35.27	11	3.54	6	31.73	5	<.001
128	14.64	11	8.18	10	6.46	1	.01
131	10.05	11	6.44	10	3.61	1	.06
132	46.57	11	5.84	8	40.73	3	<.001
134	21.49	11	4.74	8	16.75	3	<.001
137	67.18	11	6.63	7	60.55	4	<.001
141	24.97	11	6.09	9	18.88	2	<.001
142	53.32	11	5.61	8	47.71	3	<.001
144	24.36	11	5.54	8	18.82	3	<.001
145	20.81	11	5.17	8	15.64	3	.001
152	51.11	11	3.53	5	47.58	6	<.001
154	58.89	11	9.71	7	49.18	4	<.001
204	86.42	11	6.54	7	79.88	4	<.001
205	40.54	11	4.58	5	35.96	6	<.001
213	43.47	11	3.17	6	40.3	5	<.001
221	65.67	11	4.56	5	61.11	6	<.001
306	46.76	11	3.77	6	42.99	5	<.001
315	17.03	11	3.15	9	13.88	2	.001
319	34.36	11	6.48	7	27.88	4	<.001
324	22.65	11	11.25	10	11.4	1	<.001
420	29.43	11	4.76	7	24.67	4	<.001
422	64.23	11	6.18	8	58.05	3	<.001
426	27.05	11	2.43	7	24.62	4	<.001
432	56.58	11	4.39	8	52.19	3	<.001

Participant	χ^2_{null}	df_{null}	χ^2_{final}	df_{final}	χ^2_{diff}	df_{diff}	p
434	56.10	11	11.91	7	44.19	4	<.001
606	78.65	11	9.13	7	69.52	4	<.001
612	88.45	11	4.37	6	84.08	5	<.001
615	46.30	11	6.62	6	39.68	5	<.001
623	53.97	11	5.71	8	48.26	3	<.001

Note. Dash indicates no estimated value.

Table 3

Mixed-Effect Regression Results for the Interaction Between Time and Residual Variance

Variable	AIC	β	SE	t	p	Random effects	d
Block 1	397.2						
Intercept		5.69	.43	13.16	<.001	5.56	3.24
Time		.08	.04	2.21	.03	.03	0.54
Block 2	395.7						
Intercept		6.29	1.55	4.06	<.001	5.87	1.00
Time		.08	.04	2.21	.03	.03	0.54
Residual variance		-.87	2.15	-0.40	.69	—	0.10
Block 3	392.4						
Intercept		4.22	1.72	2.45	.02	5.58	0.60
Time		.41	.12	3.30	.002	.02	0.81
Residual variance		2.14	2.41	0.88	.39	—	0.22
Time $\times$ Residual Variance		-.48	.17	-2.77	.009	—	0.68

Note. AIC = Akaike's information criteria; d = Cohen's d . Dashes indicate no random effect parameter estimates.

Table 4
Mixed-Effect Regression Results for the Interaction Between Time and Very High-Frequency Power

Variable	AIC	β	SE	t	p	Random effects	d
Block 1	397.2						
Intercept		5.69	.43	13.16	<.001	5.56	3.24
Time		.08	.04	2.21	.03	.03	0.54
Block 2	408						
Intercept		6.52	.64	10.21	<.001	5.96	2.51
Time		.08	.04	2.21	.03	.03	0.55
VHFP		-.002	.004	-0.737	.47	—	—
Block 3	417.4						
Intercept		5.23	.86	6.11	<.001	5.65	1.50
Time		.22	.06	3.60	.001	.02	0.89
VHFP		.003	.004	0.63	.53	—	0.16
Time $\times$ VHFP		-.0008	.0003	-2.74	.01	—	0.67

Note. AIC = Akaike's information criteria; VHFP = very high-frequency power. Dashes indicate no random effect parameter estimates.