Article

Capturing the Ebb and Flow of Psychiatric Symptoms With Dynamical Systems Models

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Objective: Psychiatric symptoms play a crucial role in psychology and psychiatry. However, little is known about how dimensions of symptoms—other than symptom level—relate to psychiatric outcomes. Until recently, methods for measuring dynamic aspects of symptoms have not been available to clinicians or researchers. The authors sought to test whether systematic patterns of change in psychiatric symptoms can be recovered across weekly assessments of individuals at high risk for violence. A secondary objective was to explore whether dynamic features of symptoms (specifically, oscillation speed and dysregulation) are concurrently associated with violence, an important indicator of functional impairment for these individuals.

Method: Participants (N=132) were drawn from a sample of patients evaluated at the emergency room of an urban psychiatric hospital. Patients actuarially classified as being at high risk for violence were eligible for participation in the study. Participants and collateral informants were interviewed weekly for 26 weeks following an acute psychiatric evaluation. Psychiatric symptoms were assessed using the Brief Symptom Inventory. Measures of symptom fluctuation and regulation were derived using dynamical systems models. Involvement in violence was assessed using self, informant, and official reports.

Results: Individuals' symptom dynamics were recovered by a linear oscillator model that described how quickly symptoms oscillated and whether symptoms were amplifying or moving back toward equilibrium across time. Patterns of rapid symptom fluctuation and symptom amplification were concurrently associated with violence.

Conclusions: Psychiatric researchers and clinicians have long been interested in adopting more dynamic approaches to understanding symptom change. This study is the first to demonstrate that systematic fluctuations in symptom patterns may be captured by dynamic models. Moreover, the concurrent association between symptom dynamics and violence suggests avenues for future research to test how features of symptom fluctuation could affect behavior.

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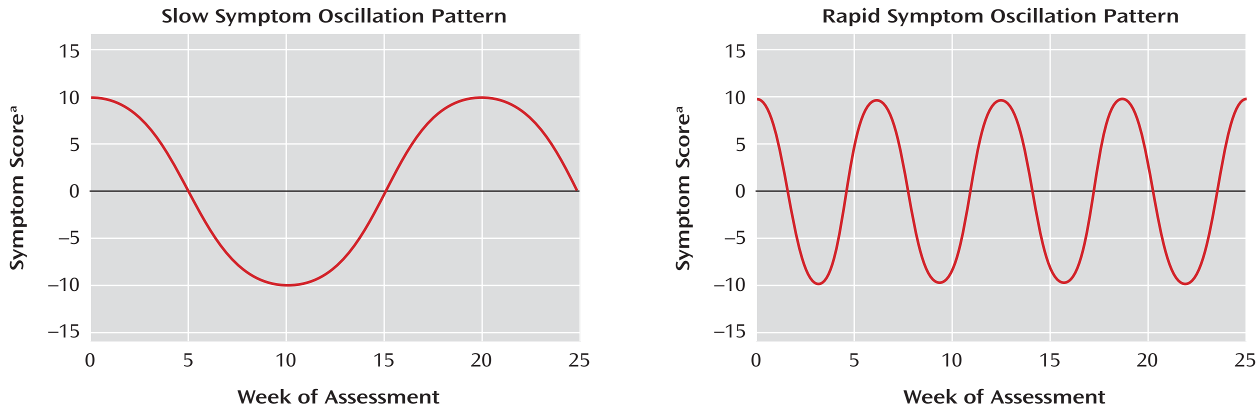
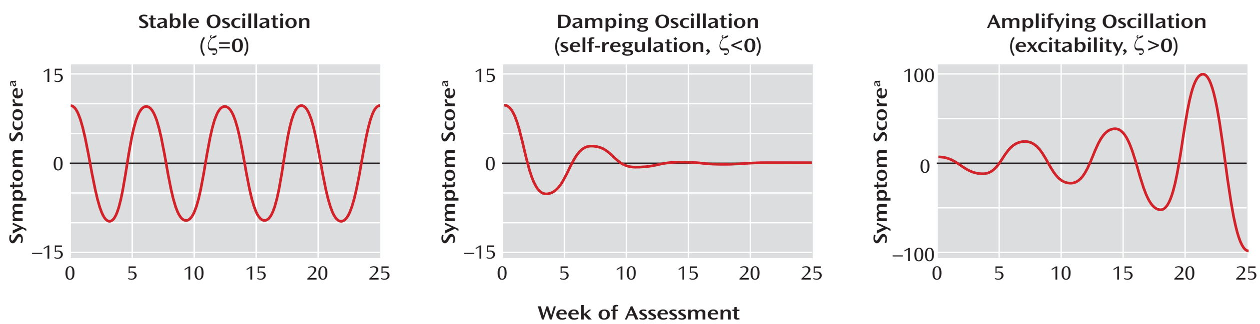
Reports of psychiatric symptoms form the basis of diagnostic protocols and serve as the primary source of information for evaluating patient functioning and prognosis. At present, research and clinical models are built on the assumption that an individual's level of symptoms is the key predictor of impairment. Although there is good reason to believe that increased symptoms are associated with impairment, we know very little about how other dimensions of symptoms may affect behavior or relate to patient outcomes. Although symptoms for many common psychiatric disorders fluctuate significantly across time and context, this fluctuation receives little empirical attention (1). Indeed, symptom change and fluctuation are integral to conceptualizing the course of many common psychiatric disorders (e.g., depression, anxiety, substance abuse). Yet, very little is known about how symptom variability is associated with patient functioning and long-term outcomes. For example, are troubled interpersonal relationships best predicted by static or dynamic measures of depressive symptoms? Is an individual's poor job performance predictable from highly volatile patterns of anxiety symptoms? Do rapid changes in symptoms precede relapse during substance abuse treatment? Unfortunately, we have not been able to answer such questions because we lack methods for characterizing symptom dynamics. In this article, we use data from a unique sample of individuals followed intensively over 26 weeks and present a methodology for capturing symptom dynamics. We illustrate how systematic patterns of variability can be recovered from repeated symptom observations among high-risk individuals and then explore associations between symptom patterns and violence, a key indicator of psychological impairment. We focus on violence as a key marker of impaired functioning for three reasons. First, violence is commonly used by clinicians as a marker of individual impairment (e.g., as an item in the DSM-IV Global Assessment of Functioning Scale). Second, violence is a costly marker of impairment. Billions of dollars in health care-related ex-

FIGURE 1. Symptom Oscillation Patterns Across the 26-Week Follow-Up Period



[a] Residualized general severity index symptom score created by removing the mean and linear or quadratic trend from individual symptom scores over the 26-week period.

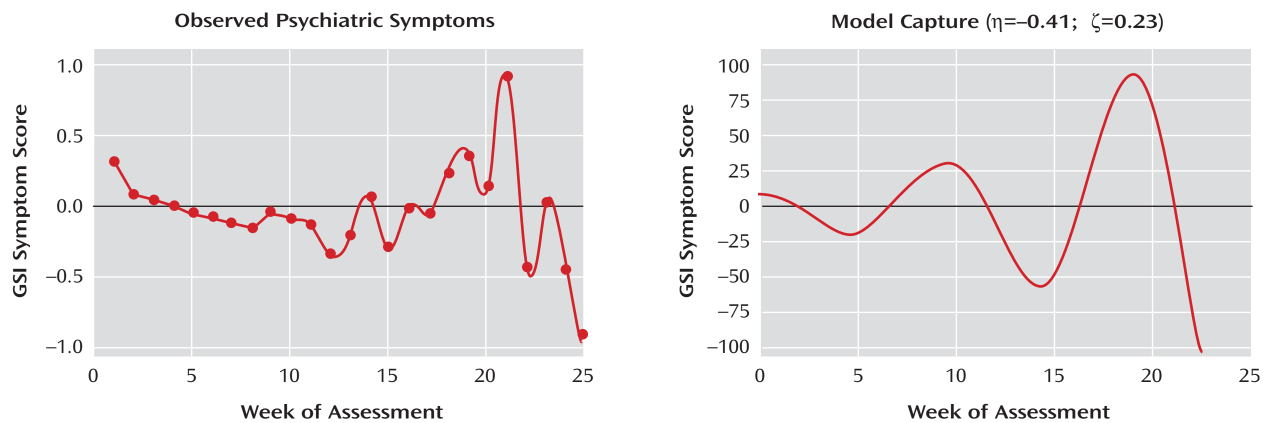
FIGURE 2. Constancy of Oscillation Magnitude Across the 26-Week Follow-Up Period



[a] Residualized general severity index symptom score created by removing the mean and linear or quadratic trend from individual symptom scores over the 26-week period.

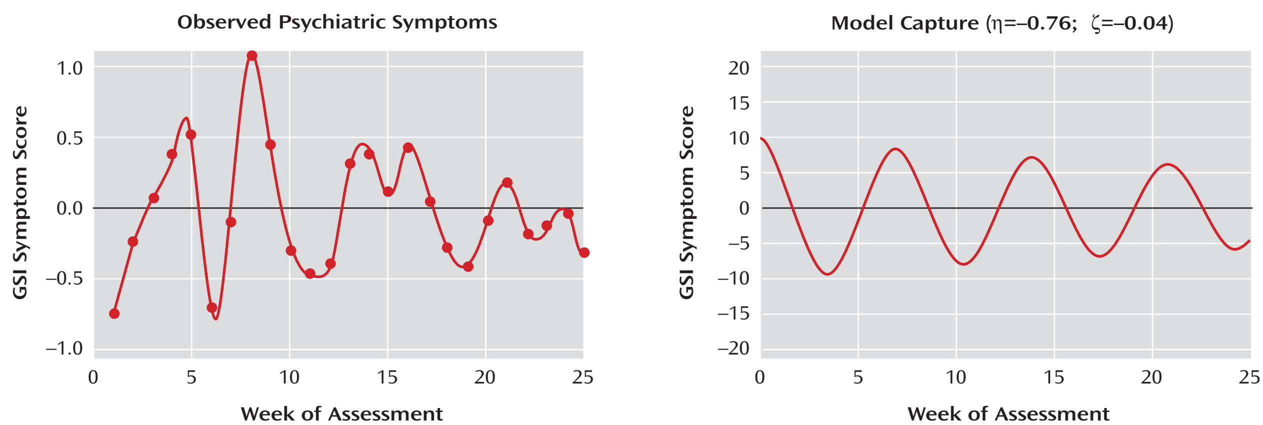
penses and productivity losses are estimated to be attributable to interpersonal and self-directed violence in the United States and elsewhere each year (2, 3). Third, the present sample was selected based on their high likelihood of recurrent violence. Therefore, it is of particular interest to test whether features of symptoms—other than symptom level—are associated with whether, and how often, violence occurs within this high-risk sample. Our prior work with this high-risk sample (4) demonstrated that elevated symptom levels (namely anger) increase the risk of violence the following week. However, our sole focus on symptom levels followed a long tradition of treating intraindividual fluctuations in psychiatric symptoms as noise, thereby ignoring potentially important and clinically useful information. The present analysis is innovative in that it applies a dynamic approach to test whether changes in symptoms from week to week within each individual demonstrate a systematic pattern or structure. The chief goal is to determine whether patterns of symptom (dys)regulation and oscillation can be reliably captured. We then explore whether parameters that summarize symptom fluctuation patterns over a 26-week period are associated with the occurrence of violence during that same period. A major reason to pursue this novel approach is that dynamical systems models align closely with how we conceptualize the course of many common psychiatric disorders. For example, depression has been characterized as a "dynamical disease" (5) in which symptoms wax and wane over time and, in more extreme cases of bipolar disorder, diagnosis is based on the presence of rapidly cycling symptom patterns (6, 7). More generally, emotion regulation and related conditions have been described as oscillating systems (8), whereby individuals fluctuate around a hypothesized equilibrium. Therefore, characterizing patterns of symptom fluctuation over time begins to bridge the chasm between theoretical conceptualizations of what psychiatric symptoms look like over time in an individual and the statistical models used to characterize them. The most common practices when assessing psychiatric symptoms are to rely only on a single snapshot (i.e., cross-sectional assessments) or to calculate a difference score between two or more assessment points (i.e., comparing pre- versus posttreatment symptoms levels) (1). The pervasiveness of static symptom assessments is unfortunate because there is a long history of interest in moving toward dynamic approaches for assessing symptom change in

FIGURE 3. Capturing an Amplifying Symptom Pattern With Moderate Oscillation[a]



[a] Subject was an 18-year-old African-American male who was admitted to the hospital involuntarily based on the criterion that he represented a danger to himself. Subject had an extensive history of arrests for robbery, assault, and sexual assault and presented with substance abuse problems and borderline intellectual functioning. During the 26-week follow-up period, subject was involved in five incidents of violence (two of which involved threats with a weapon) that occurred during weeks 3, 9, 14, 21, and 23. Individual R^2=0.80.

FIGURE 4. Capturing a Rapid Oscillation Pattern With Some Evidence of Damping[a]



[a] Subject was a 24-year-old woman of Asian descent admitted to the psychiatric hospital voluntarily with a diagnosis of bipolar disorder and a history of self-reported violence, including violence toward herself and her roommates. During the 26-week follow-up, subject was involved in 13 violent incidents, all of which involved her live-in male partner and virtually all of which (11 of 13) occurred within their home. The violent incidents occurred in weeks 1, 3, 4, 8, 9, 12, 14, 15, 16, 20, and 21. Individual R^2=0.90.

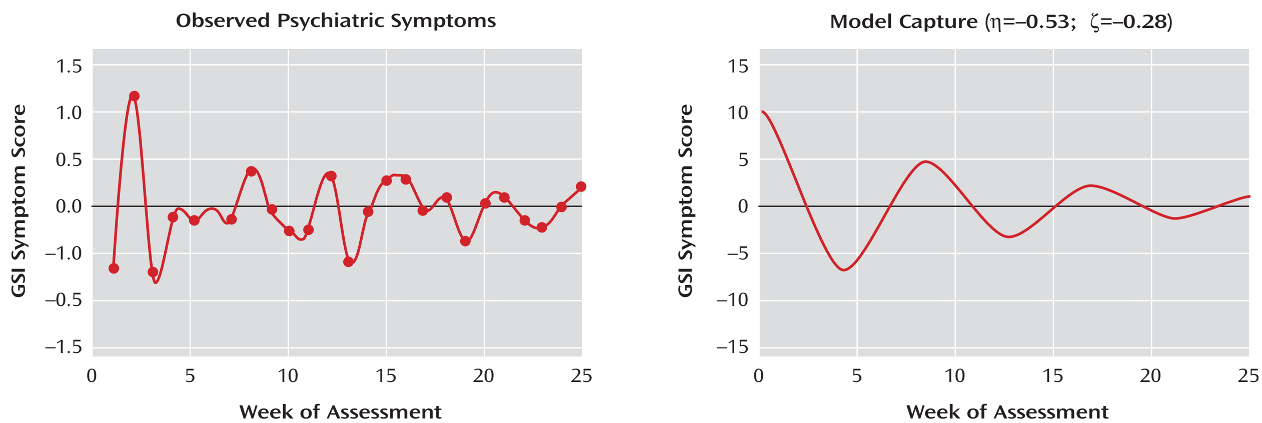
psychiatry (9, 10). Yet, with a few notable exceptions, (11) symptoms continue to be conceptualized as dynamic entities but analyzed and measured as static indicators. In short, the time is now ripe for importing a new generation of models to capture complex symptom patterns, which are likely to be the rule rather than the exception for most psychiatric disorders (10). In the present study, we demonstrate how key dimensions of short-term symptom change—namely how rapidly symptoms vary (symptom oscillation) and the pattern of that oscillation (i.e., whether symptoms are amplifying versus damping over time)—can be captured using dynamical systems models. This class of models was developed to describe systems that exhibit intrinsically predictable patterns of change (12) and also map closely to clinically relevant characteristics of symptom change (12–15), including, for example, whether symptoms are "rapidly cycling," "coming back to baseline," or "ramping up" over time (14, 16).

Method

Participants

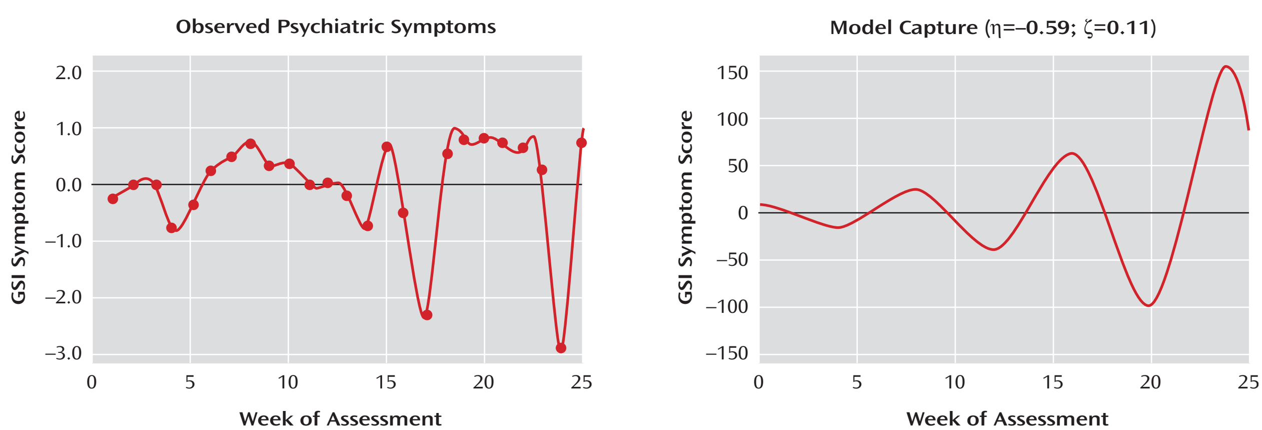
Study participants were sampled from patients evaluated at the emergency room of an urban psychiatric hospital. A two-stage recruitment procedure developed by Gardner and colleagues (17) was used to identify participants at high risk for recurrent violence within a 6-month period. The first stage of the recruitment involved a record review (N=3,356) of individuals who appeared at the psychiatric hospital emergency room over 14 months. The record review identified potential participants who were young (14–30 years old), did not exhibit thought disorder, and who had a documented history of violence. Individuals meeting these criteria (N=1,004) were invited to participate in stage two, a brief screening interview. Some potential subjects could not be located with the available record information (31%),

FIGURE 5. Capturing a Moderate-to-Rapid Symptom Oscillation Pattern With Marked Damping[a]



[a] Subject was a 30-year-old African-American woman admitted voluntarily to the hospital with a diagnosis of bipolar disorder, depressed mood, and cocaine dependence. The subject had a prior history of hospitalizations as well as a history of physical fights with her romantic partner and had attempted suicide on multiple occasions. During the 26-week follow-up period, the subject was involved in nine violent incidents, the majority of which occurred during the first half of the follow-up period, including multiple violent incidents in week 2, followed by violent incidents in weeks 5, 7, 11, 13, 17, and 18. The majority of the incidents involved hitting, with four of the violent incidents causing physical injury to the victim. Individual R^2=0.75.

FIGURE 6. Capturing an Amplifying Symptom Pattern With Moderate-to-Rapid Oscillation[a]



[a] Subject was a 21-year-old African American male admitted voluntarily to the hospital with suicidal ideation. The subject had a history of alcohol abuse and prior diagnoses of impulse control disorder, psychosis, posttraumatic stress disorder, and antisocial personality disorder. During the 26-week follow-up period, the subject was involved in nine violent incidents occurring in weeks 1, 2, 3, 6, 11, 14, 15, 24, and 25; the most serious violent incidents were reported toward the end of the series and involved violence with a weapon. Individual R^2=0.85.

and others refused to participate (20%). Thus, 517 potential participants completed the screening interview, which refined the potential sample pool by selecting those who 1) had heavy substance use in the prior 2 months, 2) had at least one violent threat or act in the prior 2 months and 3) had a score of seven or higher on the hostility subscale of the Brief Symptom Inventory. One hundred seventy-one potential participants were eligible for study participation after completing this screening interview. Of these individuals, 89% (N=152) agreed to complete the baseline interview and 26 weekly interviews. Study participants also nominated an individual who knew him/her well to act as a collateral informant. This collateral informant was also interviewed on a weekly basis. After complete description of the study to the subjects, written informed consent was obtained

The final sample comprised 132 individuals. Participants completed 92% of their weekly follow-up interviews. Details of the enrollment process, potential selection biases, and the operational aspects of the interviewing process are provided elsewhere (18, 19).

Measures

Psychiatric symptoms were assessed weekly using the Brief Symptom Inventory (20), a 53-item self-report inventory. Participants rated the extent to which they had been bothered ("not at all" to "extremely") in the past week by various symptoms. In the present study we report the general severity index, which captures patients' global psychological distress each week. The general severity index is the average score on all 53 items of the Brief Symptom Inventory. The scales and subscales of the Brief Symptom Inventory demonstrate good internal consistency (α=0.71 to 0.85) and test-retest reliability (r=0.68 to 0.91) in normative samples (20). Acceptable levels of internal consistency were also documented in the present (subscales α=0.76 to 0.91; general severity index α=0.97) and other studies (21). Several studies indicate that the Brief Symptom Inventory is sensitive to change (22–25).

The nature, frequency, and severity of the participant's involvement in violent incidents were assessed at each weekly interview. Each participant was asked if he or she had engaged in any of nine categories of aggressive acts (e.g., pushing, hitting, using a weapon) based on an adaptation (26) of the Conflict Tactic Scale (27). Here we report involvement in serious violence, which is defined as an incident that resulted in a physical injury, a sexual assault, a threat made with a weapon in hand, or an aggressive act that involved the use of a weapon (28). We report the percentage of individuals involved in a serious violent incident over the 26-week period (yes/no) as well as the average number of incidents for each person. We also assessed minor violence, which included aggressive acts that did not result in injury. For the purposes of this study, we report only the results for serious violence, since results did not differ for minor violence

Statistical Analyses

Analyses proceeded in three steps. First, we estimated the first and second derivatives from the residualized general severity index symptom scores using local linear approximation, a reliable and robust estimation technique (14). The first derivative (d1) represents the change in symptoms in relation to time (e.g., rate of change). The second derivative (d2) represents the acceleration in symptoms over time (e.g., change in the rate of change). Second, based on prior applications by Boker and colleagues (12–16, 29), we fitted a damped linear oscillator model to characterize short-term symptom change. A review of procedures for modeling a damped linear oscillator can be found elsewhere (8, 30–32). Briefly, the damped oscillator can be expressed as a linear regression

$$d2_i = \eta d1_i + \zeta X_i + e_i$$

in which the speed at which symptoms change (acceleration, d2) is the outcome, and initial symptom state (X) and the change in symptoms (velocity, d1) are the predictor variables. The first parameter of interest in the equation is the coefficient η (eta), which represents the frequency of the oscillation, or how rapidly symptoms oscillate over time (a relatively slow versus a rapidly oscillating symptom pattern for two subjects over the 26-week follow-up period is presented in Figure 1). The second parameter of interest in the equation is the coefficient ζ (zeta), which indexes the constancy of the magnitude of oscillations over time. When patterns are damping, $\zeta<0$; when patterns are amplifying, $\zeta>0$. In the present study, damping of symptoms across time would represent an individual whose symptoms have regulated back to equilibrium (similar to how a thermostat controls a heater to maintain a set temperature). Conversely, symptom amplification, or "excitability" would represent a pattern of symptom fluctuation that is becoming increasingly dysregulated (14). In Figure 2, the first graph depicts an individual whose symptoms are oscillating in a constant manner around a set equilibrium (in this case $\zeta=0$). The second graph illustrates a damped pattern for an individual whose symptoms have regulated back to equilibrium (in this case $\zeta<0$). This is an example of a damped linear oscillator which, after being set into motion, oscillates back and forth and eventually comes to rest, similar to a pendulum with friction. In psychological terms, a damping symptom pattern has been described as "resiliency" following a shock or potentially traumatic event. In a recent study, damping was assessed as the ability of recent widows to self-regulate their affective symptoms of emotional well-being back to an equilibrium in the months following the death of their spouse (16, 29). In contrast, the third graph of Figure 2 provides an example of an individual whose symptoms are becoming increasingly dysregulated or amplified across time (in this case $\zeta>0$). The model was fitted as a random coefficients oscillator model using scripts written in R (33). The model was specified to allow the two key model parameters (symptom oscillation [η] and symptom regulation [ζ]) to vary across individuals. Model fit was evaluated to determine how closely the estimated coefficients recovered the observed symptom pattern for each individual. The third step of the analyses applied multiple logistic and Poisson regression models to test whether key dimensions of symptom fluctuation were concurrently associated with involvement in serious violence across the 26-week series.

Results

Can Fluctuation in Psychiatric Symptoms Be Captured Using Dynamical Systems Models?

The overall R^2 for the linear oscillator model was 0.73, suggesting that the variability in psychiatric symptoms among high-risk individuals can be captured by a linear oscillator model (12). In other words, there was a relatively high congruence between predicted versus observed symptom oscillation across the series. With respect to fixed effects (the sample average), the model captured a significant oscillation parameter ($\eta=-0.32$, SD=0.16). The damping parameter was also significant and negative ($\zeta=-0.06$, SD=0.17), suggesting that on average, the oscillation in psychiatric symptoms following a visit to the psychiatric emergency room damped across the 26-week period. Because the application of dynamic models is relatively new to psychiatry, we present four case examples to illustrate how the parameters in a linear oscillator model are able to capture study members' symptom fluctuation patterns. As shown in Figure 3, the subject's psychiatric symptoms amplified across the 26 weeks ($\zeta=0.23$) and exhibited a moderate pattern of oscillation ($\eta=-0.41$), with a full cycle completing in approximately 10 weeks. In contrast, the subject represented in Figure 4 exhibited a more rapid pattern of symptom oscillation ($\eta=-0.76$), with some evidence of damping ($\zeta=-0.04$). The subject depicted in Figure 5 exhibited marked damping ($\zeta=-0.28$) and moderate-to-rapid cycling of symptoms across the 26 weeks ($\eta=-0.53$), whereas the subject in Figure 6 exhibited amplification in symptoms across time ($\zeta=0.11$) and moderate-to-rapid cycling of symptoms ($\eta=-0.59$). These four examples allow for a visual inspection of how well-observed symptom patterns for individual cases can be recovered using the two parameters derived from a damped linear oscillator model.

Study members varied widely with respect to the frequency of symptom oscillation, from a very rapid (–0.76) to an extremely slow (–0.06) oscillation pattern. A Shapiro-Wilk test (34) rejected the null hypothesis that the sample was drawn from a normal distribution of scores ($p<0.001$). Given the bimodal distribution, 26.6% of study members with a score above the binomial split ($\eta>-0.41$) were characterized as rapid oscillators for the following analyses. Study members also varied significantly on ζ, with estimates ranging from well below zero (–0.72, complete damping) to well above zero (0.69, extreme amplification). While the majority of study members displayed a damped ($\zeta<0$) or constant pattern ($\zeta=0$) of symptom fluctuation,

TABLE 1. Logistic Regression Analysis of Predictors of Whether Serious Violence Occurred Across the 26 Weeks (N=132)

	Estimates				
Variable	B	SE	Odds Ratio	95% Confidence Interval	p
Rapid symptom oscillation (eta)	1.02	0.48	2.78	1.07–7.18	0.04
Trait-level general severity index symptoms	–0.05	0.22	0.95	0.62–1.47	0.82
Symptom amplification (zeta)	–0.40	1.16	0.67	0.07–6.42	0.73
Sex (1= female)	0.57	0.40	1.76	0.81–3.83	0.15
Days in the community	0.001	0.003	1.00	1.00–1.01	0.87

28.7% of participants experienced symptom amplification ($\zeta>0$). Because symptom dysregulation is of particular interest to clinicians monitoring patients, the following analyses test whether there is a relationship between amplified symptom patterns ($\zeta>0$) and violence.

External Validation: Is Rapid Symptom Oscillation or Amplification Across the 26 Weeks Associated With Violence During the Same Period?

The majority of participants (59.1%) engaged in at least one incident of serious violence: the average number of serious violent incidents was 2.3 (SD=3.1; range=0–16) per person. The results of a multiple logistic regression predicting whether violence had occurred across the 26-week period (yes/no) are reported in Table 1 and illustrate two key points. First, rapid versus slow oscillators were 2.78 ($p=0.04$) times more likely to be involved in a violent incident over the observation period. In percentage terms, 76.0% of rapid oscillators versus 54.0% of slow oscillators engaged in violence over the 26-week period. This relationship held after controlling for mean-level psychiatric symptoms, gender, and days in the community. Second, there was no association between symptom levels and whether violence occurred, nor was there an association between symptom amplification and the occurrence of violence. Next we asked whether symptom dimensions predicted the number of violent incidents across the 26-week follow up. A Poisson regression model was applied to adjust for the count distribution of violent incidents (35). Study members with an amplifying symptom pattern, on average, engaged in 1.57 (IRR=1.57, 95% CI=1.17–2.11; $p=0.003$) more incidents of serious violence across the 26 weeks. This relationship held after we controlled for mean-level psychiatric symptoms, gender, and days in the community. However, no relationship was found between the speed of symptom oscillation and number of violent incidents.

Discussion

This study applied a novel approach for mapping patterns of psychiatric symptom change at the weekly level. Findings from this research advance what is known about the assessment of psychiatric symptoms in two ways. First, our results demonstrate that symptom patterns for many high-risk individuals can be recovered within a dynamical systems framework. Among this group of individuals, psychiatric symptoms exhibited systematic patterns of change that could be described by two clinically relevant parameters: η (how quickly symptoms oscillated) and ζ (whether the individual's symptoms regulated back to a set point or became dysregulated over time). Electronic diaries and real time assessments are increasingly being used in medical research (36). This means that we are now able to test not only whether a given treatment influences symptom levels, but also whether treatment alters the ebb and flow of symptoms over time. This is important because many treatments aim to improve patients' ability to regulate their symptoms or cope with external stressors, treatment outcomes that cannot be assessed using static measures. These results indicate the promise of dynamic models for this purpose. Second, our findings demonstrated a concurrent association between dynamic assessments of symptoms and involvement in serious violence. That is, high-risk individuals who experienced rapid (versus slow) fluctuations in psychiatric symptoms were more likely to be involved in violence during the follow-up period. In addition, individuals with an amplified symptom pattern were involved in a greater number of serious violent incidents. These findings serve as an important external validation check for our dynamic symptoms parameters by illustrating that the parameters relate in a theoretically coherent manner to an important indicator of functioning. We cannot, however, determine the causal ordering of this relationship. Because assessments of violence and symptoms were aggregated across the same 26-week period, it is plausible that involvement in violence precipitated symptom fluctuations or that a common third cause was driving both symptom fluctuations and violence. These hypotheses have somewhat less face validity than the hypothesis that symptom patterns increase the likelihood of violence, but they cannot be ruled out from the data presented here.

Limitations

This study demonstrates proof of principal that symptom patterns can be recovered among a relatively homogenous sample of high-risk individuals. However, it is not known whether general clinical or population samples would contain sufficient variability in psychiatric symptoms to replicate these findings. Future research is required to test whether dynamic models are a useful analytic tool for characterizing symptom ebb and flow within other segments of the population. In addition, dimensions of symptoms and involvement in serious violence were both assessed across a 26-week follow-up. As such, our findings do not inform the temporal ordering of symptom fluctuation and our indicator of functional impairment. Future research applying more advanced models (37, 38) is required to determine the extent to which psychiatric symptoms and markers of functional impairment move together.

Implications

Although these early findings cannot directly inform clinical practice, it is intriguing to think of how the application of dynamic models may lead to new strategies in clinical research. We note that weekly observations of symptoms occur frequently in practice and are increasingly being gathered in clinical trials: these assessment strategies are opening up new possibilities for testing what may matter most about psychiatric symptoms, namely, that it may be important to consider how rapidly symptoms fluctuate and/or whether symptoms dampen over time. With such methods in hand, there is value in collecting fine-grained assessments of symptoms or other aspects of functioning. As evidenced here, psychiatric symptoms in particular demonstrate complex patterns of change relevant to outcomes of both clinical and policy interest. Documenting patterns of symptom fluctuation also holds potential for assessing patient response to a broad range of drug and psychosocial treatments. That is, treatment goals of inducing symptom stability and effective symptom regulation can now be mapped with some precision. Such methods may also assist in identifying early markers of treatment failure or signals of disorder onset. For example, destabilization or loosening of fixed patterns of symptoms has been described as preceding breakthroughs and sudden gains (e.g., recovery) or losses (e.g., relapse) during treatment (39, 40). Thus, clinically, the promise of moving toward more dynamic assessments of psychiatric symptoms is that we may come closer to understanding the circumstances under which a system becomes dysregulated or goes awry. Theoretically, dynamic symptom assessments hold the potential to improve the theory-method fit in psychiatric research, thereby opening up a realm of possibilities for identifying mechanisms of change in both treatment and naturalistic settings.

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