# A Dynamical Systems View of Psychiatric Disorders - Practical Implications

*A Review*

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# A Dynamical Systems View of Psychiatric Disorders—Practical Implications
## A Review

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**IMPORTANCE** Dynamical systems theory is widely used to explain tipping points, cycles, and chaos in complex systems ranging from the climate to ecosystems. It has been suggested that the same theory may be used to explain the nature and dynamics of psychiatric disorders, which may come and go with symptoms changing over a lifetime. Here we review evidence for the practical applicability of this theory and its quantitative tools in psychiatry.

**OBSERVATIONS** Emerging results suggest that time series of mood and behavior may be used to monitor the resilience of patients using the same generic dynamical indicators that are now employed globally to monitor the risks of collapse of complex systems, such as tropical rainforest and tipping elements of the climate system. Other dynamical systems tools used in ecology and climate science open ways to infer personalized webs of causality for patients that may be used to identify targets for intervention. Meanwhile, experiences in ecological restoration help make sense of the occasional long-term success of short interventions.

**CONCLUSIONS AND RELEVANCE** Those observations, while promising, evoke follow-up questions on how best to collect dynamic data, infer informative timescales, construct mechanistic models, and measure the effect of interventions on resilience. Done well, monitoring resilience to inform well-timed interventions may be integrated into approaches that give patients an active role in the lifelong challenge of managing their resilience and knowing when to seek professional help.

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In 1887, the biologist Stephen A. Forbes wrote an article with the title "The Lake as a Microcosm." It is now recognized as the starting point for ecology as a science. After describing what goes on in a floodplain lake on retreat of the river, Forbes writes: "A lake forms a little world within itself, a microcosm within which all the elemental forces are at work. The play of life goes on in full, but on so small a scale as to bring it easily within the mental grasp. Nowhere can one see more clearly the impossibility of studying completely any species out of relation to the others." Since then, the science of ecology has become a huge field of research, studying the dynamical interplay of the species and other elements that shape ecosystems such as a lake. None of the elements can be understood without taking that interplay into account.

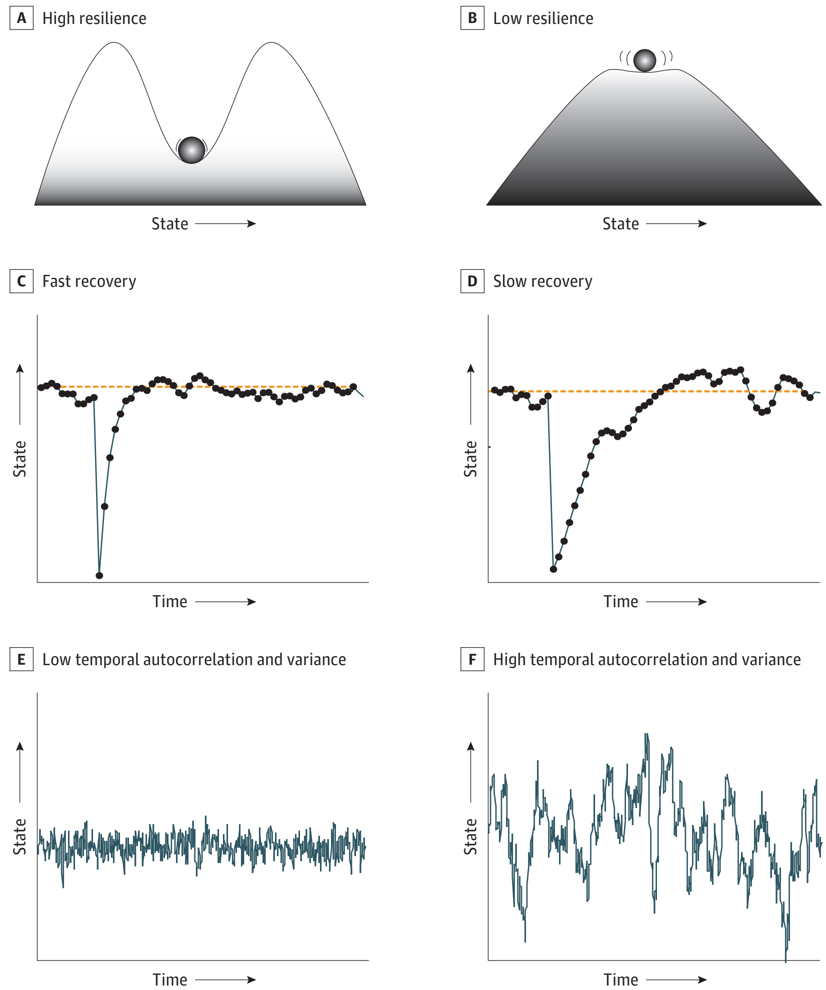
It is widely agreed upon that the only way to get a grip on this complexity is to combine observations, experiments, and mathematical models. Starting with the influential work of Alfred Lotka and Vito Volterra, the mathematical approach has a history of more than a century, and with the rising availability of massive data, this side has become ever more important. The same is true for studies of the climate and other complex dynamical systems. The basic mathematical framework describing how such systems of interacting components work is dynamical systems theory. In part 1 of this 2-part article, we explained the basics of this framework and suggested how psychiatry may piggyback on this solid body of work using generic techniques for understanding the dynamics of disorders, inferring causality from time series, and quantifying resilience.[1] Here we review concrete examples and propose a research agenda.

## Measuring Resilience

Quantifying resilience is useful not just to indicate the chances of a transition (for better or worse) but also to evaluate the effects of interventions aimed at promoting resilience of the healthy state. The traditional way to assess mental health is to gather information on such aspects as mood, insomnia, fatigue, suicidal ideation, or anxiety.[2] However, recent work on dynamical systems theory suggests complementary generic approaches to assess resilience,[3-5] inspiring application to psychiatry.[6-10]

One approach is to compute dynamic indicators of resilience (DIORs) based on a fundamental principle known as critical slowing down. It implies that as the basin of attraction around the status quo shrinks, dynamics of the fluctuations around that equilibrium change in a characteristic way (**Figure 1**).[11] As the stability basin

Figure 1. Dynamic Indicators of Resilience



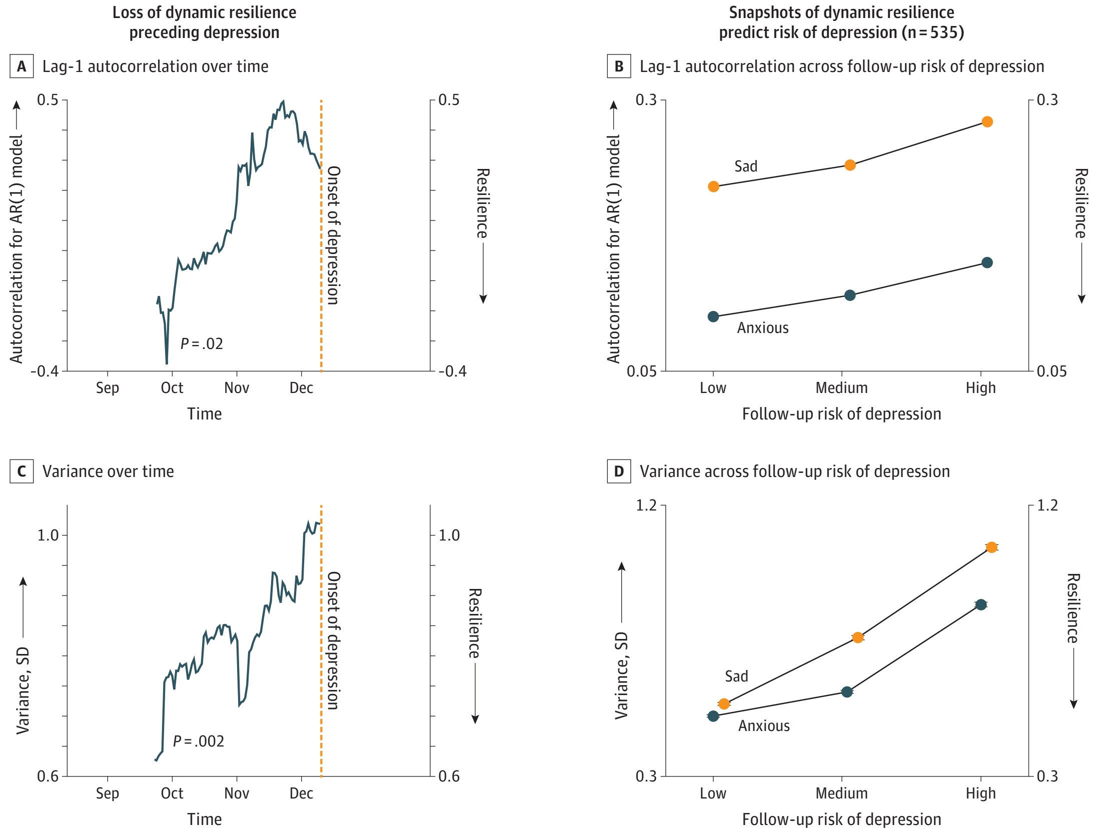

As resilience of a state is low (B), recovery from small perturbations is slow (D), and the variance and temporal autocorrelation of natural fluctuations is high (F) as compared with situations of high resilience (A, C, and E).[11] Dashed lines in panels C and D indicate the equilibrium at the bottom of the valleys depicted in panels A and B.

shrinks, the slopes around the equilibrium become flatter, implying that return rate to the equilibrium upon small perturbations becomes slower. An experimental perturbation approach is often not possible. However, natural fluctuations can also reflect the change in the stability landscape. This is because the reduced speed of recovery (low return rates to equilibrium) implies that the system lingers longer in states to which it has become pushed by random events and fluctuations in external conditions. This is reflected in higher variance, but also in higher temporal autocorrelation. As changes in the state become slower, the "memory" in the signal increases. As an intuitive example, think of a mood perturbation by an event such as receiving a ticket for speeding. If the mood of a person is back to normal in a few hours, their healthy mental state may be considered more resilient than when it takes days to get over it.

Surprisingly, DIORs have been shown to be generic enough to indicate a loss of resilience in systems as diverse as the climate,[12] societies,[13] human postural balance,[14] and ecosystems.[15] For example, climate tipping points such as collapse of icecaps, ocean currents, or the Amazon rainforest are now a major concern.[16] Over millions of years, such tipping points have repeatedly happened, and time series reveal that over and over again, they were announced by DIORs.[12] Therefore, those indicators are now used to monitor the climate system. Such work revealed that the Atlantic meridional overturning circulation is approaching a tipping point with major implications for weather worldwide.[17,18] As another example, a global map of the resilience of tropical rainforest reveals how the risk of collapse into a savanna state differs from place to place. This map is based on DIORs computed from fluctuations in greenness obtained from satellite data.[15]

In the field of psychiatry, DIORs in time series of self-reported mood and other parameters may be predictive of the risk of a major depression[7,8] (**Figure 2**) or state shifts in bipolar disorder.[19] The traditional approach requires a large amount of data, which may be hard to obtain for ecological momentary assessments (EMAs).[6] An alternative is to collect such data in short bursts, namely short, high-resolution time series reflecting the state of a patient at a given moment, rather than monitoring continuously.[20] Another way forward is to quantify resilience on time series data that go beyond mood-based EMAs. For instance, as variations in mood, beliefs, and behaviors affect each other, DIORs may be echoed in the dynamics of any of those variables, some of which might be monitored automatically or passively (eg, physical activity).[21] Meanwhile, new techniques are being developed for obtaining indicators of cognitive and affective conditions computationally from natural language (eg,

Figure 2. Computing Dynamic Indicators of Resilience From Time Series of Ecological Momentary Assessments (EMAs) of Mood or Other Variables




Examples show 2 indicators of critical slowing down, known as a sign of dwindling resilience in complex dynamical systems: lag-1 autocorrelation (panels A and B) and variance (panels C and D). Left-side panels show the rise of those early-warning signals in a mood indicator for a person subject to double-blind tapering of medication.[7] Right-side panels show how across a group of individuals, resilience indicators computed from EMA data collected on 5 subsequent days predict the risk for a person to fall into a depression later in life.[8] AR(1) indicates autoregression model of order 1.

coherence and affect), opening up entirely new approaches to noninvasive dynamic assessment of key components of mental health.[22-24]

In addition to DIORs, there are other techniques to estimate dynamic resilience. One approach is to first infer stochastic dynamical models from time series.[25] Those individualized models then allow estimating ecological resilience, expressed as the expected time a person will stay in the current state (either the healthy state or a disorder). Times to remittance or recurrence are already routinely reported for cohort studies, but those time-series techniques offer the prospect of providing for a prediction per individual. In summary, various approaches from the dynamical systems toolbox may be used to quantify resilience on the basis of time series.

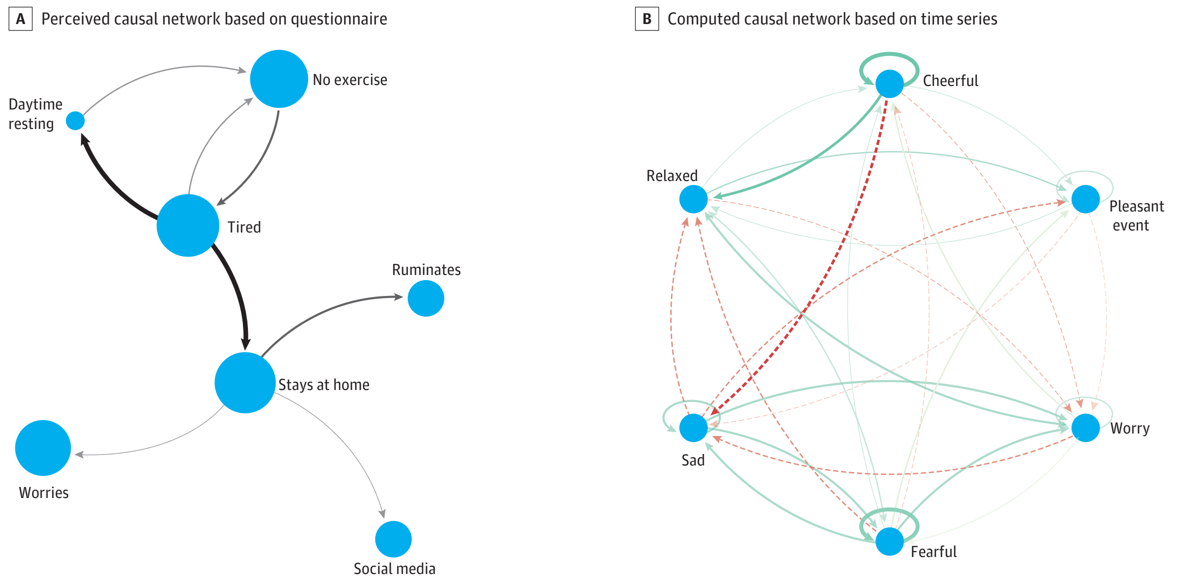
## Planning Intervention

In addition to offering ways for quantifying resilience, the dynamical systems view may offer fresh views on ways to plan interventions. While this is new in psychiatry, it has become common practice in ecosystem restoration.[26] For instance, as is the case in humans, resilience of ecosystems may vary over time, and insight into such variation may help find the best moment to nudge them over a tipping point for recovery. This approach is used to restore forest in degraded drylands.[27,28] Rainfall in Peru and northern Chile is higher during El Niño periods, but not enough to let forest recover, as rabbits and goats are quick to eat the seedlings. Fencing out those animals is not enough to allow trees to settle during normal dry years but can nudge forest recovery during wet El Niño events. Such windows of opportunity are predictable months in advance, allowing preparation for this type of adaptive management.

Also, lakes can have 2 alternative states, clear or turbid, each of them stabilized by a set of feedback mechanisms. To make a turbid lake clear again, shock therapy in the form of temporary removal of fish may work. But not if the turbid state is too resilient. Therefore, managers first aim at undermining resilience of the turbid state by reducing pollution. By itself this is often not enough, as the turbid state (much like depression) is a self-stabilizing trap. Fish removal is then used to tip the balance, and once clear, lakes often remain in that state for many years.[29] As with people, all lakes are different. For instance, resilience depends on multiple factors, including their size and water depth and the climate.[29,30] Therefore, a tailored approach to restoration is taken.

In psychiatry, similar framing might be useful to think of effects of brief interventions aimed at tipping a patient into a recovered state. The dynamical systems toolbox may also help detect

Figure 3. Networks Depicting How for a Given Individual, One Thing May Lead to Another




Such networks help identify individualized intervention targets. One way to infer such networks of causality is to use interviews or questionnaires (A).[32] Another approach is to take a dynamical systems view and estimate causality from time series using computational approaches. Panel B is an example of such a computationally inferred network based on autoregressive modeling.[33]

individualized targets for interventions aimed at strengthening resilience of the healthy state or eroding resilience of a specific disorder. Bolstering resilience of the healthy state may be done by training specific skills and habits, while the probability of escaping from a particular disorder can be increased by targeting the particular beliefs and behaviors involved in the self-reinforcing feedbacks that stabilize the disorder in a given patient.[31] Obviously, the most promising feedbacks for individualized targeted intervention should depend on how things work in a person. Such personalized webs of causality may be inferred in 2 ways (**Figure 3**).[32,33] The traditional approach is through interviews or questionnaires.[32] As a complement to such subjective qualitative approaches, dynamical systems tools may help unravel the causal web of interactions that govern mental health. This can be done using techniques for detecting causality from multivariate time series.[34] Two distinct approaches stand out. First, there is the possibility to derive autoregressive models that show how the value of a key variable (eg, mood) is related to the value of that variable as well as other variables (eg, physical activity, social activity, sleep, etc) on the previous day (or hour or week). A related, more sophisticated approach, known as convergent cross-mapping, allows probing in more depth whether the observed relationships reflect real causality.[35]

## Research Questions

The focus on dynamical resilience invites a host of follow-up research questions. Here are 5 examples.

### How to Collect Relevant Dynamic Data

The tools to infer resilience and causality we highlighted require time series. Momentary assessment of self-reported mood has become widespread. However, mood is only 1 dimension of the complex dynamical system that shapes mental health and disorders. It would be exciting to analyze complementary high-resolution data reflecting cognition, mood, and behavior. Wearable electronics and phones are obvious sources generating data ranging from physical activity and mobility to swiping patterns on phone screens or real-time analysis of natural language. Such data may seem more indirect than self-reported mood and behavior but could reflect the dynamics of the dynamical system in ways that are more objective and less burdensome.

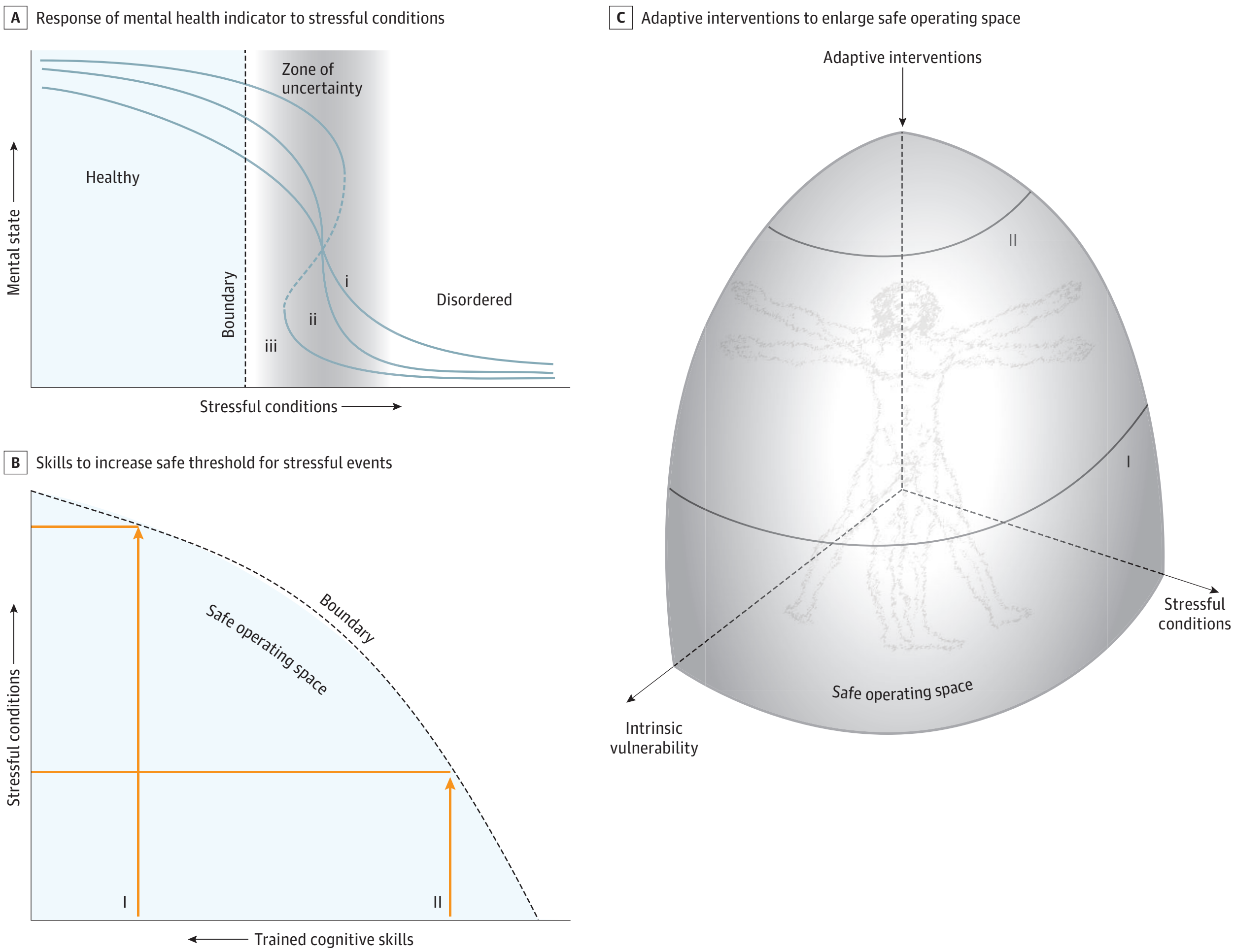
### How to Detect the Relevant Timescale

Ecological momentary assessment time series typically have resolutions in the order of hours, while automatic sensors give much higher resolutions. Such information may be informative, for instance, to reveal dynamics in the fast roller coaster of mood and behavior. On the other hand, those fast fluctuations can be hard to interpret and may be strongly driven by random events and diurnal cycles. Therefore, day-to-day dynamics may sometimes be more informative to study dynamics that reflect the resilience of behavioral or mood patterns. Indeed, the early-warning pattern reported in Figure 2 panels A and C, based on daily averages, is much clearer than a version computed on the original EMA data.[7] In a general sense, it will be important to explore which time-step is relevant to address a certain mechanism.

### How to Construct Mechanistic Models

There is a long tradition of modeling dynamics of networks of neurons in the brain.[36-38] While such computational neuroscience has generated useful insights, accurate predictive models of the broader dynamics of mental health and disorders are still out of reach. This is because, unlike for the weather or climate, we cannot derive equa-

Figure 4. Managing a Safe Operating Space for Mental Health




A, Response of an indicator of mental health (eg, mood) to stressful conditions (eg, social isolation) is difficult to predict (eg, i, ii, or iii), but beyond a safe boundary level, depending on a person's intrinsic vulnerability, stressful conditions become likely to cause a transition into the disordered state (eg, a major depressive episode). B, The safe threshold for stressful events may be increased (eg, from level II to I) by skills that can be promoted by techniques such as preventive cognitive training. C, A 3-dimensional representation reflecting how adaptive interventions may enlarge the safe operating space as needed when vulnerable persons are driven to the border of their safe operating space through stressful conditions combined with changing intrinsic vulnerability depending on genes as well as conditions evolving over time.[55,56]

tions that govern dynamics of phenomena such as rumination, depression, or psychosis from first principles (such as air pressure and flow). Nonetheless, minimal models of selected interactions between key elements of behavior, cognition, and mood can help thinking about the nature of complex phenomena[39] such as depression[8] or panic disorder.[40] Pursuing this approach to write hypotheses in the form of differential equations could help sharpen hypotheses on how many disorders work. As a complementary strategy, it may be interesting to explore the novel artificial intelligence–based approaches to derive the simplest set of equations that can reproduce observed dynamics.[41-43]

## How to Measure the Impact of Interventions on Resilience

Population studies suggest that mental health may be improved through lifestyle elements such as physical exercise,[44] social activity,[45] and diet composition.[46,47] However, for any individual it may be challenging to reveal which lifestyle changes or therapies[48] work. Data on traditional end points such as recurrence may take long to obtain. By contrast, the possibility to quantify resilience offers the possibility to rapidly evaluate the effect of interventions, at least in theory. Monitoring trials with resilience indicators alongside traditional end points could reveal if such a resilience-based evaluation of effects is indeed informative.

## How to Link Signal Complexity to Resilience

Looking under the hood of what keeps an organism alive, fluctuations in heartbeat and other indicators of regulatory functions reflect permanent responsive dynamics, a turmoil that is in seeming contrast to the classical homeostasis idea.[49] A host of health problems are related to a reduced complexity or variability of the natural fluctuations in heart rates.[50] This includes cognitive functioning.[51] As brain activity likewise reflects essential complex fluctuations, there has been much interest in finding ways of linking risk of disorders to abnormal electrical brain (electroencephalography) patterns.[52-54] It would be exciting if this emerging field of signal analysis could be linked to the concept of dynamic resilience presented here.

## Outlook

The time is ripe for a paradigm shift in psychiatric care, seeking strategies to improve the quality of life for vulnerable individuals through adaptive management of their resilience. We may think of this as the challenge to maintain a safe operating space depending on a person's needs (**Figure 4**[55,56]), similar to current views on creating a safe operating space for ecosystems[56] and for humanity.[57] The potential for building resilience is illustrated by the observation that a single 2-month preventive cognitive therapy can substantially reduce the risk of relapse of major depressive episodes over as long as 20 years.[48] Nevertheless, for many vulnerable patients, a lifelong adaptive strategy of monitoring and well-timed specific interventions may often be needed. This sounds perhaps unfeasible, but it is not. Facilitating a central role for the patient will be crucial, and this may be facilitated by tools such as phone app–based self-monitoring combined with guided app-based personalized intervention modules.[31] The concepts we reviewed may help make good use of such new technological possibilities. Dynamic indicators of resilience may be computed from self-collected time series, while analysis of monitored symptom networks may point to feedbacks that can be targeted to strengthen resilience of the healthy state while reducing vulnerability. In short, a dynamical systems view may serve as the backbone for strategies of lifelong comanagement of mental health by individuals themselves, schools, and mental and physical health care teams. Resilience monitoring and well-timed interventions may be integrated into approaches that give patients an active role in the lifelong challenge of managing their resilience and knowing when to seek professional help. The possibility of reaping the fruits of technological development for aiding such an approach provides reason for optimism regarding feasibility.

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