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Bringmann, Laura; Helmich, Marieke; Eronen, Markus; Voelkle, Manuel

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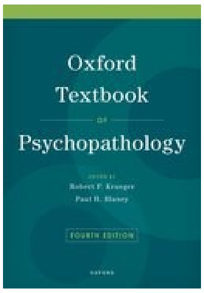

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CHAPTER

5 Complex Systems Approaches to Psychopathology

Laura Bringmann, Marieke Helmich, Markus Eronen, Manuel Voelkle

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Abstract

Clinical research and practice are permeated by complexity. In recent years, researchers have witnessed a sharp increase in scientific studies that acknowledge this complexity and approach psychopathology from the perspective of complex systems. In this chapter, the authors provide an introduction to the complex systems approaches that have received the most attention in psychopathology. They begin by discussing the general idea of complexity and complex systems and then turn to the framework of complex dynamic system models and how they have been applied to psychopathology. After this, the authors discuss early warning signals, which hold the promise of using insights from complexity science to enable personalized prediction and timely intervention. Finally, the authors go through the recently popular network approach to psychopathology and how it is related to the broader framework of complex systems. Throughout the chapter, the authors discuss the applications, challenges, and limitations of these approaches.

Keywords: complexity, dynamical system, network, centrality, early warning signal, experience sampling method

Subject: Clinical Psychology

Collection: Oxford Clinical Psychology

Abbreviations

EMA

ecological momentary assessment

ESM

experience sampling method

EWS

early warning signal

OCD

obsessive-compulsive disorder

VAR

vector autoregressive

Introduction

Science is permeated by complexity. In biology, systems such as insect colonies, flocks of birds, or ecosystems exhibit extremely complex behavior. For example, ant colonies construct large and elaborately structured nests, without any central control or leader ant, but rather through the intricate interactions of thousands of individual ants (Mitchell, 2009; Richardson et al., 2014). The human brain is a paradigmatic complex system, consisting of a vast number of interconnected neurons that are constantly interacting with each other. The Internet is a complex human-made system of interconnected servers, computers, and other elements. As well, social systems, such as economies or the stock market, are complex systems (Newman, 2018). Complexity thus occurs in (nearly) all scientific disciplines.

Clinical psychologists and psychiatrists also encounter complexity in their research and daily practice. Mental disorders, such as major depressive disorder, are the result of complex interactions at multiple levels, from the genes to maladaptive behavior and social influences (Freeman, 1992; Orsucci, 2006). In recent years, we have witnessed a sharp increase in studies that approach psychopathology from the perspective of complex systems. However, the idea that psychological and social processes are dynamical and complex is far from new; it goes back at least to the 1930s (Lewin, 1936; Richardson et al., 2014). Elaborate models of mental disorders based on complex systems theory were introduced already in the 1970s (Zeeman, 1976; see also von Bertalanffy, 1967) and further developed especially in the 1990s (Tschacher et al., 1992; van der Maas & Molenaar, 1992). One of the key challenges has been, and continues to be, how to translate these theoretical models into practical applications.

In this chapter, we provide an introduction to those complex systems approaches that have received the most attention in psychopathology. We start by discussing the general idea of complexity and complex systems and what those terms entail. We then turn to the framework of complex dynamic system models and how they have been applied to psychopathology. After this, we discuss early warning signals (EWSs), which hold the promise of providing a clinically useful application of the theoretical ideas of complex dynamic systems models. Finally, we go through the recent popular network approach to psychopathology and how it is related to the broader framework of complex systems. In all of these sections, we discuss both the promises and possible applications as well as the challenges and limitations of these approaches.

Complex Dynamic Systems

Although complex systems studied in different disciplines are highly diverse (e.g., ant colonies, the Internet, or the human brain), it is thought that they share some common features and can therefore be studied with similar techniques. For this reason, the study of complex systems has emerged as a meta-paradigm or interdisciplinary field of its own (Orsucci, 2006). However, even among complexity p. 104 ↳ researchers, there is no agreement on what complexity or a complex system is precisely. The different definitions in the literature strongly diverge. For example, Orsucci writes, "Complexity science can be regarded as a scientific toolbox, containing some tools to deal, empirically and theoretically, with complex dynamical systems (i.e., many variables [in] systems changing in time)" (Orsucci, 2006, p. 390). On the other hand, Weng and colleagues characterize complexity based on our capabilities to understand a system.

> In a general sense, the adjective "complex" describes a system or component that by design or function or both is difficult to understand and verify. . . . In physical systems, complexity is determined by such factors as the number of components and the intricacy of the interfaces between them, the number and intricacy of conditional branches, the degree of nesting, and the types of data structures. (Weng et al., 1999, p. 92)

Foote (2007), in contrast, lists several key features of complex systems.

> In recent years the scientific community has coined the rubric "complex system" to describe phenomena, structures, aggregates, organisms, or problems that share some common themes: (i) They are inherently complicated or intricate, in that they have factors such as the number of parameters affecting the system or the rules governing interactions of components of the system; (ii) they are rarely completely deterministic, and state parameters or measurement data may only be known in terms of probabilities; (iii) mathematical models of the system are usually complex and involve nonlinear, ill-posed, or chaotic behavior; and (iv) the systems are predisposed to unexpected outcomes (so-called "emergent behavior"). (Foote, 2007, p. 410)

In sum, researchers define complexity or complex systems in wildly different ways.

One key and oft-noted characteristic of complex systems is *nonlinearity*. In nonlinear systems, changes in the input do not result in proportional changes in the output. Mathematically, a linear function can be plotted as a straight line, whereas a nonlinear function will have a more complex shape, such as a u- or s-shape (Salvatore & Tschacher, 2012), which can be described, for instance, with higher-order polynomial functions. For example, when gradually reducing the medication of individuals suffering from depression, the effect on mood is usually not linear but often results in sudden shifts in mood (Helmich et al., 2020). In general, nonlinearity "comes closer than does a straight line to therapists' and clients' clinical experience" (Barkham et al., 1993, p. 676). However, it is important to note that nonlinearity is a very general and common feature. In nature, nonlinearity is the rule rather than the exception: "calling a science 'nonlinear' is like calling zoology the 'study of non-human animals' " Stanislaw Ulam, quoted in (Orsucci, 2006, p. 390). However, modeling the behavior of nonlinear systems does not always require nonlinear functions because complex nonlinear behavior can also arise from linear interactions of simple components. For example, in an ant colony, even if the behavior of individual ants is linear and based on simple rules, the result is complex nonlinear overall behavior (Bonabeau et al., 1997).

In addition to nonlinearity, a typical feature of a complex system is that its behavior is the result of *self-organization*: there is no central controller or external designer, just many individual components interacting (Richardson et al., 2014; van Geert, 2019). For example, in a flock of starlings, there is no leading bird that decides where the flock goes, but rather individual birds whose interactions with their neighbors result in the behavior of the flock. Often, this behavior of a complex system, where the system-level behavior is difficult to anticipate or predict based on the individual components, is called *emergence* (Richardson et al., 2014). Such interacting components can also be seen as a *network*, an approach recently introduced into psychopathology research and something we will come back to in later sections. Sometimes complex systems can result in unpredictable emergent behavior, even when they consist of relatively simple components, which is referred to as *chaotic behavior*. In chaotic systems, tiny variations in the initial conditions can result in vastly different overall outcomes, making prediction difficult or impossible (Richardson et al., 2014). For example, tiny differences in the locations of individual birds can completely change the direction in which the flock is flying.

An essential feature of complex systems is that they are *dynamic*, which is why they are often referred to as *complex dynamic(al) systems* (Thelen & Smith, 1994). That is, the behavior of the system changes or evolves and unfolds over time in such a way that the current state of the system is dependent on its past states (van Geert, 2019). Thus, in order to study and model the system, *time* must be taken into account (Voelkle et al.,
p. 105 2018). The dynamic behavior of psychological processes becomes clear ↳ from examples such as emotions. Feelings of positive affect generally fluctuate throughout the day, from hour to hour or even minute to minute (Kuppens et al., 2010).

The importance of such changes is also apparent in symptoms of mental disorders. Mental disorders are usually not trait-like phenomena but dynamical processes, in which during some weeks one has more symptoms while at other times the symptoms seem to wane. This is clearly illustrated by Caspi et al.'s (2020) study of more than 1,000 individuals from New Zealand, followed from ages of 11 to 45. They found that mental disorders not only ebb and flow over years and decades, but that individuals also often experience several different mental disorders in their lifetimes. Finally, it is important to emphasize that change is also central to clinical practice, as one of the main aims of therapy is to instigate change (e.g., from an episode of major depression to no longer having a depression).

Traditionally, researchers have studied psychopathology as a trait-like phenomenon (Hamaker, 2012; see also Chapter 6, this volume). Following this paradigm, it is natural to just measure individuals once, for example with questionnaires concerning their symptoms, at a single time point. Such questionnaires mostly include retrospective items referring to a period of several weeks or even a whole life span (Kruijshaar et al., 2005). These measures and the statistical methods associated with them are meaningful and useful in their own right, such as when the goal is to compare two groups to find out which form of medication works better, information that is important for therapists and policymakers (Lichtwarck-Aschoff et al., 2008).

In contrast, when researchers want to study psychopathology as a process, the dynamic approach becomes important. The first step is to capture the process over time, for which time series or (intensive) longitudinal data are needed. Such data consist of many measurements, for example over days, weeks, or months, sometimes also multiple times per day, typically gathered using methods known as the experience sampling method (ESM), ecological momentary assessment (EMA), or ambulatory assessment (aan het Rot et al., 2012; Csikszentmihalyi & Larson, 1987; Ebner-Priemer et al., 2009). Although these methods have different historical backgrounds, they are overlapping, and the terms are increasingly used interchangeably. These methods are focused on the individual and describe the individual in context, taking the dynamics of and variability in emotions, cognition, and behavior into account (Devries, 1987; Myin-Germeys et al., 2009). In this way, biases of more traditional methods are reduced, such as retrospective recall bias. Take as an example a study by Mokros (1993), in which patients were asked to report their symptoms during the week and also to recall the symptoms they had experienced at the end of the week. This study vividly showed that the symptoms that were reported in the moment during the week were strikingly different from the symptoms that were recalled at the end of the week (see also aan het Rot et al., 2012).

The change processes in complex dynamic systems can also occur at several different time scales, even within one system. For example, changes in affect may take place over several minutes or even hours, whereas changes in the underlying neural circuits of the brain occur much faster, at the time scale of 10–100 ms, and the firing of a neuron takes only around 1 ms (Bertenthal, 2007).

These differences in time scale can make it difficult to determine whether a process should be studied with state- or trait-like measures: sometimes a process seems to be trait-like until it is examined on a different time scale, when one can see that it is actually a succession of different states. For example, an individual with obsessive-compulsive disorder (OCD; see also Chapter 6) may be characterized by repetitive behaviors such as hand washing according to specific rules. When OCD is thus fully developed, it may seem like a stable trait-like characteristic of an individual that can be captured with a retrospective questionnaire at a single time point. However, taking a different perspective and measuring the symptoms of OCD at a more fine-grained timescale, one could actually capture the *process* in which such rituals develop and become established. In the latter case, a mental disorder such as OCD can be seen as a process that needs to be studied dynamically in order to understand and perhaps even prevent it. Thus, depending on the time scale, one can perceive a phenomenon, such as a mental disorder, as either trait-like or state-like.

Notably, these different time scales in complex dynamic systems are typically not distinct but hierarchically related (Bertenthal, 2007; Eronen, 2021). For example, an episode of depression unfolds over a time scale of weeks or months. However, the episode of depression itself consists of symptoms, such as insomnia, pessimistic thoughts, or rumination, which take place at a faster time scale of weeks or days. These symptoms, in turn, can be seen as consisting of moment-to-moment changes and ↳ interactions among affect states (Wichers, 2014). Specifically, experiences of negative affect may not be disabling if they occur every now and then, but become problematic and disabling when they occur repeatedly or are constantly present, turning into a symptom of depression. Thus, studying mood in daily life at the time scale of minutes or hours can give a more fine-grained picture of the development of symptoms related to depression (Wichers, Wigman, & Myin-Germeys, 2015).

In this way, complex dynamic systems can be seen as having a hierarchical structure, forming multiple levels at different time scales (see also Jeronimus, 2019). Moreover, whether a level is (higher) macro-level or (lower) micro-level depends on the context: if the starting point is disorders or diagnostic categories, individual symptoms can be seen as forming a micro-level from which disorders arise, but from the perspective of daily life at the time scale of minutes or hours, symptoms themselves can be seen as a higher macro-level. In general, none of these levels should be seen as a priori good or bad; instead, their suitability and importance should depend on the question at hand (Bertenthal, 2007; Eronen, 2021; Lichtwarck-Aschoff et al., 2008).

Complex Dynamic System Models

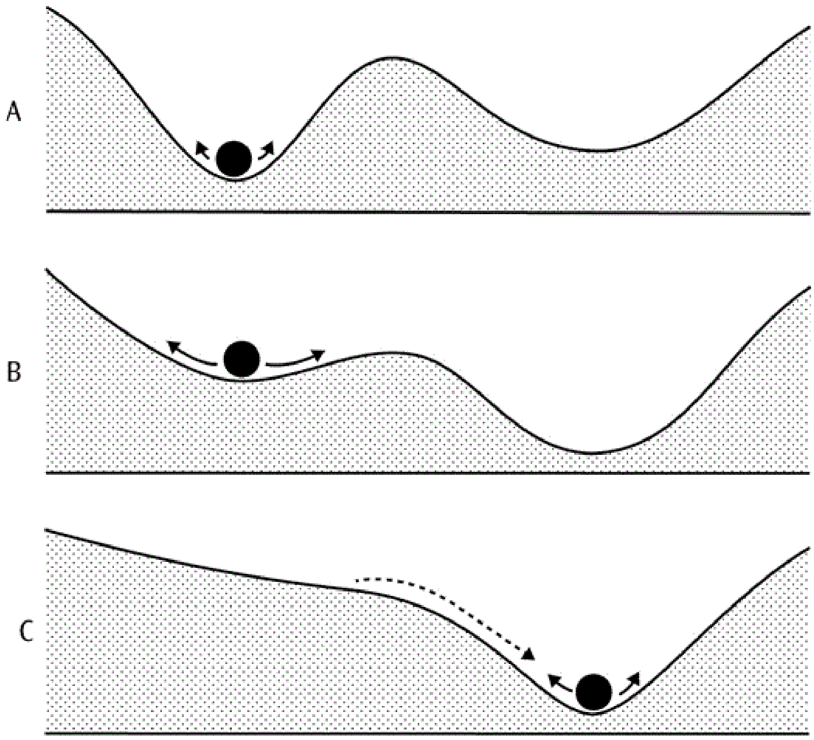
Dynamic system models can be understood very broadly as mathematical descriptions of how a system changes or evolves over time and how the state of a system depends on its past states (Laurenceau et al., 2007; Richardson et al., 2014). Formally, the state of a system is defined as the current value of the variable(s) that describes the system (Richardson et al., 2014). A dynamic system model is then a set of mathematical equations (e.g., differential equations, see below) that specify how the state of the system changes from one moment to the next as a function of the past (Granic, 2005). In contrast, static models, such as mixed-effect or multilevel models (Snijders & Bosker, 2011) or (latent) growth curve models (McArdle, 2009), are far more dominant in clinical psychology, especially in longitudinal research (Voelkle & Oud, 2015). However, unlike dynamic models, static models do not capture how the state of a system depends on its state at a previous moment (Laurenceau et al., 2007). In other words, static models often resort to explaining changes by the mere passage of time, whereas dynamic models use past behavior to explain future behavior (Voelkle et al., 2018).

Commonly used static models also have further limitations when applied to mental disorders. For example, a standard linear growth function assumes that there is unbounded increase or decrease ad infinitum when extrapolating into the future or past. This is not realistic when studying an individual with, for example, major depressive disorder. The symptoms of depression do not just increase indefinitely, but rather fluctuate around an equilibrium, also known as an *attractor* in the dynamic systems literature (Johnson & Nowak, 2002). One can have more symptoms one day and fewer symptoms on another day as the system is influenced by (external) factors such as stressful (e.g., a fight with one's partner) or positive (e.g., getting a promotion) events (Laurenceau et al., 2007). These fluctuations can then occur either around a nondepressed attractor, when the person tends to return to a nondepressed state after perturbations, or an attractor corresponding to depressed state, when the person tends to return to a depressed state after perturbations. The goal of treatment can be seen as helping the individual to shift from one attractor (a depressed state) to another (a nondepressed state).

In the dynamical systems literature, a common approach has been to use sets of differential equations, which have a long tradition in physics where they were originally used to model the dynamics in systems such as pendulums or planetary systems (Richardson et al., 2014). Today, differential equations are also increasingly used in psychological research (Boker & Wenger, 2007; van Montfort et al., 2018; Ryan et al., 2018). As they specify the amount of change occurring in a variable at a specific moment (i.e., over an infinitesimally small time interval), they are particularly well suited for modeling change processes in psychology (Boker et al., 2016).

Importantly, differential equation models can indicate that there are specific attractors toward which the system tends to move over time (Wood et al., 2018). Thus, internal factors or external stressors can "push" the system away from its stable state, and it will take a certain amount of time for the system to return to a stable state, depending on how strong the attractor is. By observing the variables of the system for a period of time, these fluctuations around a stable state can be mapped in such a way that they visually describe the "landscape" of the system (Richardson et al., 2014). One central aim in dynamic systems modeling is to capture and study this *stability landscape* and its attractors in the system of interest.

Figure 5.1



Visual representation of alternative stability landscapes. The stability landscape represents a person's psychological system, where the shape of the system reflects how resilient a person is to external shocks (e.g., psychologically impactful events). The ball represents the current state of the system (e.g., current emotion) and the attractors the possible stable states that the system can be in (e.g., depressed state). A. The system shows a strong ("deep") attractor. B. The system is destabilizing and the attractor has weakened. C. The ball has "tipped over" into the new attractor, and the old attractor disappears.

Adapted from Helmich, M. A. (2021). Early warning signals and critical transitions in psychopathology: challenges and recommendations. *Current Opinion in Psychology, 41,* 51–58. Copyright 2021 by Marieke Helmich. Adapted with permission.

p. 107 Figure 5.1 provides a simplified visualization of such a stability landscape, which represents the ↳ person as a psychological system. The basins represent attractors in the system (e.g., a depressed and nondepressed state) and the ball symbolizes the individual's psychological state at a given time (e.g., current emotions). The shape of the landscape and the depth of the basins, in particular, reveal how resilient a person is to external shocks or stressors (e.g., psychologically influential events): they are likely to recover more quickly when the basin is "deep" and the ball is less likely to move far away from the bottom of the basin.

For example, in a landscape with one deep attractor, shown in Figure 5.1c, the system has a single stable resting point around which it varies and to which it returns over time. However, a system may also be *bistable*, having two attractors in the stability landscape (e.g., a depressed and nondepressed state), as in Figure 5.1a and 5.1b, or have multiple attractors between which it can switch. Not only can there be several attractors in a dynamic system, but the number and type of attractors in the system can also *change* in response to internal or external factors (Richardson et al., 2014). For instance, a bistable landscape with two attractors (depressed and nondepressed state; Figure 5.1b) may develop into a landscape with just one attractor (depressed state; Figure 5.1c).

A particular focus of interest has been cases where gradual change in external variables results in a sudden dramatic change in the stability landscape and thus the behavior of the system (Chow et al., 2015; Richardson et al., 2014). These are called *catastrophes*, and a mathematical framework to describe them is provided by *catastrophe theory* (Chow et al., 2015; van der Maas & Molenaar, 1992; Zeeman, 1977).[1] There are several different types of catastrophe models in the literature, of which a specific model called the *cusp* *catastrophe model* has been the most popular one, also in psychology (Chow, 2019; Richardson et al., 2014). p. 108 The cusp model is one of ↳ the simplest catastrophe models, and it describes how the interplay of just two independent variables (called *control parameters*) results in sudden changes in the behavior of the system (represented by one dependent variable).

One of the earliest applications of catastrophe theory to clinical psychology was Zeeman's model of anorexia nervosa (Scott, 1985; Zeeman, 1976). According to this model (which comes from Zeeman and does not necessarily reflect current knowledge about anorexia nervosa), sudden changes in eating behavior occur even though the underlying factors, namely hunger and abnormal attitude toward food, change only gradually (Nelson et al., 2017; Zeeman, 1976). As abnormal attitude toward food increases and diets become more restrictive, hunger also steadily increases. At some point, behavior may then switch abruptly from fasting to the other extreme, binge eating.

In dynamic systems terms, the control parameters in this catastrophe model are abnormal attitude toward food and hunger, and the dependent variable is eating behavior. Initially, there is only one attractor in the system—namely, fasting—meaning that the person tends to return to fasting behavior after perturbations, such as attempts to normalize eating behavior. However, as the control parameters (abnormal attitude toward food and hunger) steadily increase, the stability landscape of the system changes in a sudden and catastrophic way. A new landscape emerges, now with two attractors: fasting and binging. Eating behavior will then jump between these two extremes, fasting and binging. Thus, with the catastrophe model, these interactions between the abnormal attitudes toward food and hunger (the control parameters) and eating behavior (the attractors; fasting and binging) can be mathematically described.

Although catastrophe theory provides an elegant mathematical framework, in practice it is often very difficult to fit a catastrophe model to (clinical) data (Chow, 2019; Chow et al., 2015). Therefore, in psychology, the focus has been on so-called *catastrophe flags*, which are specific features that can indicate that the system exhibits catastrophic behavior (Gilmore, 1981; Kunnen & van Geert, 2012). Of most interest for clinical psychology have been flags that can be observed right before or during a sudden change or transition: anomalous variance, divergence of response, and critical slowing down (van der Maas & Hopkins, 1998). First, *anomalous variance* refers to the phenomenon that the variance of the key variable (e.g., eating behavior in the anorexia example) increases markedly before a transition occurs, meaning that the spread of the values of the variable becomes wider. Second, *divergence of response* means that, before a transition occurs, even small external stressors result in large fluctuations in the behavior of the system. Finally, a closely related flag is *critical slowing down*, meaning that when it is close to a transition, the system takes more time to recover and returns more slowly to its stable state when perturbed.

These flags can be detected from time series data (e.g., ESM/EMA data). As fitting a (cusp) catastrophe model can be very challenging, a common solution is to, for example, detect anomalous variance by checking if there is a sudden change in the data (e.g., with change point analysis; Wichers, Schreuder, Goekoop, & Groen, 2019). These flags are not only indicators of catastrophic behavior of the system in general, but also central candidates for EWSs, which we will discuss in more detail in the next section. Importantly, while a given flag may suggest that the system exhibits catastrophic behavior, taken alone it cannot sustain the conclusion that a (cusp) catastrophe model applies (van der Maas & Molenaar, 1992). Furthermore, there is a large translational step from the dynamic (catastrophe) models to time series models, and many assumptions and choices have to be made regarding, for example, time scale, number of measurements, and relevant variables measured, which can all influence the outcomes (Haslbeck & Ryan, 2021). These issues will be also touched upon in the next section.

Early Warning Signals

EWSs are the part of complex dynamic systems modeling that has drawn the most attention in psychopathological research. EWSs occur when the stability landscape is slowly changing as the system approaches a tipping point, it becomes less resilient to shocks, and a sudden "critical transition" to a new state may be imminent (Scheffer et al., 2009). To explain this, we return to Figure 5.1. In Figure 5.1a, the system appears relatively stable, the basin is "deep"—the attractor is strong—and even though the ball will move around in response to external stressors, with time, the ball will be pulled back to the bottom of the basin. Note that, while a potential alternative attractor appears on the right side of Figure 5.1a, only a very strong impulse would cause the ball to be pushed into that basin.

Translated to psychology: if we view the left side of the figure as an individual's mental state, which is
p. 109 currently relatively stable and healthy, it would ↳ require a strong trigger—like losing a loved one—for the system to switch to the right side, which can be understood as a more negative, possibly depressed, stable state. In Figure 5.1b, the system has lost resilience and the current attractor has become weaker and the basin shallower. As a result of this change in the stability landscape, the system in Figure 5.1b is more vulnerable to "tip over" with a sudden shift to the alternative attractor on the right side of the figure: no longer does the ball need a large impulse to be pushed over the edge of the left-hand basin; even a small push could effectively cause a critical transition to a depressed state or another psychopathological state.

As complex dynamical systems are composed of interacting variables that can change at different rates, zooming in on the moment-to-moment changes in one variable can be informative of an upcoming change in another, slower changing variable. In the context of psychopathology, this had led to the hypothesis that EWSs may be detectable in momentary affective states before a sudden shift in symptoms, such as a depressive relapse (Wichers et al., 2016, 2020) or sudden improvements in the context of therapy (Olthof et al., 2020).

The clinical promise of EWSs is that clinically important symptom changes could be anticipated by monitoring individuals' moment-to-moment (affective) experiences in the course of daily life (e.g., based on ESM/EMA data). The idea that EWSs could be used as "generic" indicators of future symptoms shifts has led researchers to speculate about the potential of monitoring individual patients or at-risk individuals and using EWSs to make personalized prediction and timely intervention possible. For instance, if EWSs are found to be consistently effective at predicting impending changes in individuals, their application in clinical practice could include early detection of episodes of mental illness (Kuppens et al., 2012; Wichers et al., 2019), thus identifying sensitive periods in which psychological treatment may be more likely to effectuate positive symptom change (Hayes & Yasinski, 2015; Schiepek, 2003), as well as improving timely intervention in cases of depressive relapse and suicide attempts (Bryan & Rudd, 2018; Wichers et al., 2016, 2020).

Examples of Early Warning Signals

Many different possible EWSs have been discussed in the literature; here we focus on those that have received the most attention in psychology: critical slowing down, flickering, and critical fluctuations (similar to anomalous variance). The latter is a notion developed in recent years in ecology, a field in which many other EWSs also have been described (e.g., spatial variance and spatial skewness; Scheffer et al., 2009). Further EWSs have also been explored in simulations studies (e.g., dominant eigenvalue of the covariance matrix; Chen et al., 2019). However, these have not been tested in clinical data yet.

The first one, *critical slowing down*, was already briefly mentioned as a catastrophe flag in the previous section. In the context of EWSs, critical slowing down can be inferred from changes in the temporal dynamics of the system's variables, which then serve as an EWS. This "critical slowing" of the system means that the current attractor becomes weaker (the basin in Figure 5.1a changes to that in Figure 5.1b), and this changing landscape can be inferred from how the system recovers (returns to its stable state) from perturbations. Thus, in the landscape in Figure 5.1b, the ball tends to go farther away from the stable state and takes longer to return than in the landscape in Figure 5.1a. In other words, it takes longer for the system to recover after perturbations.

In statistical terms, this has been taken to imply an increase in *autocorrelation*. In brief, autocorrelation indicates how well the value of a variable (e.g., an emotion) at a given point in time predicts the value of the same variable at the next point in time (e.g., the same emotion at the next time point). Thus, as the ball spends more time away from its stable position (the mean), consecutive states are more similar and more highly correlated with previous states, which results in higher autocorrelation. Moreover, as the distance from the stable position also increases, critical slowing down is expected to correspond to a higher variance (i.e., more spread in the values of the variable) over time. Translated to the individual's psychological viewpoint, and specifically to momentary affect, the effect of critical slowing down would show as emotions that become increasingly volatile as the system is destabilizing (increased variance), and, once something triggers an emotional reaction, this feeling is likely to linger longer over time (increased autocorrelation).

A second possible EWS that has been studied in psychology is a phenomenon known as *flickering*, where the system moves back and forth between two alternative attractors (Scheffer et al., 2009). This can happen when the landscape changes in a way that makes it easier for the ball to roll from one basin (attractor) to
p. 110 another, as in Figure 5.1b. This, too, can be considered an EWS because the system ↳ may end up being shifted permanently to the alternative state and restabilize into a new (single) stable state. When statistically analyzing the changes in the system based on time series (ESM/EMA) data, flickering can be observed as bimodality or skewness in the distribution of the variables measured and can also be indicated by increases in variance (Scheffer et al., 2009). In psychopathology, bimodality has been observed in the (frequency) distribution of symptoms of major depressive disorder (Hosenfeld et al., 2015) and has been hypothesized to be of particular interest for patients with bipolar disorder, where the manic and depressed state may represent alternative stable states of the system (Goldbeter, 2011; Johnson & Nowak, 2002).

Finally, as the system is destabilizing, but has not yet settled into a new attractor, EWSs in the form of *critical fluctuations* may occur (Hayes et al., 2007; Olthof et al., 2020). With the stability landscape losing resilience and the current attractor losing strength—or even disappearing—the system starts moving between many different alternative states. These critical fluctuations occur over more dimensions than can be shown in Figure 5.1, and, in contrast to flickering, where the ball is rolling back and forth between two basins (i.e., attractors), in critical fluctuations the ball is rolling wildly around a destabilized landscape until it settles into a new stable attractor (Hayes et al., 2007). This behavior of jumping around in the destabilized landscape appears as large fluctuations and can be statistically observed as increases in indicators such as variance (or entropy; Olthof et al., 2020).

In general, what holds for all these EWSs is that if the "normal," dynamically stable state of the system is known, for example through studying the system over a long period of time, the EWSs can be identified as deviations from what would be expected if the system was stable. For instance, if the autocorrelation or variance of the system no longer fluctuates around the expected stable value but starts to increase, these increasing trends can function as EWSs.

Early Warning Signals in Psychopathological Research

EWSs have been studied in psychopathology at both the group (nomothetic) and individual (idiographic) levels, mostly focusing on major depressive disorder. Group-level studies have examined, based on time series (ESM/EMA) data, whether indications of instability and destabilization *on average* relate to stronger concurrent symptoms (Koval et al., 2013; Sperry et al., 2020) or later symptom change (Curtiss et al., 2019; Kuppens et al., 2012; Kuranova et al., 2020; Olthof et al., 2020; Schreuder, Hartman, et al., 2020; van de Leemput et al., 2014). These studies show that, on average, persons with higher levels of autocorrelation and variance in their daily affective experiences are more likely to have a psychopathological diagnosis or experience a change in symptoms later in time. While this provides some evidence for the hypothesis that (developing) psychopathology is related to the temporal dynamics associated with EWSs, this group-level evidence is indirect, and a true test of this hypothesis requires studies at the individual level (see also Bos & de Jonge, 2014).

Indeed, because EWSs hold the promise of informing person-specific predictions, they should also be studied and tested at the individual level. This requires examining the temporal dynamics in time series of individual subjects as they experience changes in symptoms. Because such an intensive longitudinal design is not (yet) common in psychopathology research, only a few studies have been able to test empirically whether sudden symptom transitions were indeed preceded by EWSs in individual time series data (Olthof et al., 2020; Wichers et al., 2016, 2020).

For instance, Wichers and colleagues (2016) monitored one individual with a history of major depressive episodes while he was tapering his antidepressant medication. The participant completed 10 ESM questionnaires each day, which were sent at semi-randomly determined times across the day, and his depressive symptoms were assessed every week, over a period of about 8 months (239 days).[2] While the participant's symptoms were stable at the start of the study period, reducing medication dosage increased the risk of a depressive relapse, and the participant did relapse after 18 weeks. Upon examination of the temporal dynamics in the data, the researchers found that EWSs in the form of autocorrelation and variance rose significantly in the weeks preceding the symptom transition. This study was the first to show empirical evidence of EWSs for a specific individual in the context of psychopathology. Since then, the same
p. 111 researchers have replicated this result in one more participant, finding ↳ that autocorrelation and variance started rising a month before a transition in symptoms—again, a depressive relapse—occurred (Wichers et al., 2020).

Moreover, F. M. Bos and colleagues (2021) conducted an exploratory study of whether EWSs (again, rises in autocorrelation and variance) in EMA-measured affective time series preceded transitions to depression and mania in a sample of 20 bipolar I/II patients. Eleven patients experienced one or more transitions to depression or mania during the 4-month observation period, but the results regarding the added predictive value of EWSs were mixed both between and within persons.

In sum, these first empirical studies provide tentative evidence that a rise in autocorrelation and variance preceded a transition in depressive symptoms and could therefore function as an EWS. However, much more research and consistent evidence is required to substantiate the utility of these EWSs for personalized predictions.

Promises and Problems

Although the focus in studies of EWSs in psychopathology has been on rises in autocorrelation and variance, there is no consensus on how to best search for EWSs in clinical research and practice. Here we discuss some important challenges and open questions, as well as possible solutions.

The first challenge is in collecting data that are suited for detecting EWSs and testing the hypothesis that EWSs serve as indicators for symptom changes (Helmich, Snippe et al., 2021; Schreuder, Groen, Wigman, Hartman, & Wichers, 2020). For optimal chances of detecting EWSs, individual time series of several patients, consisting of many (several hundred) observations per patient, are needed to ensure that the EWSs can be calculated reliably. A key question is deciding which variables are the most suitable for detecting EWSs (e.g., mood, affect, or symptom variables) and therefore should be measured. It has also been suggested that it may be worthwhile to consider combining several variables, or combining different EWSs (Dablander et al., 2020), to improve the power to detect an effect.

An additional challenge is that, in order to test the hypothesis that EWSs precede transitions, the data also have to include such a transition. Therefore, the data collection should cover a period in which transitions are more likely to occur (e.g., during psychological therapy, while tapering antidepressant medication, or in a group of patients who are prone to showing sudden symptom shifts, such as bipolar patients). Relatedly, the data should include a baseline period to be able to determine if the potential EWSs (e.g., autocorrelation or variance) are really changing relative to what is "normal" for that person.

Regarding transitions, because psychopathology is notoriously heterogeneous in how it is expressed in different individuals, it is important to consider what constitutes a "transition" for a specific individual (Helmich, Olthof et al., 2021). The relative speed, magnitude, and frequency at which symptom shifts occur may strongly vary between persons, disorders, and direction of change (i.e., symptom improvement vs. deterioration). Thus, for one individual a certain increase in depressive symptoms might be an exceptional change, whereas for another individual the same increase may be just usual day-to-day fluctuation. Currently, there is insufficient knowledge of how to generally or specifically identify "critical transitions" in psychopathology, and it is an important and challenging task to explore which change patterns EWSs can actually warn us about.

Finally, an important limitation when focusing on autocorrelation and variance is that increases in them can occur for many different reasons. Therefore, although an increase in autocorrelation or variance can be an indicator of critical slowing down, it can also precede more gradual transitions, or autocorrelation or variance can go up and then down without any transition occurring. It is also possible that critical transitions sometimes occur in a system without being preceded by an EWS (Dablander et al., 2020). Furthermore, an issue that has been recently raised is that it is not clear how much predictive value autocorrelation has over and above the mean (Dejonckheere et al., 2019), as the mean is a function of the intercept and the autocorrelation (see Bringmann et al., 2017, for more details).

In conclusion, although EWSs provide a promising opportunity to apply complexity and dynamical systems theory to improve clinical predictions of changes, many challenges and open questions remain. Several studies are expected to be completed in the coming years that will provide further indications of whether EWSs will deliver on their promise.

Psychopathological Networks

In the past decade, the network approach to psychopathology has become increasingly popular in clinical
p. 112 research and is also finding its way to clinical practice (Robinaugh et al., 2020; von Klipstein et ↳ al., 2020). In this section, we describe this approach and also explain how it is related to the other complex systems approaches discussed above.

The network approach focuses on psychological symptoms and their interrelations, the central idea being that these symptoms causally influence each other in a way that eventually results in a mental disorder (Borsboom & Cramer, 2013). For example, sleeping problems can lead to fatigue, which in turn leads to concentration problems and feelings of sadness, and these latter two then lead to even more sleeping problems (Cramer et al., 2016). As symptoms keep causing and sustaining other symptoms in this way, the result is an episode of depression. Thus, mental disorders are conceptualized as networks of interacting symptoms.

A network can be understood, in the most general terms, as a representation that describes how elements in a system are connected (Bringmann & Eronen, 2018). In network terminology, the elements are called *nodes* and the connections between them are called *edges* (Newman, 2018). For example, if we look at a railway network, the nodes are cities or stations, and the edges are the railways connecting them. Other examples of networks are the Internet, networks connecting brain regions, or social networks (e.g., representing the friendship relations between people). In psychopathological networks, the nodes are symptoms, and the edges are (causal) connections between the symptoms.

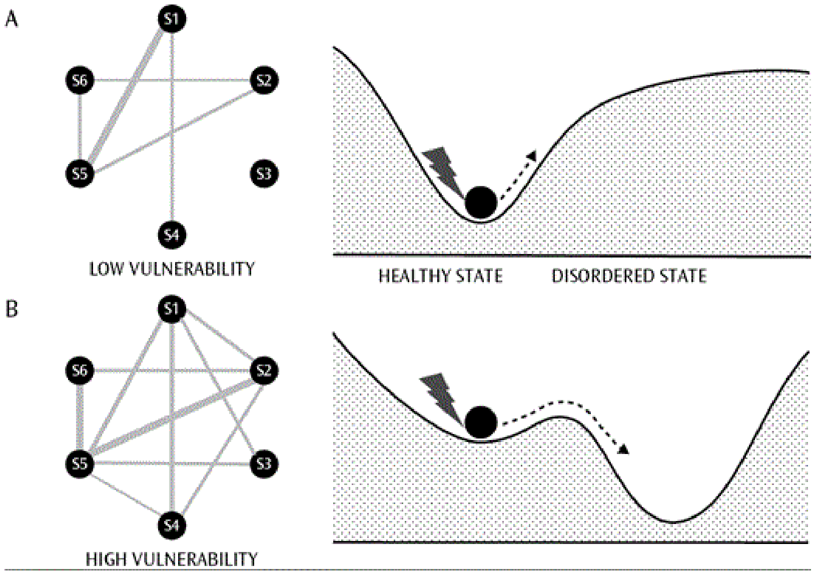
By placing the focus on symptoms and their interactions, the network approach provides an alternative to the medical disease model (Cramer et al., 2010). According to this model, the symptoms of mental disorders have a clear (biological) root cause, analogous to how viruses cause flu symptoms or tumors cause cancer symptoms (Borsboom et al., 2019). The proponents of the network approach argue that no such root causes have been found for mental disorders and that they are likely not to exist: instead, mental disorders simply are networks of interacting symptoms. Therefore, they should also be treated and studied at the level of psychological symptoms. This also fits well with traditional ideas in cognitive behavioral therapy, where interactions between mental states (e.g., Beck's negative triad; Beck, 1979) are seen as central for treating mental disorders (Bringmann et al., 2022).

Constructing a Psychological Network

Networks such as railway networks or social networks can be constructed by simply observing the nodes and connections (e.g., by looking whether there is a railway between two cities or asking whether individuals are friends with each other). These raw data can then be immediately visualized as a network, such as a friendship network that illustrates which children in a school class are friends with each other. However, in psychopathological networks, the edges (i.e., the connections between the symptoms, such as causal relationships) are not visible in the raw data but have to be inferred (Bringmann et al. 2019). Therefore, several existing modeling techniques have been applied to infer psychopathological networks. We focus here on two modeling approaches that have been the most widely used so far.

In the first approach, the edges (or connections) between symptoms are inferred from correlational analyses of data obtained from large groups of persons (Borsboom & Cramer, 2013). In such networks, the nodes are symptoms that are measured once per individual, and the edges are (partial) correlations between symptoms. This results in a symptom network with undirected edges, meaning that the edges do not give information on the direction of the causal influence between the nodes over time (see also the networks in Figure 5.2). Estimating direct (causal) relationships between symptoms is in principle possible but requires strong assumptions (Malinsky & Danks, 2018) and is, in practice, rarely done for psychopathological networks. One shortcoming of cross-sectional networks is that because they are based on aggregating data from many individuals, it is unclear to what extent they reflect within-person processes and thus whether they give information on the network of any specific individual (Hamaker, 2012). Moreover, as cross-sectional networks are based on one measurement occasion, they cannot give information about how psychopathological processes evolve over time (see the earlier section on "Complex Dynamic Systems").

Figure 5.2



Symptom network structure and vulnerability for psychopathological change in a complex dynamical system. This figure shows how the network structure and stability landscape of an individual are expected to differ depending on how vulnerable the system is. The left panel (A) represents a symptom network in a system with low vulnerability: the six symptom nodes (S1–6) are sparsely connected, and the connections are weak, as represented by thinner lines. The right side of A reflects the stability landscape in which such a network may be observed: stressors (the lightning bolt) may push the ball away from its stable point, but the basin is deep and the system will recover rapidly. Moreover, if any of the symptoms are triggered, the other symptoms are not likely to be triggered as well. In B, the left panel displays a more densely connected symptom network in a system with high vulnerability. The stability landscape in the right panel shows that the system is currently still resting in a healthy state but the basin of attraction is weaker (shallower). Here, a stressor is more likely to cause the system to tip over into the "disordered" attractor, and, furthermore, the densely connected symptom network makes it more likely that the individual will remain in this state, as the connections between symptoms reinforce each other.

The second modeling approach is based on time series or intensive longitudinal (ESM/EMA) data. As described in the section "Complex Dynamic Systems", these data consist of repeated measurements over time, where, for example, often measurements at 60 time points or more per person are collected. The most widely used method at the moment to infer networks from such data is the vector autoregressive (VAR) model, in which an individual network for each person is inferred (Bringmann et al., 2013). A VAR-based network is a directed network where an edge between symptoms A and B reflects the extent to which variance in symptom B can be predicted based on variance p. 113 ↳ in symptom A while controlling for all other nodes in the network (Bringmann et al., 2022). Therefore, in contrast to cross-sectional networks, VAR-based networks are person-specific, directional, and explicitly represent relationships over time. VAR-based networks can also include self-loops (i.e., an edge from a symptom to itself, reflecting the extent to which variance in the symptom at one point predicts variance in the same symptom at the next time point) and can also be used to infer contemporaneous effects (e.g., the concurrent [partial] correlations between symptoms within an individual; Epskamp, van Borkulo, et al., 2018).

Importantly, however, VAR-based networks represent just predictive relationships over time, which do not automatically translate to causal relationships (Bringmann, 2021). Indeed, in a recent simulation study, Haslbeck and Ryan (2021) tested how well current VAR-methods recover the causal relationships of a relatively simple system. They concluded that, due to problems such as insufficient frequency of measurements, VAR-based models in most circumstances cannot be used to reliably infer the causal structure of symptom interactions (Haslbeck & Ryan, 2021).

In addition to these modeling techniques, psychopathological networks have also been constructed based on perceived causal relationships (Frewen et al., 2013). The idea behind this approach is that clinicians (or patients) are asked about how they think that symptoms are related to each other, and then networks are constructed based on these expert judgments (Deserno et al., 2020). Thus, the edges in the networks still represent the strength of the (causal) relationship between two symptoms, but instead of being derived from data, they are now based on the estimates of clinical experts or patients. These networks can be person-specific, describing the network of one individual, or general expert estimates on how the symptoms of a disorder are expected to relate to one another. For example, Deserno and colleagues (2020) asked experienced clinicians to rate the relationships between pairs of symptoms of autism spectrum disorder, and then p. 114 ↳ constructed a network based on the average of these ratings. Such perceived causal networks can be seen as hypotheses about the causal symptom structure of patients and can provide a good starting point for further research.

Another possibility is to construct networks based on diagnostic manuals such as the *DSM* or *ICD*, for example by looking at how symptoms of different disorders overlap. Borsboom and colleagues (2011) used this approach to study the symptoms structure of the *DSM-IV* by taking the symptoms as nodes and drawing an edge between two symptoms whenever they appear in the same disorder. This resulted in a network illustrating the symptom overlap in the *DSM-IV*, showing, for example, that there is considerable overlap among the symptoms of mood, anxiety, and substance abuse disorders. Tio and colleagues (2016) used the same approach to compare the symptom structure of *DSM-IV* and *ICD-10* and found clear structural differences between the two diagnostic systems (e.g., that there was more symptom overlap in *ICD-10* than in *DSM-IV*).

Perceived causal networks and diagnostic manual networks are promising approaches but have received relatively little attention in the psychological network literature so far. Note that although the ways that these networks are constructed are very different from cross-sectional or VAR-based networks, they have nevertheless been analyzed using the same network techniques (described in the next section).

Density and Centrality

Once a network has been constructed, it can be further analyzed with a whole toolbox of techniques stemming from network science. We focus here on *density* and *centrality*, which have been the most commonly used network measures in psychopathology. The density (also known as *connectivity* in the psychopathological network literature) of a network refers to the relative number of edges in the network: a network with many edges and therefore many connections between the nodes is said to be *dense,* whereas a network with few edges is said to be *sparse* (Newman, 2018). In the psychological network literature, density is also used to refer to the mean strength of the edges: a network with stronger connections is denser than a network with weaker connections, even if they have the same number of edges (Pe et al., 2015).

One hypothesis is that individuals suffering from depression have a denser symptom or emotion network than do nondepressed people and are therefore more resistant to change (Pe et al., 2015). In a dense network, the symptoms or negative emotions can easily strengthen each other, making it more difficult to get out of a state of depression or a spiral of negative mood. This hypothesis has been studied in cross-sectional setups, but the results are inconclusive (Robinaugh et al., 2020), and it is also unclear to what extent cross-sectional studies can give information about the density of individual networks (Bos & Wanders, 2016). Time series analyses based on the VAR-model have found some evidence for denser networks in depressed individuals but have focused more on emotion or affect networks than on symptom networks.

For instance, Pe and colleagues (2015) conducted an ESM study comparing a healthy control group (n = 53) with participants diagnosed with major depression (n = 53). Over the course of 7 days, participants were prompted eight times per day to assess their negative (seven items) and positive (four items) affect using a 4-point scale. Networks were then inferred using a multilevel version of the VAR model. Density was calculated based on the absolute values of the connection strengths between the affect variables (i.e., the slope coefficients of the multilevel VAR model). When comparing the networks of the depressed and healthy individuals, the results indicated that depressed individuals had a denser network of (negative) emotions than did healthy individuals. Using the same method, Wigman and colleagues (2015) also found evidence for a more strongly connected network of thoughts and affect states in individuals with a diagnosis of depression than in healthy individuals.

However, results of density studies may be sensitive to specific methodological or modeling choices, such as whether the estimated parameters are penalized to limit the complexity of the model (de Vos et al., 2017). Ideally, the density hypothesis should also be studied within an individual. For example, in the study described in section "Early Warning Signals in Psychopathological Research," Wichers and colleagues (2016) also followed the network density in a person who first was in a healthy state and then transitioned abruptly to an episode of depression. Indeed, results seem to indicate that the network density of affect states increased over time for this specific individual, but replication studies are still needed before any conclusions can be drawn (see also Wichers et al., 2020).

Perhaps the most widely used network measures in psychopathology are *centrality measures*. These
p. 115 measures are intended to indicate which nodes in ↳ the network are important. The underlying idea is that nodes with a high centrality have strong connections to other symptoms and therefore play an important role in the network (Newman, 2018). In psychopathological network theory, an important hypothesis has been that the highly central symptoms can spread the activation of symptoms in the network and therefore intervening on such symptoms would be an important goal for clinical practice (Borsboom & Cramer, 2013). In this way, the focus is shifted from the state of the overall network to individual symptoms (Robinaugh et al., 2020). Following these theoretical ideas, many empirical studies have aimed at finding the most central symptoms in psychopathological networks (Boschloo et al., 2016; Rodebaugh et al., 2018).

There are many centrality measures, but those most widely used in this field have been *degree* and *betweenness* centrality (Bringmann et al., 2019). Degree centrality is calculated simply by taking the sum of the edges that a node has. Therefore, nodes that are connected to many other nodes have a higher degree centrality than nodes that are connected to only a few other nodes. For example, in a network representing the friendship relationships in a school class, the child with the most friends would have the highest number of edges and therefore the highest degree centrality. If the network is weighted—that is, the edges can have different weights—the sum of the (absolute) weights is taken, and the measure is called *strength* centrality.

Betweenness centrality is a more complex measure and is calculated based on the shortest paths between nodes (Freeman, 1977). A node that lies on many shortest paths between other nodes has a higher betweenness centrality than a node that lies on only a few shortest paths. For example, if a city in a railroad network lies on many shortest paths between other pairs of cities, then that city has a high betweenness centrality.

Translating these measures to psychopathological symptom networks is not always straightforward (Dablander & Hinne, 2019; Hallquist et al., 2021). It may at first blush seem intuitively plausible that a symptom with many connections to other symptoms (i.e., degree centrality) or a symptom that is on many shortest paths between other symptoms (i.e., betweenness centrality) plays an important role in the symptom network. However, the centrality measures were originally developed with social networks in mind, and, as we have mentioned earlier, there are important differences between social networks and psychopathological networks (Bringmann et al., 2019). For instance, in psychopathological networks the edges are often negative (representing, e.g., a negative partial correlation), whereas in the kind of networks for which the measures were developed, there are only positive edges (e.g., there cannot be a negative railroad path: there is either a path or there is not). Researchers using psychological networks deal with this generally by using absolute values of the edges when calculating centrality measures, making the negative edges positive. The result is that crucial information (e.g., that the partial correlation was negative) is lost. Due to this and many other issues (Bringmann et al., 2019), some experts on psychological networks have refrained from using centrality measures in their network analyses (e.g., Epskamp, van Borkulo, et al., 2018).

Networks and Complex Systems

In its early days, the network approach was not connected to complex systems theory (Borsboom, 2008), or the nature of the connection between the two was not explicitly spelled out (Cramer et al., 2010). However, there is considerable overlap between the two approaches, and, in recent years, the connection between them has also been clarified and discussed (Borsboom, 2017).

A starting point for connecting the complex dynamic systems and network approaches is network density (see section "Density and Centrality" above). Following Borsboom (2017), a network of symptoms can be seen as a complex dynamic system that can be in different stable states. These different stable states correspond to attractors in the system: for instance, a depressed and a healthy state. The idea is then that the density of the network partly determines how many attractors there are and whether a system transitions easily from one attractor (e.g., healthy state) to another (e.g., depressed state).

First, let us consider a network with low density, illustrated in the left panel of Figure 5.2a. Because the connections between symptoms are weak (indicated by thinner lines), external stressors do not easily result in symptoms activating each other. The stability landscape associated with this network is shown in the right panel of Figure 5.2a: there is just one attractor (the deep basin) in the system, corresponding to the stable healthy state, and the system tends to return to this attractor after perturbations (Borsboom, 2017).

However, in a dense symptom network, illustrated in the left panel of Figure 5.2b, the edges between
 symptoms are strong, and the activation of ↳ a symptom after an external stressor easily leads to symptom spread throughout the network. In complex systems terms, there are two attractors in the stability landscape of the system: one corresponding to a stable healthy state and one to a stable depressed state (Borsboom, 2017). The stability landscape in the right panel of Figure 5.2b illustrates how the system is currently still resting in a healthy state, but the attractor (the basin) is weaker (shallower) than the attractor corresponding to the depressed state (the deeper basin on the right). Between these attractors is a tipping point (the ridge), and, when this tipping point is reached (through perturbation and symptom activation), the system transitions from a healthy to a depressed state (Borsboom, 2017). Thus, stressors may cause the system to tip over into the "depressed" attractor, and furthermore, the densely connected symptom network makes it more likely that the individual will remain in this state (the deeper basin) because the connections between symptoms reinforce each other. Based on this conceptual framework, Borsboom (2017) defines mental health as "the stable state of a weakly connected symptom network" and mental disorders as "alternative stable states of highly connected (sub)networks of symptoms."

This theoretical framework has direct connections to the EWS literature discussed in the previous section. In addition to measures such as autocorrelation, network density also can be interpreted as an EWS, the idea being that the density of the network increases before the transition is reached. In other words, close to a transition, the variables of the system start to behave more similarly and are thus more highly correlated. In fact, these two measures, autocorrelation and density, are closely linked: autocorrelation is represented as self-loops in the VAR-based network, and therefore network density also partly reflects the strength of the autocorrelation of symptoms (Pe et al., 2015). Indeed, as discussed above in section “Density and Centrality,” preliminary research suggests that the density of the network also is increasing before a transition into a depressed state (Wichers et al., 2016, 2020).

Challenges and Future Outlooks

Although these theoretical ideas are promising, there are still important unresolved issues. To start with, in the current network literature we often observe networks that not only contain symptoms and negative affect states, but also positive affect states as “happy” or “excited” (Pe et al., 2015). However, the original network theory as described above is based on symptom networks, and the idea that a dense network is associated with psychopathology crucially relies on the assumption that the nodes are symptoms or negative variables, which then keep easily activating each other. In a network with nodes representing positive affect states included (i.e., positive nodes), the reasoning does not work in the same way. In a dense network, these positive nodes also are more easily activated, which can lead toward a more positive overall state as positive nodes keep activating each other. Therefore, the link between density and psychopathology is conceptually unclear in networks where positive nodes are included.

The same holds for autocorrelation or self-loops: with positive nodes such as “happy,” a high autocorrelation is unlikely to function as an EWS for depression. Moreover, not only the strength of the autocorrelation (and whether the node is positive or negative) but also the mean level of the node is crucial. If the mean level is low, a high autocorrelation actually implies that the node will tend to stay at a low mean level. Thus, even in symptom or negative affect networks, a high autocorrelation is unlikely to be an EWS if the mean symptom levels are very low. This highlights that although the edges are often the focus of interest in networks and complex dynamic systems, the simple mean should not be forgotten when studying psychopathology (Bringmann & Eronen, 2018).

Another way to connect network theory and complex systems theory is via formal theories using differential equations, which have recently received much attention (Burger et al., 2020; Robinaugh et al., 2021; see also Goldbeter, 2011). In the formal theory approach, a model is constructed where the nodes and the relationships between them are specified in a mathematically precise way, typically with differential equations that describe how each variable changes over time as a function of the other variables. Thus, in contrast to a data-driven model such as the VAR model, where the edges are purely determined by the data, the formal approach starts from theory, from which testable models are then derived.

Robinaugh and colleagues (2019), for example, used this approach to develop a model of panic disorder, including variables such as arousal, perceived threat, and escape behavior. Based on theoretical considerations, they formulated a set of differential equations that represent the presumed relationships
p. 117 between these variables. At the core of this model is a bidirectional causal relationship between perceived
↳ threat and arousal, which is moderated by a context variable (representing the presence or absence of an anxiety-inducing context) and arousal schema (representing beliefs and learned associations regarding arousal).

By means of computational modeling (simulations), Robinaugh and colleagues (2019) studied the behavior of their proposed model and evaluated its ability to produce common features of panic attacks and panic disorders. According to the authors, the model successfully reproduces some key features of panic disorder, such as the rapid onset of panic attacks. It also makes predictions that can be tested: for example, the model initially did not reproduce the phenomenon of nonclinical panic attacks because, in the simulations, occurrence of panic attacks always resulted in developing a full-blown panic disorder. This led the authors to add an “escape schema” variable to the model, representing beliefs concerning the effectiveness of escape behavior as a way to respond to perceived threat. However, a shortcoming of the model is that it remains highly theoretical: the parameter values and functions are not based on empirical data, but on their theoretical plausibility and ability to produce the relevant behavior (Robinaugh et al., 2019).

More generally, Burger and colleagues (2020) propose to use these kinds of theory-driven models based on differential equations to model mental disorders and also argue that they can be useful to inform case conceptualization in clinical practice. Overall, there seem to be relevant links between networks and complex dynamic systems models and ways in which they can be fruitfully combined to model and understand psychopathology.

Conclusion

In this chapter, we have shown that there are many different approaches to studying psychopathology in terms of complex systems. We started out by discussing what complexity means and what complex systems are. After this, we turned to complex dynamic models that appear in the psychological literature and how these models are currently used in the field of psychopathology in the form of EWSs and psychological networks.

An important point to emphasize is that there are many different definitions of complexity or complex systems and that, even focusing just on the psychological literature, there is no exact definition for these terms that would be currently agreed upon. Even more so, the translation of the theoretical concepts and ideas associated with complex systems to actual models and applications is challenging and has taken place in very heterogeneous ways. For instance, nonlinearity and self-organization are central to theories of complex dynamic systems, the idea being that complex nonlinear behavior emerges from the interactions of many components. However, in practice, when applying a complex systems approach in clinical psychology, researchers are often just looking at increases in autocorrelation or variance in one variable (e.g., negative affect), which does not reflect the idea of complex behavior emerging from the interactions of many components.

Similarly, approaches that focus on individual symptoms, such as centrality measures, may not capture or reflect the complexity of mental disorders (Bringmann et al., 2019). It is hard to understand the behavior of a complex system by studying individual components (Cramer et al., 2010); instead, a more promising approach is to focus on the dynamics of the system as a whole (Bringmann et al., 2019). Furthermore, standard network models such as partial correlations or VAR models are linear models, and, even more so, partial correlation models are static, not dynamic, models. A promising approach that can help in translating the ideas of complex dynamic systems theory to psychological models is the recent turn in the network approach to formal models based on differential equations.

A further open question that needs to be emphasized is: What is the "system" when we talk about complex dynamic systems in psychopathology? Depending on the context and the author, it can be the person (as in most examples in this chapter), the mental disorder (Kossakowski et al., 2019), a network of symptoms (Nuijten et al., 2016), or many other things. This question is important, not only because it determines the focus of research, but also because variables that belong to the internal dynamics of the system are treated differently than external influences when modeling the behavior of the system.

In conclusion, complex systems approaches have become an integral part of psychopathological research, and many different pathways of implementing these approaches have evolved in the past decades. It is up to future research to disentangle the conceptual landscape of complexity and develop further ways of applying the theoretical ideas to the field of psychopathology.

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Notes

1 A similar approach coming from a different theoretical background is the synergetics approach building on the theory of Hermann Haken (Tschacher et al., 1992).

2 The data are openly available here: https://openpsychologydata.metajnl.com/articles/10.5334/jopd.29/