**Bouncing back from life's perturbations:
Formalizing psychological resilience from a complex systems perspective**

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Declaration of Interest

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Abstract

Resilience refers to the ability to return to normal psychological functioning despite facing adversity. It remains an open question how to anticipate and study resilience, due to its dynamic and multifactorial nature. This paper presents a novel formalized simulation framework for studying resilience from a complex systems perspective. From this view, resilience is a *property* of a system that arises if a system is located in a stable and healthy state despite facing adversity. We use the network theory of psychopathology, which states that mental disorders are self-sustaining endpoints of direct symptom-symptom interactions organized in a network system. The internal structure of the network determines the most likely trajectory of symptom development. We introduce the *resilience quadrant*, which organizes the state of symptom networks on two domains: 1) healthy versus disordered, and 2) stable versus unstable. The quadrant captures different behaviors along those dimensions: resilient trajectories in the face of adversity, as well as persistent symptoms despite treatment interventions. Subsequently, we introduce a systematic methodology, using simulated perturbations, to determine where in the resilience quadrant an observed network is currently located. As such, we present a novel outlook on resilience by combining existing statistical symptom network models with simulation techniques.

Introduction

Why do some people suffer from mental illness after a disruptive, stressful life event, while others seem to bounce back relatively rapidly from such adversity without developing (lasting) psychopathology? Around 90% of people in Western countries experience at least one potentially traumatizing event during their lifetime, but the lifetime prevalence of posttraumatic stress disorder is only about 8% (de Vries & Olf, 2009; Kilpatrick et al., 2013). In the immediate aftermath of a stressful life event, depressive symptoms occur quite frequently (e.g., 25% according to Cénat & Derivois, 2014), but many initially afflicted people return to healthy physical and psychological functioning (Bonanno et al., 2004). The ability to preserve or quickly bounce back to psychological health and normal functioning after adversity is referred to as *resilience* (Bonanno, 2004; Kalisch et al., 2017; Werner, 1995). A meta-analysis of 54 studies that reported response trajectories of individuals after facing stress and potentially traumatic events identified different trajectory types (resilience, recovery, chronic, and delayed onset). The resilient trajectory was the most prevalent (Galatzer-Levy et al., 2018). Individuals characterized by a resilient trajectory may face mild to moderate disruptions in normal functioning (e.g., a few weeks of poor sleep and bouts of sadness), but overall maintain a stable trajectory of healthy functioning. On the contrary, a chronic trajectory is characterized by severe disruptions in functioning, which do not diminish over time without some type of intervention.

Investigating how these individual differences in resilience arise is not straightforward. The first reason for this is that resilience is a *disposition* that expresses a tendency or capacity that manifests under certain conditions or situations (Mumford, 2003). Resilience refers to a response after facing adversity, which, naturally, cannot be induced in experimental research for ethical reasons. The second reason is that the concept of resilience is complicated to analyze. Resilience is associated with many distinct variables across domains (e.g., self-compassion; MacBeth & Gumley, 2012), social support (Gariépy et al., 2016) and positive emotions (Tugade

& Fredrickson, 2004) and is thus inherently *multifactorial*. There is no evidence for a set of key predictors that can explain all individual differences in resilience levels (Bonanno, 2021; Modesto-Lowe et al., 2021). Instead, resilience results from many different *protective factors* (e.g., optimism; Ellis et al., 2017) and *risk factors* (e.g., neuroticism; Roberts & Kendler, 1999) which respectively help or hinder people in maintaining or rapidly bouncing back into their normal functioning (Fritz et al., 2018; Xu & Kajikawa, 2018). Importantly, these risk and protective factors do not operate in isolation but interact with one another (Ellis et al., 2017; Gijzel et al., 2019; Riley & Masten, 2005; Weinans et al., 2021). For example, two people with a similar level of neuroticism can still have different responses to stressful events, such as losing their job. A person who scores high on neuroticism and also has suffered from a difficult childhood is more likely to have a lower level of resilience than a person who also scores high on neuroticism but had a happy childhood. A further element that makes the study of resilience complicated is its *dynamic nature* by which someone is successfully (or not) adapting to its environment and various stressors over time (Shafi et al., 2020; Crameri et al., 2021; Hill et al., 2018; Kalisch et al., 2017; Rutter, 2012; Sapienza & Masten, 2011; Stainton et al., 2019). Instead of representing resilience as a static trait that permanently shields someone from all types of misery, evidence suggests that resilience levels within individuals can change over time (Infurna, 2021; Stainton et al., 2019). Thus, resilience involves complex and dynamic interactions between risk and protective factors as well as the stressors a person faces, which current accounts of resilience fail to accommodate (Kalisch et al., 2019).

The network theory of psychopathology offers a theory and modeling framework that allows taking the multifactorial and dynamic nature of resilience into account (Borsboom 2017; Kalisch et al., 2019). The central idea of this theory is that mental disorders act as *complex systems* (Borsboom, 2017; Borsboom & Cramer, 2013). Complex systems consist of interacting elements that produce a pattern of behavior (Meadows, 2008). The take-away message from

the complex systems approach is that a system's behavior follows from its internal structure. To study the system's behavior, one should understand how the whole system operates instead of studying every variable or component in isolation. The internal structure of the system can lead to a *self-sustaining state*, meaning that the system gets 'stuck' in a certain state that is difficult to break (Scheffer et al., 1993). The network theory of psychopathology proposes that a mental disorder is such a self-sustaining state, ultimately caused by direct symptom-symptoms interactions (Borsboom, 2017). Symptoms are organized in a network and directly affect each other: for example, insomnia causes fatigue, which, in turn, results in concentration problems (Borsboom & Cramer, 2013). The concentration problems might trigger a depressed mood, which, over time, results in feelings of worthlessness. The end result of these symptom-symptom interactions (i.e., insomnia -> fatigue -> concentration problems -> depressed mood -> feelings of worthlessness) is a depressive episode (Borsboom, 2017). The number of active symptoms defines the *state* of the symptom network. One may use DSM diagnostic cut-offs to determine the number of symptoms that depict the network's state: 1) relatively few symptoms active (below a diagnostic cut-off), a *healthy state*; or 2) relatively many symptoms active (above a diagnostic cut-off), a *disordered state*.

Figure 1*An Example of a Symptom Network Model*

Note. The *nodes* in the network (the circles in the figure) represent symptoms, such as ‘insomnia’ or ‘depressed mood’. The node parameters (illustrated by the node borders) are called *thresholds* and express the preference of a symptom to be present. Strong thresholds (shown by thick borders) indicate a symptom’s large preference to be absent, meaning that the symptom is less likely to activate. Contrary, weak thresholds (thin borders) indicate that a symptom has a minor preference to be absent and can become present more easily. The *edges* in the network (the lines between the nodes in the figure) represent the association between the symptoms. The stronger the association (thicker lines), the stronger the preference of symptoms to be in the same state. Thus, when one symptom is present, a strongly connected neighboring node is more likely to become present as well.

The most likely behavior of the symptom network is determined by its *architecture* (i.e., the internal structure). The network’s architecture consists of 1) the *connections* between the symptoms and 2) the *thresholds* of each symptom to become active. Strongly connected symptoms are more likely to activate each other (Cramer et al., 2016). For example, suppose the depressive symptom ‘insomnia’ is strongly connected to ‘excessive worrying’. In that case, the presence of insomnia increases the likelihood that excessive worry will activate as well, and vice versa. In this way, symptom networks with weak connectivity are more likely to become stuck in a vicious cycle of symptom-symptom interactions (van Borkulo et al., 2015). In addition, each symptom has a threshold for activation. Symptoms with *low* thresholds (e.g., insomnia) are more easily activated when faced with some perturbation (e.g., a stressful event)

than symptoms with *high* thresholds (e.g., suicidal ideation; Schweren et al., 2018). In this way, individual differences in the development of psychopathology could potentially be explained by differences in the network architecture across people.

However, it remains an open question how to study the resilience of networks, specifically, what type of outcome should be used to define whether a network is resilient. It is currently unknown how the network's architecture relates to resilience. To answer that question, one needs to study how the symptom network's behavior is affected by adversity. One can expose the symptom network to perturbations by simulating data under different conditions that represent adversity. In this way, it is possible to investigate how the network's behavior would evolve according to the model. Alternatively, one can explore how a specific symptom network would respond to treatment interventions after getting stuck in a disorder state. By simulating data under the situation that a network receives treatment interventions, one can study how susceptible a depressed network is to change. In other words, one can investigate the *stability* of the network's state against simulated perturbations that represent stressors or treatment interventions. Thus, by using simulations, we can study how resilient a network is against adversity (i.e., the stability of a healthy state) and how easily a network will respond to treatment interventions (i.e., the stability of the disorder state). As such, one can generate clear, testable, and specific hypotheses on what factors contribute to the system's resilience that can be used for empirical validation.

This paper will show how to study resilience using a statistical network model of psychopathology combined with simulations. The paper is set up as follows. Section two ("The Resilience Quadrant") introduces the *resilience quadrant*, which organizes symptom networks based on their most likely state (healthy or disordered) and stability against perturbations. We show that the quadrant captures different behaviors along those dimensions: resilient trajectories in the face of adversity, as well as persistent symptoms despite treatment

interventions. Section three (“Proof-of-concept”) shows how to study in which regime of the quadrant symptom networks are currently located using simulations with exemplary architectures. Section four (“Discussion”) concludes with the necessary steps to further the study of resilience from a complex systems approach, such as implementing risk and protective factors to symptom networks.

The Resilience Quadrant

We present the resilience quadrant as a formalized simulation framework that shows the four different resilience regimes in which a symptom network can be located (see Figure 2). The framework is formalized because it explains how different network architectures lead to differences in resilience and how we could study the resilience of networks. The quadrant organizes networks by two dimensions: the network’s *projected state* (state-axis) and the *stability* of that state (stability-axis). The state-axis denotes whether the system can be expected to be in a healthy or disorder state, given the network’s architecture. The stability axis indicates how susceptible the projected state is to change when faced with perturbations. Using the example of Major Depressive Disorder (MDD), a network of depression symptoms can be located in a resilient, remitting, relapsing, or chronically depressed regime of the quadrant.

Figure 2*The Resilience Quadrant*

Note. The center shows the resilience quadrant of a (simplified) mental health system with two alternative stable states: healthy and depressed. The valleys in each quadrant represent the underlying attractor landscape for the two alternative states. For example, in the “resilient” regime, the system is located within the deep, steep, and wide attractor basin of the healthy state, and therefore unlikely to fall into the shallow attractor basin of the depressed state, even in the face of adversity. The corresponding boxes show the current location in the system's trajectory, where the upper trajectory represents the healthy state and the lower trajectory the depressed state. The switch from one state to the other is called a *sudden jump*, which can also be represented by shifting from one attractor basin into another. Within each box, corresponding network architectures are shown. Nodes represent depression symptoms, and edges represent associations (e.g., logistic regression coefficients) between symptoms, while the thickness of edges represents the strength of this relationship. The thickness of red borders around nodes represents the magnitude of threshold parameters, which differ per node.

A visual metaphor that can explain the discussed link between the stability of the network's state and resilience is the ball-in-a-cup metaphor (see Figure 3, which is often used in dynamical systems theory (e.g., see Scheffer et al., 2018)). The cup represents the *attractor basin* of the network, which corresponds to the state the network is gravitating towards. As introduced above, the states are simplified to two options: a healthy state with few active symptoms and a disordered state with many active symptoms. The ball represents the system's current state, which can take on all possible combinations of active and inactive symptoms. The steepness and width of the cup represent how stable the ball lies in the attractor. If the attractor basin is broad, deep, and steep, the ball is likely to stay at the lowest point and unlikely to move and be pushed over the edge. In contrast, an attractor basin that is narrow, shallow, and flat is unstable since the ball is likely to roll out of the attractor basin (Holling, 1973). The ball can be pushed by perturbations, such as minor daily stressors or adverse life events (e.g., divorce or the death of a loved one; Fried et al., 2015). However, the external events may also represent alleviating interventions, such as clinical treatments that aim to move a patient towards a healthy state. The influence of the perturbation on the ball's behavior depends on the force pushing the ball forwards (i.e., how strong the perturbation itself is) and the form of the cup (i.e., how deep and steep the attractor is). Together, these determine the probability that the ball will switch from one state to another. Thus, a network situated in a healthy and stable attractor, with an unstable attractor for the disordered state, will show a resilient trajectory. This means that resilience is no longer a specific component of the network (e.g., a variable in the network or a particular set of factors) but a *property* of the network.

Figure 3*Ball-In-A-Cup Metaphor*

Note. The depth and width of the attractor determine how easily an imaginary ball falls into and out of the attractor, and thus, how stable the system is currently located in the attractor. The left basin is stable, represented by its wide and steep valley. In contrast, the right basin is unstable due to its shallow and narrow form.

In the resilient regime (the upper-right area of Figure 2), the network is located in a healthy and stable state. This means that the network's small number of active symptoms is stable in the face of adversity. Some symptoms may be triggered after an event, but these will show spontaneous recovery. Networks with weak connectivity and high thresholds will be located in this regime. The healthy state can also be unstable in which symptoms are more easily activated after facing perturbations, which is depicted in the lower-right regime (“remitting”) of the quadrant (see Figure 2). For example, patients in remission may be characterized by an unstable healthy state and thus not resilient even though their profile and number of depression symptoms might fall below the clinical cut-off for diagnosis. Networks with slightly stronger connectivity but lower thresholds than the resilient network are located in the remitting regime. The left part of the quadrant depicts the unhealthy state of the network, whereas the upper left shows the chronic depression regime. A network in this regime is stuck in an unhealthy stable state and therefore unresponsive to clinical interventions. Patients who suffer from chronic depression can be hypothesized to fit this category, as they are often not responsive to many (first) treatment interventions (Fava, 2003; Hölzel et al., 2011). Networks

with strong connectivity and low thresholds will be located in this regime. Disordered symptom networks can also be unstable, representing, for example, groups of patients that are relapsing into depressive states (shown in the bottom-left regime of the quadrant). The relapsing networks also have strong connectivity and low thresholds, but these parameters are less extreme than in the chronically depressed network.

We use simulations to study where in the quadrant a network is located in two steps. First, we check the location of the network on the state-axis (i.e., the projected state of the network): healthy versus disordered. To study the projected state of the network, we simulate many observations² from the network. We calculate the mean number of active symptoms, representing the most likely state in which the network will end up. Second, we study the location of the network on the stability-axis: stable versus unstable. We investigate the stability of the projected state simulating perturbations to the network. Note that different perturbations are needed to examine the stability of a healthy or disordered projected state. To study the stability of a healthy projected state, we apply *aggravating interventions* mirroring the development of depressive symptoms due to an adverse life event. Aggravating interventions temporarily increase the level of symptoms in the simulations. To the contrary, we apply *alleviating interventions* to investigate whether a disordered projected state is susceptible to change. Alleviating interventions represent treatment interventions by forcing symptoms to be inactive at specific moments of the simulation. In the following section, we provide a proof-of-

² For specific types of network models, the most likely state of a network can also be calculated analytically. For example, the most likely state of the model used in this paper (the Ising model) can be solved analytically for networks up to ten nodes using the R-package *IsingSampler* (Epskamp, 2020). However, as we also simulate perturbations to check the stability of the most likely state, we use the same type of simulations to position the network on both the state- and stability-axis.

concept of how we can assess in which regime of the resilience quadrant symptom networks are currently located.

Proof-of-concept

In the current section, we explain how to identify typical cases of networks for every regime in the resilience quadrant. We constructed four different networks to show resilient, remitting, relapsing, or chronically depressed trajectories. We constructed these networks by altering the architecture (i.e., threshold and connectivity parameters) of an empirically estimated baseline symptom network in four ways (See Figure 4). The baseline symptom network represents nine depression symptoms in a population with healthy and depressed participants. The four networks differ in their architecture, specifically their connectivity and thresholds, and were constructed to mimic characteristic behavior for each quadrant in Figure 2. To construct the network in the resilient regime, we decreased the connectivity and made the thresholds higher (i.e., the symptoms will be less likely to activate), which will make the healthy state of the network more stable. We did the opposite for the network located in the chronically depressed regime by increasing the connectivity and making the thresholds lower (i.e., making the symptoms more likely to activate). We made the network's projected states more unstable for the remitting and relapsing networks by altering the connectivity and threshold parameters in opposite directions (see Appendix A in the supplementary materials for a detailed description of how we constructed the networks).

All analysis code and research materials are available at <https://osf.io/gv46e/>. Analyses were done with R, version 4.1.2 (R Core Team, 2021) and the packages *IsingFit*, version 0.3.1 (van Borkulo et al., 2014), *qgraph*, version 1.9 (Epskamp et al., 2012), *ggplot2*, version 3.3.5 (Wickham, 2016), *tidyverse*, version 1.3.1 (Wickham et al., 2019) and *ggpubr*, version 0.4.0

(Kassambara & Kassambara, 2020). This study's design and its analysis were not pre-registered.

Figure 4

Constructing Resilient, Relapsing, Remitting, and Chronically Depressed Network Models

Note. We create four networks that show resilient, remitting, relapsing, and chronically depressed trajectories by manipulating an empirical baseline network model (in the center). The four networks are created by multiplying the connectivity and threshold parameters of the baseline model's architecture, and in this way, increasing or decreasing the parameters. The four constructed networks show behavior that fits the four regimes of the Resilience Quadrant. The thickness of edges represents the magnitude of the connectivity, and the thickness of node borders represents the strength of the thresholds. As can be seen from the figure, the relapsing and remitting networks have quite similar architectures. See Appendix B of the Supplementary Materials for the exact values with which the baseline model parameters are multiplied to construct the four novel models. Abbreviations of the nodes refer to depression symptoms as follows: dpm = depressed mood, lss = loss of interest, app = appetite disturbance, slp = sleep disturbance, mtr = psychomotor agitation, ftg = fatigue, wrt = feelings of worthlessness, cnc = concentration problems, and dth = thoughts of death.

Health versus Disorder: Simulating Observations without Perturbations

The first dimension in the resilience quadrant is health versus disorder. To assess whether a system characteristically displays healthy or disorder patterns, one can evaluate whether the expected number of active symptoms exceeds a clinical cutoff. For instance, in the present case, we simulated data from the four networks to show that these specific networks end up in different projected states (healthy or depressed). Appendix B in the supplementary materials explains the simulation technique used to simulate the observations from the networks in detail. The simulated observations can be seen as ‘repeated measures’ of the nine depression symptoms for the same fictitious population of participants that each network represents. In that way, the simulated observations approximate the most likely symptom developments of every network, given the network’s architecture. We calculated the projected state of every network by taking the mean of the sum scores of active symptoms over all simulated observations. The mean sum score falls below or above a specific clinical cut-off value for diagnosis. The clinical cut-off value used in these simulations is the (simplified³) clinical cut-off value for diagnosing MDD, namely a sum score of five or more active symptoms denoting a depressed state and less than five active symptoms indicating a healthy state.

Table 1 and Figure 6 show the results from the simulations. The projected state for the *resilient network* is healthy since the mean sum score of simulated observations falls below the cut-off of 5 symptoms (mean = 0.03, sd=0.19). The *remitting network* showed more fluctuations. There is no clear state for this model and the number of active symptoms switched from a few active symptoms to a state with a high number of active symptoms. However, based

³ The Diagnostic and Statistical Manual of Mental Disorders (5th ed.; DSM–5; American Psychiatric

Association, 2013) states that for a diagnosis of MDD, 5 symptoms should be present, of which ‘loss of interest’ or ‘depressed mood’ should be present (American Psychiatric Association, 2013). For simplicity, here we do not consider which specific symptoms are present.

on the mean of the active symptoms (mean = 3.83, sd = 3.95) the projected state of the networks falls below the cut-off value of five or more active symptoms. It is therefore located within the healthy regime of the resilience quadrant. The *relapsing network* showed some fluctuating symptom evolutions but with more active symptoms. The mean sum score of the relapsing network falls above the cut-off value (mean = 8.36, sd=0.87), and its projected state is therefore depressed. The *chronically depressed network* model showed many active symptoms (mean = 8.87, sd=0.47), and its projected state is consequently depressed.

Stability versus Instability: Simulating Observations with Perturbations

After evaluating whether the characteristic behavior exhibits healthy or disorder states, we assessed the second domain of the resilience quadrant: stability versus instability. To this end, we perturbed the networks to study how stable their projected state is. We applied aggravating interventions to networks with a healthy projected state by activating all symptoms for specific moments in the simulation. We applied alleviating interventions for networks with a projected disordered state by forcing all symptoms to be inactive at particular moments. Figure 5 gives an example of simulated aggravating interventions, and Appendix B in the supplementary materials explains the simulations in detail. After the interventions, the simulation of observations continued in its regular fashion. The network's architecture determines whether the following simulated observations can get 'stuck' in the absence or presence of symptoms. We calculated the effect of the interventions by computing the mean of the active symptoms over all observations. This symptom mean can again fall above or below the chosen clinical cut-off value, determining whether the system's projected state after facing aggravating or alleviating interventions remains healthy or depressed.

Figure 5*An Example of Simulated Aggravating Interventions*

Note. Simulations are based on the estimated baseline depression model (see Appendix A in the supplementary materials). The x-axis represents the simulated observations, the y-axis the sum scores of the active depression symptoms. The red vertical lines represent every moment an aggravating intervention is simulated, meaning that all symptoms are forced to be active for one moment in the simulation. The dashed red line denotes the (simplified) clinical cut-off value for diagnosing MDD, namely a sum score of five active symptoms. The lower figure zoomed in on one intervention to show how the system recovers in detail. In this plot, the network with these estimated parameters generating these dynamics will fall below the clinical cut-off value for diagnosing depression most of the time.

Based on the previous results, we simulated aggravating perturbations for the networks projected to be in the healthy state and alleviating interventions for the networks projected to be in the unhealthy state (See Table 1 and Figure 6). The *resilient network* bounced back very quickly from every aggravating intervention and remained in a healthy state with almost no actively present symptoms (mean = 0.19, sd = 0.85). Interventions had more effect on the *remitting network*, in which the state of the network sometimes reached a depressed state. However, symptom evolution patterns were still highly fluctuating. The mean sum score of the network now falls above the cut-off (mean = 5.76, sd = 3.65). In the *relapsing network*, the applied alleviating interventions successfully diminished the number of symptoms but with high fluctuations (mean = 4.13, sd = 4.1). The *chronically depressed network* model remained depressed most of the time despite alleviating interventions. However, the alleviating interventions seem to have some effect as symptom presence fluctuated (mean = 7.41, sd = 3.22).

Table 1

Simulated Dynamics with and without Perturbations for All Constructed Networks

Symptom Sum Score	Constructed Symptom Networks							
	Resilient		Remitting		Relapsing		Chronically depressed	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Without perturbations	0.04	0.19	3.83	3.95	8.36	0.87	8.87	0.47
With perturbations	0.19	0.85	5.76	3.65	4.13	4.1	7.41	3.22

Note. This table shows the means and standard deviations of the simulated dynamics with and without perturbations for all constructed networks.

Determining the Position of the Networks in the Resilience Quadrant

We can evaluate where the networks are located in the resilience quadrant by comparing the previous results. First, we assessed the networks on the health versus disorder domain to locate them on the left or right side of the state-axis in the quadrant (See Figure 2). If the network's projected regime fell below (above) the clinical cut-off, we positioned the network on the healthy (depressed) domain in the right (left) side of the quadrant. Second, we evaluated the networks on the stable versus unstable domain to locate them on the upper or lower side of the stability-axis in the quadrant. If the network's projected state after perturbations remains the same as the state without perturbations (i.e., the mean sum score of active symptoms still falls below or above the clinical cut-off; healthy or depressed), we positioned the network on the stable regime on the upper side of the quadrant. Otherwise, we located it in the unstable regime on the lower side of the quadrant.

Figure 6 shows the results of all the simulations for the four networks. The *resilient network* showed a healthy state, which was stable against aggravating interventions and is therefore located in the “resilient” regime of the resilience quadrant. The *remitting network* showed unstable dynamics, with a symptom mean score below the cut-off, but which jumped towards an unhealthy state after aggravating interventions. Therefore, the *remitting network* is located in the unstable healthy (“remission”) regime. The *relapsing network* is projected to be in an unstable depressed state, which can jump to a healthy state after alleviating interventions and is therefore placed in the “relapsing” regime of the quadrant. The *chronically depressed network* remained depressed despite alleviating interventions and is thus situated in the resilience quadrant's stable depressed (“chronically depressed”) regime.

Figure 6

The Projected Symptom Evolutions for Four Networks in Distinct Regimes of the Resilience Quadrant

Note. The x-axis of every plot shows the simulated observations, and the y-axis the sum of the present symptoms, where a higher score indicates a higher level of depression. The dashed horizontal red line indicates the clinical cut-off value of 5 symptoms or more for a diagnosis of MDD. The vertical lines indicate the moments where interventions are simulated, where red lines indicate aggravating interventions (all symptoms are forced to be present), and green lines indicate alleviating interventions (all symptoms are forced to be absent). The upper-right plot shows the symptom evolutions for the symptom network located in the resilient regime. Despite aggravating interventions, it displays a healthy and stable state, which follows from the projected low number of present symptoms. The lower-right panel shows the results for the network that was constructed to show an unstable healthy state located in the remitting regime of the quadrant. The projected state of the network is healthy, but it is heavily affected by the aggravating interventions. The lower-left panel shows the projected evolutions of the network located in the relapsing regime, which is characterized by an unstable depressed state that recovers from alleviating interventions. The upper-left panel shows the results for the network located in the chronically depressed regime, which is characterized by high levels of symptomatology despite alleviating interventions. The chronically depressed network is therefore unlikely to be susceptible to treatment interventions.

The Relation between Network Architecture and Resilience

The networks in the four quadrants were constructed from a baseline, estimated network. We arrived at the typical networks by systematically altering the parameters of the baseline network. This process is represented in Figure 4. As is shown in the Figure, a *chronically depressed network* arises when interactions between symptoms are strong (increased edge weights), and the tendency of each symptom to be active is stronger (lower thresholds). Thus, both stronger interactions with other symptoms and the degree to which symptoms have an autonomous tendency to be active contribute to a loss of resilience. In contrast, the *resilient network* is a perfect mirror of the chronically depressed network: it features weaker symptom-symptom interactions and a more favorable threshold of the individual nodes. Notably, the *relapsing* and *remitting* networks are located in the parameter space in between the chronically depressed and resilient networks. They have slightly less favourable thresholds and somewhat higher edge weights. In this area of the parameter space, simulations suggest that many (nearly) equivalent models can be constructed through slight changes in the model parameters. This indicates that to assess resilience, the threshold parameters of the model cannot be ignored, as lower thresholds can offset stronger interactions and vice versa. In addition, observe that small changes in the model's parameters suffice to alter their position in the resilience quadrant. We return to the implications of these results in the discussion.

Discussion

This paper proposed a novel framework to formalize and study resilience using a complex systems approach to psychopathology. Specifically, we combined (estimated) symptom network models with simulations to study how resilient a symptom network is based on its architecture. We have introduced a systematic methodology to determine where a given

network is located in the resilience quadrant, which operates in two steps. First, assess whether the system characteristically exhibits symptom activation beyond the clinical cut-off. Second, evaluate whether the system state is robust against perturbations using simulations (where these are either aggravating or alleviating depending on the characteristic state of the system). Applying this analysis to a baseline symptom network of depression, an expected finding is that stronger connectivity and less favorable thresholds together can make a network chronically depressed. However, two important additional findings emerged. First, the effects of changes in thresholds and connections can offset each other (see also Kruis, 2021). This finding is important to incorporate in research. It implies that empirical tests, such as those based on the Network Comparison Test (van Borkulo, *in press*) which compares networks based on only their connectivity, should not be confused with tests of resilience. This is because two networks with equal connectivity but different thresholds may show different levels of resilience. Second, the differences in parameter values that result in different quadrants are slight. This potentially explains why resilience is thought to be dependent on complex configurations of factors thought to support resilience, in which many factors interact and have relatively weak connections to each other.

It is our hope that thinking about and studying resilience from a complex systems approach will ultimately lead to novel methods that can improve the assessment and prediction of response trajectories to adverse events or treatment efficacy. For example, to help decide what the network structure of a patient may look like and, as such, help decide in which regime of the resilience quadrant patients could be located. This may contribute in determining optimal intervention strategies, as patients with more resilient network structures may need less strong interventions compared with patients with less stable symptom networks. In the remaining section, we will outline the most critical steps that, in our view, will help advance the research program of resilience from a complex systems approach in psychology.

Extend the Ideas Presented in this Paper to Other Statistical Network Models

The network model that was used in our simulations (see Appendix A of the supplementary materials for details) is helpful for theoretical exercises since it is a relatively simple model that can accommodate various complex phenomena aligning with mental disorders, such as phase transitions from healthy to depressed states (Finnemann et al., 2021). However, the model used in this paper originates in physics and is designed to explain ferromagnetism (Ising, 1925; see Appendix A of the supplementary materials). The model is potentially too simplified to be a realistic representation of the dynamic course of symptom development. For example, symptoms can only be active or inactive in the model, and the associations between symptoms cannot change over time. The ideas outlined in this paper could be extended to other models, which are more useful to represent the course of depressive complaints or resilient responses. The Gaussian Graphical Model (GGM; Epskamp et al., 2018) allows for continuous and ordinal data, such as symptoms measured on a Likert-scale. The Mixed Graphical Model (MGM; Haslbeck & Waldorp, 2020) is a network model that can be estimated from both continuous and categorical data and is thus a suitable candidate to study the relationships between symptoms and various types of risk or protective factors. Vector Auto-Regressive models (VAR models; Bringmann et al., 2013) can be used to study the relationships of variables over time (e.g., see Henry et al., 2021), such as daily fluctuations of moods and affect states (e.g., see: Snippe et al., 2017; Wichers et al., 2015). One could also add interventions to continuous time VAR models (Ryan & Hamaker, 2021). Ideally, models would also be built from the ground up to allow for specific time-varying elements of resilience (Robinaugh et al., 2020), such as the computational model for Panic Disorder (Robinaugh et al., 2021).

Expanding the Modeling of Perturbations

This paper proposed a way to represent and study the resilience of symptom networks as an outcome by comparing simulated dynamics before and after alleviating or aggravating interventions. Perturbations could be extended such that they represent different types of adversity or treatment interventions in life. Instead of representing interventions as (de)activating all symptoms at specific moments, one could also model interventions that represent chronic stressors, minor daily hassles or permanent treatments (i.e., taking medication that permanently impacts symptom development). One could, for example, (de)activate specific symptoms for the duration of the simulations. In addition, one could target specific symptoms for alleviating or aggravating interventions to investigate which symptom is projected to have the largest influence on the resilience level of the network (Lunansky et al., 2021a). Alternatively, one could target a random number of symptoms for every intervention, realistically representing stressful life events or treatment interventions.

Include Risk and Protective Factors to Symptom Networks

Resilience results from various risk and protective factors across domains (Fritz et al., 2018; Xu & Kajikawa, 2018). This paper assessed resilience from a symptom network architecture by studying the stability of symptom evolutions after facing perturbations. Symptom networks could also be extended with risk and protective factors that help or hinder the further development of symptoms. These risk and protective factors may directly affect the symptom network's architecture such that it becomes more or less resilient (See Figure 7) (Isvoranu et al., 2017; Kalisch et al., 2019; Lunansky et al., 2021b). For example, the risk factor of being sexually abused in childhood is directly linked to the development of feelings of guilt later in life (Isvoranu et al., 2017), while the protective factor 'social support' may hinder the evolution of 'depressed mood' (e.g., Gariépy et al., 2016). Risk (or protective) factors may

directly influence the development of symptoms and strengthen (or weaken) their connections or thresholds. Networks targeted by many risk factors may have stronger connections between symptoms, making them more vulnerable to stressful events. In these networks, stressors could lead to vicious cycles of persistent symptom activation resulting in full-blown depressive episodes in which the network gets stuck (Cramer et al., 2016).

Figure 7

Representation of a symptom network with risk and protective factors

Note. A representation of a symptom network model (the black nodes represent symptoms), where symptoms are related to other factors from distinct domains (the nodes in grey tones; e.g., personality, social factors, biological factors). These external factors can act as protective factors by lowering the possibility that symptoms occur, or as risk factors by increasing the likelihood that symptoms will develop. Relations between all variables in the model may vary in strength (shown by the thickness of the lines). In addition, external perturbations (aggravating interventions; the lightning bolts, and alleviating interventions; the medical case) may also influence the symptom-symptom interactions. Protective factors, such as relationship quality or partnership satisfaction, may dampen the interactions between symptoms. When a person starts feeling worried, their spouse can decrease the probability

that worrying will lead to other symptoms by offering social support (Røsand et al., 2012). (The figure is an adaptation of Figure 1 in Lunansky et al., 2021b).

One could study whether groups of people that score high on certain risk or protective factors have, indeed, a different symptom network structure. This could be achieved by estimating a network from both symptom data and risk and protective factors (using, for example, the MGM network model for mixed data; Haslbeck & Waldorp, 2020). Afterward, one may condition on specific values of the risk and protective factors, such as the presence of protective factors and the absence of risk factors, to obtain the symptom network structure for the people represented by that situation. One could feed that symptom network into the proposed framework in this paper by simulating data and perturbations from the specific symptom network architecture. In this way, one could study whether specific risk and protective factors lead to differences in resilience from a complexity approach. However, the problem is that the simulation techniques presented in this paper currently only work for binary data. Future research could apply the proposed logic to networks estimated from different data, such as mixed data (i.e., symptoms and risk or protective factors measured on different scales).

Work on a Personalized Framework of Resilience Assessment and Prediction

Our presented framework may be helpful to generate hypotheses on network models of different participant groups, such as comparing clinically depressed patients with healthy individuals. One could compare the networks of groups of people that did and did not develop mental disorders over time (van Borkulo et al., 2015). Using our proposed framework, an exciting possibility is to investigate whether differences between these groups could already be detected at baseline. However, this does not mean that we can predict response trajectories or assess the resilience of every individual from these groups. One of the biggest challenges for formalizing psychological phenomena such as mental health is the heterogeneity of people

(Molenaar, 2004). Heterogeneity implies that trajectories at the group-level do not directly translate to every individual (Hamaker, 2012). To personalize a formal framework of resilience, our proposed framework needs to be adapted to individual models. A recent example of a study in this direction suggests monitoring individuals over time on stressor exposure and mental health problems (Kalisch et al., 2021). Deviations of the individuals from a ‘normative’ trajectory (for example, based on the mean of the studied sample of participants) could be detected early and related to later outcomes. Another example is to combine intensive data collection of daily momentary moods and stressful events with periodic assessments of symptom evolutions (Kuranova et al., 2020). In this way, one could study if the recovery from adverse events, in terms of maintaining positive momentary moods, could be related to an increase in symptom development or resilient responses.

Concluding

Resilience is an inherently multifactorial and dynamic concept. As such, we have to understand how different mechanisms work together to make a person cope, thrive, or break apart after facing hardship (Ioannidis et al., 2020; Kalisch et al., 2017). This paper presented a novel way to study resilience from a complex systems perspective in psychology by combining existing statistical symptom network models with simulation techniques. We hope that the general framework will aid future researchers from different domains to advance the study of resilience collaboratively.

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Supplementary materials

Appendix A: Constructing the four symptom networks for the simulations

In the manuscript, we present a proof-of-concept in which we construct four symptom networks that can be placed in the four regimes of the resilience quadrant. Here, we will explain how we constructed the four networks. To make sure that the constructed networks are somewhat bound to empirically estimated parameter values, we first estimate a symptom network from empirical data containing assessments of nine Major Depressive Disorder (MDD) symptoms as our baseline model. Second, we alter the parameters of the baseline model in such a way that the resilience levels of the networks change.

The baseline MDD model

Data. The data come from the Virginia Adult Twin Study of Psychiatric and Substance Use Disorders (VATSPSUD; Kendler et al., 1999) and contain binary data on the presence/absence of nine MDD symptoms from 8973 twins from the Mid-Atlantic Twin Registry. The symptoms are: (1) Depressed most of the day, nearly every day, (2) Markedly diminished interest or pleasure in all, or almost all, activities most of the day, nearly every day, (3) Significant weight loss when not dieting or weight gain (e.g., change of more than 5% of body weight in a month), or decrease or increase in appetite nearly every day, (4) Insomnia or hypersomnia nearly every day, (5) Psychomotor agitation or retardation nearly every day, (6) Fatigue or loss of energy nearly every day, (7) Feelings of worthlessness or excessive or inappropriate guilt nearly every day, (8) Diminished ability to think or concentrate, or indecisiveness, nearly every day, and (9) Recurrent thoughts of death, recurrent suicidal ideation without a specific plan, or a suicide attempt or a specific plan for committing suicide. Symptoms were measured during a psychiatric interview using an adaptation of the Structured Clinical Interview for DSM-III-R (Spitzer et al., 1992).

Model. We estimate the symptom network model using the Ising model (Ising, 1925). The Ising model is a relatively simple model which has been frequently applied to mental health and specifically depression for its ability to show complex behavior in line with the development of psychiatric disorders (Ising, 1925; see van Borkulo et al., 2014, Marsman et al., 2018 and Finneman et al., 2021 for an extensive description of the Ising model used in psychology). Symptoms are encoded as either “present” (1) or “absent” (0). The Ising model is symmetric, meaning that the relationships between the nodes are undirected; e.g., the relationship from “insomnia” to “depressed mood” is the same as the relationship from “depressed mood” to “insomnia”. The connections between symptoms are called *edge weights* and are estimated with logistic regression analyses. The internal dispositions of symptoms are called *threshold parameters*, which are calculated as the intercept of the logistic regression equation (van Borkulo et al., 2014).

Altering the parameters of the baseline model

To construct the resilient network, we decrease the edge weight parameters of the baseline MDD model by multiplying the baseline edge weights with 0.8, and increase the threshold parameters by multiplying the baseline thresholds with 1.2. For the remitting network, we multiply the parameters in the opposite direction but with smaller values, in order increase the instability of the network’s dynamics. We multiply the edge weights of the baseline model with 1.1 and the threshold parameters of the baseline model with 0.95. For the relapsing network, we multiply the edge weights of the baseline model with 1.1 and the thresholds with 0.9. To construct the chronically depressed network, we increase the connectivity of the depressed model by multiplying the edge weights of the baseline model with 1.2 and decrease the threshold parameters (i.e., making the preference for absence weaker) by multiplying the baseline thresholds with 0.8. In the simulations with the Glauber dynamics (see Appendix B) we set the beta parameter to 1.5 instead of the usual setting of 1. This leads to a stronger effect from the parameters and more stable simulations.

Appendix B: Simulating the projected and perturbed observations

In this section, we explain the techniques used to simulate the projected observations and perturbed observations for the three Ising network models (see Appendix A) as described in the manuscript.

Simulating observations without perturbations

The symptom development patterns of the Ising model will always strive to be in the configuration of symptoms that costs less *energy* (Dalege et al., 2019). The energy for every possible configuration of symptoms (i.e., all combinations of absent and present symptoms) depends on the threshold parameters and the edge weight parameters. The energy for every symptom combination in the Ising model is calculated with the Hamiltonian in Formula 1.

$$(1) \quad H(X) = - \sum_i \tau_i X_i - \sum_{\langle i,j \rangle} W_{i,j} X_i X_j$$

Formula 1 gives the Hamiltonian energy for two symptoms i and j , but can be extended for networks with more symptoms. The energy for the configuration X of the network (for example, both symptoms are present) is calculated from the threshold τ_i of symptom i , the edge weights $W_{i,j}$ between symptom i and its neighboring symptom j , and the current presence or absence $X_i X_j$ of both symptoms.

Simulating observations with perturbations

Ising model dynamics can be simulated using an algorithm called Glauber dynamics (Glauber, 1963). Glauber dynamics are an established method for simulating dynamics from an Ising model (e.g., see Levin et al., 2008). The idea behind the method is that for every simulated observation only one symptom can change its state from presence to absence or vice versa, in order to mimic a continuous process of development. The algorithm selects one random symptom for every novel simulated observation. The state of the symptom is then flipped, meaning that if the symptom was currently present it gets deactivated (denoted by changing the state of the symptom from a $1 \rightarrow 0$) and vice versa⁴. The difference between the current state and the flipped state of the symptom is calculated by computing the energy difference between the two situations (see Formula 1). The energy difference between the current and flipped state of the symptom determines the probability that the symptom either changes its state or remains in the current state; the lower the energy of the alternative state, the higher the probability the symptom's state will change. A stochastic process is added to the simulation by adding a transition probability. In our simulations we simulate 10.000 observations for every network, to ensure the stability of our results.

To simulate the alleviating and aggravating interventions as described in the manuscript, we perturb the simulations every 1000th observation (see Figure 4 in the manuscript). Thus, perturbations are administered 10 times. We stop the Glauber dynamics algorithm every 1000th observation, and force all symptoms to be present or absent, depending on whether we are simulating an alleviating or aggravating intervention. Afterwards, the algorithm continues in its ordinary fashion, calculating which symptom configuration is most likely for every observation. Depending on the parameters for every network model, the symptoms 'recover' from this intervention, or they maintain stuck in a situation with high or low symptom activation.

⁴ Following the suggestions as made in Haslbeck, Epskamp, Marsman & Waldorp (2018), we use the transformed $\{0,1\}$ parameters of the Ising model (instead of the $\{-1,1\}$ parameters) to compute the Glauber dynamics with networks that are estimated from $\{0,1\}$ binary data.