Suicidal Behavior from a Complex System Perspective: Individual, Dynamical, and Contextual

Derek de Beurs, Remco de Winter, Marco Helbich, and Claudi Bockting

Contents

D. de Beurs (✉)
Head of Epidemiology, Trimbos-Institute for Mental Health and Addiction Research, Utrecht, The Netherlands
e-mail: dbeurs@trimbos.nl

R. de Winter
Medical Directorate Mental Health Institute Rivierduinen, Leiden, The Netherlands
e-mail: R.deWinter@rivierduinen.nl

M. Helbich
Department of Human Geography and Spatial Planning, Faculty of Geosciences, Utrecht University, Utrecht, The Netherlands
e-mail: m.helbich@uu.nl

C. Bockting
Department of Psychiatry, Amsterdam UMC, Location AMC, University of Amsterdam, Amsterdam, The Netherlands
e-mail: c.l.bockting@amsterdamumc.nl

M. Pompili (ed.), *Suicide Risk Assessment and Prevention*,
https://doi.org/10.1007/978-3-030-41319-4_35-1

Abstract

Suicidal behavior is the result of the complex interaction between many different components that interact over time. Still, traditional study designs operationalize suicidal behavior as static behavior, without any room for individual differences. But it seems times are changing. Novel technology such as data collection via apps and the collaboration with other disciplines such as ecology have resulted in an exciting new line of research within the field of psychopathology. These developments can also have an impact on how we think about, treat, and study suicidal behavior. By introducing complex system science within the field of suicide prevention, we hope to open up a whole range of novel concepts and testable hypotheses that can help us study suicidal behavior from a different perspective: individual, dynamic(al), and contextual.

Keywords

Suicidal behavior · Complexity science · Network analysis · Ideographic · Context

Introduction

Times Are Changing

Suicidal behavior is the result of the complex interaction between many different components that interact over time, ranging from genetics, individual psychological factors, to environmental factors [46]. Still, suicide prevention such as crisis hotlines tends to focus mostly on the management of single risk factors, such as the reduction of suicidal thinking [19, 37]. Suicidal behavior is also argued to be highly individual; however, most studies rely on group averages [2]. Finally, suicidal behavior is highly dynamical, although almost all studies assess patients only a few times during a period of years [23, 31, 32, 40]. No wonder it remains difficult to predict suicidal behavior [10, 19].

All these arguments do not only hold for the field of suicide prevention but for psychopathology in general [20, 28]. Both clinicians and researchers have realized since long that there is no such thing as an average patient, that a patient changes over time, and that the context matters [2]. However, research has remained focused on cross-sectional studies based on mutually excluding DSM diagnoses or on randomized trials that tried to control for any difference between persons via randomization [18]. But it seems times are changing.

The last years saw the rise in the appreciation and understanding of the complexity of psychopathology [8, 20, 28, 41, 48, 49]. One of the signs on the wall was the enthusiasm with which the network perspective of psychopathology was received by scientists, clinicians, patients, and funding bodies. The network perspective states that psychopathology is the result of the complex interaction between symptoms

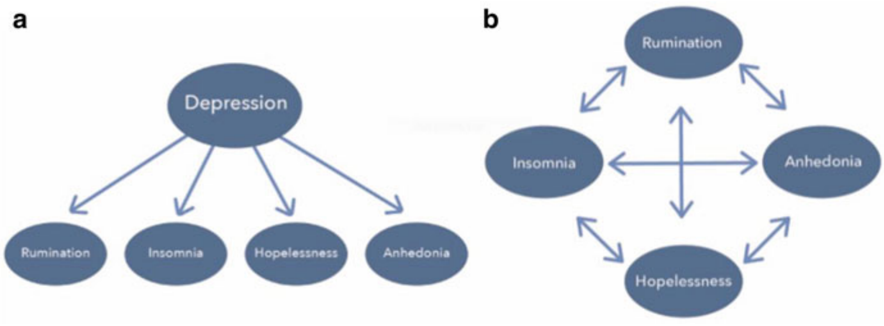

Fig. 1 (**a**) Psychopathology is the result of a brain−/genetic-related latent construct that causes symptoms. (**b**) Psychopathology is the result of the interaction between symptoms

[4]. This is a radically different theoretical starting point when compared to the traditional medical model, in which a latent factor is a single cause that causes symptoms (Fig. 1). Many papers have since been published using network analysis to better understand the complexity of depression, PTSD, and eating disorders and, recently, also suicidal behavior [15, 42].

In this chapter, we will introduce the latest insights from this new line of research, with a focus on suicide prevention. We will point out that network analysis is only the starting point for a more complex understanding of the development of psychopathology. By introducing complex systems science within the field of suicide prevention, we hope to open up a whole range of novel concepts and testable hypotheses that can help us study suicidal behavior from a different perspective: individual, dynamic(al), and contextual.

Complex Systems Are Everywhere

We encounter complex systems every day [1, 43]. Complex systems exist of many different variables that are highly interconnected and which interactions change over time when stress is added or just as the result of time moving on. Well-known examples of complex systems are the weather, coral reefs, shallow lakes, bird flocks, and also population growth and the outbreak of pathogens [43].

Nobody would think that predicting tomorrow's weather would be possible by just considering one variable, such as the amount of rain on the day before. Rather, we rely on models that take into account numerous variables including the interactions between these variables and how they change over time. One could think of temperature, wind, solar input, and pressure that are influenced by forces such as gravity, gas laws, and radiation laws. Still, human behaviour, which is arguably the mnost complex system in the world, is mainly studied with relative simple models only [20]. For example, psychiatry and psychology often rely on experimental designs, copied from physical science, studying one to two isolated factors that could be manipulated predominantly in lab settings in which all other variables were controlled. In the diagnostic and statistical manual of mental disorders (DSM), the complexity of mental health is reduced to a set of fictional bounded disorders, based on a restricted number of symptoms.

Within the traditional medical model, symptoms of psychopathology, such as worrying or suicide ideation, are caused by some specific neurobiological condition [4]. However, we still have no solid understanding of what a mental disorder is. This has prompted researchers to look for alternative models or a paradigm shift. Within the network perspective, there is no latent construct (i.e., a single cause), located in the brain that causes symptoms such as rumination or insomnia. Rather, it is the symptoms themselves that interact with each other over time and trigger other symptoms, resulting in a mental health condition ([4]; Fig. 1).

What holds for general psychopathology also holds for suicidal behavior. Although never categorized as a DSM diagnosis (although some have been arguing for that [39]), suicidal behavior has also been studied from a narrow focus, for example, by focusing on cognition or problems with self-regulation [37]. Epidemiological studies also keep on showing the same risk factors for suicidal behavior (such as a previous attempt), but a meta-analysis showed that our ability to predict suicidal behavior has not improved since the first longitudinal epidemiological study was done in 1965 [19]. To gain a better understanding, it has been proposed to also study suicidal behavior from a network perspective [12, 17].

Both a Symptom and the Result of the Interaction of Symptoms

Suicidality can be seen as a continuum, ranging from mild suicidal thoughts to actual (fatal) suicide attempts. From a network perspective, we argue that suicidality can be both part of a network and the result of a network. For example, (mild) suicide ideation can be seen as a symptom, such as rumination, that interacts with other symptoms and subsequently trigger other symptoms to in the end cause psychopathology. Take, for example, a dormant, stable network (Fig. 2, phase one). Due to the influence of stress, rumination gets activated, which triggers a sad mood and feelings of guilt. These variables enter a positive feedback loop, thereby increasing one another. When a certain threshold is reached, the node suicide ideation gets activated. Suicide ideation then becomes part of the feedback loop, affecting the other symptoms and being affected by them mutually. We pose that from this dynamical network of interacting variables, more severe suicidal ideation or even a suicide attempt might emerge. A suicide attempt or severe suicidal ideation is then conceptualized as the result of the interaction between the different variables over time and their circular feedback loop. Whether this line of reasoning holds true is an empirical question that needs to be tested in the coming years.

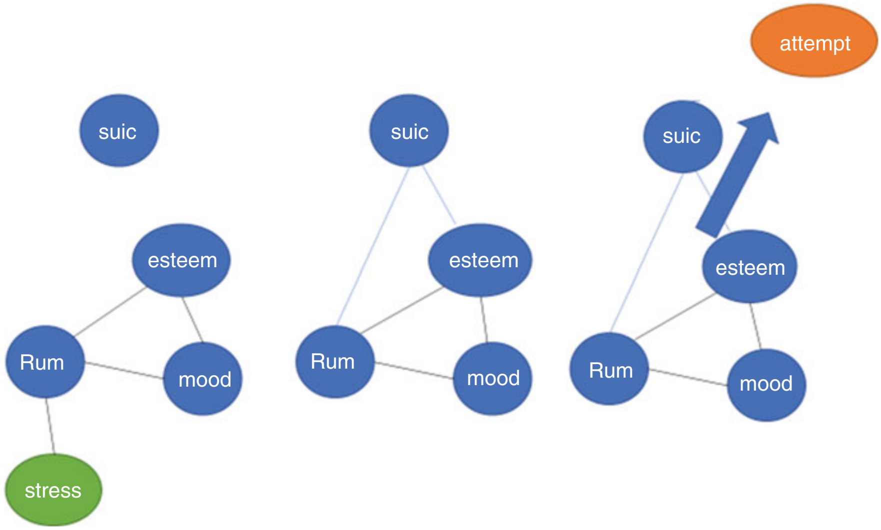

Fig. 2 Suicide attempt emerges from the interaction and feedback loops of risk factors: In phase one, stress activates rumination, which in return activates mood and sleep. After some time, the interaction between rumination, mood, and sleep also activates the node suicide ideation. In phase three, a suicide attempt *emerges* from the interaction between the four risk factors

Vulnerability for Psychopathology as the Result of Network Structure

One of the proposed hypotheses from the network perspective was that people that are more vulnerable to psychopathology have more densely connected networks [5]. Consider the two individual networks from Bob and Alice. Within the network of Bob, a stressor activates the feelings of rumination and worthlessness that activate feelings of entrapment and suicidal thoughts. Within the network of Alice, one sees that suicide ideation is never activated because there is no direct link of stress (Fig. 3).

The first study to empirically support this theoretical notion was done by van Borkulo et al., when they showed that patients who were still depressed at 2-year follow-up indeed had stronger connected networks compared to patients who did not have depression at follow-up [47]. However, a replication failed to find similar effects [44]. Within the field of suicide prevention, the first paper applying the network perspective tested the hypothesis that, indeed, participants treated for a recent episode of self-harm with a higher density of risk factors at baseline where at higher risk for future suicidal behavior at follow-up [14]. Using data collected from several hospitals in Glasgow, the baseline networks of the items of the Beck Scale for Suicide Ideation of patients with and without suicidal behavior at follow-up were estimated and compared. However, no differences between network densities were found between the groups. It is still an empirical question whether this null finding was due to a small sample size or whether there indeed is no difference between the baseline network structure of the two groups.

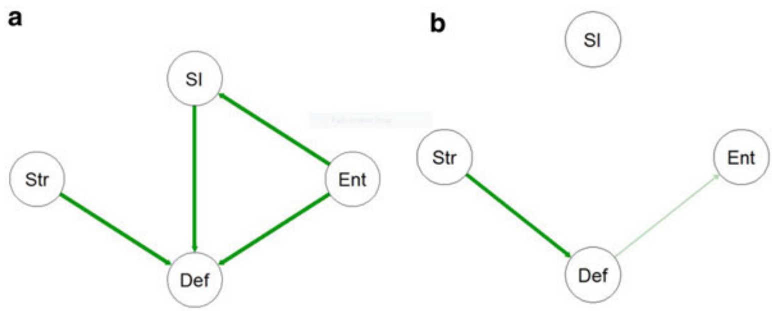

Fig. 3 (**a**) The symptom network of Bob, in which all symptoms are connected. (**b**) Symptom network of Alice, in which no symptom is connected directly to suicide ideation. Str, stress; Def, feelings of defeat; ent, feelings of entrapment; si, suicide ideation

The Role of the Most Central Symptom

Network analysis has a longer tradition in sociology where they estimate networks, for example, of the relationship between peers. An important metric within these social networks is called centrality [38]. Centrality relates to the connection a node has with other nodes in the network. A node that is highly connected (i.e., has strong direct links with other nodes) is argued to be most important. This node has the best potential to influence other nodes. For example, in the earlier mentioned study, de Beurs et al. estimated the network structure of the 19 separate items of the Beck Scale for Suicide Ideation. We found the item "I have a desire to kill myself" was most central in the network [14]. One could argue that targeting this node results in the most effect, as it will impact all surrounding nodes. Others suggest that the most central nodes are actually most difficult to target, because other nodes will trigger the central nodes quickly. And, importantly, in psychiatry we scarcely have interventions that focus solely on one symptom only. Finally, the whole concept of centrality within psychopathology is up for debate [9]. The metric comes from social sciences, where associations represent actual relations, such as the number of friends one has. Within psychopathology, the relation between, for example, worrying and rumination cannot be directly counted and must be indirectly estimated using statistics. Therefore, centrality means something different within the social sciences than in psychiatry, and nobody is yet sure what centrality entails within the field of psychopathology.

Using Networks to Test Theory

Network analysis can also be used to test theoretical models. For example, using a cross-sectional data from the Glasgow well-being study, de Beurs et al. used network analysis to examine the relation between the core components of the interpersonal theory of suicidal behavior (thwarted belongingness and perceived

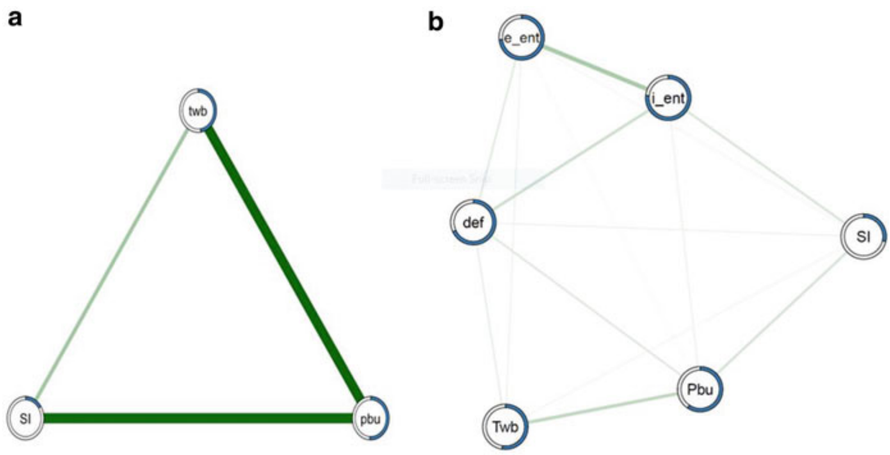

Fig. 4 (**a**) A network of the core components of the IPT model. (**b**) A network of the core components of both the IPT and the IMV model

burdensomeness), the core components of the integrated motivational volitional model (internal and external entrapment and defeat), and suicide ideation (Fig. 4: [16]). As the IPT states that thwarted belongingness and perceived burdensomeness cause suicide ideation, one would expect only these variables to be directly related to suicide ideation. When adding the core components of the IMV, network analysis showed that both internal entrapment and perceived burdensomeness were directly related to suicide ideation and the other variables only indirectly.

As argued by several authors, a next step would be to more accurately quantify the relation between any two nodes over time ([24, 41]. Do they affect each other in a linear way? Is a sigmoidal function more appropriate? These kinds of modeling require the input from not only psychiatrists or psychologists but also from mathematicians or computer systems scientists.

Ecological Momentary Data

It is interesting that the network *theory* focuses on individual differences, while most network studies to this day rely on cross-sectional group networks [42]. While cross-sectional analysis can definitely learn us about the co-occurrence of symptoms on a group level and help to develop a novel testable hypothesis, the unique added value of the network analysis lies in the *dynamical* interaction of symptoms over time [8]. Only then do networks really offer more than a pretty picture, as often vocalized by its critics. Theoretically, networks of symptoms are not some stable entity but rather ever-changing systems with a highly individualized dynamic [1]. There are several reasons why despite the logic to study individual differences, this has not taken off yet within the field of psychopathology [2]. For one, there just are not so much good-quality individual person data sets available. This field, called ecological momentary assessment, has been gaining momentum as mobile phones have been more readily available and the software more stable [45]. Still, available apps are still under development, with no real stable app that everybody seems to use. It remains difficult to let patients fill in momentary data, especially for a longer period. Methodologically, there is no consensus as to how to best analyze ecological momentary data. An original study offered the same individual patient data set to different international research groups [3]. The results showed a disturbing lack of similarity in chosen methods, and more worrisome, a disturbing lack of similarity across reported results.

Within the field of suicide prevention, some extra challenges arise [13, 36]. For one, patients need to have a certain kind of risk for suicidal behavior, making inclusion of patients more challenging. Also, we do not know the effect on a patients mood of frequently answering items on suicidality, although some initial studies found no negative effect of continuously assessing suicidality [11, 30]. A challenge from a methodological perspective is that to learn about transition phases between somebody who is stable, and somebody who either suddenly or gradually becomes suicidal, enough suicidal episodes during the assessment periods need to have taken place.

The few ecological momentary studies among suicidal patients that have been conducted show that suicide ideation fluctuates heavily over a short period of time [23, 31]. Up until now, only one paper has applied network analysis to study the network structure of risk factors for suicidal behavior over time [40]. As the data per person consisted of 60 beeps, we were only able to estimate a group dynamical model. So, the results present the *average* network structure over time of 74 patients. A total of 74 patients answered 10 assessments a day for a period of 6 days. The average time between beeps was 1.5 h. Within the average timeframe of 1.5 h, the best predictor of suicide ideation was suicide ideation itself. Classical risk factors such as hopelessness or depression did not predict suicide ideation at the next time point. When studying the nontemporal, cross-sectional relation, these risk factors wére related over time. This might indicate that all risk factors interact at a much faster pace than 1.5 h. It would be interesting to test the even longer-term dynamics within individuals as compared to several control groups, including healthy control groups. Hopelessness might predict suicide ideation a day or a week later. Currently, we are in the process of analyzing ecological momentary data over a much longer period of time, hoping to learn about the longer-term dynamics of suicidal behavior [36].

Suddenly or Gradually? The Move from Networks to Complexity

Networks are interesting on their own, but only one of the building blocks of which complex systems are built [1]. As psychological scientists became more interested in the dynamics of networks over time, they landed on the field of complex system theory, dynamical systems theory, or catastrophe theory. One academic field that has studied complex systems for a much longer time is the field of ecology, a branch of biology that studies the interaction between organisms and their environment [43]. One of the leading experts in complexity within the field of ecology, Marten Scheffer, noted that the principles that applied to different ecological systems such as shallow lakes might, on a high abstraction level at least, also be applicable to a range of other fields such as economics, sociology, and recently mental health [43, 48].

As an expert on shallow lakes, Sheffer studies the transition from clear to turbid lakes. Lakes do not gradually become turbid but, suddenly, as the result of a positive feedback loop of the interaction between various variables that made the system unstable. In 2013, Professor Borsboom, who introduced the network perspective within the field of psychopathology, teamed up with Marten Scheffer to apply these principles of complexity as found within ecology to better understand the etiology of psychological disorders. Analogous to the results in shallow lakes, they argued that persons with strongly connected networks of symptoms might be more vulnerable to reach an alternative stable state after an eternal stressor such as new measurements impact the network.

Consider again Bob and Alice who are in the same stable state A, i.e., they are both relaxed, and not depressed. When both listened to the same press conference on new corona restrictions, Alice starts to ruminate a bit, causing a small increase in experienced stress and a lowering of mood. However, after some hours, when she discussed the impact of the restrictions with her family, her stress level gets back to normal. Bob, on the other hand, cannot stop ruminating after the press conference; he starts losing sleep and starts feeling fatigued, which makes him ruminate even more. After a week or so, although the initial stressor moved to the background, the symptoms keep reinforcing themselves, resulting in even more worrying and less sleep. After some time, the system of Chris reaches a tipping point. His mood does not get back to his normal healthy state but instead gets pushed into an alternative stable state in which Bob cannot stop thinking about killing himself. So, even though the baseline state was similar, as was the stressor, for Bob the stressor activated a positive feedback loop among symptoms, which causes the transition to an alternative state.

Critical Transitions

If this is indeed how suicidal behavior develops over time, at least for some patients, this offers unique possibilities for prevention. As is shown in the field ecology but also in the field of depression in at least one study, transitions to alternative stable states are preceded by so-called early warning signals [49]. Critical slowing down means that when a system (or in our case, a suicidal person) nears a tipping point for a transition, the system shows slower recovery after a perturbation. The proof for critical transitions and critically slowing down in psychopathology has been limited to one case study, in which a mental healthcare user monitored himself for 239 days during gradual discontinuation of antidepressant medication. Future studies should examine whether any critical slowing down occurs before a new suicidal crisis [35].

Context

We discussed the individual and dynamic(al) perspective, but not yet the contextual. This is a growing field in suicidology, as contextual factors on the group level traditionally were hard to incorporate in models. Of course, background factors such as life events and childhood trauma are often shown to be of importance, even so much that a recent paper argues it overrides genetic effects [33]. However, to fully understand the day-to-day dynamics of an individual over time, one needs to take the specific dynamical interaction between context and for example psychological risk factors into account. Psychological factors, genetics, social economic status, family factors, the economic situation, and friendships, all these factors influence each other over time and limit the generalizability of our current laboratory-based, static research strategies that focus on group averages.

There is of course a very good reason not to focus on the many factors including contextual factors including the interactions and dynamics over time. It makes the data collection and analysis very complicated. Advances in unobtrusive methods to collect data with mobile phones might offer new opportunities. Modern phones can collect physical activity, location, and even social activity via Bluetooth. Within the field of social geography, interesting studies investigate the impact of geographical locations, mobility, and suicidality [25]. Advances in complex systems science enable us to integrate the factors, their interaction, and the dynamics over time.

The literature suggests various environmental characteristics possibly being associated with suicide mortality. These can be broadly grouped into two domains: the social and the physical environment. The former includes, but is not limited to, deprivation and social fragmentation [22], while the latter includes green space [34], air pollution, etc. [7]. However, empirical results on how the social and physical environment is associated to suicide mortality turned out to be inconclusive. Taking green space as an example, an ecological cross-sectional study in the Netherlands found a protective association of exposure to green space against suicide [26]. This finding was supported by stress reduction theory and attention restoration theory arguing that people's psychological and physiological functioning is positively stimulated by greenery (Hartig et al. 2014) and therefore makes people less vulnerable to suicidal thoughts. As suicide and greenery data was considered only on a municipality level, the possibility of confounding from using ecological inference was substantial due to disregarding person-level factors. Reassessing the suicide-green space associations based on individualized neighborhoods in a case-control setting did not confirm earlier findings [27].

Bringing It All Together

If we expand the current psychological networks with genetic, biological, social and environmental variables, they become to large and uninterpretable [29]. One suggestion is to work with multilayered networks [21].

However, no such longitudinal data set with detailed information at the individual level is yet available, and one wonders if it will ever be possible to fully study human behavior in all its complexity. Developments are going fast, and funders seem interested to support studies that push the field of psychiatry more towards complexity. One suggestion would be to add one extra layer at a time. Several studies showed that it is feasible to collect information on psychological factors of suicidal patients for a longer period of time. A next step would be to add, for example, location data or information on social contact via Bluetooth [25]. Then hopefully, step by step, we will learn how to understand suicidal behavior from an integrated individual, dynamical, and contextual perspective, in order to find new target points to preventive suicide.

References

1. Barabasi A. Linked. Basic Books, New York; 2014.
2. Barlow DH, Nock MK. Why can't we be more idiographic in our research? Perspect Psychol Sci. 2009; https://doi.org/10.1111/j.1745-6924.2009.01088.x.
3. Bastiaansen JA, Kunkels YK, Blaauw FJ, Boker SM, Chen M, Chow S, De Jonge P, Emerencia AC, Fisher AJ, Hamaker EL, Kuppens P, Lutz W, Joseph M, Moulder R, Oravecz Z, Rubel J, Servaas MN, Sjobeck G, Snippe E, Trull TJ, Van Der Veen DC, Wichers M, Wood PK, Woods WC, Wright AGC, Albers CJ, Bringmann LF, Mental F, Care H, Studies F, Sciences B, Bringmann LF. Time to get personal? The impact of researchers' choices on the selection of treatment targets using the experience sampling methodology. psyarxiv; 2019.
4. Borsboom D. A network theory of mental disorders. World Psychiatry. 2017;16:5–13. https://doi.org/10.1002/wps.20375.
5. Borsboom D, Cramer AOJ. Network analysis: an integrative approach to the structure of psychopathology. Annu Rev Clin Psychol. 2013;9:91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608.
6. Borsboom D, Cramer A, Kalis A. Brain disorders? Not really. . . Why network structures block reductionism in psychopathology research. Behav Brain Sci. 2018:1–54. https://doi.org/10.1017/S0140525X17002266.
7. Braithwaite I, Zhang S, Kirkbride JB, Osborn DPJ, Hayes JF. Air pollution (particulate matter) exposure and associations with depression, anxiety, bipolar, psychosis and suicide risk: a systematic review and meta-analysis. Environ Health Perspect. 2019; https://doi.org/10.1289/EHP4595.
8. Bringmann LF, Eronen M. Don't blame the model: reconsidering the network approach to psychopathology. Psychol Rev. 2018;125:606–15.
9. Bringmann LF, Elmer T, Epskamp S, Krause RW, Schoch D, Wichers M, Wigman JTW, Snippe E. What do centrality measures measure in psychological networks? J Abnorm Psychol. 2019; https://doi.org/10.1037/abn0000446.
10. Chan MKY, Bhatti H, Meader N, Stockton S, Evans J, O'Connor RC, Kapur N, Kendall T. Predicting suicide following self-harm: systematic review of risk factors and risk scales. Br J Psychiatry. 2016; https://doi.org/10.1192/bjp.bp.115.170050.
11. Coppersmith DD, Fortgang R, Kleiman E, Millner A, Yeager A, Mair P, Nock. Frequent assessment of suicidal thinking does not increase suicidal thinking: evidence from a high-resolution real-time monitoring study. Psyarxiv; 2020.
12. de Beurs D. Network analysis: a novel approach to understand suicidal behaviour. Int J Environ Res Public Health. 2017; https://doi.org/10.3390/ijerph14030219.
13. De Beurs D, Kirtley O, Kerkhof A, Portzky G, O'Connor RC. The role of mobile phone technology in understanding and preventing suicidal behavior. Crisis. 2015;36:79–82.

14. de Beurs DP, van Borkulo CD, O'Connor RC. Association between suicidal symptoms and repeat suicidal behaviour within a sample of hospital-treated suicide attempters. Br J Psychiatry Open. 2017;3:120–126.
15. de Beurs D, Fried E, Wetheral K, Cleare S, O'Connor D, Ferguson E, O'Carroll R, O'Connor R. Exploring the psychology of suicidal ideation: a theory driven network analysis. Preprint. 2018. https://os.
16. De Beurs D, Fried EI, Wetherall K, Cleare S, O'Connor DB, Ferguson E, O'Carroll RE, O'Connor RC. Exploring the psychology of suicidal ideation: a theory driven network analysis. Behav Res Ther. 2019; https://doi.org/10.1016/j.brat.2019.103419.
17. De Beurs DP, De Beurs D, Bockting C, Kerkhof A, Scheepers F, O'Connor R, Penninx B, Van De Leemput I. A network perspective on suicidal behavior: understanding suicidality as a complex system. Suicide Life-Threat Behav. 2020;51(1):115–126
18. Fox KR, Huang X, Guzmán EM, Funsch KM, Cha CB, Ribeiro JD, Franklin JC. Interventions for suicide and self-injury: a meta-analysis of randomized controlled trials across nearly 50 years of research. Psychol Bull. 2020; https://doi.org/10.1037/bul0000305.
19. Franklin JC, Ribeiro JD, Fox KR, Bentley KH, Kleiman EM, Huang X, Musacchio KM, Jaroszewski AC, Chang BP, Nock MK. Risk factors for suicidal thoughts and behaviors: a meta-analysis of 50 years of research. Psychol Bull. 2016; https://doi.org/10.1037/bul0000084.
20. Fried EI, Robinaugh DJ. Systems all the way down: embracing complexity in mental health research. BMC Med. 2020; https://doi.org/10.1186/s12916-020-01668-w.
21. Guloksuz S, Pries LK, Van Os J. Application of network methods for understanding mental disorders: Pitfalls and promise. Psychol Med. 2017; https://doi.org/10.1017/S0033291717001350.
22. Hagedoorn P, Groenewegen PP, Roberts H, Helbich M. Is suicide mortality associated with neighbourhood social fragmentation and deprivation? A Dutch register-based case-control study using individualised neighbourhoods. J Epidemiol Community Health. 2020; https://doi.org/10.1136/jech-2019-212699.
23. Hallensleben N, Spangenberg L, Forkmann T, Rath D, Hegerl U, Kersting A, Kallert TW, Glaesmer H. Investigating the dynamics of suicidal ideation: preliminary findings from a study using ecological momentary assessments in psychiatric inpatients. Crisis. 2018; https://doi.org/10.1027/0227-5910/a000464.
24. Haslbeck J, Oisín R, Robinaugh D, Waldorp L, Borsboom D. Modeling psychopathology: from data models to formal theories. Preprint; 2019.
25. Helbich M. Dynamic Urban environmental exposures on Depression and Suicide (NEEDS) in the Netherlands: a protocol for a cross-sectional smartphone tracking study and a longitudinal population register study. BMJ Open. 2019; https://doi.org/10.1136/bmjopen-2019-030075.
26. Helbich M, de Beurs D, Kwan M-P, O'Connor RC, Groenewegen PP. Natural environments and suicide mortality in the Netherlands: a cross-sectional, ecological study. Lancet Planet Health. 2018;2 https://doi.org/10.1016/S2542-5196(18)30033-0.
27. Helbich M, O'Connor RC, Nieuwenhuijsen M, Hagedoorn P. Greenery exposure and suicide mortality later in life: a longitudinal register-based case-control study. Environ Int. 2020; https://doi.org/10.1016/j.envint.2020.105982.
28. Holmes EA, Ghaderi A, Harmer CJ, Ramchandani PG, Cuijpers P, Morrison AP, Roiser JP, Bockting CLH, O'Connor RC, Shafran R, Moulds ML, Craske MG. The Lancet Psychiatry Commission on psychological treatments research in tomorrow's science. Lancet Psychiatry. 2018; https://doi.org/10.1016/S2215-0366(17)30513-8.
29. Jones PJ, Heeren A, McNally RJ. Commentary: a network theory of mental disorders. Front Psychol. 2017; https://doi.org/10.3389/fpsyg.2017.01305.
30. Kleiman EM, Nock MK. Real-time assessment of suicidal thoughts and behaviors. Curr Opin Psychol. 2018; https://doi.org/10.1016/j.copsyc.2017.07.026.
31. Kleiman EM, Turner BJ, Fedor S, Beale EE, Huffman JC, Nock MK. Examination of real-time fluctuations in suicidal ideation and its risk factors: results from two ecological momentary assessment studies. J Abnorm Psychol. 2017; https://doi.org/10.1037/abn0000273.

32. Kleiman EM, Coppersmith DDL, Millner AJ, Franz PJ, Fox KR, Nock MK. Are suicidal thoughts reinforcing? A preliminary real-time monitoring study on the potential affect regulation function of suicidal thinking. J Affect Disord. 2018; https://doi.org/10.1016/j.jad.2018.02.033.
33. Marsman A, Pries L-K, ten Have M, de Graaf R, van Dorsselaer S, Bak M, Kenis G, Lin BD, Luykx JJ, Rutten BPF, Guloksuz S, van Os J. Do current measures of polygenic risk for mental disorders contribute to population variance in mental health? Schizophr Bull. 2020; https://doi.org/10.1093/schbul/sbaa086.
34. Mitchell R, Popham F. Effect of exposure to natural environment on health inequalities: an observational population study. Lancet. 2008; https://doi.org/10.1016/S0140-6736(08)61689-X.
35. Nuij C, Van Ballegooijen W, Ruwaard J, de Beurs D, O'Connor RC, Smit JH, Riper H, Kerkhof A. Smartphone-based safety planning and self-monitoring for suicidal patients: a conceptual basis for the CASPAR (Continuous Assessment for Suicide Prevention and Research) study. 2017; https://doi.org/10.20944/preprints201704.0103.v1.
36. Nuij C, van Ballegooijen W, Ruwaard J, de Beurs D, Mokkenstorm J, van Duijn E, de Winter RFP, O'Connor RC, Smit JH, Riper H, Kerkhof A. Smartphone-based safety planning and self-monitoring for suicidal patients: rationale and study protocol of the CASPAR (Continuous Assessment for Suicide Prevention And Research) study. Internet Interv. 2018;13 https://doi.org/10.1016/j.invent.2018.04.005.
37. O'Connor RC, Kirtley OJ. The integrated motivational–volitional model of suicidal behaviour. Philos Trans R Soc B Biol Sci. 2018; https://doi.org/10.1098/rstb.2017.0268.
38. Opsahl T, Agneessens F, Skvoretz J. Node centrality in weighted networks: generalizing degree and shortest paths. Soc Networks. 2010;32:245–51. https://doi.org/10.1016/j.socnet.2010.03.006.
39. Oquendo MA, Baca-García E, Mann JJ, Giner J. Issues for DSM-V: suicidal behavior as a separate diagnosis on a separate axis. Am J Psychiatry. 2008; https://doi.org/10.1176/appi.ajp.2008.08020281.
40. Rath D, de Beurs D, Hallensleben N, Spangenberg L, Glaesmer H, Forkmann T. Modelling suicide ideation from beep to beep: application of network analysis to ecological momentary assessment data. Internet Interv. 2019; https://doi.org/10.1016/j.invent.2019.100292.
41. Robinaugh DJ, Haslbeck JMB, Waldorp LJ, Kossakowski JJ, Fried EI, Millner AJ, McNally RJ, van Nes EH, Scheffer M, Kendler KS, Borsboom D. Advancing the network theory of mental disorders: a computational model of panic disorder. Preprint. 2019; https://doi.org/10.31234/osf.io/km37w.
42. Robinaugh DJ, Hoekstra RHA, Toner ER, Borsboom D. The network approach to psychopathology: a review of the literature 2008–2018 and an agenda for future research. Psychol Med. 2019;50(3):353–366.
43. Scheffer M. Critical transitions in nature and society. Princeton studies in complexity, 2009.
44. Schweren L, van Borkulo CD, Fried EI, Goodyer I. Assessment of symptom network density as a prognostic marker of treatment response in adolescent depression. JAMA Psychiatry. 2018;75:98–100.
45. Trull TJ, Ebner-Priemer UW. Using experience sampling methods/ecological momentary assessment (ESM/EMA) in clinical assessment and clinical research: introduction to the special section. Psychol Assess. 2009; https://doi.org/10.1037/a0017653.
46. Turecki G, Brent DA. Suicide and suicidal behaviour. Lancet. 2016; https://doi.org/10.1016/S0140-6736(15)00234-2.
47. van Borkulo C, Boschloo L, Borsboom D, Penninx BWJH, Waldorp LJ, Schoevers RA. Association of symptom network structure with the course of longitudinal depression. JAMA Psychiat. 2015;1219 https://doi.org/10.1001/jamapsychiatry.2015.2079.
48. van de Leemput IA, Wichers M, Cramer AOJ, Borsboom D, Tuerlinckx F, Kuppens P, van Nes EH, Viechtbauer W, Giltay EJ, Aggen SH, Derom C, Jacobs N, Kendler KS, van der Maas HLJ, Neale MC, Peeters F, Thiery E, Zachar P, Scheffer M. Critical slowing down as early warning for the onset and termination of depression. Proc Natl Acad Sci U S A. 2014;111:87–92. https://doi.org/10.1073/pnas.1312114110.
49. Wichers M, Groot PC. Critical slowing down as a personalized early warning signal for depression. Psychother Psychosom. 2016; https://doi.org/10.1159/000441458.