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Methodological paper

A Network Control Theory of Dynamic Systems Approach to Personalize Therapy

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Contemporary latent disease models of psychopathology have shown limited clinical utility and the efficacy of conventional treatments have been disappointing. An alternative approach offers the network approach and a dynamic systems perspective to psychopathology and treatment change. To understand and modify dynamic systems, engineering and mathematics have been relying on principles of network control theory. This article will discuss the application of network control theory of dynamic systems approach to personalize therapy. Network control theory can be used as a guide for personalizing treatment by choosing the most promising intervention strategy targeting the change processes based on the network structure. A composit case illustration will demonstrate the principles and application of network control theory to therapy in practice within the framework of process-based therapy. In conclusion, a network control theory of dynamic systems approach is highly relevant and applicable to clinical science.

Keywords: CBT; process-based therapy; processes; network control theory; dynamic systems

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MENTAL HEALTH problems are common. A survey of more than 156,000 people from 29 countries suggest that by age 75 years, approximately half the population will develop at least 1 of 13 possible mental disorders that typically emerge at a young age (McGrath et al., 2023). Therefore, early and effective treatments can significantly improve a person's quality of life and lessen the economic burden to society. One of the most cost-effective interventions for virtually all mental disorders is cognitive behavioral therapy (CBT; for a review, see, for example, Hofmann et al., 2012). But despite the remarkable success of CBT, the response rates have not been improving over the years. For example, the efficacy CBT for the most common disorders, such as mood (Cuijpers et al., 2024) and anxiety disorders (Bhattacharya et al., 2023), has not been improving over the years as compared to control treatments.

One of the reasons for this state of affairs may be related to the shift from person to syndrome as the focus of therapy over the years. Early clinical scientists focused on the individual and processes of change rather than groups of individuals sharing the same syndrome or underlying disease. This has been highlighted by Gordon Paul's now famous question that should guide intervention science: "What treatment, by whom, is most effective for this individual with that specific problem, under which set of circumstances, and how does it come about?" (Paul, 1969, p. 44). Expanding this tradition of personalized evidence-based psychological, process-based therapy (PBT) has developed as a new framework to understand psychopathology and treatment change (Hayes, Hofmann, & Ciarrochi, 2020; Hofmann & Hayes, 2019). PBT is a general framework to conceptualize psychopathology and treatment change. Accordingly, psychopathology is considered as a maladaptation to a given context. Based on evolutionary science, adaptation is a context-dependent function of variation, selection, and retention of relevant aspects of human function and experience that are organized along basic psychological dimensions, including cognition, attention, affect, behavior, self, and motivation, as well as biophysiological and sociocultural levels (Hayes, Hofmann, & Wilson, 2020). These dimensions and levels comprise the extended evolutionary meta model (EEMM) of PBT (Hayes, Hofmann, & Wilson, 2020). Although the therapeutic concept of PBT has been applied in principle (e.g., Ong et al., 2022), one critical question that remained was how to select and personalize specific intervention strategies to a given client within the PBT framework.

In this article, I will further build on this approach and introduce network control theory of dynamic systems, a concept from engineering, as a guide to develop an algorithm to select and personalize therapeutic strategies. This approach will necessitate a critical examination of the contemporary paradigms of mental health and therapeutic change. I will begin by describing the traditional paradigm of psychiatry and how psychotherapy, especially CBT, aligned itself with it over the years.

The Syndromal View of the Latent Disease Model

With the increasing popularity of randomized controlled trials, combined with the medicalization of psychological problems, clinical scientists developed treatment manuals and protocols to treat ever so specific problems as defined by a particular nosological system under controlled scientific conditions. CBT began as a nonsyndromal intervention rooted in cognitive and behavioral sciences. The essential ingredients of cognitive therapy, introduced by Aaron T. Beck, were applied to any therapy session, regardless of the client's diagnosis. These ingredients included general therapeutic skills, such as setting an agenda, providing feedback, empathic skills, interpersonal effectiveness, and techniques defining the approach itself, such as guided discovery, collaborative empiricism, focusing on key cognitions and behaviors, and homework assignments (Young & Beck, 1980). The specific case was conceptualized using a CBT framework. The specific diagnostic label was of little importance. This changed over the years. Various cognitive models were developed for clearly defined DSM-defined disorders (for a review, see Hofmann et al., 2013). Today, libraries of books can be found on CBT approaches for virtually every syndrome and disorder listed in the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5; American Psychiatric Association [APA], 2013) and the *International Statistical Classification of Diseases and Related Health Problems* (ICD; 11th rev., World Health Organization [WHO], 2022). Paradoxically, CBT became one of the prime beneficiaries of a syndrome-based psychiatry because it was often used as the psychological comparison treatment for pharmacotherapy for specific syndromes. For this reason, CBT manuals and protocols developed, specifically tailored to a group of people sharing a specific syndrome, designed to reduce disorder-specific symptoms with little emphasis on any interindividual differences or the underlying processes of change. In fact, any factors unrelated to the specific target syndrome were controlled or eliminated in an attempt to examine the pure net effect of an intervention on a specific syndrome.

Such a syndromal view of mental health closely aligns with a latent disease model of psychopathology. Accordingly, a mood disorder, anxiety, or a substance use disorder cannot be directly measured through a blood test, saliva test, or nasal swap (similar to a Covid test) or even an MRI scan. Rather, the existence is inferred through self-report data by the patient and their interpretation and behavioral observations by the clinician. A diagnostic label in psychiatry has been used akin to a diagnosis in other fields of medicine. In many of those subfields, improving a diagnosis led to greater insight into the psychopathology and often linked directly to better and sometimes even personalized treatment, as in the case of immunotherapy for certain cancers.

Syndromes have been traditionally defined by the contemporary nosological systems for mental disorders, which assume that mental disorders are expressions of latent disease entities. Accordingly, the existence of a disease entity is inferred based on reported or observed symptoms. The disorder itself, whether it is major depressive disorder or social anxiety disorder, cannot be directly measured, but their symptoms can be observed, usually through asking the client specific questions during a diagnostic evaluation. There is no blood test or MRI test that is used to determine or even inform the diagnosis. Instead, it is based on the clinician's interpretation of the client's responses to specific answers in conjunction with his or her behavior during the clinical interview. Not surprisingly, a diagnostic label is fraught with problems, ranging from societal stigma to unreliability of the process and outcome. Nevertheless, diagnostic categories are usually seen as necessary to establish a common language among clinical scientists and providers. To make the language more precise, the diagnostic categories became increasingly specific with the goal to form valid disease entities, attempting to carve nature at its joints.

Although the reliability of diagnostic categories might have improved over the years, their clinical utility did not and the focus of research started to shift away from the individual. Individual differences became increasingly underemphasized, while the syndromal view of mental health and mental health problems became overemphasized. Paradoxically, the very attempt to galvanize and spark research on the etiology and treatment of mental disorders by defining clear categories led to the stagnation of clinical science as a whole.

Alternatives to the Latent Disease Model

In response to the problems with the DSM and the ICD, alternatives to the contemporary nosology for mental disorders have been emerging. A prominent counter position to the DSM-5 was the Research Domain Criteria (RDoC) initiative by Thomas Insel, who was the director of the National Institute of Mental Health in the United States during the development process of the DSM-5 (Insel et al., 2010). The basic assumption was that mental disorders are brain disorders with a clear biological basis that could be translated to concrete and effective interventions. RDoC was an attempt to bridge the gap between basic science and clinical applications by establishing a general framework to direct the research to specific research domains that are of clinical relevance. After his tenure at NIMH, Insel acknowledged that the RDoC initiative failed because it did not improve the lives of people with mental illnesses in any meaningful way. However, the initiative also led to many positive developments, including the realization that an intervention requires a target engagement and the consideration that many mental health problems are dimensional in nature. Most importantly, the initiative reinvigorated attempts to improve and modernize nosology and intervention research. Since then, a number of other proposals have been introduced, most notably the Hierarchical Taxonomy of Psychopathology (HiTOP; Kotov et al., 2021).

HiTOP (Kotov et al., 2021) defines higher-order dimensions based on nomothetic self-report data, including personality questionnaires. Individual differences remain error variance and no specific implications for treatment can be derived from the system, which is primarily based on hierarchical linear modeling and factor analyses, limiting its clinical utility (Haeffel et al., 2022). The novel feature of these systems is the departure from a categorical system and allowing or embracing a dimensional view (for a review of the recent state of the science of HiTOP, see Cicero et al., 2024). However, both, RDoC and HiTOP still imply the existence of one or more latent diseases in individuals with mental health problems. RDoC assumes that the disease can be traced to biological entities or functions, such as genes, molecules, cells, and circuits, whereas HiTOP assumes the existence of a general factor of psychopathology (called p-factor), which is inferred based on self-report instruments derived from large samples. An alternative to these latent disease models is the network approach.

The Network Approach

SOME BASICS

Network theory is a subset of graph theory, a branch of mathematics focused on the visual representation of a set of objects and the links connecting pairs of these objects (e.g., Barabási & Albert, 1999). Networks consist of two main components: nodes, which represent objects, and edges, which are lines that connect two objects, indicating the type of association between them. An unweighted network simply shows whether two nodes are connected, while a weighted network also indicates the strength of their association.

In directed networks, some connections point toward a node, others point toward another node. Some connections may be bidirectional. The strength of the connection is expressed in form of different weights. The sum of inward link weights is the inward strength, and the sum of outward link weights is the out-strength of a node. Networks with many nodes with connections that are neither random nor uniform are often referred to as complex networks (Barabási & Albert, 1999). The structure, or topology, of a complex network can vary considerably. For example, some nodes may cluster into subgroups (subnetworks), while others have few or weak connections to other nodes.

Network theory allows for the calculation of centrality metrics, which highlight the importance of a node within the network. A highly central node, when activated, is likely to spread activation throughout the network via the edges linking it to other nodes. For example, a node with high degree centrality has many edges connected to it, whereas a node with high strength centrality in a weighted network has many edges with strong associations. A node with high betweenness centrality frequently lies on the shortest path between two other nodes.

The mere association between two nodes does not imply causality or directionality. Such associations can be spurious, induced by other variables within the network. To clarify these relationships, researchers sometimes estimate a Gaussian graphical model (GGM), where edges represent (regularized) partial correlations between symptom pairs, accounting for the influence of all other symptoms in the network. Regularization removes edges of very small magnitude, which are of dubious reliability. The GGM shows nonspurious associations between symptoms but does not indicate the direction of prediction or possible causal influence.

Bayesian network analysis, on the other hand, yields a directed acyclic graph (DAG). Unlike cross-sectional GGMs, a DAG includes an arrowhead at one end of each edge, indicating the direction of prediction between connected nodes (e.g., symptoms). Computing both a DAG and a GGM on the same dataset can provide complementary insights into the structure of symptoms in a cross-sectional dataset. However, the DAG does not show temporal precedence due to the cross-sectional nature of the data. Instead, it shows directional dependence (e.g., Briganti et al., 2023). To examine directionality or even causality of links between nodes within a network, changes over time need to be considered.

Networks can be calculated based on nomothetic or idiographic data. The present article follows an idiographic approach. Idiographic network models typically involve high-density data in a single individual using ecological momentary assessment data that are then analyzed with statistical methods to derive temporal and contemporaneous isographic networks. The statistical conditions to compute these networks are quite challenging. A recent simulation study suggests that 70 to 100 time points are needed to compute a network with no more than 6 network nodes and very few missing data (Mansueto et al., 2023). Here, I will not stay within these methodological confines using empirical data. Instead, I present a proof-of-concept approach to guide with treatment selection based on network control theory of dynamic systems.

NETWORK CONNECTIVITY, RESILIENCE, AND CRITICAL TRANSITIONS

Network connectivity refers to the extent to which nodes are interconnected. A network exhibits a high level of homogeneity when its nodes display significant similarity. Homogeneous and highly connected networks often demonstrate bistability, meaning they can exist in either a pathological or nonpathological state. A key characteristic of a dynamic system is its attractor states, where a network achieves equilibrium and increased stability. When in such a stable state, disturbances typically disrupt the equilibrium only temporarily, as the network quickly returns to the attractor state once the disturbance subsides. However, certain disturbances can push the network beyond a critical threshold (the tipping point), leading to a new stable state. For instance, a major stressor might destabilize a healthy network, causing the individual to shift from an adaptive (healthy) to a maladaptive (psychopathology) network, or vice versa.

The ease with which the system changes from one state to the next is determined by its stability (i.e., strength of the attractor). The stability of a system is often referred to as resilience. Resilience refers to how quickly a system recovers from disturbances. Highly connected and homogeneous networks tend to be resilient to change; destabilizing events only temporarily alter the configuration of nodes. Strong local connectivity among neighboring nodes promotes local resilience, as the entire network can compensate for the effects of local perturbations. This compensatory ability is linked to the network's structure, with highly connected networks being more stable. A complex system in a pathological state is resilient if attempts to change it fail, indicating a strong attractor state that prevents the system from reaching a tipping point and transitioning to another state. Conversely, weak connectivity typically causes the network to change gradually in response to external influences, as weakly connected and isolated nodes tend to shift independently. In contrast, in homogeneous and highly connected systems, a local perturbation can trigger a domino effect, leading to an abrupt systemic transition to another attractor state once a tipping point is reached (e.g., Scheffer et al., 2024). An important indicator of such a transition is the phenomenon called *critical slowing down*, where a network exhibits slow recovery from local perturbations due to external stressors. This indicates a loss of resilience, making the network more susceptible to tipping into an alternative state. Signs of critical slowing down include fluctuations in the network's configuration, evidenced by increased variance in changes of some network elements and higher lag-1 autocorrelations. These features can be assessed when collecting high-density ecological momentary assessment data or relevant variables that represent or are highly correlated with the critical nodes of the network.

The network approach offers a fresh new look at psychopathology and, as will be described here, for therapy. This approach does not require the presumption of the existence of latent constructs, whether dimensional or categorical. A person's mental health problem is not seen as a reflection of a brain or other form of latent disease entity. A network approach also does not presume that mental health problems need to be dimensional or categorical in nature. Instead, mental health problems are conceptualized as phenomena that arise from a network of connections and interactions among its constitutive elements (e.g., Borsboom & Cramer, 2013; Hofmann et al., 2016; McNally, 2021; Scheffer et al., 2024; Schmittmann et al., 2013).

A DYNAMIC SYSTEMS PERSPECTIVE TO MENTAL HEALTH

Individual or local networks, in particular, can offer valuable insights for treatment planning and identifying treatment targets. Networks that change over time are also referred to as *dynamic systems*. In general, a dynamic system is a system that evolves over time according to a set of defined rules and that consists of variables that change and interact with one another. These rules can be described using mathematical models, such as differential equations or difference equations, which are beyond the scope of this article. The key characteristics of dynamic systems include the state variables that define the state of the system at any given time, the system's behavior changes over time, which can be continuous or discrete, and feedback loops, that can occur when the output of a system influences its own input, creating a loop of interactions that affect the system's evolution.

Many dynamic systems exhibit nonlinear behavior (e.g., small changes in initial conditions or inputs can lead to large and sometimes unpredictable changes in the system's state). They can also have stable or unstable equilibrium points (attractor states and tipping points), where changes in parameters can lead to bifurcations, where the system's qualitative behavior changes dramatically within a short period of time.

Dynamic systems are commonly observed in sociology, and neuroscience. They also apply to psychopathology and (as shown in this article) to psychotherapy. In highly connected networks, transitions between states are rarely linear. Instead, changes often happen suddenly when the system reaches a tipping point. Tracking psychological problems longitudinally can reveal how networks evolve over time, such as the trajectory or recovery from a mental disorder (Barabási et al., 2011). Psychotherapy is a method to influence and control the network from a maladaptive (disease) state to an adaptive (healthy) state. The rules to control a network are described in network control theory.

Network Control Theory

SOME BASICS

Network control theory is a branch of engineering and mathematics, primarily dealing with robotics, industrial automation, aerospace, and automotive. In general, network control theory aims to understand the behavior of dynamical systems and how to control them in order to improve the performance and stability of the systems (e.g., Ogata, 2010).

In traditional network control theory, a system utilizes the comparison between the output and the reference input to maintain a specific relationship between the output and the refence input, called a *feedback control system* (such as in the case of a thermostat to regulate the room temperature). This is also an example of a *closed-loop control system* because the difference between an input signal and the feedback signal leads the internal controller of the system to reduce the discrepancy. In contrast, in the case of an *open-loop system*, the output has no influence on the control action. For example, a traditional washing machine will complete its predetermined cycles even if the clothes are still dirty. One benefit of a closed-loop control system is its ability to utilize feedback, which helps the system maintain a consistent response despite external disturbances and internal variations in system parameters. However, a significant problem of closed-loop systems is its stability because there is a risk of overcorrection that may lead to oscillations of either constant or varying amplitudes. Network control theory enables a systematic, theory-driven evaluation of the overall difficulty in inducing changes throughout the entire network following alterations of one or more nodes or edges. The impact of these changes is the *controllability*.

The term *control* here implies that a variable is measured and manipulated to correct or limit the discrepancy between actual vale from the desired value. Other important terms in network control theory are *process*, *system*, and *disturbance* (Ogata, 2010). A *process* refers to the operation that is being controlled; a *system* is the combination of components that interact toward a particular objective, and a *disturbance* is a force that impacts the value of the output of a system. It can be internal if it is generated within the system, or external if it is generated outside of the system. For network control theory to effectively inform psychological interventions, it is crucial to examine if and how the engineering concepts underlying network control theory apply to psychological networks.

APPLICATION TO MENTAL HEALTH

Fundamentally, the idea is that an intervention influences one or more elements in a network, such as affective states, thoughts, attention, or behaviors. The degree of influence is in proportion to the intervention's intensity and the elements' characteristics, referred to as the *locally linearizable assumption* (Robinaugh et al., 2021). This concept, fundamental in engineering and more recently in neuroscience, enables analytical treatment of observed phenomena and stimulated progress in understanding psychological states under various stimulations (Bemporad et al., 2010; Liu et al., 2011; Stocker et al., 2023).

Although mental health follows many of the principles of classical control theory, there are a number of obvious and unique features. Although there are many different feedback loops to maintain the system, the parameters of the constituents of the system do not remain stable. Therefore, human mental health is not a closed-loop time-invariant system with an internal controller and clearly predetermined setpoints. Instead, the system is often chaotic in nature and highly dynamic and subject to constant and unpredictable outside disturbances. Even the mere passage of time can change the system. For example, major depressive disorder is by definition a form of psychopathology that changes with time because the time-limited major depressive episode defines the disorder.

Because mental health and psychopathology is a time-sensitive and dynamic system, therapy is akin to hitting a moving target to control the system toward a more desirable state. Therapy can act on one or more nodes of a problem network, one or more edges of a network, and one or more subnetworks of system. This is done through treatment strategies to target specific processes that, in turn, can change the entire system depending on the amount of control energy delivered to the system.

Applying Network Control Theory to Therapy

CONTROL ENERGY IN THERAPY

Treatment change aligns with the idea that a dynamic system can occupy bi-stable states through critical transitions, making a network perspective highly relevant to clinical science. The efficacy of an intervention is a function of the stability (or resilience) of the system and the control (or intervention) energy. The totality of effect of the intervention strategies on the processes is the total control energy exerted on the network. The control energy (E) can be quantified as the sum of the weighted processes targeting the network (Formula 1):

$E = \sum \beta Pi$, where β is the weight determined by the efficacy of a process (Pi).

The more stable the system, the more energy is required to perturbate the system. Moving a highly resilient system over the tipping point will require forcefully targeting critical nodes, multiple nodes simultaneously, and/or one or more edges that contribute to the stability of the system. Although there are too many unknown or uncertain variables to precisely calculate the controllability of a system and the energy necessary to change the system (at least as of now), we can apply the principles of network control theory to guide us with choosing the most promising intervention strategy based on the network structure, presumed change processes, and intervention strategies to target these change processes.

CHANGE PROCESSES

Change processes have been traditionally studied in psychotherapy through mediation analyses. Traditional mediation analyses have had limited success to understand and study change processes. The main problems include (1) the violation of key statistical assumptions needed to apply mediational results tested at a group level to individuals, (2) the fact that change processes often involve multiple variables extended over time, (3) the fact that mediator, outcome, and independent variables usually do not have a strict unidirectional and stable relationship, but instead often form bidirectional relationships that change over time, and (4) the fact that change processes are often nonlinear (Hofmann et al., 2020).

An alternative approach to study change processes is through methods from network science and dynamic systems. The term *process* is preferred over *mechanism* or *mediator* because it is a clearly defined term in dynamic systems. More specifically, we previously defined processes as "a set of theory-based, dynamic, progressive, and multilevel changes that occur in predictable empirically established sequences oriented toward the desirable outcomes" (Hofmann & Hayes, 2019, p. 38).

An example of a high-level process may be psychological flexibility (Ong et al., 2024, Westhoff et al., 2024). In contrast, a low-level process might be reappraisal of a particular experience. Multiple lower-order processes can be subsumed under the same high-level process. For example, psychological flexibility is necessary for a person to view an event from a different perspective in order to reevaluate a range of ambiguous situations. Similarly, changes in attentional focus are necessary for reappraisal processes, all requiring cognitive flexibility, which may be considered as a form of psychological flexibility.

When applied to dynamic systems, we assume that a change process impacts one or more nodes of a network. Processes can also impact edges, but for simplicity the following example is limited to the assumption that the processes primarily target the nodes of the network. If there was good evidence to suggest that the edges are also relevant targets, we could apply the same principles to edges that are outlined here for the nodes.

In the case of a maladaptive psychopathology network, an effective intervention represents the external disturbance. In the case of therapy, therapeutic processes can perturbate a maladaptive network by activating one or more network nodes. The same process can target one or multiple nodes at the same time, and multiple processes can act on the same node. The network control theory matrix depicted in Table 1 examines which change process is likely to target which network node. A case illustration will follow later. If the process is assumed to target specific edges, the first column, named network nodes, is replaced by network edges.

For simplicity's sake, we assume that processes are clearly identifiable, testable, and distinguishable from pathological states. Unfortunately, however, therapeutic change processes are still not as well understood and more research is necessary. For example, it could be argued that there is no clear distinction between psychopathological states and maladaptive processes (e.g., worrying can be the primary maladaptive process or a consequence of a maladaptive process).

Table 1
Control Theory Matrix of Change Processes and Network Nodes

	Change Processes		
Network Nodes	P1	P2	. . .
N1			
N2			
. . .			

TREATMENT STRATEGIES

Treatment strategies are the methods, strategies, or techniques employed in order to target the processes of change. They are the specific methods that are implemented in therapy. The strategies act on the treatment targets through specific processes (formerly also known as *mechanisms* or *mediators*) that are intended to lead to the desirable treatment goal. Treatment strategies differ in their degree of sensitivity and specificity of controllability. Here, *sensitivity* is defined as the extent to which the intervention works in the desired direction, whereas *specificity* is defined as the efficiency of the perturbation in changing the specific target of the intervention (a specific node or edge) in a way it was intended. With knowledge of these parameters, it becomes possible to estimate the amount of energy (intervention power) required to change state variables (i.e., the psychological parameters being studied) and to determine the relative average importance of each variable in affecting the other variables (e.g., Stocker et al., 2023). Most importantly, one could design interventions that are optimal regarding the required energy, deviation from initial values, or time.

For example, as part of exposure therapy a person is repeatedly and gradually confronted with a feared or avoided stimulus (object or situation). The procedure of confronting the person to the stimuli in a therapeutic context is the particular therapeutic strategy. It is a commonly used and generally effective method for treating various forms of anxiety and related disorders. However, not everybody shows a positive response. In addition, the therapeutic process involved is still not fully understood. Although extinction learning might be involved (Hofmann, 2008), other processes have also been discussed (Carpenter et al., 2019, Craske et al., 2014), which led to specific recommendations for enhancing the effect of exposure therapy focusing on inhibitory learning and retrieval (Craske et al., 2014, 2022). Specifically, the contemporary recommendations to enhance exposure strategies include enhancing expectancy violation, manipulating attention to feared stimulus/situation, removal of safety signals, mental rehearsal after exposure, deepening extinction, occasional reinforced extinction, and promoting generalization of learning through retrieval cues, multiple contexts, stimulus variability, and positive affect (Craske et al., 2022).

This example illustrates that confrontation strategy that is part of exposure therapy shows moderate specificity because it targets several different processes to varying degrees in different people. Some processes, such as violation of expectancy, and extinction (and habituation) learning, probably play a role in many (if not all) cases, whereas other processes might be primary for only some individuals. In other words, a treatment strategy of moderate specificity targets multiple processes and some processes are of greater importance for some individuals than for others. Dealing with a moderate specificity of a therapeutic strategy appears to be the rule rather than the exception in psychotherapy. The extreme version, of course, is the view that no therapeutic strategy shows any specificity and all effective treatments primarily work through the common factors embedded in a good therapeutic relationship and through positive treatment expectation (Wampold, 2015). This extreme view ignores a wealth of evidence contradicting it. Still, personalization is key to be most effective in treatment. For this, the therapist needs to explore which strategy most likely targets which primary process or processes in a given client and to account for both sensitivity and specificity of the particular approach. This can be systematically presented in the control theory matrix displayed in Table 2 examining the relationship between treatment strategies and change processes.

Similar to the distinction between psychopathological states and therapeutic processes, it is assumed that there is a clearer distinction between processes and strategies than there is in reality. For example, expectancy violation could be conceptualized as strategy as well, because one could formulate the expectancy and set up the confrontation in a way that maximizes the likelihood of expectancy violation, thereby designing a strategy in a way to target a process with great sensitivity and specificity.

This exercise can enhance efficiency and precision in psychotherapy. It is not feasible to employ all possible strategies in a given client. Not all strategies are equally effective. Some strategies might even be countertherapeutic. The matrix can guide in the selection of the best intervention strategy or strategies for a given client. Strategies are most effective if they exert a maximum degree of control energy. The degree of controllability can be estimated by examining (1) the degree to which a strategy influences one or more processes and (2) the degree to which a process influences one or more nodes in the network. This will be illustrated in a concrete case.

Table 2
Control Theory Matrix of Treatment Strategies and Change Processes

	Treatment Strategies		
Change Processes	S1	S2	...
P1			
P2			
...			

Case Illustration

To illustrate the application of network control theory to therapy in practice, I will discuss a simple composite case of an individual with social anxiety using a simple paper-and-pencil approach (rather than using wearables and EMA data with complicated computer-algorithms). The fictitious name of the case is Bill, a 30-year-old male with the DSM-5 diagnosis of social anxiety disorder, performance subtype.

Which treatment should be chosen? Many approaches are possible based on this diagnosis, including medication (such as an SSRI), a certain cognitive strategy, exposure therapy, social skills training, relaxation, and a mindfulness-based approach, to name only a few. The choice of the specific intervention may be guided by the therapist's orientation or patient's preference. In practice, therapists often follow a trial-and-error approach guided by their personal preferences and theoretical orientations. This can lead to a great level of frustration for both patient and therapist. Furthermore, such an approach is inefficient and costly. An alternative solution is a process-based approach guided by network control theory to offer a systematic and cost-effective alternative to select the best treatment for Bill.

STEP 1: BUILDING A NETWORK

The therapist begins at a conceptual level by depicting the client's mental health problem using a network approach. The network should be a visual depiction of the mental health problem from the client's perspective. Using an empathic, open-minded, nonjudgmental, and curious approach, it is advisable to ask open-ended questions and use the client's answers to generate the network. For example, the therapist might ask: "What do you think your main problem is?" Guided by the EEMM dimensions, the therapist then identifies the main problem nodes on various dimensions and their connections.

During this discussion, Bill reports an upcoming speech that causes him great distress. Specifically, he has to give a presentation in front of his class at his university. This triggers the thought "I am socially awkward" and the belief that his anxiety would be out of control, which triggers avoidance tendencies ("I want to escape"). The negative view about himself causes him to feel bad, which also feeds into his avoidance tendencies, which, in turn, makes him feel bad (Figure 1).

This simple 5-node network includes a context as a triggering event (having to give a presentation), negative thoughts about himself, as well as affective and behavioral effects. The node representing negative self-focused thoughts and the behavioral node representing his desire to avoid are the two most central nodes. Both receive input from at least two other nodes (the self node is activated by both the behavioral node and the context directly, and the behavioral node receives input from the two affect nodes and the self node) and they activate at least two other nodes. Moreover, they form a subnetwork with a positive feedback loop together with the affect node ("I am feeling bad"). Therefore, it seems reasonable to select these two nodes ("I am socially awkward" and "I want to escape") as the preliminary target because modifying those should result in the greatest change in the entire network. It should be noted, however, that it is still an open question in the network science as to whether targeting central nodes is more effective in perturbating the system than targeting strong edges (Bastiaansen et al., 2020; Lee et al., 2024). Because the approach outlined here can be applied to both nodes and edges, this issue becomes an empirical question for future studies.

For illustration purpose, the network presented here is quite simple. In reality it is most likely more complicated. However, in general, it should be as complex as necessary but as simple as possible. Networks that are too complex tend to be unworkable if there are too many nodes and too many edges comprising the network. In this case, it is advisable to break down the problem into subproblems that can be targeted one by one. Another common problem is to develop networks that lack concreteness. It is best to use the client's own words and let the client build the network.

The EEMM dimensions serve as a guide for the therapist to cover the range of human experience. Not all EEMM dimensions need to be represented and it is not essential to assign the "right" label for a node. For example, it is completely acceptable to label the node "I am socially awkward" as "cognition" rather than "self." Labeling the nodes simply serves as a way to ensure that critical dimensions were not left unexplored. Therefore, the labeling of nodes should be best done by the therapist when finalizing the initial network. It is essential that at the end, the client sees the network as an accurate reflection of the problem. The edges and direction of edges are based on the best guess and serve as a working hypothesis that remains to be tested. The therapist can make suggestions but should refrain from directing and interpreting the client's answers.

As already noted, the network here was chosen to illustrate the clinical value of network control theory of dynamic systems. In reality, cases are likely to be considerably more complex and the nodes may not be so clearly linked to the EEMM dimensions.

STEP 2: DEVELOPING A PROCESS MATRIX

Once a workable network has been developed, the therapist develops a matrix that explores the processes that need to be targeted to perturbate the nodes and/or edges of the network. The same process can target more than one node, and the same node can be targeted by more than one process. To develop the matrix, the therapist relies on his knowledge, clinical intuition, and the client's responses when discussing the likely effects of the processes on the network with the client. For example, the therapist might ask Bill, "If you

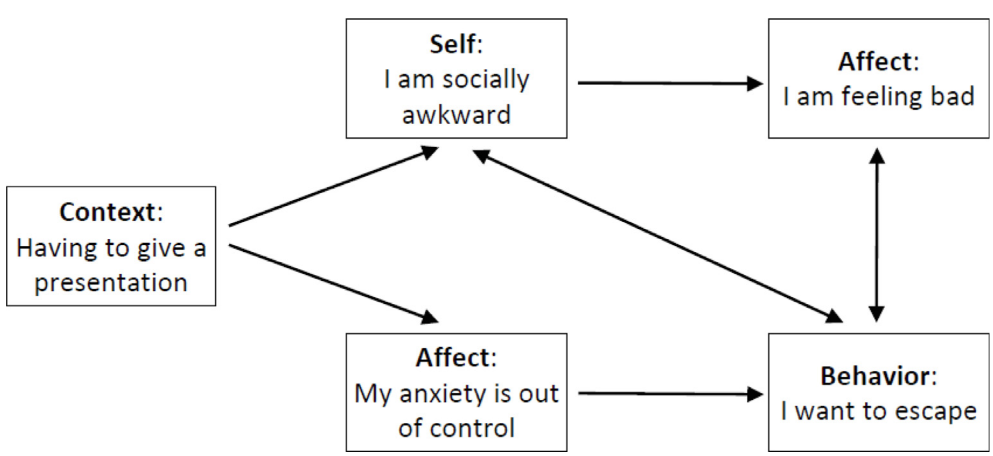

FIGURE 1 Bill's problem network.

could tolerate your distress and fear, would this have any effect on how bad you feel about yourself? And if so, how much?" Generating such *counter factual*s can further clarify the problem. If valued direction in life was included in the network, the therapist might ask about the client's valued direction in this context. For example, if the client would like to give a lively presentation on something he/she values, the therapist might ask, "If you could tolerate your distress and fear, would this have any effect on your ability to give a lively presentation on something you care about?"

To estimate the possible effect of a process on a network node the therapist quantifies its expected influence. A strong effect is marked with "++", a moderate expected effect with "+", no expected effect with "0", and a moderate and strong negative expected effect with "−" and "− −" respectively (Table 3). A review of the list of frequently studied mediators might also be used as a guide for identifying the presumed process (Hayes et al., 2022).

The matrix shows that enhancing *distress tolerance* may be effective at targeting the node "I want to escape the feeling" and also the node "My anxiety is out of control." Distress tolerance may also be considered an important process for reducing the association between "I am feeling bad" and "I want to escape the feeling." This would be an example for a process targeting a critical edge if we were to focus on edges rather than primarily nodes.

To a lesser degree, distress tolerance is likely to target the nodes "I am socially awkward" and "I feel bad about myself." Similarly, changes in *social skills* is likely to have only a moderate effect on these nodes. No significant effect can be expected on "I want to escape the feeling" and "my anxiety is out of control." Changes in *self-focused attention* can be assumed to target all network nodes in an adaptive direction, especially the node "I feel bad about myself." *Arousal reduction* may target "my anxiety is out of control" to a strong degree and to a moderate degree "I want to escape the feeling," but not any of the other nodes.

To quantify the control energy of each process on the network, each + sign counts as one point. As a result, we can conclude that the processes *distress tolerance* and *self-focused attention* are each associated with the greatest control energy (6 points each) as compared to the other process (2 points for *social skills*, and 3 points for *arousal reduction*), according to formula 1. We can draw the preliminary conclusion that *distress tolerance* and *self-focused attention* are the two most promising processes to perturbate Bill's maladaptive network.

Step 3: Developing a Treatment Strategies Matrix

In the next step, the therapist needs to identify the best strategy to target the specific processes. Some processes logically point to specific strategies. For example, exposure is a known strategy to enhance distress tolerance, social skills training is a known strategy to enhance social skills, attention training is effective for modifying self-focused attention, and relaxation training is known to reduce arousal, etc.

A matrix (Table 4) is needed because the same strategy can target more than one process, and the same process can be targeted by different processes. In Bill's case, distress tolerance is also targeted to some extend through relaxation, and self-focused attention through exposure, social skills training, and relaxation.

Again, the control energy of the strategies is quantified using the method described above. The most effective strategy to target *distress tolerance* is exposure, and exposure also targets, to a lesser degree, *self-focused attention*, which is primarily targeted through attention training. Taken together, exposure therapy plus attention training will result in the greatest likelihood of targeting the central nodes ("I am social awkward" and "I want to escape") and thereby perturbating the maladaptive network.

Table 3
Bill's Control Theory Matrix of Change Processes and Network Nodes

Change Processes				
	Distress Tolerance	Social Skills	Self-focused Attention	Arousal Reduction
I want to escape the feeling	++	0	+	+
I am socially awkward	+	+	++	0
I feel bad about myself	+	+	++	0
My anxiety is out of control	++	0	+	++

Table 4
Bill's Control Theory Matrix of Change Strategies and Processes

Treatment Strategies				
	Exposure	Social Skills Training	Attention Training	Relaxation
Distress Tolerance	++	0	0	+
Social Skills	0	++	0	0
Self-focused attention	+	+	++	+
Arousal Reduction	–	0	0	++

STEP 4: PERTURBATE THE SYSTEM BY IMPLEMENTING STRATEGIES

Distress tolerance and self-focused attention are the two processes with the greatest control energy based on the presumed network. Exposure with attention training is the most effective intervention to target these two processes and thereby generating the greatest control energy to perturbate the maladaptive network. Therefore, the answer to the initial question (Which treatment should be chosen for Bill?) is: exposure plus attention training, based on the initial network.

This is not to say that other strategies are unimportant or completely ineffective. They can also be effective for targeting other processes, but network control theory predicts that these processes will be less effective for Bill's specific problem, which is represented in the specific network we used as a foundation. A different network may well have led us to very different strategies.

It is important to conceive this approach as an iterative exercise with a feedback loop. The process starts out at a conceptual level, moving toward the specific level of the strategies that need to be implemented in order to perturbate the system. The network should be redrawn after each implementation phase. Alternative, adaptive processes could be considered to form an adaptive network and alternative attractor state.

Discussion

Network theory has been used primarily in nomothetic analyses of large cross-sectional datasets. Cross-sectional networks require many subjects measured at a single point in time, allowing visualization of the functional relationships between pairs of symptoms at the group level. Time series networks require numerous data points per subject and can be computed for both individual subjects and groups of subjects. But the principles of network control theory can also be used without any computational support. In this article, I presented a proof-of-concept idea of applying network control theory of dynamic systems to personalize psychotherapy within the broader framework of PBT.

A process-based approach begins with developing an idiographic problem network to depict the primary problem of a given client. After a general introduction and creating a comfortable and suitable therapeutic environment, the PBT therapist usually starts out with the question *What is the primary problem in your life right now?* A few pieces of paper and pencil are enough to start generating the client's individual problem network. It is advisable to have the client draw this network rather than the therapist. The network should be a visual depiction of a particular problem from the viewpoint of the client, without filtering or interpreting the client's response. Brief, single sentences are the preferred notes for the network. For example, if the client reports "I am thinking of getting married and I am freaking out," then nodes "thinking of getting married" and "freaking out" could be two nodes, connected by a single-headed arrow.

A critical missing piece in treatment approaches using individual networks has been a conceptual framework of how to select strategies linked to processes derived from a particular network. Network control theory of dynamic systems offers precisely such a framework with concrete recommendations for therapy.

The therapist begins at a conceptual level by depicting the client's mental health problem using a network approach from the view of the client's perspective (step 1), followed by developing a process matrix by identifying specific processes that act on specific nodes, edges, or subnetworks of the problem network to perturbate the problem network (step 2), developing a strategy matrix by identifying specific treatment strategies targeting the specific processes (step 3), implementing the strategies to perturbate the problem network (step 4), and reexamining the network to derive feedback about success and to determine controllability of the system (step 5). The entire therapy process is a closed-loop feedback system with well-being as the target by oscillating between a conceptual network level and a specific level of implementing specific treatment strategies (Figure 2).

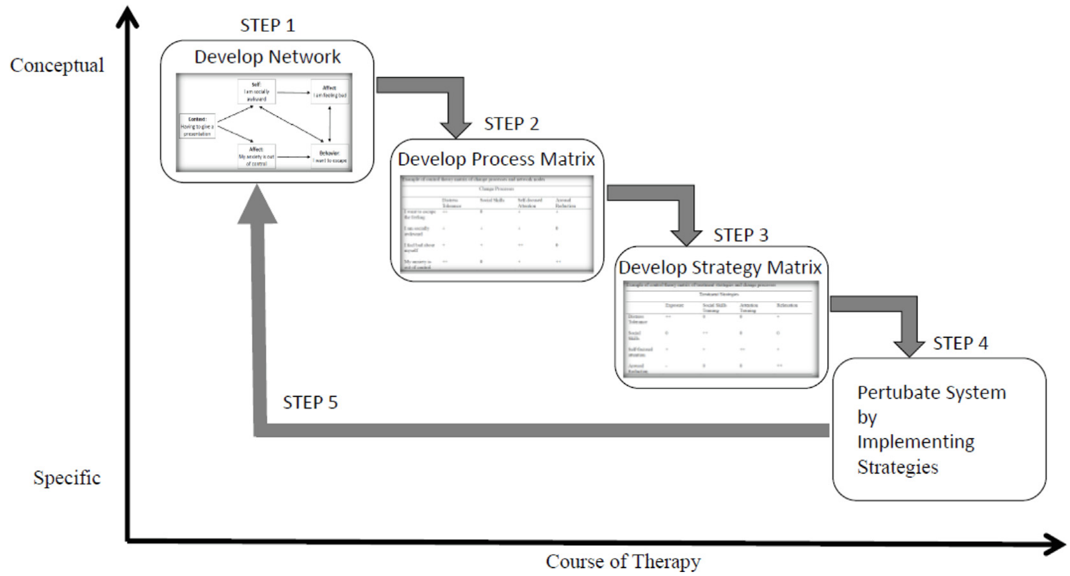

FIGURE 2 Therapeutic process of therapy informed by control theory.

Following the principles of adaptation (selection, variation, and retention in a given context) should also apply to the therapeutic approach itself. Therefore, a network that does not seem to match the client's case, processes that do not seem to be relevant, and strategies that do not seem to target the processes should not be retained and new approaches should be considered.

Network control theory, an established framework to modify the behavior or dynamic systems, seems highly relevant and applicable to clinical science. The limitation of this approach can be the potential complexity of it. But the approach becomes feasible if the complexity is kept to a level that is workable. Ideally, a client's idiographic network is later tested through data gathered from high-density ecological momentary assessments. This can place a great deal of burden on the client. Obviously, we still need more data on the possible processes of change involved in our therapies. But most important of all is the need to test this approach in clinical practice and compare it against traditional interventions.

Future research needs to answer a number of critical questions. The first question is how to define and operationalize the nodes that comprise an individual network. PBT and its EEMM offer a general framework to develop such a network in a given client. Another important question is whether the most effective strategy to perturbate the network is to primarily target the critical nodes (which was done in the illustrative case) or to target specific edges or both (Spiller et al., 2020). This is also an empirical question than can be answered in future studies. Finally, another remaining question is how to define and distinguish therapeutic processes and treatment strategies. Unfortunately, traditional therapy mechanism research has been limited by mediation studies that have been constrained by nomothetic research, often testing whether a single variable serves as a mediator using linear models assuming unidirectional relationships. The results from these studies tell us very little about the processes of therapeutic change, let alone about the therapeutic techniques and strategies that initiate these processes and how these strategies are distinguishable from processes conceptually and practically. Although more research is needed to answer these questions, this article has demonstrated that the network control theory approach could already be an important step toward personalizing psychotherapy.

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