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# How Perceived Causal Networks Can Complement Case Conceptualization, Diagnostic Classification, and Data-Based Networks: An Introduction to a Method for Constructing Personalized Networks

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The personalization of psychopathology through the use of personalized symptom networks appears to be a promising approach for gaining deeper insights into the development and maintenance of mental disorders. One way to create such networks is by using the perceived causal networks (PECAN) method. In this method, respondents are systematically asked to quantify how their symptoms are causally linked. Answers are then visualized, either for the individual or aggregated for a group, as a directed network. PECAN can represent causal relations irrespective of their timescales and requires no data-hungry estimations. The following guidelines are intended to assist clinicians and researchers in the creation of personalized networks using the PECAN method. These networks can facilitate case conceptualization and personalization of treatments for individual patients and the description of groups of patients, revealing recurring feedback loops and central symptoms. Additionally, recommendations are provided regarding the procedures to be employed in the selection of nodes, assessment of edges, and visualization of the data. Furthermore, the potential for evaluating the reliability, validity, and clinical usefulness, as well as strengths, limitations, and future challenges of PECAN, is discussed. We conclude with an overview of the challenges of PECAN and a research agenda that highlights opportunities to improve the still very young method and implement it in clinical research and practice.

***General Scientific Summary***
Perceived causal networks is a transdiagnostic method that maps out how patients perceive how their symptoms influence each other. This can be used by therapists to target the most influential symptom for a particular patient or by researchers to describe a group of patients and which symptoms tend to be perceived as most influential.

*Keywords:* network analysis, personalized psychotherapy, case conceptualization

*Supplemental materials:* https://doi.org/10.1037/abn0001036.supp

*Example 1:* Malik is a psychotherapist who sees a patient presenting with a depressed mood, loss of interest, and fatigue. The patient often feels anxious, has trouble falling asleep, and has difficulties concentrating at work. He avoids many social situations due to the anxiety they provoke, and sometimes has panic attacks in social contexts he can't avoid. He is often plagued by loneliness. He meets the criteria for both depression and social anxiety. What therapeutic interventions would be most helpful for this specific patient?

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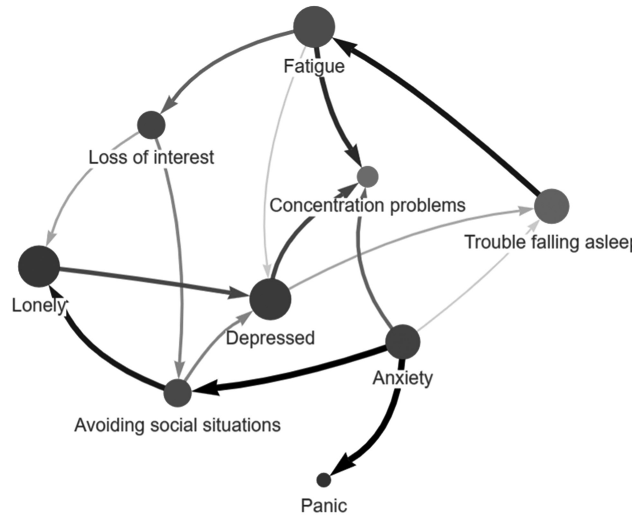
*Example 2:* Miriam is a researcher studying patients with substance use and comorbid depression. She is interested in the potential pathways between these two problems: for how many patients does substance use cause depression, for how many does depression cause substance use, and for how many is the relationship bidirectional, with problems contributing to each other? If she creates a manualized intervention package for this heterogeneous population, which problem areas would be most important to address?

The network approach to psychopathology has gained interest in both mental health research (Jones & Robinaugh, 2021) and clinical practice (Andreasson et al, 2023; Scheffer et al., 2024). According to the network approach, psychopathological symptoms are organized into networks. In these networks, the nodes represent the symptoms, complaints, or problems that the patient presents with. Directed edges (arrows) show the causal relations between the nodes (Borsboom, 2017). The development and maintenance of mental illnesses are proposed to be explained by the mutual activation and reinforcement of symptoms, resulting in a stable mental disorder state (Borsboom, 2017). As personalized symptom networks may contain symptoms of different mental disorders as defined in diagnostic nosologies, the emergence of comorbidity can be well explained by this approach (Bringmann et al., 2022; Jones et al., 2021). Network theory also provides a framework for understanding the heterogeneity of mental disorders, suggesting that within a patient population, individuals display unique sets of symptoms and causal interactions among them (Borsboom, 2017; Bringmann et al., 2022). To acquire insights on symptoms and their causal relations for a given client, personalized networks can be created and considered as case conceptualization. Case conceptualization has been defined as the clinician's understanding of the patient's problems as viewed through a particular theoretical orientation (John & Segal, 2014). It is intended to guide the clinician's decisions about the selection of treatment targets and interventions (Gilboa-Schechtman, 2024). Given that case conceptualizations and subsequent clinical decisions often differ between clinicians (Bucci et al., 2016), several methods to formalize case conceptualization have been suggested, aiming to minimize clinical judgment biases by guiding clinical decisions based on statistical parameters (Burger et al., 2020). In this context, personalized symptom networks, such as the network created for Malik's patient (see Figure 1), can be regarded as a formalized case conceptualization (Burger et al., 2022). It is, however, important to emphasize that there are already approaches to formalized case conceptualization that are based on the perception of causal relations (Mumma et al., 2018). A notable example of such a formalized approach is the functional analytic clinical case model (Haynes et al., 1997), in which the causal relations assumed by the clinician between variables (e.g., behavioral patterns of individuals) are defined and quantified (e.g., the modifiability of a certain variable) in a vector model. In contrast to other approaches of formalized case conceptualization, personalized symptom networks are embedded in the theoretical and methodological framework of network theory. This enables the analysis and interpretation of resulting networks based on network analysis and in the context of assumptions of network theory. This facilitates the identification of nodes that are perceived to have particularly strong causal effects on other nodes, and provides statistical parameters (e.g., centrality of a symptom) on which clinical decisions can be based. Consequently, the network approach is linked to the field of personalized psychotherapy (Scholten et al., 2022).

**Figure 1**
*Example Network for Malik's Patient*




*Note.* Node size shows frequency (bigger = higher), and color saturation shows how severe (darker = higher) his patient experienced the symptoms. Edge width shows how often the causal link was perceived by the patient (i.e., how often one symptom leads to another).

There are two main methods for creating personalized networks: (a) estimating them based on longitudinal data and (b) querying individuals about their perception of causal relations. The next section will discuss these two methods, starting with the most commonly used: estimating edges in the networks from intensive time series data and then shift to our main focus: the use of systematic assessments of respondents' perceptions based on the perceived causal networks (PECAN) method (Frewen et al., 2012; Klintwall et al., 2023).

## Constructing Personalized Networks

So far, most researchers have constructed personalized directed networks based on time series data (Bringmann et al., 2022; Burger et al., 2022; Mansueto et al., 2022), using data from ecological momentary assessments (EMA). In this method, the patient is asked several times per day about which symptoms are experienced at that moment or since the last assessment (Ebner-Priemer & Trull, 2009). Directed edges between the nodes are then statistically estimated based on their lagged covariation (Bringmann et al., 2022). Particular strengths are that EMA reduces recall biases (Wright & Zimmermann, 2019) and does not require the patient to understand the causes of their symptoms, only to report on their moment-to-moment experiences. With time series analysis, it is possible to explore relations between symptoms and thus uncover a network that was previously unseen by both the patient and their therapist.

Time series networks typically estimated on EMA data, such as vector autoregressive models, have several limitations. They rely on strong statistical assumptions such as linearity (i.e., all relationships between variables are linear) and stationarity (i.e., the relationships among variables do not change over time; Bringmann et al., 2022), which are unlikely to hold for personalized networks in the context of psychotherapy (Siepe et al., 2024). Another important limitation is that models fail to capture symptoms that interact on timescales that are faster or slower than the spacing of the assessments (von Klipstein et al., 2020). To give an example, for Malik, the panic in social situations occurs in a matter of seconds, way faster than the assessments in a realistic EMA design, and will therefore not show up as an edge in the estimated temporal network. Conversely, even though his patient's insomnia is in fact causing fatigue, this works on a timescale spanning multiple days and will also not be identified using time series analysis (von Klipstein et al., 2020). Additionally, since edges are estimated from the data, there must be variation in symptoms to estimate effects between nodes. If Malik's patient always reports fatigue with the same intensity, the analysis cannot uncover the causes and effects of fatigue. In short, time series analysis may result in networks with low sensitivity and thus may miss significant edges in a patient's network (Mansueto et al., 2022). Due to these limitations, networks based on temporal data do not lend themselves to derive causal interpretations (Bringmann et al., 2022; von Klipstein et al., 2020).

An alternative method to create personalized directed networks is to ask patients how they perceive the causal relations between their symptoms. The PECAN (Klintwall et al., 2023), a clinical adaptation of the perceived causal relation (PCR) method (Frewen et al., 2012), is built on the observation that patients have thoughts and beliefs about what is causing their mental health issues (Hansson et al., 2010). PECAN constructs personalized networks by asking the patient to quantify the causal relations of specific symptom–symptom relations one by one.

## Definition of PECAN

We define the PECAN method by these two components:

1. An idiographic model of an individual's psychopathology of their PCRs between the nodes in a system. The nodes can constitute symptoms or complaints from one or multiple mental disorders and related problems. The respondent may be either a patient answering about themselves or a therapist, parent, or spouse. Creating this model entails (a) node selection, i.e., finding the relevant nodes for the network (e.g., emotions, behaviors, or contextual factors) and (b) causal ratings, in which the individual reports their perceptions about the causal relation between every combination of the selected nodes, in both directions.
2. The visualization of this model in the form of a personalized network or aggregated group network consisting of nodes (e.g., symptoms) and directed edges between nodes (arrows) representing the PCRs. Optionally, further analyses of features such as centrality, density, or feedback loops within these networks can be conducted.

As PECAN captures relations between nodes directly from individuals' perceptions, it has the particular strength that it does not require time series data with statistical assumptions to create a personalized directed network. Causal relations can be found regardless of what timescale they occur on and do not require variation in nodes. Conversely, PECAN may be more susceptible to biases. A certain degree of introspection is also necessary to apply the method, thus rendering it more suitable for certain individuals than for others (see the Challenges and Research Agenda for PECAN section). The PECAN method described in this article could be especially useful in situations where symptoms vary on different time scales (e.g., sleep quality and dysfunctional thoughts), if subjective perceptions of causal connections between symptoms are of particular interest, or if extensive data collection with EMA is not feasible.

For Malik, using PECAN would mean having his patient formulate the present symptoms by interviewing him during a therapy session. Then, for each selected symptom, he would ask to what extent it has a causal influence on the other symptoms. Using the visualization of the personalized network, they could collaboratively identify which of the nodes seem to be most influential within his patient's network and would thus be candidates for targeted intervention. He might also use further analyses to support his impression with metrics on centrality of specific nodes and feedback loops.

Miriam would proceed in the same way as Malik, except that she would present a predefined list of symptoms relevant to the disorders being studied in her sample and complete the rating for each individual, using a questionnaire with or without interviewer support. Miriam would get a collection of individual patient networks, which she can then aggregate into a group network. She can identify which nodes are central across patients and which loops often occur.

A few studies already exist that have applied the PECAN method at the group or individual level. Despite the paucity of studies to date, and the fact that some have been based on small sample sizes, they nevertheless provide initial evidence of the good feasibility and reliability of PECAN. Here, we will give some examples to showcase different methodological variations of PECAN and illustrate the way PECAN can be applied to different populations. (a) Klintwall et al. (2023) introduced the PECAN method in a sample of $n = 231$ adult individuals screened positive for depression. The authors administered PECAN via an online questionnaire, in which individuals could choose between seven and 15 symptoms they had experienced in the past week from a list of 26 possible symptoms associated with depression. For each symptom selected, individuals were asked to rate the severity of the symptom and indicate the extent to which up to three other symptoms had caused the symptom. (b) Vogel et al. (2025) adapted the PECAN method for use with children and adolescents from the age of 10 years (PECAN-CA). Here, it was shown that a prerequisite for good feasibility in young people was the implementation of the method via face-to-face interview, simplification of questions and scales, and a prior education with age-appropriate psychoeducational videos on concepts such as symptoms and symptom networks. (c) Burger et al. (2024) applied the PECAN method by conducting brief daily assessments of perceived symptom interactions over 4 weeks to reduce recall bias. About 40% of $n = 20$ adult respondents with depressive symptoms achieved stable networks, and the method was shown to be time-efficient and well received. We provide an overview of these and other studies in Table 1 in the online supplemental materials. An updatable version of the table can also be found on the Open Science Framework to provide an up-to-date overview of PECAN studies (https://osf.io/hpysk/files/osfstorage).

## Scope of the Guidelines

This article is intended as a guide for clinicians and researchers who plan to use PECAN to create networks based on an individual's perception of causal relations. The guidelines have these goals:

1. Help researchers and clinicians create networks using PECAN: planning, data collection, visualization, and analysis of networks.

2. Present strengths and limitations of the method.
3. Facilitate communication between researchers working with PECAN in order to make the contents of the PECAN method comparable between different PECAN studies. A collaborative platform will be provided to facilitate content synthesis, for example, item pools or visualization tools.

We decided to develop these guidelines at an early stage in the development of the PECAN research field, because there are still many degrees of freedom in the way the PECAN method can be conducted. Therefore, we aim at helping researchers and clinicians make decisions in planning their own PECAN procedure and to join our research efforts to identify and derive optimal procedures.

## How to Set Up a PECAN Study?

Miriam and Malik will require different setups of PECAN. Malik may allocate a few sessions to create a network together with his patient, whereas Miriam will likely rely on an online questionnaire sent out to patients. We will describe choices that need to be made about the data collection and the visualization and analysis of the resulting networks. An overview of these steps of creating a network is presented in Figure 2.

### Data Collection

PECAN data collection involves selecting nodes for the networks, deciding what features of those nodes may be relevant (e.g., frequency, modifiability, or severity), setting up how to assess the individuals' perceptions about the edges, and then collecting the data, for example, via a questionnaire or interview.

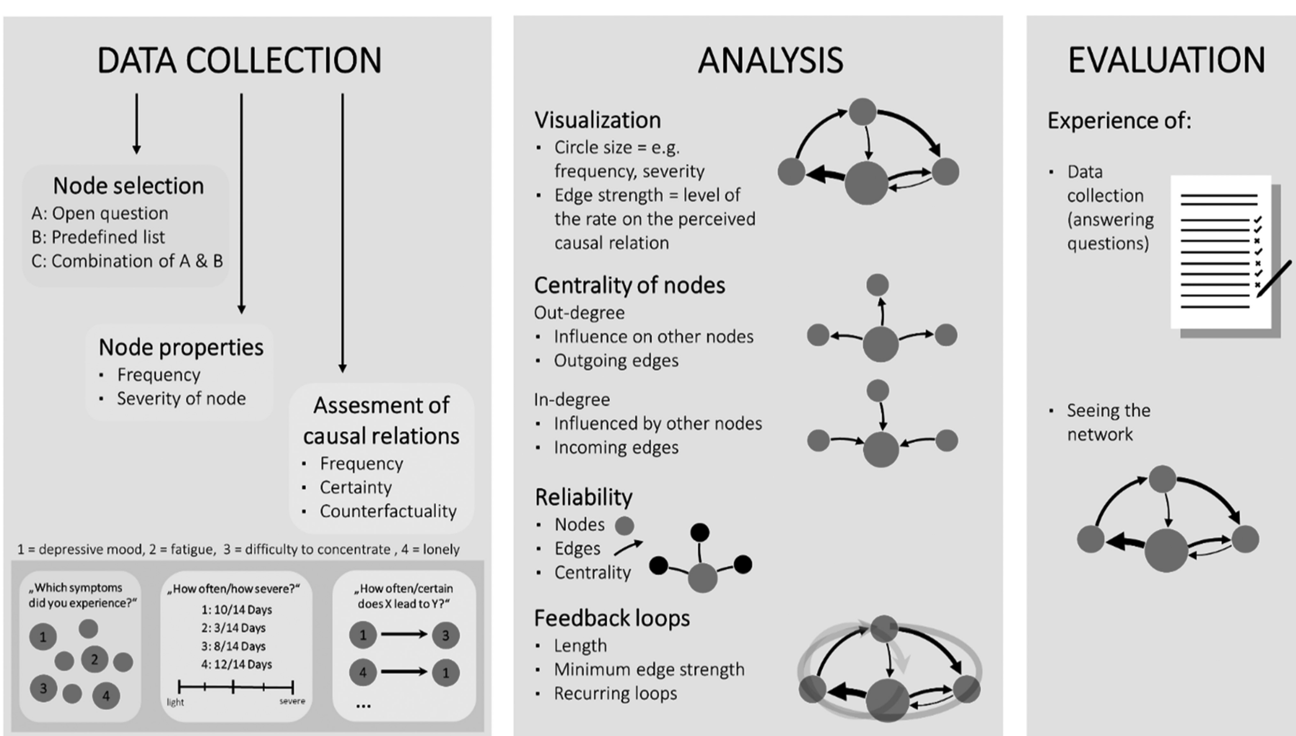
#### *Selecting Nodes*

Which nodes should be in the network for Malik, and which nodes should be in the networks for the patients in Miriam's study?

**Completely Personalized Nodes.** Malik could ask his patient to write down a list of all the symptoms or problems he experienced in the last week or month. Literature indicates that the individualization of symptom selection in clinical research or practice, for instance, by inquiring about patients' most significant symptoms, is associated with psychometrically sound outcomes (e.g., Weisz et al., 2011). It may be helpful to have a clinician guide participants in formulating nodes to avoid content overlap (e.g., two nodes for different aspects of the same emotion) or a skewed focus only on specific areas of functioning (e.g., only including aspects of social functioning while neglecting cognitions or contextual factors). A good starting point might be the use of existing problem-focused measures (see Lloyd et al., 2019; Sales & Alves, 2016; Weisz et al., 2011) or to look at the criteria for the disorders the patient has been diagnosed with, but be responsive to other important problems in his life. Although this would work well for a specific patient like Malik, it might not be ideal for Miriam doing a population study: if all her patients have personalized nodes, it will be hard to aggregate the networks.

**Predetermined List of Nodes.** Another possibility is to prepare a list of potential problems, from which the individual can pick those that are relevant. This predetermined list should encompass the most prevalent problems in the target population. The selection of which nodes to include in the network for a particular individual can be done in different ways, such as by the person herself (simply checking yes/no) or by a clinician who knows a patient well.

**Figure 2**
*Overview of Steps*



**Predetermined List That Is Individualized.** This can be achieved through free-text questions ("You selected insomnia, please describe the specific sleep problems you experience") or let the individual select from some options ("Which of these problems related to sleep do you experience: difficulty falling asleep, frequent awakenings, or early awakenings?").

Regardless of the method used to select nodes, it is advisable to set a maximum number of nodes, as the resulting network might be overwhelming with too many nodes. Keep in mind that for two present symptoms A and B, we ask whether A causes B and whether B causes A. Thus, if a participant selects 10 nodes, they already have to rate $10 \times 9 = 90$ edges. How should the number of nodes be limited? It is a balance between including all relevant symptoms and not including too many nodes to avoid an overly complex and confusing network. Determining the optimal limit remains an area for further research. In the context of PECAN-CA, data show that networks with more than six nodes can be of very low reliability and feasibility in younger individuals, suggesting that a limit should be set (Vogel et al., 2025).

Malik and his patient decided on phrasing the PECAN nodes together, and came up with nine nodes (e.g., depressive mood, loss of interest, fatigue, avoiding social situations, anxiety, panic, trouble falling asleep, difficulty to concentrate, and lonely). Miriam decided on a list of 20 items taken from the diagnostic criteria of substance abuse and depression, and added some factors based on her clinical experience: conflicts with spouse, overwhelmed at work, body dissatisfaction, and so on.

### *Node Properties*

Frequency can be reported by the individuals using scales (e.g., from *never* to *every day*) or the number of occurrences during the period in question.

Severity of the problems might be of interest, both if there is a need to prioritize which problems should be included as nodes, and as a feature to visualize in the resulting network. Modifiability or controllability of the different nodes could be relevant, as this might be combined with centrality metrics to select viable treatment targets.

### *Assessing Edges*

Edges and quantification of their strength can be defined and asked about in different ways. We will describe three: edges quantified as frequency, certainty, and contrafactual effects.

Assessing an edge in terms of frequency could be done by asking, "When you experience X, how often does it lead to Y?" The response alternatives can be presented as percentages or using verbal equivalents (e.g., "never," "sometimes," and "always"). If the question is probabilistic, the resulting edge is relative to the frequency of the connecting node. In other words, if node X is infrequent but "always" leads to Y, this strong edge may mislead readers of the visualized network into thinking that this edge is significant. Thus, in the visualization, edges can be weighed based on the frequency of their source node.

Alternatively, an edge strength can be levels of certainty, such as when asking "Do you think Y is caused by X?" or "Do you think X leads to Y?," with response options represented by percentages or verbal labels (e.g., "I am certain it is not," "I am unsure either way," and "I am completely certain that it is").

Finally, another alternative is to ask about counterfactuals as a way to quantify the causal effect of one node on another. An example of this would be to ask, "If you no longer had the problem X, how much would Y decrease?," which can be answered on a scale from "Y would no longer be a problem" to "Y would still be just as big of a problem." This has the benefit of giving an interpretable metric on the causal strength, with the downside that it is quite cumbersome. As can be seen, there are some degrees of freedom here in which researchers/clinicians can make decisions about the definition of edges in the resulting network (e.g., certainty and frequency). It should be considered in advance what is reasonable to answer the research question.

Miriam plans to collect data from a large number of participants using an online questionnaire without interviewer support, and she opts to ask about the certainty of causes: "Do you think your fatigue is caused by your excessive drinking?" Malik, on the other hand, who can spend more time creating his single network and is interested in identifying which nodes or edges to intervene on for a maximum effect on the entire network, could opt to ask about contrafactual effects.

## Considerations Regarding Time Scale and Validity

The decision on which time period and context the PECAN queries may have an impact on the resulting networks. Should the individuals be asked to report in reference to their current life (e.g., "in the past month"), or to a specific period of their life ("the last period you felt depressed"), or a specific situation ("when you have to speak publicly"). For Malik, it seems indicated to ask about the past few weeks, as his patient's problems are current. For Miriam's study, on the other hand, asking the individuals about a specific situation in which patients have taken substances and different depressive symptoms have occurred may be more useful. Furthermore, it is important to note that different time scales can also exist at the level of the nodes (e.g., symptoms) to be selected and at the level of the edges between nodes (e.g., mood may change by the minute and fatigue may change over weeks or months). In contrast to networks based on time series data, there are no statistical reasons against integrating these differently time-scaled variables into a PECAN model. However, it is also necessary to consider the extent to which the relations shown in the network can be interpreted. Given that these are the patient's perceptions, it is conceivable that the symptoms of fatigue could be perceived in the long term as a result of negative mood, even if subject to minute-by-minute changes. It is important to note that there are also degrees of freedom with regard to the time period. To date, no studies have investigated the influence of the time period on PECAN networks. Consequently, it is not possible to make a decision based on data. It is therefore important to emphasise the necessity of researchers deciding and reporting transparently in advance which time period is to be used to record nodes and edges in the context of PECAN.

It is also advisable to explain the purpose of PECAN to the respondent before collecting data. This way, the respondent will be motivated to make an effort to provide valid responses. This can be done verbally by an interviewer, through a concise text, or perhaps ideally via an instructional video illustrating the idea of personalized networks and their applications (Vogel et al., 2025).

Conducting the data collection with interviewer support, rather than a questionnaire to be filled out independently, is another avenue to enhance quality. However, an active interviewer may introduce biases, potentially influencing the results, so that a structured interview guide seems important. Utilizing an interview to complete the data collection is particularly valuable in children and adolescents (Kaariniemi et al., 2025; Vogel et al., 2025).

## Analysis

### *Visualization*

**Visualizing Individual Networks.** Visualizing a network for a single person is a straightforward process. All required information to create a network is readily available using the PECAN method, without the need for estimating edges. However, deciding which information to include in the network and how to present it depends on how edges were assessed. First of all, it makes sense to present all nodes that were selected by the individual. Second, node size and color can be used to represent node properties, for example, severity or frequency or some categorization (such as being criteria for different diagnoses). Third, if edge quantification (e.g., frequency or certainty) can be drawn in varying widths or color shades. Alternatively, color could be used to illustrate information such as grouping, severity, or frequency. For his patient, Malik decides that node size should indicate frequency (how often the problem occurs). Additionally, he utilizes color to denote symptom severity, employing a spectrum from "light red" to "dark red," with the latter indicating more severe symptoms. For the edges, Malik decides to base both width and color on edge strength. To accomplish this, he employs a color spectrum ranging from "light gray" to "black." A network using these parameters is presented in Figure 1. Note that, especially if the prospective user of the network is a patient, resisting the temptation to include all available information should be avoided so as to not be overwhelming.

**Visualizing Aggregated Networks.** Before aggregating the networks, it is crucial to consider whether all nodes are relevant to the research question. PECAN offers significant advantages in customizing symptom lists, tailored to specific populations or individuals, free from standardized questionnaires. However, this flexibility also poses challenges, such as the potential for excessively long lists containing numerous irrelevant nodes for a particular research inquiry. To address this issue, researchers can choose to exclude nodes when aggregating networks. For instance, it may be wise to exclude nodes that were only rarely experienced in the group. While this approach improves the network's relevance on a population level, it results in information loss. It is important to note that, unlike estimated network analyses on cross-sectional or time series data, excluding nodes within PECAN does not affect the overall network structure, as in PECAN, the self-reported links are not conditional relations, as is the case in commonly estimated network models. Therefore, within PECAN, only the specific node and its associated edges will be removed from the network without affecting the other edges (it might influence node centralities, though).

In PECAN, aggregation mainly involves calculating absence/presence percentages or finding the average/median values of attributes like node severity or edge strength.

If the assessment only determines whether a node is present or absent, simple percentages may suffice. However, when aggregating node attributes, such as severity, additional considerations arise. For instance, when a node is absent for an individual, its severity can either be considered as zero or treated as a missing value when calculating the mean. A node with a mean severity score of 100/100 may seem significant, but its importance on a group level might be misleading if it is present in only a small group of individuals. Conversely, a node that is present in 50% of individuals with a severity score of 1/100 may not be as important as one that is present in 45% of individuals with a severity score of 98/100. Therefore, depending on the research question of interest, it may be beneficial to incorporate both pieces of information, severity and presence frequency, which could be achieved by using both node size and coloration in the visualization.

The same questions that arise for nodes also apply to edges. However, when considering edges, one must also decide how to address the absence of an edge. In a data frame, the absence of an edge may stem from a person not perceiving a causal relation between two nodes, or because one or both nodes were absent for that person. Treating these absent edges as zeros when calculating the percentage may lead to misleading interpretations (e.g., there is a difference between "anxiety causes social isolation for 10% of the sample" and "for patients in the sample that have both anxiety and social isolation, anxiety causes social isolation for 100%"). It is important to remember that nodes are preselected for a network, and the absence of a node in the final selection for a person does not necessarily imply its overall absence. When aggregating the network, it is crucial to be specific about the research interest and make sure that the aggregated network aligns with this research interest. As can be seen here, researchers have a number of degrees of freedom and decisions to make if they want to create an aggregated network (e.g., which nodes to exclude and how to deal with missing values). These decisions should be made a priori and depending on the research question. There are also degrees of freedom with regard to the interpretation of aggregated networks (e.g., absence of edges), which should be reported and discussed transparently by the researchers.

Miriam decides to aggregate nodes present in at least 20% of her sample, resulting in a network with 10 nodes presented in Figure 3.

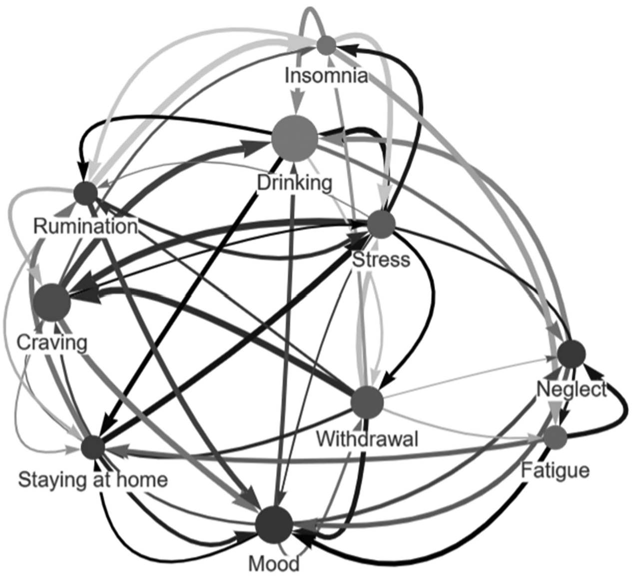
**Simplification.** When communicating study results or in discussion with a patient about a personalized network, it may be necessary to simplify the network, showing only the most important edges. There are no clear rules for how to simplify a PECAN visualization.

On an individual level, simplifying a network is easily done if edges have attributes (e.g., level of certainty, frequency). On a group level, simplification can be done based on percentages or other edge features. While simplifying networks can provide valuable insights, centrality should typically be calculated using original edges.

Miriam and Malik both decide to simplify their networks so that the number of edges equals the number of nodes (this seems to be a good rule of thumb). Malik decides to simplify using edge strength (Figure 4), and Miriam decides to simplify by the percentage of people who reported the edge if they had both corresponding nodes (Figure 5).

**How to Visualize PECAN Networks With R.** There are several possibilities to create network graphics with R. One useful R package for PECAN is the visNetwork package (Almende & Thieurmel, 2022) as it allows to create and edit networks. This feature is especially useful in clinical settings when patients want to add nodes or edges while viewing their network. The network graphics in this article were created by the PECAN2 package (Reichert & Vogel, 2024). The PECAN2 package is a wrapper

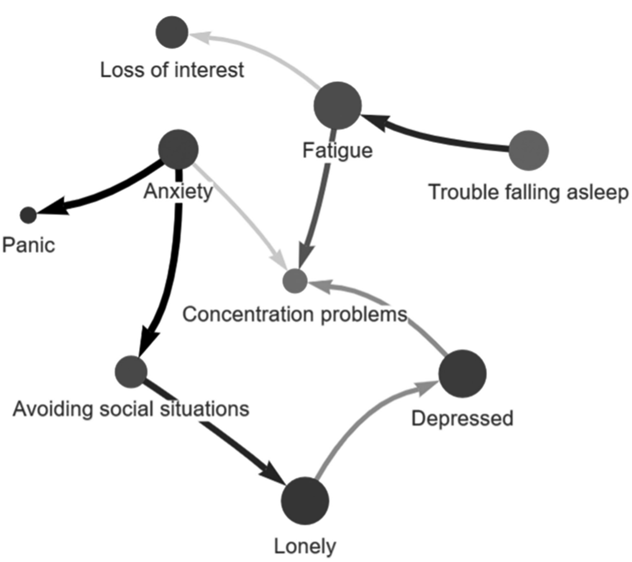
**Figure 3**
*Hypothetical Aggregated Group Network From Miriam's Study*




*Note.* Nodes included are present in at least 20% of patients. Node size is based on frequency in the sample. Edge width represents how many patients reported edge when both nodes were present, and edge color indicates mean edge strength, with "light gray" indicating low and "black" high strength.

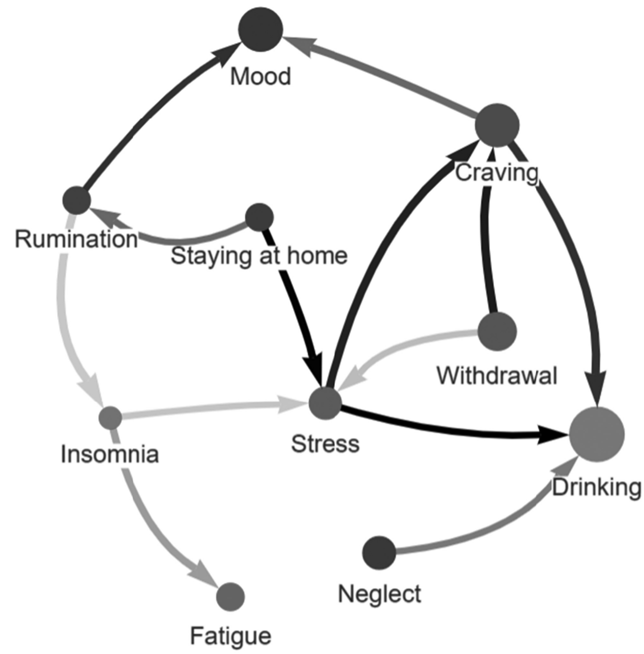
around the visNetwork package with the purpose of simplifying the workflow of PECAN. It allows users to aggregate networks, calculate centrality measures, and use specific coloring and simplification. For visualization, the PECAN2 package can either be used to prepare data for the visNetwork package or to directly visualize them via visNetwork. The latter comes with a predefined setup of PECAN-specific defaults and enables simplification and coloring in one function. Example code on how to use the PECAN2 package can be found at https://github.com/JR-psych/PECAN2.

**Figure 4**
*Simplified Network for Malik's Patient*




*Note.* The original network is displayed in Figure 1.

**Figure 5**
*Simplified Aggregated Network From Miriam's Study*




## Description of the Network

When analyzing a network, whether for an individual or aggregated for a group, two aspects are likely to be important: the centrality of the nodes and the feedback loops they are involved in.

In the context of PECAN, the following centrality metrics can be calculated, which are also known from networks that are estimated from data (see Bringmann et al., 2019): (a) Out-degree centrality, describing how much each node in the network influences other nodes in the network through one-step edges. It is defined as the number of outgoing edges of a given node. (b) In-degree centrality describes how much each node in the network is influenced by the other nodes. It is defined as the number of incoming edges of a given node. If weighted, this metric is referred to as in-strength centrality.

Another interesting description of an individual network is the feedback loops that it contains. These loops can be of different lengths, with the shortest only including two nodes (X causes Y and Y causes X), up to any number of steps in length.

## Reliability

For any interpretation of an individual network to be meaningful, it must be ascertained whether the answers given by the respondent are random or consistent when asked repeatedly. If the respondents are asked to select from a predefined list of potential nodes twice, do they select the same ones? If the nodes are completely open, does the respondent create the same nodes twice? If node properties such as frequency or severity are asked about, how consistent does the respondent report these? This can be reported as a within-person correlation.

Perhaps more importantly, how consistently does the respondent report the edges? This can be computed as a within-person Spearman correlation, where each data-point-pair is that same edge on the two assessments. However, in case different nodes were selected on two assessments, some of these pairs will be missing a member. These pairs can be omitted when computing the Spearman correlation, or alternatively, all potential pairs can be included in the correlation (i.e., all pairs of unselected nodes are pairs of 0s). Reliability from two assessments with a patient can be visualized in the same network (Kaariniemi et al., 2025).

Finally, even if individual edges are not reported consistently (if asked about twice), the centrality of the nodes in the network might still be consistent across time. Thus, it is interesting to look at the reliability of the centrality of the nodes. Again, this can be computed as a within-person correlation, comparing centrality from two interviews or questionnaires from the same patient. As with edges, a decision needs to be made with regard to whether nodes that are not selected on one or both of the two assessments should be given a centrality of zero or omitted when computing this correlation.

In all of the above, it is not clear what should be considered an acceptable within-person reliability. However, the paucity of extant studies employing PECAN does suggest that PECAN networks appear to demonstrate stability over time. Klintwall et al. (2023) reported a mean retest reliability of $r = .53$ for edges and $r = .81$ for centrality indices. Vogel et al. (2025) demonstrated that the reliability observed in young subjects was comparable to that of the adult sample in the Klintwall et al. (2023) study, even after a retest interval of 4 weeks.

## Evaluation of the Data Collection and Visualization

Evaluation of the data collection and the resulting network could cover negative effects (e.g., whether seeing the network made the problems feel overwhelming), positive effects (e.g., whether seeing the network gave insights into what might be maintaining the problems), clinical utility (e.g., if seeing the network gave the respondent ideas for behavioral changes) and what might be missing and should be added to the network (nodes or edges). For some suggestions of evaluation items, see our Open Science Framework project (https://osf.io/zwx9n/files/osfstorage?view_only=7631e79287e84c23b0cb07168df9c20b).

# Discussion

## Summary

The PECAN method can be used both by clinicians (interested in an individual patient) and researchers (interested in a group of patients). As compared to widely used time series methods to create personalized networks, this method has the benefits of being able to capture causal relations between problems irrespective of timescales and variation, but with the downside that it relies on insight on behalf of the respondent. Valid and reliable networks require careful selection of nodes to be included in the network and systematically collecting data about respondent perceptions of the causal relations between these. There are many degrees of freedom in how this can be done (e.g., asking respondents about causal relations in terms of frequency, certainty, or effect sizes), which should be decided in advance and reported transparently. This also goes for subsequent visualization of networks, which can be done in different ways: using node size and color to denote different features, and simplifying the network to optimize readability of the network. Individual and group networks can be analyzed both qualitatively and quantitatively (e.g., centralities). In the above, we hope we have provided the interested reader with a toolbox comprehensive enough to set up their own PECAN study. In this last section, we turn to the conceptual and empirical work that remains to be done.

## Reliability and Validity in the Context of PECAN

Given that networks resulting from PECAN can serve as a basis for therapeutic decisions or for conclusions about pathomechanisms, concepts such as reliability and validity are important when using PECAN.

### *Reliability*

As outlined above, there are a number of decisions involved in measuring the reliability of the PECAN method, which makes measuring and reporting reliability in the context of PECAN a complex issue. Since PECAN is a novel method, there are still a number of open questions on reliability to which we also do not yet have answers and which require further research and reflection. Nevertheless, we would like to present here some of our reflections on reliability in the context of PECAN.

Let us consider a scenario in which Malik, during the initial stages of therapy, repeatedly inquires about the patient's symptoms and their causal relations over a specific time period (e.g., the last 4 weeks prior to the commencement of therapy). What retest reliability would be satisfactory? A reliability of self-reported causal relations close to 1 may not be realistic. One reason might be that thinking about causal relations might lead to a change in the perception of them. This might lead to altered responses when individuals are asked a second time. Of course, on the other hand, a correlation of 0 over assessments would not be helpful, as it would be akin to arbitrary answers. In this context, a central question seems to be how reliable PECAN needs to be in order to be used as a useful measurement tool and, for example, to be able to predict the success of a therapy. This has to be determined in further research depending on the sample (e.g., children vs. adults, specific patient groups), the survey method used (e.g., face-to-face interview vs. online survey), the time period to which the query refers (e.g., symptomatology in the last 2 weeks or in a specific past situation), and the variable to be assessed (e.g., highly fluctuating symptomatology or rather stable constructs).

### *Validity*

Traditionally, validity is defined as the property of a measure or method to represent what it claims to represent. In the context of PECAN, validity might be understood as the extent to which the PCRs are representative of the true causal system. As the "true causal system" is unknown, it needs to be approximated through different angles. One possibility could be to validate PECAN networks against therapist-based case formulation networks. Another possibility would be to test subcomponents of the PECAN networks, such as specific edges through small thought- or behavior experiments (Burger et al., 2022). Aside from construct validity, a perhaps more natural approach would be to evaluate face validity by having clinicians reflect on the client's perceived network (Reichert et al., 2025; Scholten et al., 2025). Also, to use PECAN with several respondents (e.g., spouse and parent) answering about the same patient, and then aggregate these networks to increase validity, might be a promising approach. A key question is whether PECAN can predict treatment outcomes, and whether the PECAN-based selection of specific treatment targets and appropriate interventions can contribute to better treatment outcomes. For our examples, we might ask whether Malik is able to provide a more effective therapy because he selected interventions based on PECAN. Will Miriam's therapy programme be more effective because she has identified relevant causal relationships between symptoms based on PECAN?

## Challenges and Research Agenda for PECAN

First, assessing information on mental health problems based on an individual's perception is inherently influenced by recall bias and self-report issue (Schmier & Halpern, 2004). PECAN is based on the individual's perception of relations between such problems. The literature suggests that bias in retrospective symptom ratings depends on characteristics, such as the availability of symptoms (e.g., severe and distinct symptoms may be more salient), the distance to the period being rated (e.g., recency bias), and the current state at the time of rating (e.g., state bias; Schmier & Halpern, 2004). However, how recall bias affects the reporting of causal relations between two symptoms is still unclear. A possible approach to reduce recall bias might be to use shorter but repeated PECAN assessments (Burger et al., 2024). In this study, respondents were asked every evening for a month to indicate which symptoms they had experienced and whether any of the other symptoms were causing this, which was the aggregated to a network (Burger et al., 2024). It seems likely that not only does this reduce recall bias, but it also trains the respondents to observe causal relations that they might not have been previously aware of. Another option is to use PECAN to create priors of which edges to expect, and then update this with data from EMA (Burger et al., 2022; Scholten et al., 2025). Future research on such hybrid approaches with either pure EMA or a pure PECAN method would be important to verify the added value of supporting PECAN with EMA.

Second, the PECAN method possibly suits some groups better than others. In the existing PECAN studies to date, there was a wide variation in reliability across individuals (e.g., Klintwall et al., 2023; Vogel et al., 2025). This finding could indicate that there are differences between individuals in the ability to estimate their own causal relations. Accordingly, the question arises as to what the ability to assess one's own causal relations depends on. Besides prior knowledge of the variables (e.g., symptoms) and network theory, cognitive abilities, introspection, or social desirability could play a role. Certain variables and causal relations might be better assessed based on individuals' perceptions than others. In this respect, PECAN, based on patient perception, could work less well for some disorders, which may be characterized by poor insight into symptoms and symptom relations. Notwithstanding the presence of multiple psychopathologies in an individual patient, the PECAN assessment may primarily reflect psychopathologies with which the patient has sufficient insight. Therefore, evaluation of the procedure by respondents, as well as investigating how to increase reliability, would be important to identify optimal procedures. Additionally, it is important to consider how PECAN can be tailored to be used with specific populations, such as individuals with poor insight into their own symptomatology. Overall, further research is needed to investigate to what extent PECAN is useful for certain psychopathologies or groups and how the method might need to be adapted.

Third, there are challenges concerning the structure and procedure of PECAN data collection in order to achieve valid networks. The conceptualization of the PECAN method leaves room for variation in the way individuals choose from symptoms and assess causal relations. Actually, experience from previous PECAN studies (see Table 1 in the online supplemental materials) shows that it is advisable to adapt the PECAN procedure to the study design, setting, and sample. Nevertheless, it is so far unclear how decisions regarding the specific PECAN procedure will affect the resulting data. Moreover, it is an open question how much the respondent needs to know about relevant concepts (e.g., causality, symptoms, and network theory). An initial study suggests that it is important, at least for children and young people, to inform them about these concepts in advance (Vogel et al., 2025). An understanding of how each node is defined (e.g., what is meant by "safety behavior") seems to be an important precondition for valid data as well (Vogel et al., 2025). Furthermore, the setting (interview or questionnaire), the way individuals select the variables or which they later estimate causal relations (e.g., opportunity to name variables freely and select variables from a list) as well as the wording of questions regarding causality could also influence the data. In this context, the synthesis of materials (e.g., instructional videos, lists of variables for psychopathologies), contents/variations of the PECAN process (e.g., formulations), and evaluation questions for the PECAN process on an open science platform seem to be important steps for the stepwise refinement of the PECAN method. This might also help create recommendations for sufficient reliability.

Fourth, there is the question of how to deal with diverging information from different sources or how to integrate this different information. For example, different individuals (e.g., patient and therapist, child and parent) might select different nodes and consider different causal relations important, resulting in different PECAN networks. Likewise, personalized networks representing an individual's mental problems based on EMA data could differ significantly compared to networks created based on PECAN (Scholten et al., 2025). For these challenges, which also exist in the context of other methods with multiple informants or the measurement of constructs using different methods, there are not yet any recommendations. Thus, a worthwhile avenue might be to explore how PECAN can be used with several parallel informants (parent, spouse, and patient) and combined with other network methods to triangulate a high-validity personalized network.

Finally, the value of the PECAN method will be ultimately judged by the extent to which it can help improve predictions of courses of mental disorders and make psychotherapy more effective. Given that no research yet exists that has examined the predictive potential of PECAN networks or the effectiveness of personalized therapy based on PECAN, this would be an important next step to investigate these issues.

## Conclusion

As PECAN can be conducted as a single session interview or an online questionnaire, and can be tailored to specific patients or patient populations, it might be an applicable method in the context of psychotherapy and clinical studies. However, the question arises as to how the directed networks resulting from the PECAN method could be used in these contexts. PECAN offers a promising approach to personalize psychotherapy by using directed networks as a decision-making tool to select particularly effective treatment targets. From the perspective of network theory of psychopathology, focusing on specific symptom–symptom interactions would be a viable strategy to effectively destabilize a stable symptom network, and ultimately contribute to the remission of mental disorders (Borsboom, 2017). From the elements of directed networks based on PECAN presented in the current article, one could consider selecting symptoms that display strong severity, exhibit many/strong connections to other symptoms, or have particularly strong connections between symptoms as targets for conducting individualized, targeted interventions. It remains unclear, however, as to which of these elements estimated from the individual's perception are capable of predicting treatment outcomes and can thereby act as promising targets. In this context, PECAN might complement the toolbox of estimating directed networks to address precisely this question in clinical studies of whether and which elements of directed networks (based on an individual's perception) can make an incremental contribution to the prediction of treatment outcomes. Moreover, PECAN-derived networks may facilitate formalized case conceptualization based on network theory (Burger et al., 2022), for instance, to discuss a treatment rationale with patients.

## References


Almende, B. V., & Thieurmel, B. (2022). *visNetwork: Network Visualization using, vis.js" Library* (2.1.2) [Software]. https://cran.r-project.org/web/packages/visNetwork/index.html

Andreasson, M., Schenström, J., Bjureberg, J., & Klintwall, L. (2023). Perceived causal networks: Clinical utility evaluated by therapists and patients. *Journal for Person-Oriented Research*, *9*(1), 29–41. https://doi.org/10.17505/jpor.2023.25260

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, *16*(1), 5–13. https://doi.org/10.1002/wps.20375

Bringmann, L. F., Albers, C., Bockting, C., Borsboom, D., Ceulemans, E., Cramer, A., Epskamp, S., Eronen, M. I., Hamaker, E., Kuppens, P., Lutz, W., McNally, R. J., Molenaar, P., Tio, P., Voelkle, M. C., & Wichers, M. (2022). Psychopathological networks: Theory, methods and practice. *Behaviour Research and Therapy*, *149*, Article 104011. https://doi.org/10.1016/j.brat.2021.104011

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T. W., & Snippe, E. (2019). What do centrality measures measure in psychological networks? *Journal of Abnormal Psychology*, *128*(8), 892–903. https://doi.org/10.1037/abn0000446

Bucci, S., French, L., & Berry, K. (2016). Measures assessing the quality of case conceptualization: A systematic review. *Journal of Clinical Psychology*, *72*(6), 517–533. https://doi.org/10.1002/jclp.22280

Burger, J., Andikkhash, V., Jäger, N., Anderbro, T., Blanken, T. F., & Klintwall, L. (2024). A novel approach for constructing personalized networks from longitudinal perceived causal relations. *Behaviour Research and Therapy*, *173*, Article 104456. https://doi.org/10.1016/j.brat.2023.104456

Burger, J., Epskamp, S., Van Der Veen, D. C., Dablander, F., Schoevers, R. A., Fried, E. I., & Riese, H. (2022). A clinical PREMISE for personalized models: Toward a formal integration of case formulations and statistical networks. *Journal of Psychopathology and Clinical Science*, *131*(8), 906–916. https://doi.org/10.1037/abn0000779

Burger, J., van der Veen, D. C., Robinaugh, D. J., Quax, R., Riese, H., Schoevers, R. A., & Epskamp, S. (2020). Bridging the gap between complexity science and clinical practice by formalizing idiographic theories: A computational model of functional analysis. *BMC Medicine*, *18*(1), Article 99. https://doi.org/10.1186/s12916-020-01558-1

Ebner-Priemer, U. W., & Trull, T. J. (2009). Ambulatory assessment: An innovative and promising approach for clinical psychology. *European Psychologist*, *14*(2), 109–119. https://doi.org/10.1027/1016-9040.14.2.109

Frewen, P. A., Allen, S. L., Lanius, R. A., & Neufeld, R. W. J. (2012). Perceived causal relations: Novel methodology for assessing client attributions about causal associations between variables including symptoms and functional impairment. *Assessment*, *19*(4), 480–493. https://doi.org/10.1177/1073191111418297

Gilboa-Schechtman, E. (2024). Case conceptualization in clinical practice and training. *Clinical Psychology in Europe*, *6*(Special Issue), Article e12103. https://doi.org/10.32872/cpe.12103

Hansson, M., Chotai, J., & Bodlund, O. (2010). Patients' beliefs about the cause of their depression. *Journal of Affective Disorders*, *124*(1–2), 54–59. https://doi.org/10.1016/j.jad.2009.10.032

Haynes, S. N., Leisen, M. B., & Blaine, D. D. (1997). Design of individualized behavioral treatment programs using functional analytic clinical case models. *Psychological Assessment*, *9*(4), 334–348. https://doi.org/10.1037/1040-3590.9.4.334

John, S., & Segal, D. L. (2014). Case conceptualization. In R. L. Cautin & S. O. Lilienfeld (Eds.), *The encyclopedia of clinical psychology* (Vol. 1, pp. 1–4). Wiley. https://doi.org/10.1002/9781118625392.wbecp106

Jones, P. J., Ma, R., & McNally, R. J. (2021). Bridge centrality: A network approach to understanding comorbidity. *Multivariate Behavioral Research*, *56*(2), 353–367. https://doi.org/10.1080/00273171.2019.1614898

Jones, P. J., & Robinaugh, D. R. (2021). An answer to, So What?" Implications of network theory for research and practice. *Focus (American Psychiatric Publishing)*, *19*(2), 204–210. https://doi.org/10.1176/appi.focus.20200050

Kaariniemi, E., Bosund, V., Reichert, J., Bjureberg, J., & Klintwall, L. (2025). Perceived causal networks created using structured interviews: Feasibility and reliability. *Cognitive Behaviour Therapy*, *54*(5), 685–707. https://doi.org/10.1080/16506073.2025.2464637

Klintwall, L., Bellander, M., & Cervin, M. (2023). Perceived causal problem networks: Reliability, central problems, and clinical utility for depression. *Assessment*, *30*(1), 73–83. https://doi.org/10.1177/10731911211039281

Lloyd, C. E. M., Duncan, C., & Cooper, M. (2019). Goal measures for psychotherapy: A systematic review of self-report, idiographic instruments. *Clinical Psychology: Science and Practice*, *26*(3), Article e12281. https://doi.org/10.1111/cpsp.12281

Mansueto, A. C., Wiers, R. W., & Epskamp, S. (2022). *Investigating the feasibility of idiographic network models*.

Mumma, G. H., Marshall, A. J., & Mauer, C. (2018). Person-specific validation and testing of functional relations in cognitive-behavioural case formulation: Guidelines and options. *Clinical Psychology & Psychotherapy*, *25*(5), 672–691. https://doi.org/10.1002/cpp.2298

Reichert, J., Klimov, M., Kachel, A., Tei, V., Beiner, E., Vogel, F., Klintwall, L., & Tesarz, J. (2025). *Perceived causal networks in patients with fibromyalgia and depression: Construction of a structured interview and testing reliability*. Research Square. https://doi.org/10.21203/rs.3.rs-6352353/v1

Reichert, J., & Vogel, F. (2024). *PECAN2: Create PECAN Networks*. Rpackage Version 0.1.0, https://github.com/JR-psych/PECAN2

Sales, C. M. D., & Alves, P. C. G. (2016). Patient-centered assessment in psychotherapy: A review of individualized tools. *Clinical Psychology: Science and Practice*, *23*(3), 265–283. https://doi.org/10.1111/cpsp.12162

Scheffer, M., Bockting, C. L., Borsboom, D., Cools, R., Delecroix, C., Hartmann, J. A., Kendler, K. S., Van De Leemput, I., Van Der Maas, H. L. J., Van Nes, E., Mattson, M., McGorry, P. D., & Nelson, B. (2024). A dynamical systems view of psychiatric disorders—Practical implications: A review. *JAMA Psychiatry*, *81*(6), Article 624. https://doi.org/10.1001/jamapsychiatry.2024.0228

Schmier, J. K., & Halpern, M. T. (2004). Patient recall and recall bias of health state and health status. *Expert Review of Pharmacoeconomics & Outcomes Research*, *4*(2), 159–163. https://doi.org/10.1586/14737167.4.2.159

Scholten, S., Klintwall, L., Glombiewski, J. A., & Burger, J. (2025). Updating patient perceptions with intensive longitudinal data for enhanced case conceptualizations: An approach with Bayesian informative priors. *Journal of Psychopathology and Clinical Science*, *134*(5), 585–599. https://doi.org/10.1037/abn0000993

Scholten, S., Lischetzke, T., & Glombiewski, J. A. (2022). Integrating theory-based and data-driven methods to case conceptualization: A functional analysis approach with ecological momentary assessment. *Psychotherapy Research*, *32*(1), 52–64. https://doi.org/10.1080/10503307.2021.1916639

Siepe, B. S., Sander, C., Schultze, M., Kliem, A., Ludwig, S., Hegerl, U., & Reich, H. (2024). Time-varying network models for the temporal dynamics of depressive symptomatology in patients with depressive disorders: Secondary analysis of longitudinal observational data. *JMIR Mental Health*, *11*, Article e50136. https://doi.org/10.2196/50136

Vogel, F., Fromm, C., Reichert, J., & Rupp, S. (2025). *An adaptation of perceived causal networks for children and adolescents (PECAN-CA): An evaluation of its reliability and feasibility*. https://osf.io/preprints/psyarxiv/7fv49_v1

von Klipstein, L., Riese, H., van der Veen, D. C., Servaas, M. N., & Schoevers, R. A. (2020). Using person-specific networks in psychotherapy: Challenges, limitations, and how we could use them anyway. *BMC Medicine*, *18*(1), Article 345. https://doi.org/10.1186/s12916-020-01818-0

Weisz, J. R., Chorpita, B. F., Frye, A., Ng, M. Y., Lau, N., Bearman, S. K., Ugueto, A. M., Langer, D. A., Hoagwood, K. E., & Research Network on Youth Mental Health. (2011). Youth Top Problems: Using idiographic, consumer-guided assessment to identify treatment needs and to track change during psychotherapy. *Journal of Consulting and Clinical Psychology*, *79*(3), 369–380. https://doi.org/10.1037/a0023307

Wright, A. G. C., & Zimmermann, J. (2019). Applied ambulatory assessment: Integrating idiographic and nomothetic principles of measurement. *Psychological Assessment*, *31*(12), 1467–1480. https://doi.org/10.1037/pas0000685

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