Journal of Psychopathology and Clinical Science

Updating Patient Perceptions With Intensive Longitudinal Data for Enhanced Case Conceptualizations: An Approach With Bayesian Informative Priors

Saskia Scholten, Lars Klintwall, Julia Anna Glombiewski, and Julian Burger

Online First Publication, April 14, 2025. https://dx.doi.org/10.1037/abn0000993

AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Psychopathology and Clinical Science

ISSN: 2769-7541

https://doi.org/10.1037/abn0000993

Updating Patient Perceptions With Intensive Longitudinal Data for Enhanced Case Conceptualizations: An Approach With Bayesian Informative Priors

Saskia Scholten[1], Lars Klintwall[2], Julia Anna Glombiewski[1], and Julian Burger[3, 4]

[1] Pain and Psychotherapy Research Laboratory, Department of Psychology, University of Kaiserslautern-Landau

[2] Department of Clinical Neuroscience, Centre for Psychiatry Research, Karolinska Institutet & Stockholm Health Care Services, Region Stockholm, Sweden

[3] Department of Psychology, University of Amsterdam

[4] Yale School of Public Health, Yale University

OPEN DATA OPEN MATERIALS PREREGISTERED

Addressing the persistent heterogeneity in psychopathology, treatment outcomes, and the science–practice gap requires a systematic approach to personalizing psychotherapy. Case conceptualization seeks to understand a patient's unique psychopathology by generating and continuously updating hypotheses about predisposing, precipitating, and maintaining factors. This study introduces a new data-driven method to formalize this process with personalized network estimation, combining prior elicitation and Bayesian inference. It is the first to test its clinical usefulness with 12 patients, primarily treated for depression, and their therapists (preregistered and can be found as the additional online materials: https://osf.io/38qdx). Patients employed the Perceived Causal Networks method to create personalized "prior networks," mapping how they perceived their symptoms to interact. Bayesian inference was used to update these prior networks using longitudinal data collected subsequently 6 times daily over 15 days ($N = 935$), resulting in personalized "posterior networks." Both Perceived Causal Networks and longitudinal assessments were evaluated as feasible and acceptable. Face validity was scored highest for the posterior networks. Patients emphasized the personal relevance of these networks, while therapists noted their value in guiding the therapeutic process. However, prior, posterior, and data networks showed significant dissimilarities. These differences may stem from patients' limited insight into symptom interactions, insufficient power in the longitudinal data, or variations in self-perception. Despite some inconsistencies, the study shows potential for combining two methods to create personalized models of psychopathology, highlighting the need for future research to refine this formalization process into a more rigorous theoretical-empirical cycle to test these models.

Aidan G. C. Wright served as action editor.

Saskia Scholten https://orcid.org/0000-0002-1439-8684

Lars Klintwall https://orcid.org/0000-0003-4931-6033

Julian Burger https://orcid.org/0000-0001-8177-788X

Preliminary data of the project were presented at the German Psychotherapy Congress 2024 in Berlin. Saskia Scholten was promoted as "Post-Doc with child(ren)" receiving administrative support by the project for the qualification of female junior scientists, Universität Koblenz-Landau, Germany. We would like to thank Katja Brinkmann, Lenina Maier, and Ragna Wenk for their contributions to this study. Additionally, we extend our gratitude to the entire team at the University Outpatient Clinic for their unwavering support and assistance throughout this project. The authors have no conflicts of interest to declare. During the preparation of this work, the authors used DeepL and ChatGPT in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication. The local ethics board of the University of Kaiserslautern-Landau approved the study (LEK-176a5). A previous version of the article was published as a preprint in the Open Science Framework and can be found as the additional online materials (https://osf.io/preprints/psyarxiv/7kpmh). Material, data, and code of the project are provided in the Open Science Framework and can be found as the additional online materials (Scholten, Klintwall, et al., 2024).

Saskia Scholten served as lead for investigation, project administration, and writing–original draft. Lars Klintwall served as lead for data curation and contributed equally to software. Julia Anna Glombiewski served as lead for funding acquisition. Julian Burger served as lead for formal analysis and contributed equally to data curation. Saskia Scholten, Lars Klintwall, and Julian Burger contributed equally to conceptualization and methodology. Lars Klintwall and Julia Anna Glombiewski contributed equally to supervision. Lars Klintwall, Julia Anna Glombiewski, and Julian Burger contributed equally to writing–review and editing.

The data are available at https://osf.io/r5xfg/.

The experimental materials are available at https://osf.io/r5xfg/.

The preregistered design is available at https://osf.io/38qdx.

Correspondence concerning this article should be addressed to Saskia Scholten, Pain and Psychotherapy Research Laboratory, Department of Psychology, University of Kaiserslautern-Landau, Ostbahnstraße 10, 76829 Landau, Germany. Email: saskia.scholten@rptu.de

General Scientific Summary
Case conceptualization is a process therapists use to understand a patient's problems and guide treatment decisions. This study applies and evaluates a structured, data-driven approach to improve this process. By integrating and visualizing various data sources, we create networks that represent the complexities of a patient's case.

Keywords: network analysis, Bayesian inference, case conceptualization, ecological momentary assessment, perceived causal networks

Supplemental materials: https://doi.org/10.1037/abn0000993.supp

Psychotherapy is effective (Cuijpers et al., 2024); however, despite decades of extensive research, effect sizes have not improved over time (Cuijpers et al., 2020; Hofmann et al., 2012; Miskovic-Wheatley et al., 2023; Newby et al., 2015; Vlaeyen & Crombez, 2020). The persistent heterogeneity in psychopathology and treatment outcomes remains a central challenge in psychotherapy research (Herzog & Kaiser, 2022; Kaiser & Herzog, 2023; Kaiser et al., 2022; Scholten et al., 2025). To advance the field, a systematic approach to personalizing psychotherapy is needed—one that builds on individualized models of psychopathology (Cohen et al., 2021; Deisenhofer et al., 2024; Wright & Woods, 2020).

These personalized models often conceptualize mental disorders as dynamic systems of interacting, self-sustaining processes that are specific to each individual (Roefs et al., 2022; Wright & Woods, 2020). Formal idiographic statistical models are essential to accurately reflect individual and dynamic systems at the appropriate level and time scale (Burger, Epskamp, et al., 2022; Molenaar, 2004). A key requirement is the assessment of person-specific processes over time at the individual level (Wright & Zimmermann, 2019). Recent approaches include the extensions of structural equation models (Fisher & Boswell, 2016; Wright, Gates, et al., 2019) and network models (Bringmann, 2021; von Klipstein et al., 2020), which rely on intensive longitudinal data collected through ecological momentary assessment (EMA). EMA involves multiple daily prompts (e.g., 5–10 times per day) to capture real-time self-reported symptoms (Colombo et al., 2019; Myin-Germeys & Kuppens, 2021). However, despite these advancements, research has largely overlooked how to integrate both patients' and therapists' perspectives with models estimated from data (Burger, Epskamp, et al., 2022; Burger, Ralph-Nearman, & Levinson, 2022).

Integrating patient and therapist perspectives could inform and advance idiographic models of psychopathology, thereby contributing to bridging the research–practice gap (Levinson et al., 2025). Case conceptualization is a clinical approach that directly integrates these two perspectives as it is a collaborative process between patient and clinician (Persons, 2006). It aims to understand a patient's idiographic psychopathology by incorporating both between-person factors (e.g., demographic information, living conditions, and income) and intraindividual dynamics (e.g., symptom patterns). Specifically, it focuses on how cognitions, emotions, and behaviors interact within pathological states while identifying predisposing, triggering, and perpetuating processes (Easden & Kazantzis, 2018). By systematically organizing this information, case conceptualizations provide a structured foundation for quantifying clinical observations, making them an ideal starting point for data-driven extensions (Burger, Epskamp, et al., 2022; Scholten et al., 2022). Hence, clinical insights could serve as a foundation for developing idiographic statistical models, thereby linking everyday practice with advanced research methodologies.

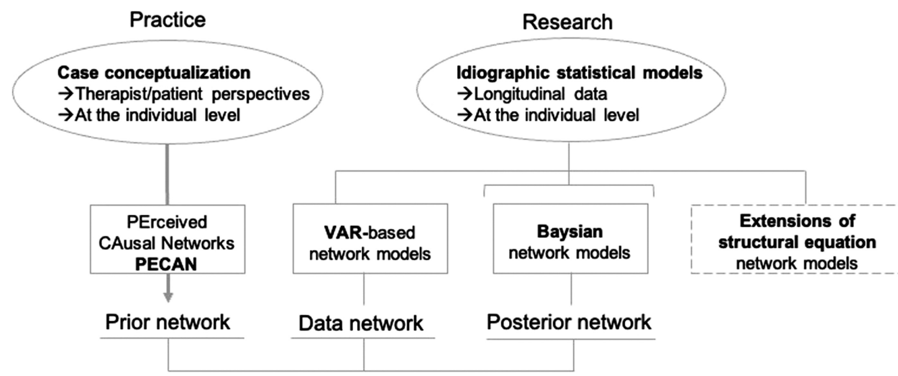
In the last decade, the network analysis approach to mental disorders has received increased attention as statistical model reflecting how symptoms of mental disorders interact and reinforce each other (Bringmann, Albers, et al., 2022; Roefs et al., 2022). Symptoms are presented as nodes in a network with edges representing their statistical relationships (Borsboom, 2017; Borsboom & Cramer, 2013). It aligns well with clinical case conceptualization and has inspired a surge of studies on data-driven case conceptualizations (Burger, Ralph-Nearman, & Levinson, 2022; Frumkin et al., 2021; Hall et al., 2023; Scholten et al., 2022; von Klipstein et al., 2020). The present study builds upon this work and extends it by integrating patient perspectives systematically. We use Perceived Causal Networks (PECAN; Frewen et al., 2012; Klintwall et al., 2023) to formalize the patient's individual case conceptualization in a prior network. It represents the patient's perceptions on how their presenting concerns interact with one another causally. Subsequently, EMA is used to sample observations on these concerns in patients' daily lives over time. Based on these intensive longitudinal data, a data network is estimated, and the prior network is updated via Bayesian inference into a posterior network (see Figure 1 for an overview of the models).

Data Networks

Vector autoregressive (VAR) models with a lag-1 are very commonly used methods to estimate temporal patterns between symptoms at the individual level (Bringmann, 2021; Wild et al., 2010). They indicate the extent to which variation in one symptom predicts variation in other symptoms at the next time point, often referred to as Granger causality (Granger, 1969; Shojaie & Fox, 2021). Such predictions can be visualized using networks of symptoms (Burger, Hoekstra, et al., 2022; Epskamp et al., 2018; Fisher et al., 2017): If variation in one symptom predicts subsequent variation in another, this relationship is represented as a directed edge (an arrow) between the two nodes (e.g., symptoms). Centrality measures indicate potentially influential nodes, although their validity as treatment targets has been strongly criticized (Bringmann et al., 2019; Dablander & Hinne, 2019). Several studies have applied EMA in clinical settings to construct VAR-based networks, yielding promising results in describing person-specific symptom dynamics (Fisher et al., 2017; Frumkin et al., 2021; Hall et al., 2023) as well as demonstrating feasibility, acceptability (Frumkin et al., 2021; Levinson et al., 2023; Scholten et al., 2022), and clinical efficacy (Levinson et al., 2023).

While VAR-based networks offer intuitive appeal for understanding symptom dynamics, they have statistical assumptions

Figure 1
Overview of the Network Models Used in the Present Study



Note. PECAN = Perceived Causal Networks; VAR = vector autoregression.

that limit clinical application. First, they may miss important connections because they rely on symptom variation; if a symptom is constant, it cannot have edges to other symptoms in the network, and its causal impact on other symptoms can go undetected (Bringmann & Eronen, 2018). For example, if a patient consistently experiences anhedonia which leads to social isolation, this relationship will not appear in a VAR-based network because there is no variation in the intensity of the anhedonia. Second, the typical assessment intervals in VAR models may fail to capture both fast-acting (e.g., catastrophizing leads to panic within a few minutes) and slow-acting relationships (e.g., physical inactivity leads to gradual increase in fatigue over several weeks), leading to either undirected networks or challenges in identifying long-term changes (Epskamp et al., 2018). Potential solutions, such as examining all possible lag-x correlations in the VAR model, may lead to a high number of Type 2 errors. Alternatively, estimating time-varying networks and plotting parameters over time requires high-dimensional data, which poses a challenge for practical implementation in clinical settings (Haslbeck, Bringmann, & Waldorp, 2021). Finally, VAR-based networks require the estimation of numerous parameters, which demands a large number of observations to ensure reliable results (Burger, Epskamp, et al., 2022). However, most clinical studies fall short in this regard, resulting in low sensitivity and the potential for undetected connections (Mansueto et al., 2023).

Prior Network

An alternative method for creating individualized case conceptualizations is a PECAN (Frewen et al., 2012; Klintwall et al., 2023). PECAN involves (a) selecting symptoms relevant to the patient and rating the perceived causal relationships between them (e.g., "How strongly does symptom X Cause symptom Y?" on a scale from 0 to 10) and (b) visualizing these relationships as a network, with symptoms represented as nodes and perceived causal relations as directed edges of varying strength (Vogel et al., 2024). This method models the patients' subjective understanding of their condition and addresses some limitations of VAR-based networks: It does not require symptoms to vary in intensity to establish causal connections, can identify causal relationships on any time scale and does not face issues related to the number of observations, as all data are collected directly from the patient, though respondent fatigue may increase with the number of edges as nodes increase. Klintwall et al. (2023) tested PECAN with 231 adults who screened positive for depression and found that it had a reasonable completion time and acceptable reliability. Therapists viewed the resulting networks as logical and helpful for identifying treatment targets. Additionally, a pilot study by Andreasson et al. (2023), involving five therapists and their patients beginning psychotherapy also found PECAN to be a useful tool. The method has further been applied with adolescents (Bångstad et al., 2022).

However, the obvious limitation with relying on patient perceptions is that patients often lack insight into the causal relations between their symptoms, especially for effects on longer time scales and perhaps especially before therapy. Indeed, it has been shown that respondents often overestimate causation between behavioral phenomena (Gloster et al., 2017). Also, common clinical experience suggests that patients are often unaware of how their behaviors, context, and emotions influence one another (Ghaemi & Rosenquist, 2004; Medalia & Thysen, 2008; Peralta & Cuesta, 1998) and retrospective biases might impact PECAN assessments (Van den Bergh & Walentynowicz, 2016).

Posterior Network

Burger, Epskamp, et al. (2022) proposed a method that combines the benefits of PECAN and VAR-based networks: the Prior Elicitation Module for Idiographic System Estimation (PREMISE). This approach involves first assessing a prior network, then sampling relevant symptoms through EMA (Burger, Ralph-Nearman, & Levinson, 2022). The method estimates both a VAR-based network from EMA data alone and an "updated" network. Bayesian inference is used to update the prior network with EMA data. In this context, the "prior" represents the initial belief, including the probability of predictions (O'Hagan, 2019), which is then integrated with the likelihood of new observations to calculate the "posterior" belief (O'Reilly et al., 2012). This approach formalizes an initial case conceptualization and updates it as new information becomes available but has only been applied to a sample of two clinical cases (Burger, Ralph-Nearman, & Levinson, 2022). Further clinical evaluation is urgently needed.

Objective and Research Questions

In the present study, we aimed to apply and evaluate PREMISE in a sample of 12 patients undergoing treatment for depression and their respective therapists. PECAN is used to construct a prior network, EMA is used to sample observations to estimate a data network,[1] and Bayesian inference is used to update the PECAN network into a posterior network. Three research questions will be answered:

Research Question 1: How feasible and acceptable are the two assessment procedures? We anticipate positive patient evaluations for both assessment procedures.

Research Question 2: Which of the three networks is evaluated as most in line with patients' and therapists' representations of the patient's problem? We anticipate that the posterior network will best align with patients' and therapists' subjective representations compared to the prior and data networks, as it integrates prior knowledge with new information. Additionally, the evaluation occurs after the EMA, allowing for any updates to subjective representations by patients and therapists since the initial PECAN construction.

Research Question 3: How useful are the networks for clinical practice? We expect patients to evaluate the three networks as useful and therapists to be more cautious about clinical utility (Frumkin et al., 2021). Generally, we expect both patients and therapists to find posterior networks most beneficial since it will contain more information.

A preregistration of the study can be found in the Open Science Framework and can be found as the additional online materials (https://osf.io/38qdx).

Method

Procedure

Participants were recruited at a university outpatient clinic, after their intake interview. Prospective participants were invited for a preassessment session to be informed about the study. After giving informed consent, the PECAN questionnaire (as outlined by Klintwall et al., 2023) was administered in the presence of a research assistant to clarify potential questions. Next, the symptoms selected in PECAN were formulated as EMA items and assessed for 15 days, 6 times per day, yielding observed data to update the priors. In addition to a data network using uninformative priors, a posterior network was estimated using PECAN as priors (see the Analysis section). A research assistant presented the resulting networks and their out-strength centrality measures to the participants in a postassessment session. Feasibility evaluations from patients were assessed via an online questionnaire immediately after completing PECAN and EMA, respectively. The overall evaluation was conducted after the postassessment session before start of therapy. Therapists were invited to evaluate the networks after two to four sessions with the patient. A semistructured interview was used to get feedback about methods and networks from patients and therapists. Financial compensation to patients was in total 50 Euros (10 Euros after PECAN and 40 Euros after EMA) for patients and 20 Euros for therapists. The local ethics board of the University of Kaiserslautern-Landau approved the study (LEK-176a5).

Sample

Patients

We included adults (age ≥18 years) whose problems were primarily depressive. Participants were required to own a smartphone to enable EMA data collection. Exclusion criteria were low self-reflective capacity (e.g., acute suicidality, acute psychosis, and acute substance abuse), illiteracy, insufficient German knowledge, and age <18 years. In general, a sample size of *n*-of-1 is sufficient for idiographic research. However, as replication enables generalization of idiographic findings (Tanious et al., 2024), we aimed to recruit 12 participants for this initial step of design development. This sample size aligns with qualitative research guidelines, which suggest that six to 25 participants are typically sufficient to reach information saturation in interview studies (Guest et al., 2006; Turner-Bowker et al., 2018). Information saturation occurs when no new ideas or concepts emerge after a specific number of interviews. Following these guidelines and recommendations for qualitative feasibility studies, 12 participants provide a practical sample for evaluating feasibility and acceptability through semistructured interviews. This approach is also consistent with similar small-scale feasibility studies (Frumkin et al., 2021).

Therapists

There were no further inclusion or exclusion criteria apart from the role as a reference therapist for one of the patient participants.

Materials and Measures

PECAN Assessment

First, the patient selected between three and 10 problems from a predefined list (Scholten, Klintwall, et al., 2024). The list comprised core symptoms of major depression according to the *Diagnostic and Statistical Manual of Mental Disorders*, fifth edition, such as "sad" and "loss of interest" and behaviors related to these symptoms, such as "physical inactivity" or "social isolation" (American Psychiatric Association, 2018). We also included typical comorbid problems/symptoms such as "worry about the future" or "rumination about the past." The list was a slightly revised and translated version from that used in Klintwall et al. (2023). Insomnia was omitted from the list, as this problem could not be assessed throughout the day in the subsequent EMA procedure. Respondents were asked to select problems that they had experienced every day in the past week. Important missing problems could also be added by the patient.

Respondents were then asked to describe the selected problems in their own words and personalize the items with individual examples (e.g., if the patient had selected "pain" from the predefined list, he or she might then personalize this problem as "headaches"). The severity of each selected problem was rated using a visual analog slider on a scale from 0 (*no burden at all*) to 100 (*very severe burden*).

[1] Strictly speaking, the data network is also a posterior network, but it is based on uninformative priors. We will use the term "data network" to simplify wording.

Next, directed edges were assessed as perceived causal strengths between each combination of selected problems. This was done by asking "Which of the following caused you to experience *pain* 3 hr later?" Beforehand, a training session was conducted using practical examples to clarify the concept of causes. This training made sure the respondent understood the causal question and the instruction to allocate percentage influence of individual causes, ensuring the total added up to 100%. A time frame of 3 hr was used to match the EMA data collection. Also, a change was made from the standard PECAN procedure: problems were available as potential causes to themselves (e.g., when asked about why he or she experiences pain, the respondent could select the cause as being pain 3 hr earlier).

As the number of edges in a network increase exponentially with number of nodes, rating many potential causes can induce respondent fatigue and thus lower the validity of ratings. To avoid this, respondents were limited to selecting not more than three potential causal problems for each problem. Thus, a node could not have more than three ingoing edges in the PECAN (indeed, maxing out at selecting three causes was the most common response style). After selecting up to three causal nodes, the respondent was asked to distribute percentages across these and a fourth alternative: "other causes/don't know" (in line with the procedure in Klintwall et al., 2023). PECAN was implemented in Qualtrics (https://www.qualtrics.com/de/).

EMA Data Collection

The selected symptoms were assessed using EMA across 15 days with a fixed sampling scheme at six time points three hours apart (7 a.m., 10 a.m., 1 p.m., etc.). The item instruction also referred to a retrospective assessment of the past 3 hr (e.g., "Were your stressed in the past 3 hr?") Delay allowed to respond was 60 min. EMA was assessed using Smartphone Ecological Momentary Assessment (https://sema3.com/index.html), particularly programmed as open-source solution for the assessment of intensive longitudinal data (O'Brien et al., 2024).

Evaluation

Feasibility and acceptance of the data collection methods (Research Question 1) were evaluated by patients using adapted versions of the evaluation questionnaires used by Scholten et al. (2022) and Frumkin et al. (2021). The feasibility, comprehensibility, degree of difficulty, effort, time burden, effects, and applicability of the PECAN assessment and EMA were assessed. Evaluation questionnaires consisted of 23 items each, with 12 statements (e.g., "I always knew what to do;" "I was overwhelmed with the processing") rated on a 5-point Likert scale from 1 (*strongly disagree*) to 5 (*agree completely*) and 11 statements (e.g., "The processing was overall") with a semantic differential rated on a 5-point scale (e.g., 1 = *easy*; −5 = *difficult*). Two additional items asked whether the patients would participate in the study again and recommend the study to others. The questionnaires were assessed immediately after each assessment method. For a detailed presentation of the evaluation questionnaires, see Scholten, Klintwall, et al. (2024).

To evaluate the three resulting networks (Research Question 2), these were presented separately and in randomized order to patients and therapists. The type of the network ("prior," "data-driven," and "posterior") was indicated in the presentation. Patients and therapists answered seven statements such as "The network shows how my complaints are connected" or "The network helps me to better understand my complaints" (Brooke, 1996; Frumkin et al., 2021; Klintwall et al., 2023; Sauro & Lewis, 2011). They were rated on a 5-point Likert scale from 1 (*disagree*) to 5 (*strongly agree*; Scholten, Klintwall, et al., 2024). Then, patients and therapists were asked to indicate which of the three networks described the patient best.

Finally, clinical usefulness was evaluated for all three networks (Research Question 3). Overall usefulness (six statements such as "I think the networks are absolutely useful.") and comprehensibility (five statements such as "The networks were easy to understand.") of the networks were assessed on a 5-point Likert scale from 1 (*disagree*) to 5 (*strongly agree*). The visualization of the networks was evaluated with the visual aesthetics scale of the modular evaluation of key Components of User Experience (Minge & Thüring, 2018; Minge et al., 2017) comprising three items (e.g., "The design looks attractive.") that are evaluated on a 5-point Likert scale from 1 (*disagree*) to 5 (*strongly agree*). Further, the presentation of the networks was evaluated with the User Experience Questionnaire-Short Form (Schrepp et al., 2017) that assesses the pragmatic and hedonic qualities of the visualization with semantic differentials on the dimensions pragmatic presentation (e.g., "complicated"–"easy") and hedonic presentation (e.g., "boring"–"exciting").

Data were collected in a personal session through online self-reports on the SoSciSurvey platform (SoSci Survey GmbH, 2020). A semistructured interview was conducted to explore additional patient and therapist experiences, comments, and relevant aspects (Scholten, Klintwall, et al., 2024).

Analysis

Network Estimation

PECAN ("Prior Network"). Edges were not estimated but are simply the percentages reported by the patients (as described above). Participants were asked to quantify causality in percent (i.e., loss of interest was 25% due to physical inactivity and 75% due to social isolation). For each edge between nodes, the perceived network was constructed using respondents' exact answers. Respondents were asked to select no more than three causal symptoms (in edges) for each symptom. They were then asked to allocate 100% of the causality to these selected edges and a "don't know/other causes" option, which was always available. The resulting network matrix was visualized using a force-directed graph.

VAR-Based Network ("Data Network"). The sampling scheme yielded a maximum of 90 data points. We decided to include data sets, with a minimum of 72 data points (80% compliance) into the analysis. There are presently no specific recommendations for exact sample sizes in network estimation (Booij et al., 2018). Nonetheless, Mansueto et al. (2023) suggested that with 75–100 observations, reducing the number of nodes to approximately six variables is advisable. Given the use of informative priors to enhance estimation, we decided to set the maximum number of nodes at 10. A lag-1 network was estimated using the default regularization priors from the PREMISE networks, assuming no prior knowledge (Burger, Epskamp, et al., 2022). These networks are in line with the standard data-driven approach that is currently prominent in time-series analysis (Epskamp et al., 2018).

Updated Network ("Posterior"). For the subsequent estimation of a Bayesian VAR model, the data from the PECAN were used as an informative prior. Bayesian inference involves defining a prior probability distribution for the parameters to be estimated. Here, we defined prior distributions for the network parameters using a Gaussian distribution for each parameter. The mean of the Gaussian prior was determined by the respective PECAN estimate, and the standard deviation is set to 0.2. Furthermore, for relations that were not reported by the patients (i.e., two nodes that are not connected), a default prior was set to a default prior with mean of 0 ($SD = 5$), resulting in minimally informative priors. The clinical prior model (i.e., the probability distribution derived from the PECAN) is shifted according to the pattern found in the EMA.

Evaluation

The research questions were answered using descriptive statistics, including frequencies and measures of central tendency and variation of the self-reported patient and clinician ratings of feasibility, acceptability, and clinical usability. We did not estimate inferential statistics due to the small sample size. Thus, comparisons are based on numeric means. Responses to the semistructured interviews were summarized descriptively.

Transparency and Openness

The study was preregistered in the Open Science Framework and can be found as the additional online materials (https://osf.io/38qdx). All data, analysis code, and research materials are publicly available (Scholten, Klintwall, et al., 2024). All analyses were performed in R (R Core Team, 2022). We used the psychometrics package (Epskamp, 2020), qgraph package (Epskamp et al., 2012), and ggplot2 (Wickham et al., 2022) as well as the STAN implementation via the rstan package (Stan Development Team, 2020).

Results

Sample Description

Patients

Forty patients were assessed for eligibility. Twenty-eight did not participate (nine could not be reached via telephone, 13 declined to participate, four dropped out because they started psychotherapy, and two dropped out for other reasons). Twelve participants gave informed consent and participated in the study, nine women and three men. Average age was 36.4 years, ranging from 23 to 62 years. Further sociodemographic information is provided in Table 1.

Therapists

Three patients did not start treatment in our outpatient clinic; therefore, we could recruit their therapists. Six therapists of the remaining nine patients decided to participate in the study. One therapist dropped out early due to the subjective perception that the study was too time-consuming. The remaining sample consisted of five therapists who were in training or licensed. Two therapists were responsible for two of the patient participants. Therapist participants completed both the evaluation questionnaire and the semistructured interview for all patients, resulting in a total of seven therapist data sets.

Feasibility and Acceptability (Research Question 1)

Feasibility and acceptability were rated for completing the PECAN questionnaire and EMA (Table 2). Numeric mean comparisons indicate the following results: The purpose was perceived slightly clearer for completing EMA compared to the PECAN questionnaire. Similarly, agreement was higher to prepare and complete EMA during the waiting period than the PECAN questionnaire. In contrast, the PECAN questionnaire was rated less overwhelming, less stressful, less time-consuming, easier to fill out, and offering clear guidance on what to do. Also, PECAN received higher ratings for the items "helped to understand complains" and "the problems assessed applied to me." The completion time of the PECAN questionnaire was 26.0 min on average (ranging from 15.4 to 39.3 min). EMA took 1–5 min to complete per single assessment, resulting in a range of 90 min–7.5 hr of total time investment. Average compliance was 86%.

In the semistructured interviews, patients considered the completion of PECAN and EMA diaries feasible (22 statements), for example, reported participation "not as stressful as expected," with "appropriate duration" of assessments and "being able to do everything from home feels safer (familiar surrounding)." They also raised some concerns regarding feasibility (eight statements), for example, "high time expenditure," "complexity," and "technical requirements." For PECAN, in particular, even more concerns were raised (17 statements), for example, because of the "amount of information asked" and "necessary concentration." There were also difficulties with EMA (29 statements) due to "time of first assessment in the morning," "short response window," or "being reminded of the problem." However, EMA also came with some advantages (11 statements), for example, because of "easy-to-use entry format" or "short questionnaire length." Nine patients indicated that EMA was easier compared to PECAN. Reasons to prefer EMA were the few, simple, repetitive questions that were stated to be more intuitive and easier to take decisions. In contrast, patients who preferred PECAN over EMA mentioned that PECAN was interesting and fun, not repetitive and tiring, and less time effort compared to EMA.

Representation of Patient's Problem (Research Question 2)

Individual Networks

The networks of all participants are presented in the Supplemental Material A in the online supplemental materials. Figure 2 shows the three networks of Participant 1 as an example. The prior network is depicted in the left panel of Figure 2. In this case, the patient perceives that anxiety causes difficulties making decisions. Also, a lack of energy is perceived to cause fatigue, which in turn causes concentration problems, procrastination, and loss of interest. The data network (middle panel of Figure 2) shows that fatigue and screen time predict procrastination and that pain strongly maintains itself. The posterior network also depicts this self-loop. The perceived causalities between lack of energy, screen time, and fatigue remain, while fatigue predicts procrastination more strongly and screen time is added as a predictor of procrastination. Further descriptions are possible based on Figure 2. In this example, fatigue (prior network, posterior network) and screen time (data network) are the most central nodes in the network. While screen time was the most central node in the data network and the second central node in the posterior network, it was only the fifth central symptom

Table 1
Sociodemographic Characteristics of the Participants

Patient	Age	Gender	Highest educational level[a]	Employment	Marital status	Nationality	Diagnosis	Duration of symptoms[b]
1	62	Male	3	Employed (full-time)	Permanent relationship	German	F33.1	4
2	29	Female	2	Employed (full-time)	Permanent relationship	German	F32.1	4
3	23	Female	2	University student	Single	German	F33.1	4
4	42	Female	2	Employed (full-time)	Single	German	F33.1	4
5	57	Female	3	Homemaker	Married	German	F33.1; F50.3	1
6	29	Female	2	University student	Married	Other	F33.1	3
7	44	Female	3	Employed (full-time)	Married	German	F41.1; F33.1	3
8	27	Male	4	University student	Permanent relationship	German	F33.2; F45.1	3
9	23	Female	2	University student	Permanent relationship	German	F33.1; F41.0	2
10	47	Male	1	Employed (full-time)	Married	German	F33.4; F41.0	4
11	26	Female	3	Employed (full-time)	Permanent relationship	German	F33.1; F45.41	2
12	28	Female	4	Employed (full-time)	Single	German	F33.0	2

Note. F33.1 = recurrent depressive disorder, current episode moderate; F50.3 = atypical bulimia nervosa; F41.1 = generalized anxiety disorder; F33.2 = recurrent depressive disorder, current episode severe without psychotic symptoms; F45.1 = undifferentiated somatoform disorder; F41.0 = panic disorder [episodic paroxysmal anxiety]; F45.4 = persistent somatoform pain disorder; F33.0 = recurrent depressive disorder, current episode mild.
[a] Highest educational level: 1 = *school-leaving qualification*; 2 = *general qualification for university entrance/advanced technical college certificate*; 3 = *completed vocational training*; 4 = *university degree*. [b] Duration of symptoms: 1 = *less than a month*; 2 = *between 6 and 12 months*; 3 = *more than a year*; 4 = *more than 5 years*.

in the prior network indicating that it was not perceived as a relevant component of psychopathology (Table 3).

Based on visual inspection of the network and of out-strength centrality, seven of the 12 patients indicated that the posterior networks best represented their problems (prior network: two patients; data network: three patients). Six therapists indicated that the posterior networks best represented their patients' problems (prior network: one therapist; data network: zero therapists).

In the semistructured interviews, patients described a knowledge gain based on the networks (30 statements), for example, "understanding symptom interactions," "offering an overview," or "it only became apparent when looking at the networks that there was something else involved." They valued the visualization of the networks (25 statements) and intended to use the network in psychotherapy (12 statements). Five patients stated that the networks matched their experience, whereas two patients found the networks "too abstract" and "not comprehensible". Two patients found some aspects of their experiences reflected in the network and others did not. The presentation of the networks was generally evaluated as factual, comprehensible, and well done (13 statements). Six therapists also found the guidelines provided for interpreting the networks helpful. Two of them stated that interpreting the networks was self-explanatory. One therapist would have preferred a more detailed introduction to network interpretation.

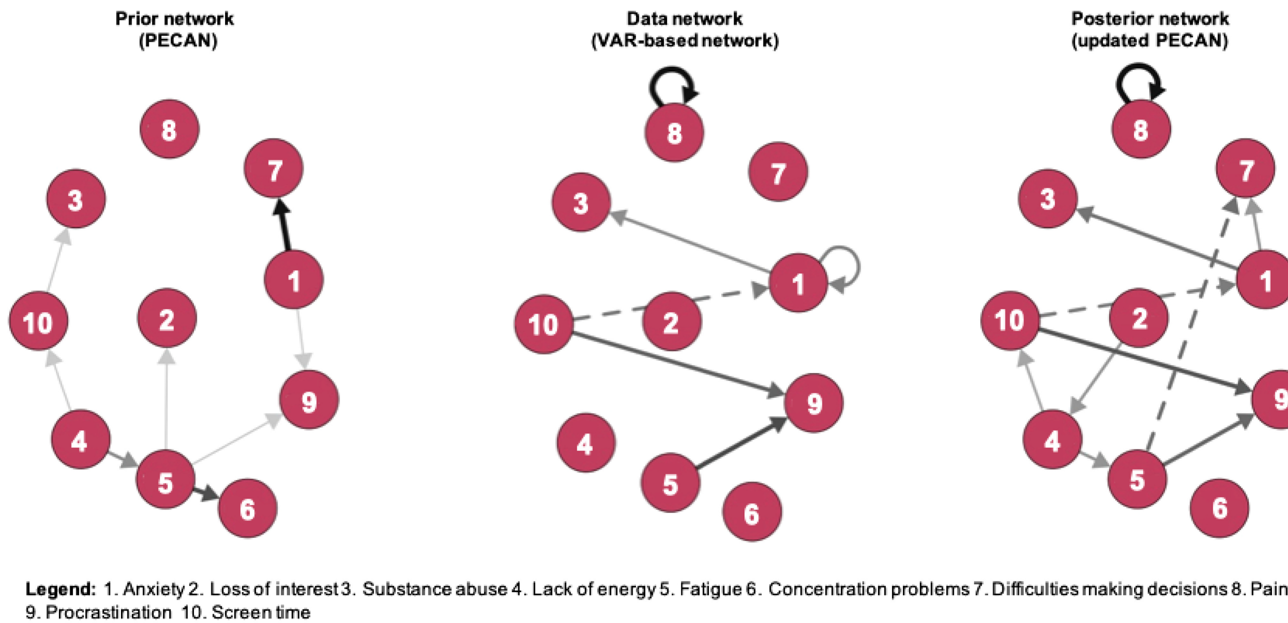
Table 2
Rating of Feasibility and Acceptability of the Assessment Methods

	PECAN questionnaire				EMA			
Item	*M*	*SD*	Min	Max	*M*	*SD*	Min	Max
"The purpose of the PECAN questionnaire/EMA was clear to me."	4.5	0.7	3	5	4.6	0.7	3	5
"I always knew what I was supposed to do."	4.4	1.1	2	5	3.9	0.8	3	5
"I was overwhelmed by the PECAN questionnaire/EMA."	3.4	1.9	2	5	4.0	1.0	2	5
"Completing the PECAN questionnaire/EMA led to stress."	3.2	0.9	2	5	3.9	1.1	2	5
"Completing the PECAN questionnaire/EMA helped me to better understand my complaints."	3.1	1.0	1	4	2. 7	1.0	1	4
"I can imagine completing the PECAN questionnaire/EMA on my own before starting psychotherapy."	3.6	1.3	1	5	3.8	1.3	1	5
"I think the PECAN questionnaire/EMA is a good way to prepare for therapy during the waiting period."	3.9	0.9	2	5	4.3	0.6	3	5
"The instructions (explanations of the tasks) of the PECAN questionnaire/EMA were: *easy to understand* (1)–*difficult to understand* (5)."	1.3	0.9	0	2	1.2	1.2	−2	2
"Overall, filling out the PECAN questionnaire/EMA was: *easy* (1)–*difficult* (5)."	1.4	0.7	0	2	0.2	1.3	−2	2
"Overall, the time requirement to fill out the PECAN questionnaire/EMA was: *low* (1)–*high* (5)."	0.6	1.3	−2	2	0.3	0.7	−1	1
"The problems assessed in the PECAN questionnaire/EMA: *applied to me* (1)–*did not apply to me* (5)."	1.5	0.5	1	2	1.2	0.7	0	2

Note. PECAN = Perceived Causal Networks; EMA = Ecological Momentary Assessment; Min = minimum; Max = maximum.

Figure 2

Prior, Data, and Posterior Network of Participant 1



Note. Prior network: edges represent quantified causalities in percent. Data network: edges represent $x - 1$ vector autoregressions. Posterior network: edges describe updates causalities. The higher the rating, the thicker the arrow, solid lines indicate positive relationships, and dashed lines indicate negative relationships. PECAN = Perceived Causal Networks; VAR = vector autoregression. See the online article for the color version of this figure.

Exploratory Analysis

To deepen our comprehension of the network properties that are shared and distinct among the networks, we performed an exploratory analysis examining different indicators of agreement and disagreement (Table 4). We correlated symptom severity and EMA means as indicators for the degree of symptom manifestation. The correlation was positive in eight out of 12 patients. The number of edges present in both the prior and the data network varied between 0 (5 times) and 3 (1 time). Relative to the edges that were indicated in either of the two networks, edges present in both networks varied between 0% and 25%. As indicators of potential target symptoms, we correlated OutDegree centrality between prior and data network. Five out of 12 patients showed positive correlations, and one of them had the same target symptom (i.e., the most central symptom) in both networks. Another five patients showed negative correlations. Analysis was not possible for two patients. Due to the small sample size, all inferential statistics should be interpreted with caution and do not allow for generalization.

In the semistructured interviews, two therapists pointed out that they rediscovered the same format across networks (node position, labels, lines and arrows, and self-loops). Three therapists identified similarities in content (symptom constellations, burden, and centrality). Four therapists found the data and posterior network more alike than the other combinations. One therapist did not identify similarities. In contrast, one therapist focused on the difference between prior and data network. Two therapists were surprised that the direction of edges changed or in one case an edge even disappeared completely in the posterior network. Another therapist pointed out that burden and centrality differed. Two therapists added that connections were less clear in the prior network in contrast to the posterior network. Based on these observations, therapists concluded that patients' explanation model might reflect their ability to assess themselves and why patients chose dysfunctional coping strategies. Two therapists said that the different networks bring up different starting points for psychotherapy.

Table 3

Three Most Central Symptoms in the Prior, Data-, and Posterior Network of Participant 1

Label	Prior	Data	Posterior
Anxiety	2	3	3
Lack of energy	3		
Fatigue	1	2	1
Screen time		1	2

Usefulness for Clinical Practice (Research Question 3)

Separate Evaluation of the Networks

Figure 3 presents the evaluation of the three different networks based on numeric mean comparisons. Overall, evaluations were high for all three networks and did not differ much between patients and therapists. Patients rated the posterior network as most useful, in particular regarding the presentation of relationships between symptoms and showing potential for change. Therapists also preferred the posterior network over the prior and data network, in particular regarding the presentation of the relationships between symptoms and showing potential to change. Patients rated all networks comparably suitable to enhance their understanding of the problem, while prior and data network were rated best to enhance the understanding of the therapist. From the patient's perspective, the data network was

Table 4
Exploratory Analysis of Agreement and Disagreement of Network Properties Among the Three Networks

Patient	Spearman correlation symptom severity and EMA means	Number of edges that were indicated as present in prior and data networks	Edges that were indicated as present in prior and data networks relative to edges that were indicated in either of the two networks	Spearman correlation of OutDegree centrality between prior and data network
1	$r = .551$ [−.120, .877]	1	0.067	$r = .598$ [−.051, .892]
2	$r = -.182$ [−.728, .506]	0	0	$r = -.187$ [−.731, .502]
3	$r = .075$ [−.582, .673]	0	0	$r = -.228$ [−.750, .469]
4	$r = .866$ [NA, NA]	1	0.5	NA
5	$r = .256$ [−.445, .763]	0	0	$r = -.588$ [−.889, .066]
6	$r = .10$ [−.858, .903]	1	0.125	$r = .344$ [−.773, .941]
7	$r = .487$ [−.537, .931]	0	0	NA
8	$r = .543$ [−.480, .940]	2	0.125	$r = -.739$ [−.969, .181]
9	$r = -.068$ [−.700, .624]	0	0	$r = -.835$ [−.964, −.384]
10	$r = -.406$ [−.916, .605]	2	0.25	$r = 1$ [1, 1]
11	$r = .538$ [−.139, .872]	3	0.176	$r = .530$ [−.150, .896]
12	$r = -.758$ [−.939, .246]	1	0.048	$r = .225$ [−.471, .749]
M (*SD*)		0.917 (0.996)	0.108 (0.149)	

Note. EMA = Ecological Momentary Assessment; NA = not available.

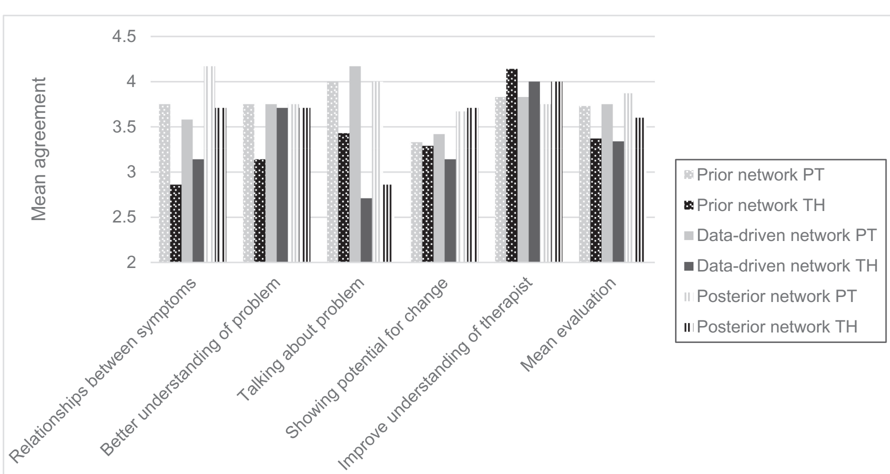
best suited to elicit a conversation about the problems. In contrast, therapists rated the data-driven and posterior network as most suitable to enhance the patient's understanding of the problem and PECAN as most suited to enhance their own understanding and to elicit a conversation about the problem. The mean evaluation indicates that patients generally rated the networks slightly better than therapists.

Overall Evaluation of the Network

Patients and therapists rated the overall usefulness of the networks for clinical practice high (patients, $M = 3.92$, $SD = 0.87$; therapists, $M = 3.70$, $SD = 0.93$). Comprehensibility of the networks was also evaluated as high (patients, $M = 3.57$, $SD = 0.92$; therapists, $M = 4.00$, $SD = 1.05$). The visualization scale of the modular evaluation of key Components of User Experience was rated high ($M = 3.75$, $SD = 0.49$) by patients and therapists ($M = 4.06$, $SD = 0.66$). On the User Experience Questionnaire, the pragmatic qualities of the visualization were rated better than average ($M = 0.88$, $SD = 0.76$) by patients and high by therapists ($M = 1.32$, $SD = 0.64$). Hedonic qualities of the visualization were also rated better than average ($M = 0.60$, $SD = 0.54$) by patients and low by therapists ($M = -1.68$, $SD = 0.64$; see Supplemental Material B, Table B1 in the online supplemental materials for further details).

The findings of the semistructured interviews suggest that patients experienced improved self-awareness (14 statements). However, some patients also reported experiencing additional burden (16 statements) next to other positive side effects (six statements) such as

Figure 3
Evaluation of the Three Networks in Comparison by Patients and Therapists



Note. PT = evaluation by patients; TH = evaluation by therapists.

"a structure during daily life," "motivation to be open and honest about problems," or "giving hope." Therapists indicated that participating in the study helped their patient to understand how their symptoms interact with each other (five statements), to structure their problems (two statements), to formulate their problems (two statements), to gain emotional access to their problems (one statement), and to receive attention and recognition prior to starting psychotherapy (one statement). Therapists reported that they had new insights into stressors of everyday life (two statements), new information for the therapy (three statements), differences between objectively measured correlations of the complaints and the subjective assessment of the patients (one statement), suggestions for the case concept (one statement), collaborative reflection of the case concept (two statements), and identification of central perpetuating factors (one statement).

Summary of the Semistructured Interviews

Summaries of the semistructured interviews are included in the respective sections above. The summary of the responses regarding expectations on applications of the methods, concerns, planning of psychotherapy and overall study evaluation is presented in Supplemental Material C in the online supplemental materials.

Discussion

Clinical information should be taken into account when formalizing idiographic statistical models (Burger, Ralph-Nearman, & Levinson, 2022). This is the first study to integrate and evaluate the clinical utility of different person-specific networks in a sample of 12 patients and their therapists. The PECAN method was used to construct a PECAN of the patient as a prior network (Klintwall et al., 2023). EMA was used for real-life observations and data network estimation (Epskamp et al., 2018). Bayesian inference was used to update the prior to a posterior network that integrates patient perceptions with longitudinal data. We demonstrated that two existing tools for creating personalized networks can be combined, resulting in networks with higher (face) validity.

Both assessment procedures were evaluated as feasible and acceptable. While PECAN was rated as less overwhelming, less stressful, less time-consuming, and easier to fill out. EMA was indicated to be better suited while waiting for therapy as it has a clear purpose and it is a good preparation for therapy. These results suggest that PECAN is an easy-to-use method to assess patients at an initial evaluation, whereas EMA could be used while waiting for therapy to start.

As expected, the posterior network most closely resonated with the subjective understandings of both patients and therapists regarding the patient's problem. While the statistical Bayesian update resulted in the posterior network, the patients might have updated their initial beliefs throughout the EMA phase that inquired them to monitor their symptoms' interactions continuously. In another study, repeated PECAN assessments resulted in a change of the networks in the majority of participants (Burger et al., 2024). This is in line with the assumption and finding that variation over time needs to be considered in network analysis (Haslbeck, Bringmann, & Waldorp, 2021; Scholten, Rubel, et al., 2024). However, the result could also be influenced by the order in which the two procedures were conducted. If the patient had completed the EMA first and was then asked to perform the PECAN, that PECAN would already reflect updates in the patient's beliefs, resulting in fewer differences between the PECAN and the updated network. With that hypothetical setup, patients would perhaps prefer the PECAN over the updated network, as it aligns more closely with their own updates rather than relying on the "old information" from the beginning of the EMA. Exploring potential updating processes aligns with current thinking in theoretical neuroscience where the idea of the Bayesian brain has inspired the conception of belief updating as a form of coding prior predictions with new information to compute an updated prediction (Friston, 2010; Friston et al., 2014). More specifically, researchers suggested that people use their prior experiences to build prior beliefs what they are about to experience. These predictions are hence combined with evidence, which can come from various sources. In recent years, this way of thinking has also advanced an understanding of mental disorders as well as relevant processes in psychotherapy research (Gibbs-Dean et al., 2023; Herzog et al., 2023; Kube & Rozenkrantz, 2021). Thus, to move idiographic research of psychopathology from network analysis toward more rigorous hypothesis testing approaches (Borsboom et al., 2021; Bringmann, Elmer, & Eronen, 2022), it might be valuable to apply more systematically the principles of Bayesian belief updating as initiated in this current work. Investigating potential order effects might be one way to address these questions.

A related question is what are the insights relevant for patients and therapists that are sparked by the different networks and in what way are they useful. Van den Bergh and Walentynowicz (2016) reflected upon the two types of information in the context of bias. They argue that the information might serve different "functional selves" (p. 303): The results from retrospective assessments as in the PECAN method might represent information as it has been encoded and consolidated in autobiographic episodic memory ("remembering self"), whereas momentary assessments reveal information as it is experienced in a "here-and-now" context ("experiencing self"). Information from the EMA with retrospective assessments of the time period since the last beep can be considered somewhere between an "experiencing self" and a "remembering self," depending on the length of the time period. Further research into the functionality of the types of information in the different networks for psychotherapy would help to identify the full potential of different networks. Qualitative research approaches are needed to shed light on these questions (De Smet et al., 2020; McLeod et al., 2021).

The practical usefulness of the derived networks in clinical settings was generally given as patients and therapists indicated that the networks depict relationships between symptoms, enhance the understanding of the problem, and serve as a starting point to talk about problems. In the semistructured interviews, therapists also reported to have gained new insights that they wanted to use for goal setting and case conceptualization. These are interactional process uses, including supporting exploration, facilitating communication, and readjusting the treatment focus, as identified in a recent meta-analysis by Låver et al. (2024). It looked at how therapists and patients use patient-generated data. In contrast, patients underlined the intrapersonal use as they primarily profited from an increase in self-awareness, motivation, and hope for psychotherapy which was also recognized by therapists who stated that patients were better prepared for psychotherapy.

Networks were rated least useful to identify the potential for change. This finding corresponds to the critique raised regarding the clinical implications that are related to centrality indices (Bringmann et al., 2019). In line with our expectations and other findings, therapists rated overall usability lower than patients (Frumkin et al., 2021). In contrast to the patients, therapists did not go through the process of constructing PECAN and conducting EMA, which might be a large part of what patients experience as helpful. Although not based on a systematic comparison, anecdotal evidence suggests that therapists rate the clinical utility of networks highly when they are involved in their creation. Stare et al. (2023) reported on a small pilot study involving three therapists who independently completed the PECAN procedure. They were then shown networks that aggregated their own ratings with those of their adolescent patient and the patient's parent. In this small study, the therapists expressed enthusiasm about the clinical utility of the networks. Collaborative PECAN construction with patients and their therapists might be a promising path forward to enhance utility that should be considered in future research.

Strengths and Limitations

It is a strength of the study that we were able to include seven dyads of patients and therapists and five patients without matching therapists. Also, the mix of quantitative and qualitative methods gives an in-depth insight into the evaluation of the procedure and results. However, the study also has limitations.

Even though we followed recommendations (Mansueto et al., 2023), EMA was probably underpowered, resulting in some networks without edges. Sensitivity is low, and edges might have remained undetected. A lack of appropriate power also results in unstable networks that should not yet be used in clinical practice. More intensive longitudinal data would be needed that is oftentimes not feasible to assess in clinical practice constraining the potential of the network approach for clinical practice. Also, the small number of participants does not allow for a generalization of the results and makes further studies with larger samples necessary.

One of the benefits of the PECAN method is that edges can be captured regardless of the time scale. However, in this project, we asked specifically about a time scale that matches the EMA beeps (3 hr). While we deemed it necessary to align the time scales of the two methods, this meant that we did not make full use of the advantages of PECAN. In contrast, the two methods differ in several important aspects. While EMA networks represent lag-1 relationships, the PECAN procedure explicitly requires causality. Answering causal questions, however, may have been challenging for patients. Future studies should consider using more intuitive causal question phrasings when assessing edges, such as focusing on frequency, levels of certainty, or counterfactuals (Vogel et al., 2024). Alternatively, conducting the PECAN procedure in an interview format rather than a questionnaire could be beneficial. Additionally, the PECAN procedure restricted respondents to selecting three ingoing edges for each node and distributing a total of 100% across these edges. This design choice stems from the original PECAN procedure (Klintwall et al., 2023), where it was implemented to simplify visual analysis in clinical settings by avoiding overly dense networks for certain patients. However, estimated networks do not share this limitation. Exploratory analyses clearly showed that network properties varied highly across persons. The highest number of edges that were present in both networks was 50%. Seven patients had almost no overlapping edges in the prior and data networks, indicating that the networks were more different than similar. The finding is consistent with prior findings comparing prior and posterior networks (Burger, Ralph-Nearman, & Levinson, 2022). The methodological deviations may in part explain the resulting differences between the two networks. Based on the provided data, we are ultimately not able to determine which type of network is closest to representing the true underlying dynamics.

Patients and therapists were not blinded to what network was presented. While we randomized the order of the presented networks, they were all labeled "prior network," "data network," or "posterior network." Thus, at least the patient's evaluation probably takes into account the construction process of the networks and not only the information that is visualized as discussed above.

Future Research and Clinical Implications

To address the persistent heterogeneity in psychopathology and treatment outcomes, psychotherapy research must prioritize the development of systematic, personalized approaches that expand current models of psychopathology. They should capture these person-specific, dynamic systems at appropriate time scales with idiographic statistical methods. Our approach allows us to collaboratively formulate a case concept of idiographic psychopathology as a PECAN. It can be used to derive testable hypotheses regarding variables of personal relevance, their contingent relationships, and their time scale (e.g., "When I feel down, I am less active the subsequent day" or "When I manage to be active, I feel content immediately after the activity"). Burger, Ralph-Nearman, and Levinson (2022) further highlight that the strength of the approach lies in identifying focus points for further exploration through thought and behavioral experiments, particularly when prior and posterior networks diverge. Such discrepancies may serve as a flagging system, guiding discussions and informing targeted assessments in subsequent data collection. For example, if the prior network shows a connection between screen time and fatigue, but the posterior network does not, the client and clinician could design brief behavioral experiments, such as comparing the effects of gaming versus outside activities, to better understand and evaluate this relationship. Single-case experimental designs could be used as an empirical method to evaluate the experimental manipulation (Krasny-Pacini & Evans, 2018; Vlaeyen et al., 2022). In order to increase the relevance for clinical practice even more, assessing context should be considered in designing EMA studies that test hypotheses or are used to monitor experiments (Von Klipstein et al., 2024). Thus, hypotheses derived from idiographic models of psychopathology can be assessed, tested, and reintegrated into the initial model resulting in a systematic empirical cycle implemented in clinical practice (Borsboom et al., 2021; Bringmann, Albers, et al., 2022). It is a step away from data-driven and exploratory techniques toward confirmation and falsification approaches (Fried, 2020; Haslbeck, Ryan, et al., 2021; Schemer et al., 2023).

Conclusion

Combining patients' perceptions of causal relations with intensive longitudinal data yields a promising data-driven strategy to complement current case conceptualization. The posterior network that integrated patient priors and momentary assessment data was deemed to be the best reflection of the case concept and most useful by both patients and therapists. Future studies might explore whether incorporating therapist priors into the case conceptualization improves the resulting network further. Above that, the method should be refined into a more rigorous theoretical-empirical cycle that formulates, tests, and updates idiographic models of psychopathology.

References

American Psychiatric Association. (2018). *Diagnostisches und Statistisches Manual Psychischer Störungen DSM-5®* [Diagnostic and Statistical Manual of Mental Disorders (DSM-5)] (P. Falkai, H.-U. Wittchen, M. Döpfner, W. Gaebel, W. Maier, W. Rief, H. Saß, & M. Zaudig, Hrsg.; 2. Aufl.). Hogrefe. https://doi.org/10.1026/02803-000

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

Bångstad, A., Fellman, J., Rosendahl, C., Bellander, M., Cervin, M., Bjureberg, J., & Klintwall, L. (2022). Perceived causal symptom network of adolescent mental health issues. *Journal of Child & Adolescent Mental Health*, *34*(1-3), 101–114. https://doi.org/10.2989/17280583.2023.2283032

Booij, S. H., Wichers, M., de Jonge, P., Sytema, S., van Os, J., Wunderink, L., & Wigman, J. T. W. (2018). Study protocol for a prospective cohort study examining the predictive potential of dynamic symptom networks for the onset and progression of psychosis: The Mapping Individual Routes of Risk and Resilience (Mirorr) study. *BMJ Open*, *8*(1), Article e019059. https://doi.org/10.1136/bmjopen-2017-019059

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

Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, *9*(1), 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Borsboom, D., van der Maas, H. L. J., Dalege, J., Kievit, R. A., & Haig, B. D. (2021). Theory construction methodology: A practical framework for building theories in psychology. *Perspectives on Psychological Science*, *16*(4), 756–766. https://doi.org/10.1177/1745691620969647

Bringmann, L. F. (2021). Person-specific networks in psychopathology: Past, present and future. *Current Opinion in Psychology*, *41*, 59–64. https://doi.org/10.1016/j.copsyc.2021.03.004

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

Bringmann, L. F., Elmer, T., & Eronen, M. I. (2022). Back to basics: The importance of conceptual clarification in psychological science. *Current Directions in Psychological Science*, *31*(4), 340–346. https://doi.org/10.1177/09637214221096485

Bringmann, L. F., & Eronen, M. I. (2018). Don't blame the model: Reconsidering the network approach to psychopathology. *Psychological Review*, *125*(4), 606–615. https://doi.org/10.1037/rev0000108

Brooke, J. (1996). Chapter 21 - SUS: A quick and dirty usability scale. In P. W. Jordan (Ed.), *Usability evaluation in industry* (pp. 189–194). Taylor & Francis.

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., Hoekstra, R. H., Mansueto, A. C., & Epskamp, S. (2022). Network estimation from time series and panel data. In A.-M. Isvoranu, S. Epskamp, L. Waldorp, & D. Borsboom (Hrsg.), *Network psychometrics with R* (pp. 169–192). Routledge.

Burger, J., Ralph-Nearman, C., & Levinson, C. A. (2022). Integrating clinician and patient case conceptualization with momentary assessment data to construct idiographic networks: Moving toward personalized treatment for eating disorders. *Behaviour Research and Therapy*, *159*, Article 104221. https://doi.org/10.1016/j.brat.2022.104221

Cohen, Z. D., Delgadillo, J., & DeRubeis, R. J. (2021). Personalized treatment approaches. In M. Barkham (Hrsg.), *Bergin and Garfield's handbook of psychotherapy and behavior change* (pp. 673–703). John Wiley & Sons.

Colombo, D., Fernández-Álvarez, J., Patané, A., Semonella, M., Kwiatkowska, M., García-Palacios, A., & Cipresso, P. (2019). Current state and future directions of technology-based ecological momentary assessment and intervention for major depressive disorder: A systematic review. *Journal of Clinical Medicine*, *8*(4), Article 465. https://doi.org/10.3390/jcm8040465

Cuijpers, P., Karyotaki, E., de Wit, L., & Ebert, D. D. (2020). The effects of fifteen evidence-supported therapies for adult depression: A meta-analytic review. *Psychotherapy Research*, *30*(3), 279–293. https://doi.org/10.1080/10503307.2019.1649732

Cuijpers, P., Miguel, C., Ciharova, M., Harrer, M., Basic, D., Cristea, I. A., de Ponti, N., Driessen, E., Hamblen, J., Larsen, S. E., Matbouriahi, M., Papola, D., Pauley, D., Plessen, C. Y., Pfund, R. A., Setkowski, K., Schnurr, P. P., van Ballegooijen, W., Wang, Y., … Karyotaki, E. (2024). Absolute and relative outcomes of psychotherapies for eight mental disorders: A systematic review and meta-analysis. *World Psychiatry*, *23*(2), 267–275. https://doi.org/10.1002/wps.21203

Dablander, F., & Hinne, M. (2019). Node centrality measures are a poor substitute for causal inference. *Scientific Reports*, *9*(1), Article 6846. https://doi.org/10.1038/s41598-019-43033-9

Deisenhofer, A.-K., Barkham, M., Beierl, E. T., Schwartz, B., Aafjes-van Doorn, K., Beevers, C. G., Berwian, I. M., Blackwell, S. E., Bockting, C. L., Brakemeier, E.-L., Brown, G., Buckman, J. E. J., Castonguay, L. G., Cusack, C. E., Dalgleish, T., De Jong, K., Delgadillo, J., DeRubeis, R. J., Driessen, E., … Cohen, Z. D. (2024). Implementing precision methods in personalizing psychological therapies: Barriers and possible ways forward. *Behaviour Research and Therapy*, *172*, Article 104443. https://doi.org/10.1016/j.brat.2023.104443

De Smet, M. M., Meganck, R., De Geest, R., Norman, U. A., Truijens, F., & Desmet, M. (2020). What "good outcome" means to patients: Understanding recovery and improvement in psychotherapy for major depression from a mixed-methods perspective. *Journal of Counseling Psychology*, *67*(1), 25–39. https://doi.org/10.1037/cou0000362

Easden, M. H., & Kazantzis, N. (2018). Case conceptualization research in cognitive behavior therapy: A state of the science review. *Journal of Clinical Psychology*, *74*(3), 356–384. https://doi.org/10.1002/jclp.22516

Epskamp, S. (2020). Psychometric network models from time-series and panel data. *Psychometrika*, *85*(1), 206–231. https://doi.org/10.1007/s11336-020-09697-3

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). Qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*(4), 1–18. https://doi.org/10.18637/jss.v048.i04

Epskamp, S., van Borkulo, C. D., van der Veen, D. C., Servaas, M. N., Isvoranu, A.-M., Riese, H., & Cramer, A. O. J. (2018). Personalized network modeling in psychopathology: The importance of contemporaneous and temporal connections. *Clinical Psychological Science*, *6*(3), 416–427. https://doi.org/10.1177/2167702617744325

Fisher, A. J., & Boswell, J. F. (2016). Enhancing the personalization of psychotherapy with dynamic assessment and modeling. *Assessment*, *23*(4), 496–506. https://doi.org/10.1177/1073191116638735

Fisher, A. J., Reeves, J. W., Lawyer, G., Medaglia, J. D., & Rubel, J. A. (2017). Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of Abnormal Psychology*, *126*(8), 1044–1056. https://doi.org/10.1037/abn0000311

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

Fried, E. I. (2020). Lack of theory building and testing impedes progress in the factor and network literature. *Psychological Inquiry*, *31*(4), 271–288. https://doi.org/10.1080/1047840X.2020.1853461

Friston, K. J. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, *11*(2), 127–138. https://doi.org/10.1038/nrn2787

Friston, K. J., Stephan, K. E., Montague, R., & Dolan, R. J. (2014). Computational psychiatry: The brain as a phantastic organ. *The Lancet Psychiatry*, *1*(2), 148–158. https://doi.org/10.1016/S2215-0366(14)70275-5

Frumkin, M. R., Piccirillo, M. L., Beck, E. D., Grossman, J. T., & Rodebaugh, T. L. (2021). Feasibility and utility of idiographic models in the clinic: A pilot study. *Psychotherapy Research*, *31*(4), 520–534. https://doi.org/10.1080/10503307.2020.1805133

Ghaemi, S. N., & Rosenquist, K. J. (2004). Is insight in mania state-dependent?: A meta-analysis. *Journal of Nervous & Mental Disease*, *192*(11), 771–775. https://doi.org/10.1097/01.nmd.0000145036.76435.c3

Gibbs-Dean, T., Katthagen, T., Tsenkova, I., Ali, R., Liang, X., Spencer, T., & Diederen, K. (2023). Belief updating in psychosis, depression and anxiety disorders: A systematic review across computational modelling approaches. *Neuroscience & Biobehavioral Reviews*, *147*, Article 105087. https://doi.org/10.1016/j.neubiorev.2023.105087

Gloster, A. T., Meyer, A. H., Witthauer, C., Lieb, R., & Mata, J. (2017). 'I feel better when…': An analysis of the memory-experience gap for peoples' estimates of the relationship between health behaviours and experiences. *Psychology & Health*, *32*(9), 1152–1166. https://doi.org/10.1080/08870446.2017.1327586

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424–438. https://doi.org/10.2307/1912791

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Hall, M., Lappenbusch, L. M., Wiegmann, E., & Rubel, J. (2023). *To use or not to use: Exploring therapists' experiences with pre-treatment EMA-based personalized feedback in the TheraNet project*. PsyArXiv. https://doi.org/10.31234/osf.io/xjb8m

Haslbeck, J. M. B., Bringmann, L. F., & Waldorp, L. J. (2021). A tutorial on estimating time-varying vector autoregressive models. *Multivariate Behavioral Research*, *56*(1), 120–149. https://doi.org/10.1080/00273171.2020.1743630

Haslbeck, J. M. B., Ryan, O., Robinaugh, D. J., Waldorp, L. J., & Borsboom, D. (2021). Modeling psychopathology: From data models to formal theories. *Psychological Methods*, *27*(6), 930–957. https://doi.org/10.1037/met0000303

Herzog, P., & Kaiser, T. (2022). Is it worth it to personalize the treatment of PTSD?—A variance-ratio meta-analysis and estimation of treatment effect heterogeneity in RCTs of PTSD. *Journal of Anxiety Disorders*, *91*, Article 102611. https://doi.org/10.1016/j.janxdis.2022.102611

Herzog, P., Kube, T., & Rubel, J. (2023). Why some psychotherapists benefit from feedback on treatment progress more than others: A belief updating perspective. *Clinical Psychology: Science and Practice*, *30*(4), 468–479. https://doi.org/10.1037/cps0000174

Hofmann, S. G., Asnaani, A., Vonk, I. J. J., Sawyer, A. T., & Fang, A. (2012). The efficacy of cognitive behavioral therapy: A review of meta-analyses. *Cognitive Therapy and Research*, *36*(5), 427–440. https://doi.org/10.1007/s10608-012-9476-1

Kaiser, T., & Herzog, P. (2023). Is personalized treatment selection a promising avenue in bpd research? A meta-regression estimating treatment effect heterogeneity in RCTs of BPD. *Journal of Consulting and Clinical Psychology*, *91*(3), 165–170. https://doi.org/10.1037/ccp0000803

Kaiser, T., Volkmann, C., Volkmann, A., Karyotaki, E., Cuijpers, P., & Brakemeier, E.-L. (2022). Heterogeneity of treatment effects in trials on psychotherapy of depression. *Clinical Psychology: Science and Practice*, *29*(3), 294–303. https://doi.org/10.1037/cps0000079

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

Krasny-Pacini, A., & Evans, J. (2018). Single-case experimental designs to assess intervention effectiveness in rehabilitation: A practical guide. *Annals of Physical and Rehabilitation Medicine*, *61*(3), 164–179. https://doi.org/10.1016/j.rehab.2017.12.002

Kube, T., & Rozenkrantz, L. (2021). When beliefs face reality: An integrative review of belief updating in mental health and illness. *Perspectives on Psychological Science*, *16*(2), 247–274. https://doi.org/10.1177/1745691620931496

Låver, J., McAleavey, A., Valaker, I., Castonguay, L. G., & Moltu, C. (2024). Therapists' and patients' experiences of using patients' self-reported data in ongoing psychotherapy processes—A systematic review and meta-analysis of qualitative studies. *Psychotherapy Research*, *34*(3), 293–310. https://doi.org/10.1080/10503307.2023.2222896

Levinson, C. A., Christian, C., & Becker, C. B. (2025). How idiographic methodologies can move the clinical-science field forward to integrate personalized treatment into everyday clinical care and improve treatment outcomes. *Clinical Psychological Science*, *13*(1), 69–82. https://doi.org/10.1177/21677026231217316

Levinson, C. A., Williams, B. M., Christian, C., Hunt, R. A., Keshishian, A. C., Brosof, L. C., Vanzhula, I. A., Davis, G. G., Brown, M. L., Bridges-Curry, Z., Sandoval-Araujo, L. E., & Ralph-Nearman, C. (2023). Personalizing eating disorder treatment using idiographic models: An open series trial. *Journal of Consulting and Clinical Psychology*, *91*(1), 14–28. https://doi.org/10.1037/ccp0000785

Mansueto, A. C., Wiers, R. W., van Weert, J. C. M., Schouten, B. C., & Epskamp, S. (2023). Investigating the feasibility of idiographic network models. *Psychological Methods*, *28*(5), 1052–1068. https://doi.org/10.1037/met0000466

McLeod, J., Stiles, W. B., & Levitt, H. M. (2021). Qualitative research: Contributions to psychotherapy practice, theory, and policy. In M. Barkham, W. Lutz, L. G. Castonguay, A. E. Bergin, & S. L. Garfield (Hrsg.), *Bergin and Garfield's handbook of psychotherapy and behavior change* (7th ed., 50th anniversary edition, pp. 351–419). Wiley.

Medalia, A., & Thysen, J. (2008). Insight into neurocognitive dysfunction in schizophrenia. *Schizophrenia Bulletin*, *34*(6), 1221–1230. https://doi.org/10.1093/schbul/sbm144

Minge, M., & Thüring, M. (2018, July 15–20). *The MeCUE Questionnaire (2.0): Meeting Five Basic Requirements for Lean and Standardized UX Assessment*. Proceedings, Part I: Design, User Experience, and Usability: Theory and Practice: 7th International Conference, DUXU 2018, Held as Part of HCI International 2018, Las Vegas, NV, USA.

Minge, M., Thüring, M., Wagner, I., & Kuhr, C. V. (2017). The meCUE Questionnaire: A modular tool for measuring user experience.

In M. Soares, C. Falcão, & T. Z. Ahram (Hrsg.), *Advances in ergonomics modeling, usability & special populations* (Bd. 486, pp. 115–128). Springer International Publishing. https://doi.org/10.1007/978-3-319-41685-4_11

Miskovic-Wheatley, J., Bryant, E., Ong, S. H., Vatter, S., Le, A., Aouad, P., Barakat, S., Boakes, R., Brennan, L., Bryant, E., Byrne, S., Caldwell, B., Calvert, S., Carroll, B., Castle, D., Caterson, I., Chelius, B., Chiem, L., … Maguire, S. (2023). Eating disorder outcomes: Findings from a rapid review of over a decade of research. *Journal of Eating Disorders*, *11*(1), Article 85. https://doi.org/10.1186/s40337-023-00801-3

Molenaar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement: Interdisciplinary Research & Perspective*, *2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Myin-Germeys, I., & Kuppens, P. (Eds.). (2021). *The open handbook of experience sampling methodology: A step-by-step guide to designing, conducting, and analyzing ESM studies* (2nd ed.). Center for Research on Experience Sampling and Ambulatory Methods Leuven.

Newby, J. M., McKinnon, A., Kuyken, W., Gilbody, S., & Dalgleish, T. (2015). Systematic review and meta-analysis of transdiagnostic psychological treatments for anxiety and depressive disorders in adulthood. *Clinical Psychology Review*, *40*, 91–110. https://doi.org/10.1016/j.cpr.2015.06.002

O'Brien, S. T., Hinton, J. D. X., Moeck, E., Susanto, R., Jayaputera, G., Sinnott, R. O., Vu, D., Alvarez-Jimenez, M., Gleeson, J., & Koval, P. (2024). *SEMA3: A free smartphone platform for daily life surveys*. https://osf.io/4h8xd

O'Hagan, A. (2019). Expert knowledge elicitation: Subjective but scientific. *The American Statistician*, *73*(sup1), 69–81. https://doi.org/10.1080/00031305.2018.1518265

O'Reilly, J. X., Jbabdi, S., & Behrens, T. E. J. (2012). How can a Bayesian approach inform neuroscience? *European Journal of Neuroscience*, *35*(7), 1169–1179. https://doi.org/10.1111/j.1460-9568.2012.08010.x

Peralta, V., & Cuesta, M. J. (1998). Lack of insight in mood disorders. *Journal of Affective Disorders*, *49*(1), 55–58. https://doi.org/10.1016/S0165-0327(97)00198-5

Persons, J. B. (2006). Case formulation-driven psychotherapy. *Clinical Psychology: Science and Practice*, *13*(2), 167–170. https://doi.org/10.1111/j.1468-2850.2006.00019.x

R Core Team. (2022). *R: A language and environment for statistical computing* [Computer software]. https://www.R-project.org/

Roefs, A., Fried, E. I., Kindt, M., Martijn, C., Elzinga, B., Evers, A. W. M., Wiers, R. W., Borsboom, D., & Jansen, A. (2022). A new science of mental disorders: Using personalised, transdiagnostic, dynamical systems to understand, model, diagnose and treat psychopathology. *Behaviour Research and Therapy*, *153*, Article 104096. https://doi.org/10.1016/j.brat.2022.104096

Sauro, J., & Lewis, J. R. (2011). *When designing usability questionnaires, does it hurt to be positive?* Proceedings of the 2011 Annual Conference on Human Factors in Computing Systems—CHI '11 (p. 2215). ACM Press. https://doi.org/10.1145/1978942.1979266

Schemer, L., Glombiewski, J. A., & Scholten, S. (2023). All good things come in threes: A systematic review and Delphi study on the advances and challenges of ambulatory assessments, network analyses, and single-case experimental designs. *Clinical Psychology: Science and Practice*, *30*(1), 95–107. https://doi.org/10.1037/cps0000083

Scholten, S., Herzog, P., Glombiewski, J. A., & Kaiser, T. (2025). Is personalization of psychological pain treatments necessary? Evidence from a Bayesian variance ratio meta-analysis. *Pain*, *166*(2), 420–427. https://doi.org/10.1097/j.pain.0000000000003363

Scholten, S., Klintwall, L., Glombiewski, J. A., & Burger, J. (2024). *Integrating patient perceptions and intensive longitudinal data for enhanced case conceptualizations with networks: An approach with Bayesian informative priors (Material, Data, and Code)* [Data set]. https://osf.io/r5xfg/

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

Scholten, S., Rubel, J. A., Glombiewski, J. A., & Milde, C. (2024). What time-varying network models based on functional analysis tell us about the course of a patient's problem. *Psychotherapy Research*. Advance online publication. https://doi.org/10.1080/10503307.2024.2328304

Schrepp, M., Hinderks, A., & Thomaschewski, J. (2017). Design and Evaluation of a Short Version of the User Experience Questionnaire (UEQ-S). *International Journal of Interactive Multimedia and Artificial Intelligence*, *4*(6), Article 103. https://doi.org/10.9781/ijimai.2017.09.001

Shojaie, A., & Fox, E. B. (2021). *Granger causality: A review and recent advances*. arXiv. https://arxiv.org/abs/2105.02675

SoSci Survey GmbH. (2020). *SoSci Survey*. https://www.soscisurvey.de/de/index

Stan Development Team. (2020). *RStan: The R interface to Stan* (R package Version 2.17.3) [Computer software]. https://mc-stan.org/

Stare, E., Larsson, A., & Klintwall, L. (2023). *Symptom networks of adolescent problems: Inter-rater reliability between adolescent, parent, and therapist, and the clinical utility of the networks*. Clinical master Project, Mittuniversitetet.

Tanious, R., Manolov, R., Onghena, P., & Vlaeyen, J. W. S. (2024). Single-case experimental designs: The importance of randomization and replication. *Nature Reviews Methods Primers*, *4*(1), Article 27. https://doi.org/10.1038/s43586-024-00312-8

Turner-Bowker, D. M., Lamoureux, R. E., Stokes, J., Litcher-Kelly, L., Galipeau, N., Yaworsky, A., Solomon, J., & Shields, A. L. (2018). Informing a priori sample size estimation in qualitative concept elicitation interview studies for clinical outcome assessment instrument development. *Value in Health*, *21*(7), 839–842. https://doi.org/10.1016/j.jval.2017.11.014

Van den Bergh, O., & Walentynowicz, M. (2016). Accuracy and bias in retrospective symptom reporting. *Current Opinion in Psychiatry*, *29*(5), 302–308. https://doi.org/10.1097/YCO.0000000000000267

Vlaeyen, J. W. S., & Crombez, G. (2020). Behavioral conceptualization and treatment of chronic pain. *Annual Review of Clinical Psychology*, *16*(1), 187–212. https://doi.org/10.1146/annurev-clinpsy-050718-095744

Vlaeyen, J. W. S., Onghena, P., Vannest, K. J., & Kratochwill, T. R. (2022). 3.01—Single-case experimental designs: Clinical research and practice. In G. J. G. Asmundson (Hrsg.), *Comprehensive clinical psychology* (2nd ed., pp. 1–28). Elsevier. https://doi.org/10.1016/B978-0-12-818697-8.00191-6

Vogel, F., Blanken, T., Burger, J., Reichert, J., Scholten, S., & Klintwall, L. (2024). *How Perceived Causal Networks (PECAN) can complement case conceptualization, diagnostic classification and data-based networks: An introduction to a method for constructing personalized networks*. OSF. https://doi.org/10.31234/osf.io/7wfte

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

Von Klipstein, L., Stadel, M., Bos, F. M., Bringmann, L. F., Riese, H., & Servaas, M. N. (2024). *Opening the contextual black box: A case for idiographic experience sampling of context for clinical applications* (Preprint). https://doi.org/10.2196/preprints.58115

Wickham, H., Chang, W., Henry, L., Pedersen, T. L., Takahashi, K., Wilke, C., Woo, K., Yutani, H., Dunnington, D., & RStudio. (2022). *ggplot2: Create elegant data visualisations using the grammar of graphics* (Version 3.3.6) [Computer software]. https://CRAN.R-project.org/package=ggplot2

Wild, B., Eichler, M., Friederich, H.-C., Hartmann, M., Zipfel, S., & Herzog, W. (2010). A graphical vector autoregressive modelling approach to the analysis of electronic diary data. *BMC Medical Research Methodology*, *10*(1), Article 28. https://doi.org/10.1186/1471-2288-10-28

Wright, A. G. C., Gates, K. M., Arizmendi, C., Lane, S. T., Woods, W. C., & Edershile, E. A. (2019). Focusing personality assessment on the person: Modeling general, shared, and person specific processes in personality and psychopathology. *Psychological Assessment*, *31*(4), 502–515. https://doi.org/10.1037/pas0000617

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

Wright, A. G. C., & Woods, A. C. (2020). Personalized models of psychopathology. In T. Widiger & T. D. Cannon (Hrsg.), *Annual review of clinical psychology* (Bd. 16, pp. 49–74). Annual Reviews. https://doi.org/10.1146/annurev-clinpsy-102419-125032

Received September 2, 2024
Revision received January 27, 2025
Accepted February 6, 2025 ■