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Integrating clinician and patient case conceptualization with momentary assessment data to construct idiographic networks: Moving toward personalized treatment for eating disorders

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ABSTRACT

Eating disorders are serious psychiatric illnesses with treatments ineffective for about 50% of individuals due to high heterogeneity of symptom presentation even within the same diagnoses, a lack of personalized treatments to address this heterogeneity, and the fact that clinicians are left to rely upon their own judgment to decide how to personalize treatment. Idiographic (personalized) networks can be estimated from ecological momentary assessment data, and have been used to investigate central symptoms, which are theorized to be fruitful treatment targets. However, both efficacy of treatment target selection and implementation with 'real world' clinicians could be maximized if clinician input is integrated into such networks. An emerging line of research is therefore proposing to integrate case conceptualizations and statistical routines, tying together the benefits from clinical expertise as well as patient experience and idiographic networks. The current pilot compares personalized treatment implications from different approaches to constructing idiographic networks. For two patients with a diagnosis of anorexia nervosa, we compared idiographic networks 1) based on the case conceptualization from clinician and patient, 2) estimated from patient EMA data (the current default in the literature), and 3) based on a combination of case conceptualization and patient EMA data networks, drawing on informative priors in Bayesian inference. Centrality-based treatment recommendations differed to varying extent between these approaches for patients. We discuss implications from these findings, as well as how these models may inform clinical practice by pairing evidence-based treatments with identified treatment targets.

1. Introduction

Eating disorders are severe and chronic psychiatric illnesses, associated with high morbidity, mortality, and societal and personal impairment (e.g., Deloitte Access Economics, 2020, p. 92). Eating disorders carry one of the highest mortality rates amongst psychiatric illnesses. Anorexia nervosa (AN), in particular, has the second highest mortality rate of any psychiatric illness and is estimated to cost the US alone in one year 64.7 billion dollars in economic costs and 326.5 billion in loss of well-being (Deloitte Access Economics, 2020, p. 92). Treatments for eating disorders are subpar, with gold-standard treatments (Cognitive-Behavioral Therapy Enhanced; Family Based Therapy) for both adolescents and adults leading to remission in approximately 50% of cases (Chesney, Goodwin, & Fazel, 2014; Deloitte Access Economics, 2020, p. 92; Walsh, Xu, Wang, Attia, & Kaplan, 2021). These low response rates have led to a push for new and improved treatments for these deadly illnesses.

2. Heterogeneity of eating disorders

Part of the reason that gold-standard treatments may not work for about 50% of individuals is because of the high heterogeneity present in eating disorders (e.g., Steinhausen, 2009). Recent research has shown that even for individuals with the same diagnosis, symptoms presentations are significantly different (Levinson, Vanzhula, & Brosof, 2018). For example, one individual with AN may present to treatment with restriction, fears of weight gain, depression, and excessive exercise, while another individual with the same AN diagnosis may have

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symptoms of fasting, binge eating, worry, and low self-worth. Indeed, research shows that while about half of individuals with eating disorders have symptoms characterized by shape and weight concerns, the other half do not (Levinson et al., 2022). Furthermore, most (>50%) individuals with an eating disorder are given a diagnosis of other specified feeding and eating disorder (OSFED), which is essentially a catch-all diagnosis for any eating disorder that does not neatly fit into a diagnostic category (Riesco et al., 2018). As such, researchers are attempting to develop personalized eating disorder treatments that can address such heterogeneity using evidence-based methods.

3. Network analysis and treatment personalization

One way in which clinical researchers have begun to build personalized treatments is through the lens of network theory (Levinson et al., 2021, in press). Network theory proposes that psychiatric illnesses manifest and maintain themselves through dynamic symptom interactions (e.g., Borsboom & Cramer, 2013). For example, an eating disorder might develop from the symptom fear of weight gain, which directly leads to restrictive behaviors meant to alleviate this fear, which then leads to other symptoms of an eating disorder, such as binge eating and purging. Multiple cross-sectional datasets have been used to illustrate the application of network theory to data, termed network analysis, showing how the structure of eating disorders might be made of statistical relationships between symptoms, with specific *central* (i.e., or most important) symptoms theorized to be logical intervention targets, as central symptoms are hypothesized to be the symptoms that have the most impact on all other symptoms in the network (e.g., Borsboom & Cramer, 2013). Supporting this hypothesis, multiple empirical examples have shown that central symptoms are predictive of short and long term outcomes both in eating disorders (Elliott, Jones, & Schmidt, 2020; Levinson & Williams, 2020; Olatunji, Levinson, & Calebs, 2018) and related illnesses, such as depression (Levinson et al., 2017).

Cross-sectional networks provide useful insights into statistical relations among symptoms on the between-subjects level. In contrast, aspects of treatment *personalization* may best be studied at the level of the individual, termed idiographic research (Fisher, Medaglia, & Jeronimus, 2018; Molenaar, 2004; Zuidersma et al., 2020). Therefore, moving beyond cross-sectional models, idiographic network analysis uses intensive longitudinal data (typically collected via mobile applications, such as ecological momentary assessment [EMA; Mestdagh & Dejonckheere, 2021; Myin-Germeys et al., 2018; Shiffman, Stone, & Hufford, 2008]) to model the structure of pathology for one individual. This type of analysis is extremely important as it allows for identification of specific central symptoms that might maintain pathology in each specific person (Epskamp, van Borkulo et al., 2018; Jordan, Winer, & Salem, 2020). It has thus been proposed that central symptoms might be matched to evidence-based treatments and that intervention on central symptoms should weaken the overall illness (Levinson, Cusack, Brown, & Smith, in press). Recent work in the eating disorders has demonstrated the clinical utility of idiographic networks (Levinson et al., 2017, 2018; Levinson, Vanzhula, Smith, & Stice, 2020), as well as demonstrated that network-informed personalized treatment is effective at reducing eating disorder severity, eating disorder behaviors, and related anxiety and depression (Levinson et al., in press).

4. Integrating case conceptualization and idiographic networks

Importantly, to date, most investigations using idiographic network analysis to inform treatment and psychoeducation have relied solely on intensive longitudinal (i.e., ecological momentary assessment) data collected from patients to build a personalized network and subsequently select treatment targets. However, implementation of such a data-based personalized treatment depends on clinical researchers' ability to bridge the research-practice gap (Bansal, Bertels, Ewart, MacConnachie, & O'Brien, 2012), such that clinicians perceive value in data-based personalization. Recent work demonstrated barriers for implementing idiographic networks in clinical practice. For example, clinicians and their patients may see limited utility in idiographic networks if these models fail to reflect clinical expertise, intuition, and theory, or patient experience (Burger et al., 2020). Indeed, a pilot study (Frumkin, Piccirillo, Beck, Grossman, & Rodebaugh, 2020) showed that clinicians may not see the added benefit of idiographic networks over the use of existing clinical models (e.g., case conceptualization; Kuyken, Padesky, & Dudley, 2009, p. 366; Persons, 2012). These reservations have led to the conception of a new approach that aims to *integrate* rather than *contrast* case conceptualization and statistical network models (Burger et al., 2022; Scholten, Lischetzke, & Glombiewski, 2021). This line of research proposes to use clinical expertise and patient experience to construct networks of perceived relationships (Deserno et al., 2020; Klintwall, Bellander, & Cervin, 2021; Schumacher et al., 2021). In a subsequent step, networks based on case conceptualizations can be "updated" via Bayesian inference using EMA data collected by the patient. This type of additional modeling strategy has potential not only to bridge the research-practice gap, but also to conceptualize more effective models by integrating multiple perspectives into a data-based algorithm, ultimately improving both the uptake and efficacy of data-based personalized treatments.

5. Current study

This study aims to systematically integrate clinical information, from both patients and clinicians, with data-driven network estimation routines. Our ultimate goal is to illustrate how these different models can be used to help bridge the research-practice gap, and therefore foster the implementation of idiographic networks in clinical practice (Burger et al., 2022). In this article, we provide initial empirical evidence for the utility of clinically-informed networks, and showcase implications of this approach in regards to eating disorders. Specifically, we aim to investigate the extent to which centrality-based treatment recommendations differ in idiographic networks that are based on different sources of information: 1) Networks derived from clinician and patient case conceptualizations, 2) networks estimated from EMA data provided by the patient (the current default in the idiographic network literature), and 3) networks combining case conceptualization and EMA data, estimated via Bayesian inference using informative priors.

Due to the novelty of the approach, the focus of this study is exploratory, and we do not have specific hypotheses for the extent to which these networks differ from one another. Generally we did expect, based on prior literature showing clinician-judgment may result in different conceptualizations (Pisetsky, Schaefer, Wonderlich, & Peterson, 2019; Waller, 2016), that there would be differences between models, and that these differences may vary depending on the patient and clinician. We also showcase how treatment could be informed by each of the types of models we present.

6. Methods

6.1. Participants

Participants included in this study were two white self-identified women diagnosed with AN restricting subtype, who were 42 and 31 years-of-age (Patient A and B, respectively). Diagnoses were given based on two structured clinical interviews, the Structured Clinical Interview for DSM-5 (SCID-5; First, Williams, Karg, & Spitzer, 2015) and the Eating Disorder Diagnostic Inventory (Stice, Marti, Spoor, Presnell, & Shaw, 2008) by a highly trained Master's or PhD clinical psychology student. All diagnoses were double-checked independently by two additional highly trained Master's or PhD clinical psychology students. There were 100% diagnostic agreement between raters for both patients in this present study.

6.2. Materials

6.2.1. Diagnostic screening measures

Structured Clinical Interview for DSM-5. The SCID-5 (First et al., 2015) is a semi-structured interview to assess eating disorder diagnoses, severity, subtype, and course. The current study used the eating disorder modules to determine eating disorder diagnoses.

Eating Disorder Diagnostic Interview (EDDI). The EDDI (Stice et al., 2008) is a semi-structured interview to assess eating disorder symptoms over the prior year, which has been shown to have acceptable inter-rater reliability for the eating disorder diagnoses, validity and internal consistency (Stice et al., 2008). This interview was used to confirm diagnoses.

MINI International Neuropsychiatric Interview. The suicidality, mania/hypomania, and psychosis modules on the semi-structured MINI International Neuropsychiatric Interview (Sheehan et al., 1998), which has been shown to have excellent reliability and good validity, was used for exclusion criteria, which were active suicidal intent, psychosis, or mania.

6.2.2. Ecological momentary assessment (EMA)

The EMA consisted of 56 items spanning a broad range of eating disorder and related (e.g., anxiety, worry) symptoms in which participants rated how intensely they were currently experiencing each symptom (e.g., *I am terrified of gaining weight.*) from 0 (least ever) to 100 (most ever); see Levinson et al. (2021) for full EMA list and more information on the EMA battery.

6.3. Procedure

6.3.1. Data collection

All procedures were approved by the University of Louisville Human Subjects Protection Program (18.0622). Participants were recruited through advertisements across the United States, completed informed consent, and then were screened for inclusion/exclusion criteria by completing three semi-structured teleconference interviews (see diagnostic screening measures). Individuals were eligible to continue participating in the 10-session online treatment study if they had a current eating disorder diagnosis, and were not actively suicidal, psychotic, or manic. After completing baseline surveys, at the initial teleconference meeting, participants were trained on how to begin an EMA through their mobile phone five times a day for 15 days (75 timepoints; see below for more information) that would be used to guide their treatment plan. Each survey took three to five minutes to complete.

6.3.2. Clinician and patient case conceptualization

After the patients left session 2, which was a non-structured clinical interview, therapists created a clinician-informed network of symptoms by listing the top eight symptoms they perceived as most important for maintaining the patients' eating disorder (e.g., *fear of weight gain*, *excessive exercise*, *restricting food*, etc.), how these symptoms connect (e.g., *fear of weight gain AND restricting food, fear of weight gain AND excessive exercise, restricting food AND excessive exercise*), and to what strength of connection from 0 to 100 (for an example see Supplementary Fig. S1). At session 3, patients worked with their clinician to design their own network of symptoms from the patient-perspective. Similarly to the clinician-informed network, patients decided what they thought were their top eight most important symptoms, and then how they perceived that their symptoms connected to one another with arrows, as well as how strong they believed the connection was between symptoms from 0 (not at all) to 100 (the strongest). If patients had a difficult time numerically rating the symptom strength, then they could instead rate them as *weak*, *medium*, or *strong*. These sessions were completed before beginning any type of treatment. For complete direction on this portion of the procedure please email the senior author.

6.3.3. Variable selection

An important question in the context of network analysis is which variables should be included in the networks (Burger et al., 2022; Fried & Cramer, 2017). This is because network estimates consist of multivariate (partial) effects, and the set of variables therefore has a strong impact on the structure of the network itself: A node that is central within one given set of variables may be at the periphery of a different set of variables. We based the selection of variables on both, theoretical and data-driven criteria, considering the size of the network, topological overlap of items, as well as the variability and stationarity of the time-series.

Statistical power and network size. Statistical network models are highly parameterized models if many variables are used. Therefore, large numbers of observations are usually required to arrive at accurate estimates of connections in the network. Variable selection, and more specifically the number of variables to be included, is therefore directly linked to the question of statistical power and the accuracy of network estimates. To our knowledge, there is currently no principled way to estimate required sample sizes for idiographic networks. Preliminary simulation studies recommend that given the characteristics of data commonly obtained in clinical practice, no more than six variables should be included for network estimation (Mansueto, Wiers, van Weert, Schouten, & Epskamp, 2022). To this end, for both patients, we first selected items that have been specified by either the clinician or patient, and given that all of these items showed sufficient variability (see below), selected the six items with the highest mean of this subset. The means and selected items for all patients are visualized in Fig. 1a–b.

Topological overlap. In the context of mental disorders, networks consist of nodes that represent psychological constructs, such as body dissatisfaction, fear of making mistakes, and drive for thinness. In contrast to "real entities", such as individuals or objects, these psychological constructs are not always clearly separable. In the network literature, such conceptual similarities between constructs are referred to as *topological overlap* (Fried & Cramer, 2017). If constructs within one network are not clearly separable, edge estimates conflate the relationship between two nodes with their conceptual similarity. To address this problem, there are algorithms developed to detect redundancies of nodes, such as the goldbricker algorithm (Jones, 2018). These algorithms, however, can currently only be used in the context of data-driven network estimation. In this paper, we derive clinical networks from case conceptualizations, and these networks will likely show different redundancy patterns compared to their corresponding data-driven networks. For example, the algorithm detected two redundancies for patient A (*cognitive restraint – drive for thinness*, and *cognitive restraint – body dissatisfaction*). The case conceptualization network for this patient, however, defines these combinations as non-redundant, i.e., the nodes have unique relationships with other nodes in the network. For patient B, no item redundancies were identified. One of the main aims of this paper is to compare structures across the different types of networks, and it is therefore important that the networks consist of the same set of items. To this end, we focused on the items selected by clinician and patient as defined above (see *Statistical power and network size*), which reflects a combination of theory- and data-driven variable selection. Identifying node redundancies for the combination of different network structures needs to be investigated in future research.

Stationarity assumption. The models used in this paper assume stationarity, i.e., that the characteristics of the time-series do not change over time. Data in this study were collected *prior* to the intervention and over a relatively short period of time (see *Data collection*), which contributes to the feasibility of the stationarity assumption. In addition, we investigated stationarity visually (see Fig. 2a–b), and applied the Augmented Dickey-Fuller (ADF) test to check for non-stationarity (Dickey & Fuller, 1979). This test investigates the Null hypothesis that a unit root is present, indicating that the time-series is not stationary. For patient A, all time-series were stationary according to the ADF test ($p_{drivethin} = .030$; $p_{bodydiss} = .013$; $p_{fowg} = .032$; $p_{excexercse} = .027$; $p_{cogrestraint}$

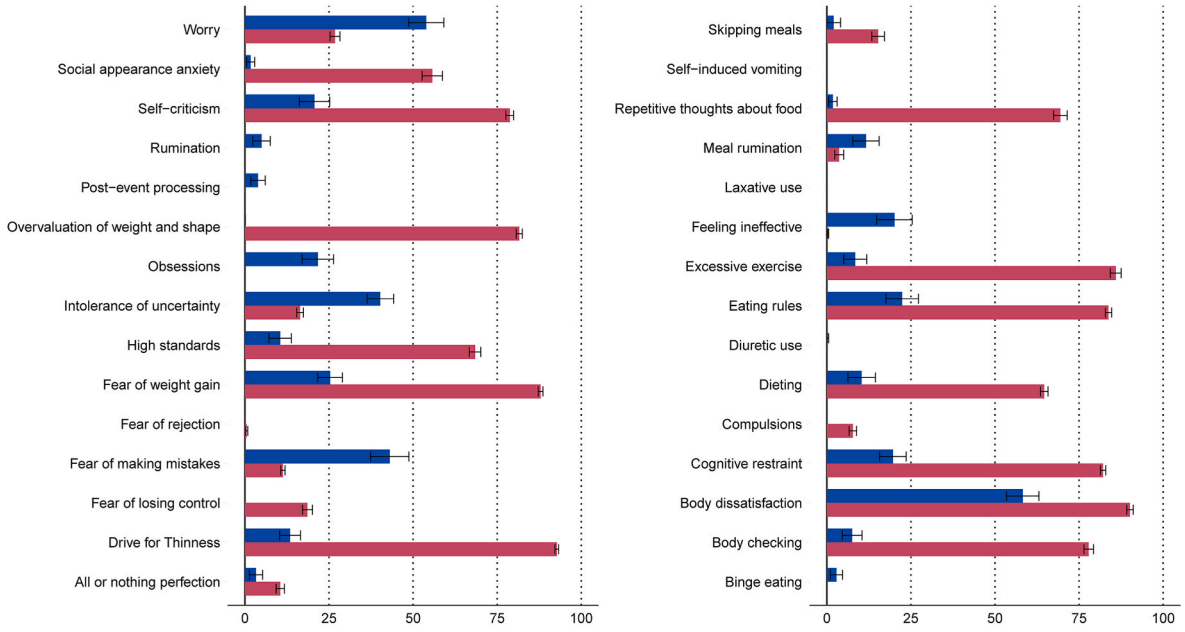

Fig. 1a. Mean scores and 95% confidence intervals for all EMA items and patients (red = patient A, blue = patient B).

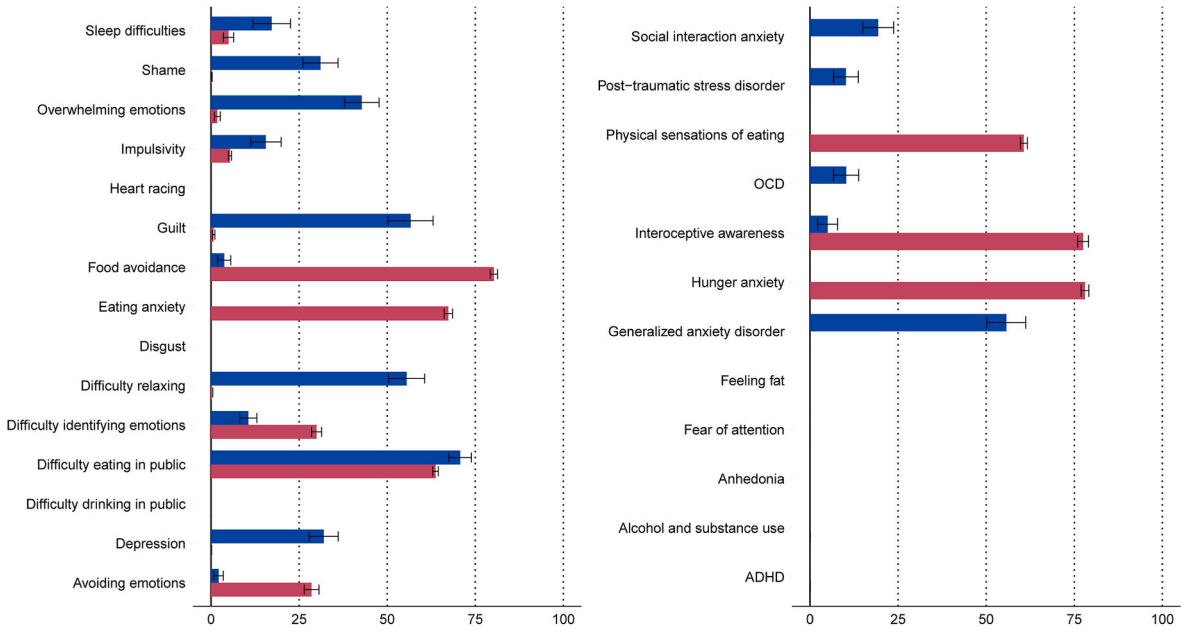

Fig. 1b. Mean scores and 95% confidence intervals for all ESM items and patients (red = patient A, blue = patient B).

= .010; $p_{overvalwtshape}$ = .018). For patient B, the majority of time-series was stationary according to the ADF test ($p_{fearmstkes}$ = .025; $p_{depression}$ = .022; $p_{eatrules}$ = .043; $p_{selfcrit}$ = .013; $p_{cogrestraint}$ = .015; $p_{bodycheck}$ = .01), but there were also time-series that are not stationary according to the ADF test ($p_{avoidemo}$ = .070; $p_{overwhlmemo}$ = .085; p_{gad} = .065; $p_{bodydiss}$ = .405). Nevertheless, we opted for not excluding them because doing so would result in removing all but two edges from the clinical network (e.g., most of the connections in the case conceptualization network are with *avoiding emotions*).

Variability of time-series. Network estimation is most commonly based on the analysis of covariance structures, and it is therefore important that items included in networks show sufficient variability around their means. Brose and Ram (2012) suggest two rules of thumb for investigating variability of time-series, a) a maximum of 80% of scores within one person and variable being identical, and b) a minimum standard deviation of 10% of the scale. We applied both criteria to all time-series to check if they showed sufficient variability. The maximum amount of identical scores for any value and time-series was 11.42% for patient A (*fear of weight gain*, score of 90; *excessive exercise* score of 100), and 54.93% for patient B (*avoiding emotions*, score of 0). For patient A, some of the time-series had comparably small standard deviations, ranging from SD = 4.39 (*drive for thinness*) to SD = 12.39 (*excessive exercise*). For patient B, except for *avoiding emotions* (SD = 8.58), the time-series showed variability well above the rule of thumb defined above, ranging from SD = 19.19 (*body checking*) to SD = 38.69 (*fear of making mistakes*). A reason for the somewhat smaller variability of *avoiding emotions* is that this item showed floor effect tendencies, with about half of the assessments (54.93%) marked at 0. This is important to

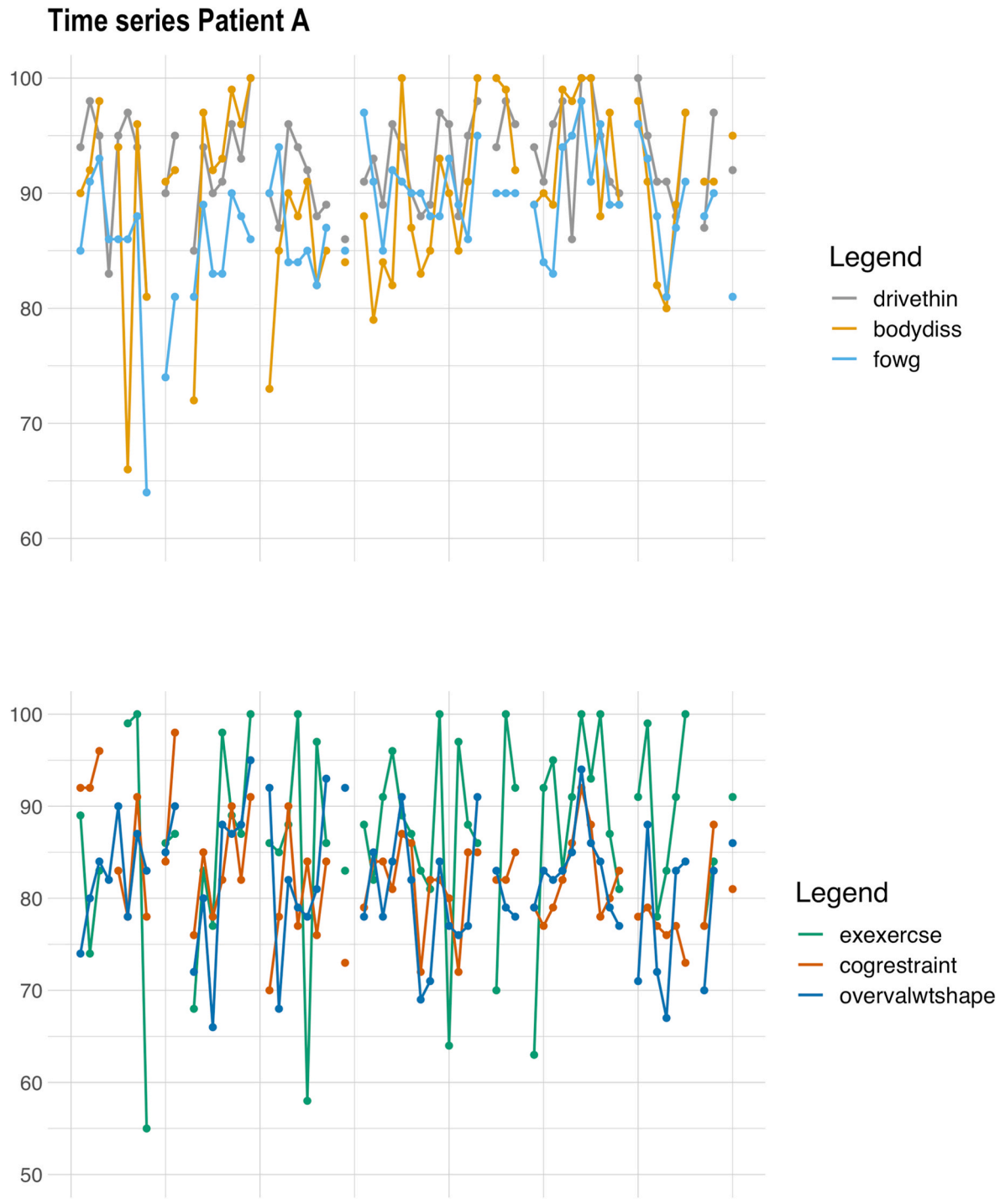

Fig. 2a. Time-series of all EMA items for patient A (labels: *drivethin* = drive for thinness; *bodydiss* = body dissatisfaction; *fowg* = fear of weight gain; *exexercse* = excessive exercise; cogrestraint = cognitive restraint; *overvalwtshape* = overvaluation of weight and shape).

keep in mind, as estimates with variables showing floor effects may be biased (Klipstein et al., 2022). However, as mentioned above, excluding the item *avoiding emotions* would lead to removing most of the edges in the case conceptualization network for patient B, and we therefore opted to include this item in the analyses.

6.3.4. Network estimation

For both patients, we used the clinician and patient case conceptualization, as well as momentary assessment data, to construct three types of networks. We investigated the case conceptualization networks separately for the clinician and patient, as well as their combination. In the main text of this paper, we use the average of the separately reported clinician and patient case conceptualizations (the "combined" case conceptualization), and provide the separate networks in the appendix (Supplementary Figs. S2–3).

Clinician and Patient Case Conceptualization (Case Conceptualization Network). First, we constructed a network based on the clinician and patient case conceptualization (in the following referred to as the *case conceptualization network*), by combining (averaging) the respective clinician and patient case conceptualizations, and subsequently making the relations undirected. We opted for using undirected relationships, which align with the notion of contemporaneous

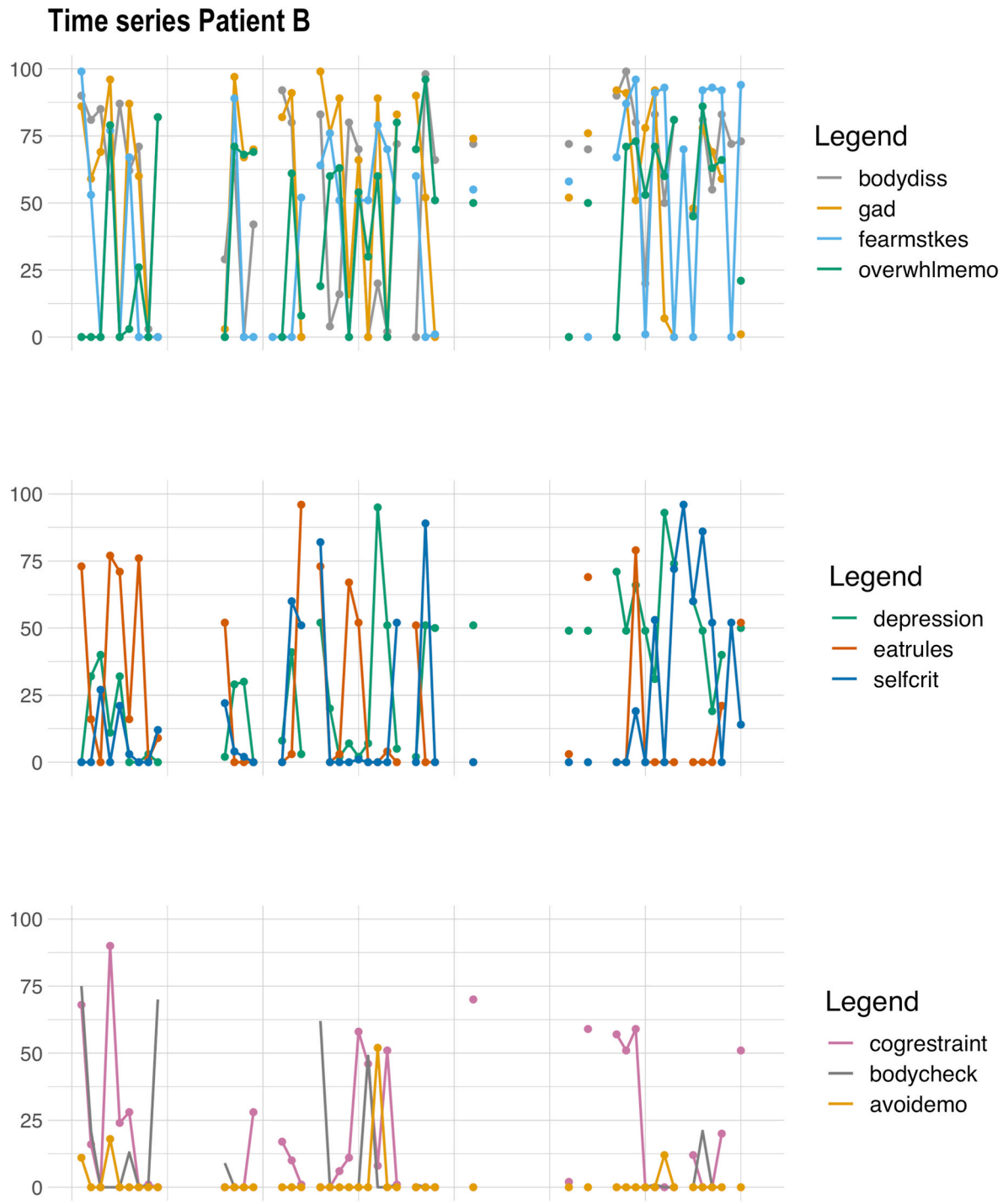

Fig. 2b. Time-series of all EMA items for patient B (labels: *bodydiss* = body dissatisfaction; *gad* = generalized anxiety disorder; *fearmstkes* = fear of making mistakes; *overwhlmemo* = overwhelming emotions; *depression* = depression; *eatrules* = eating rules; *selfcrit* = self-criticism; *cogrestraint* = cognitive restraint; *bodycheck* = body checking; *avoidemo* = avoiding emotions).

("instantaneous") networks. We did so because (undirected) contemporaneous networks are considered to better capture rapid processes commonly found in psychopathology as compared to (directed) temporal networks, which are restricted to fixed time intervals (Epskamp, van Borkulo et al., 2018). Other considerations to choosing priors and a statistical model are addressed in the discussion section.

Patient EMA Data Network (EMA Network). Second, we estimated a network from the EMA data provided by the patient (in the following referred to as the *EMA network*). The estimation was based on Bayesian partial correlation networks using a default prior without regularization (Schuurman, Grasman, & Hamaker, 2016; Williams, 2021). For more details, see the R-code in the appendix.

Integration Case Conceptualization and EMA Data (PREMISE Network). Third, we estimated a network integrating case conceptualization and EMA data using the PREMISE approach (Prior Elicitation Module for Idiographic System Estimation; Burger et al., 2022; in the following referred to as the *PREMISE-network*). The PREMISE approach estimates Bayesian partial correlation networks, which has been proposed as a fruitful alternative to frequentist estimation (Williams, 2021; Williams & Mulder, 2020). A particular advantage is the explicit

incorporation of available prior information, which allows to formally implement the approach outlined in this paper.

6.3.5. Network analysis and comparison

Network models can quantify the relative influence of specific nodes in relation to the overall network, referred to as the *centrality* of a node (Opsahl, Agneessens, & Skvoretz, 2010). In the applied network literature, centrality metrics have been used to generate hypotheses on optimal treatment targets (Elliott et al., 2020; Levinson et al., 2017; Rodebaugh et al., 2018). Here, we focus on one-step *Expected Influence (EI)* as a measure of centrality, which is defined as the sum of the weighted edges connected to a given node (Robinaugh, Millner, & McNally, 2016). For both patients, we compared the network-implied EI of the items as proxy for personalized treatment recommendations.

6.3.6. Model specifications and uncertainty of estimates

In this section, we briefly describe the main model specification settings. Note that this section is intended for the reader interested in technical details, and for researchers interested in applying the methodology in their own designs. The reader primarily interested in the results of this particular study may wish to skip these sections and continue with *Network analysis and comparison*. The R-script to run all analyses, including the model specifications discussed here, can be found in the Supplementary Materials.

Model Estimation. For the estimation of the EMA and PREMISE networks, we first estimated a Vector-Autoregressive lag-1 model (VAR; Epskamp et al., 2018; Wild et al., 2010) that accounts for the temporal dependencies in the data. We then modeled the scaled and centered residuals of the VAR estimation as multivariate normal distributions (MVN). The MVN distribution consists of two parameters, the location vector μ and the covariance matrix Σ, the latter encoding relationships between variables. In the network literature, the inverse of Σ is commonly used to construct partial correlation networks (Epskamp, Waldorp, et al., 2018). The difference in the estimation of the EMA and PREMISE network lies in the specific way Σ is modeled: For the EMA networks, we used an inverse-wishart distribution to model Σ, with parameter-settings resembling an uninformative prior (i.e., with scale matrix set to be the identity matrix, and the degrees of freedom set to the number of nodes in the network; Schuurman et al., 2016). For the PREMISE networks, we used the case conceptualization network as the scale matrix in an inverse-wishart prior distribution, with degrees of freedom set to 30. Increasing the degrees of freedom puts stronger prior probability on the scale matrix. There is potential to inform the setting for the degrees of freedom by the confidence in prior estimates, which we address in more detail in the discussion section.

Edge and Centrality Accuracy. A particular advantage of Bayesian estimation is that the uncertainty of the estimated models can be directly obtained from the resulting posterior distributions (Jongerling, Epskamp, & Williams, 2022). Network studies, such as the present paper, are often interested in centrality estimates, which are generated from previously established network structures (e.g., by summing incoming/outgoing relations). The quantification of uncertainty for metrics such as centrality is somewhat less straightforward compared to the uncertainty of edges, and can result in bias (Epskamp, Borsboom, & Fried, 2018). To counter this bias, a recent simulation study proposed a new approach to quantify uncertainty for centrality estimates, termed *post-processing shift estimation* (PPS-estimation; Jongerling et al., 2022). To assess the extent to which centrality scores of symptoms are indeed different from one another, we applied the PPS-estimation and checked if the 95% credibility intervals of the posterior distributions for the differences between each centrality score included 0, which may indicate that the difference in centrality between the two symptoms in question may be negligible.

6.3.7. Software

All analyses have been conducted in R (R core team, 2013) on 29/03/22, using version 4.1.0. We used the *psychonetrics* package version 0.9 (Epskamp, 2020) to estimate the GVAR models. We then used the STAN implementation *rstan* package version 2.26.6 (Stan Development Team, 2022) to model the multivariate normal distributions and construct the contemporaneous networks. Networks are visualized using the *qgraph* package version 1.6.9 (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012), and edge and centrality uncertainty are visualized using *ggplot2* version 3.3.5 (Wickham, 2016).

7. Results

7.1. Descriptive statistics

Fig. 1a–b shows the mean scores and 95% confidence intervals for all EMA items and patients.

7.1.1. Patient A

Following the item selection criteria, the top six symptoms specified in the perceived network for patient A were: *drive for thinness* (M = 92.73, SD = 4.39), *body dissatisfaction* (M = 90.14, SD = 7.50), *fear of weight gain* (M = 87.88, SD = 5.58), *excessive exercising* (M = 85.92, SD = 12.39), *cognitive restraint* (M = 82.14, SD = 6.03), and *overvaluation of weight and shape* (M = 81.55, SD = 6.99).

7.1.2. Patient B

For patient B, we had to extend the number of nodes from six to ten. This is because from the 10 symptoms that clinician and patient used in the case conceptualization, the six symptoms with the highest mean were unrelated. In fact, only when all 10 symptoms were included did the network show any relations, as most of the symptoms were related to the items with the lowest mean, i.e., *cognitive restraint*, *body checking*, and *avoiding emotions*. Removing these items would have result in an empty prior network, which is why we extended the number of nodes to 10 for patient B. The included symptoms were, in descending order of the respective means, *body dissatisfaction* (M = 58.25, SD = 31.86), *generalized anxiety disorder* (M = 55.70, SD = 36.09), *fear of making mistakes* (M = 43.04, SD = 38.69), *overwhelming emotions* (M = 42.79, SD = 32.06), *depression* (M = 31.98, SD = 26.91), *eating rules* (M = 22.42, SD = 31.73), *self-criticism* (M = 20.67, SD = 30.27), *cognitive restraint* (M = 19.65, SD = 25.85), *body checking* (M = 7.53, SD = 19.19), and *avoiding emotions* (M = 2.16, SD = 8.58).

7.2. Network estimation and visualization

The networks for both patients are visualized in Fig. 3a and b. In addition, we visualized the edge estimates and respective 95% and 50% credibility intervals and added the plots to the Supplementary materials (Supplementary Figs. S4–9). Note that for the perceived networks (top panel of each accuracy plot), no credibility intervals could be computed, because clinician and patient only provided point estimates for the perceived relations but no distributions. In this section, we report general characteristics of the networks and their accuracy (Burger et al., 2022), and in the next section we specifically focus on comparing the network-implied centrality scores.

7.2.1. Patient A

For patient A, edges in the case conceptualization network ranged from r = .45 (*fear of weight gain – cognitive restraint*) to r = 0.95 (*drive for thinness – fear of weight gain*; *drive for thinness – excessive exercise*; *fear of weight gain – overvaluation of weight and shape*). Edges in the EMA network ranged from r = 0.29 (*drive for thinness – cognitive restraint*) to r = 0.43 (*body dissatisfaction – cognitive restraint*). Edges in the PREMISE network ranged from r = 0.23 (*fear of weight gain – overvaluation of weight and shape; excessive exercise – overvaluation of weight and shape*) to r = 0.46 (*body dissatisfaction – cognitive restraint*).

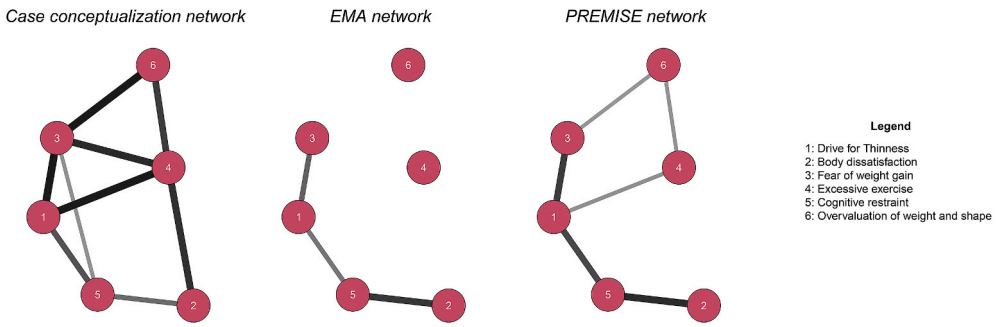

Fig. 3a. Clinician and patient case conceptualization (case conceptualization network; left), patient EMA data network (EMA network, middle), and combined case conceptualization and EMA data network (PREMISE network, right) for *patient A*.

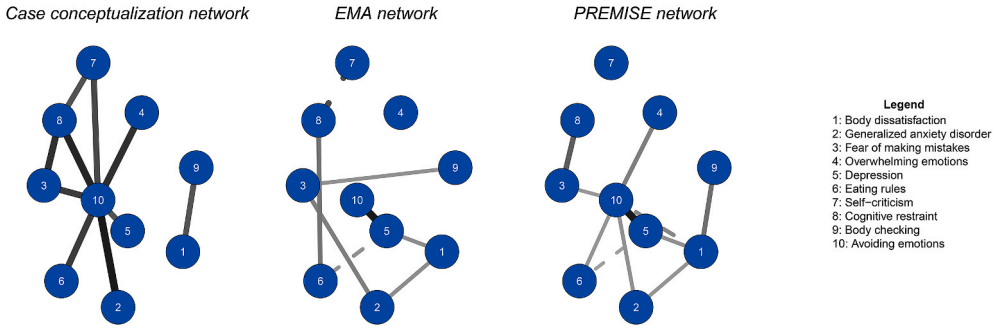

Fig. 3b. Clinician and patient case conceptualization (case conceptualization network; left), patient EMA data network (EMA network, middle), and combined case conceptualization and EMA data network (PREMISE network, right) for *patient B*.

7.2.2. Patient B

For patient B, edges in the case conceptualization network ranged from $r = 0.70$ (*self-criticism – cognitive restraint*; *body dissatisfaction – body checking*; *depression – avoiding emotions*) to $r = 0.95$ (*generalized anxiety disorder – avoiding emotions*). Edges in the EMA network ranged from $r = -0.44$ (*self-criticism – cognitive restraint*) to $r = 0.58$ (*depression – avoiding emotions*). Edges in the PREMISE network ranged from $r = -0.29$ (*body dissatisfaction – avoiding emotions*) to $r = 0.57$ (*depression – avoiding emotions*).

For all networks, the 95% credibility intervals showed, on average, relatively large overlap with one another. This means that we cannot be certain about the *specific rank-order* of edges (i.e., one edge being particularly stronger than another edge in the same network). However, we can still interpret the *overall structure* of the networks irrespective of their weight, as the edges are selected based on a pruning procedure (Jongerling et al., 2022) which only includes edges whose 95% credibility intervals do not include 0.

7.3. Network inference: Centrality-based treatment recommendations

Fig. 4a–b shows a comparison of the network-implied centrality rank orders for the case conceptualization network, the EMA network, and the PREMISE network for both patients. When comparing centrality scores of symptoms, it is important to consider the width of the posterior distributions, which inform us about the uncertainty of the estimates. For the EMA and the PREMISE network, the left panels show point estimates, as well as 50% and 95% credibility intervals. In addition, the right panels indicate for each combination of symptoms if their respective centrality scores were meaningfully different from one another (i.e., if the 95% credibility interval of the posterior distribution of their difference score does not include 0). As with the edge accuracy plots, no posterior distributions, and therefore no credibility intervals could be computed for the case conceptualization network, because the centrality metrics were directly inferred from the provided point estimates. In the following, whenever we refer to a centrality *rank order* of the symptoms, we treat symptoms whose difference posterior distribution do not meaningfully differ as defined above as a tie. Based on these comparisons, we present a list of the most central symptoms for each patient and network in Table 1.

7.3.1. Patient A

For patient A, the most central symptom in the case conceptualization network was *excessive exercising*, followed by *fear of weight gain*, and *drive for thinness*. In the EMA network, the symptoms *cognitive restraint*, *drive for thinness*, *body dissatisfaction*, and *fear of weight gain* were tied for the most central symptoms. *Overvaluation of weight and shape* was less central than *cognitive restraint* and *drive for thinness*, but not the remaining symptoms. *Excessive exercising* was less central than *cognitive restraint*, *drive for thinness*, and *body dissatisfaction*, but not *fear of weight gain* and *overvaluation of weight and shape*. In the PREMISE network, in contrast, the symptoms *drive for thinness*, *cognitive restraint*, and *fear of weight gain* were tied for the most central symptoms. *Excessive exercising* and *overvaluation of shape* were both less central than *drive for thinness* and *cognitive restraint*, but not less central than the remaining symptoms. *Body dissatisfaction* was only less central than *drive for thinness*, but not less central than any of the remaining symptoms.

7.3.2. Patient B

For patient B, the most central symptom in the case conceptualization network was *avoiding emotions*, followed by *cognitive restraint* and *fear of making mistakes*. In the EMA network, none of the symptoms differed from one another in terms of centrality, except for *self-criticism*, which was less central than *generalized anxiety disorder*, *fear of making mistakes*, *depression*, *avoiding emotions*, and *body dissatisfaction*, but not less central than the remaining symptoms. In the PREMISE network, *avoiding emotions*, *fear of making mistakes*, and *depression* were tied for the most central symptom, however, out of the three, only *avoiding emotions* was more central than the remaining symptoms in the network.

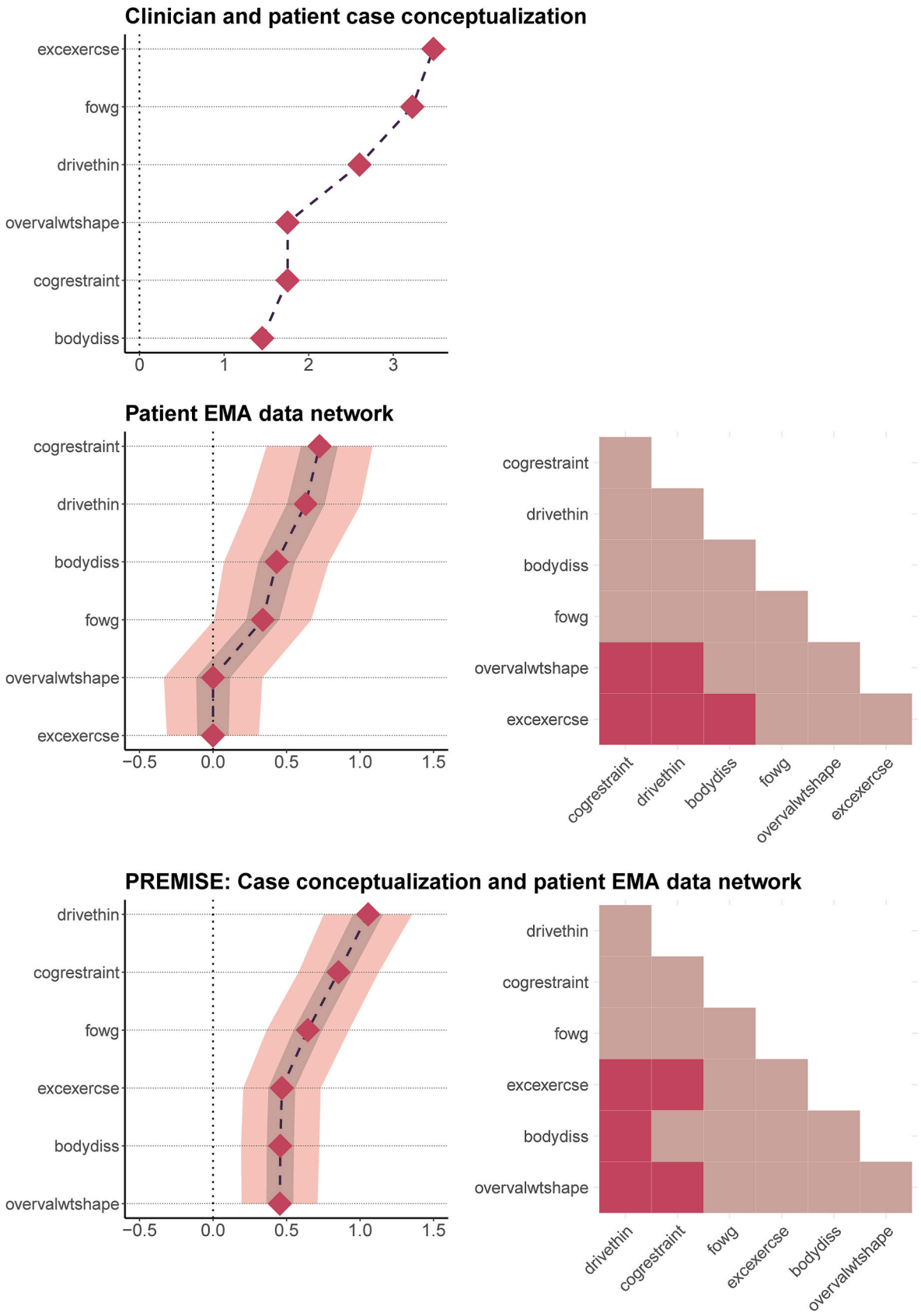

Fig. 4a. *Patient A:* Centrality scores (EI) for the case conceptualization network (top panel), as well as centrality scores and accuracy estimates based on 95% and 50% credibility intervals (left), and centrality difference test (right) for the EMA network (middle panel) and the PREMISE network (bottom panel). In the right panels, red boxes indicate meaningful differences in the centrality score of the two symptoms.

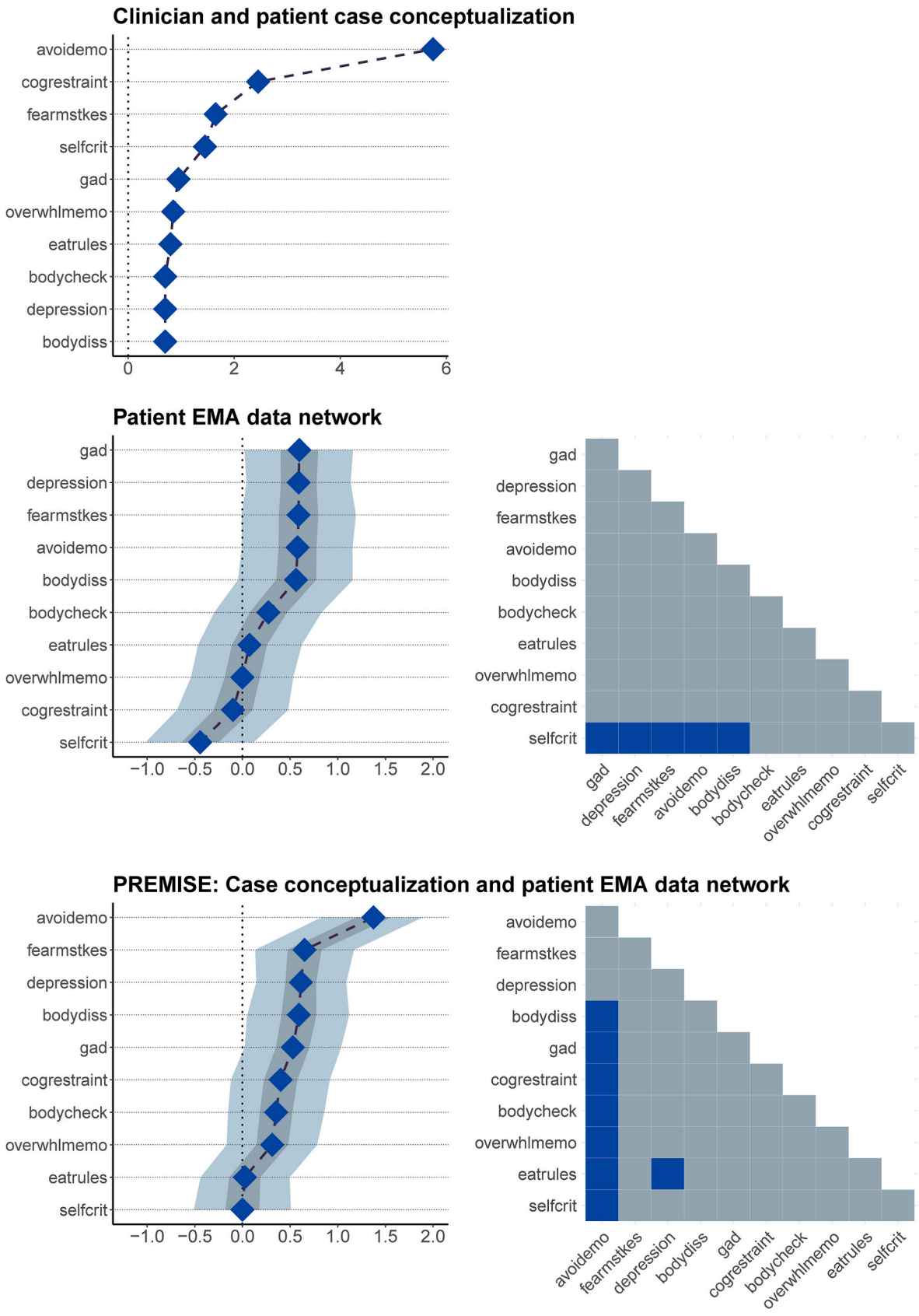

Fig. 4b. *Patient B:* Centrality scores (EI) for the case conceptualization network (top panel), as well as centrality scores and accuracy estimates based on 95% and 50% credibility intervals (left), and centrality difference test (right) for the EMA network (middle panel) and the PREMISE network (bottom panel). In the right panels, blue boxes indicate meaningful differences in the centrality score of the two symptoms.

Table 1
Most central symptoms for the case conceptualization networks, EMA networks, and PREMISE networks for both patients.

	Case conceptualization network[a]	EMA network	PREMISE network
Patient A	1. Excessive exercise (C: 3, P: 2) 2. Fear of weight gain (C: 2, P: 1) 3. Drive for thinness (C: 1, P: *n.r.*)	Cognitive restraint[b] Drive for thinness[b] Body dissatisfaction[b] Fear of weight gain[b]	Drive for thinness[b] Cognitive restraint[b] Fear of weight gain[b]
Patient B	1. Avoiding emotions (C: 2, P: *n.r.*) 2. Cognitive restraint (C: 1, P: *n.r.*) 3. Fear of making mistakes (C: 3, P: *n.r.*)	*No rank order*[c]	Avoiding emotions[b] Fear of making mistakes[b] Depression[b]

[a] For the case conceptualization network, we present the rank-order based on the average clinician-patient network, and in brackets the rank-order of the symptom for both clinician (C) and patient (P) separately. *n.r.* ("not ranked") indicates that the symptom was unconnected.

[b] Shows the rank order of the point estimates, however, the 95% credibility intervals of the posterior difference distributions included 0. The rank order of these symptoms should therefore be interpreted with caution.

[c] None of the centrality scores of any of the symptoms was meaningfully different from one another, according to the 95% credibility intervals of the posterior difference distributions, except for *self-criticism*, which was less central than most other symptoms.

7.4. Clinical treatment example

We provided two case examples of three different approaches (case conceptualization, EMA data only, combined case and EMA) for arriving at idiographic network models. For patient A, treatment recommendations would defer based on type of algorithm. For this case conceptualization, the top two targets were *excessive exercise* and *fear of weight gain*, which could be matched to evidence-based treatments such as CBT for reducing *excessive exercise* (Mathisen et al., 2018) and imaginal exposure for *fear of weight gain* (Levinson, Christian, et al., 2020). Alternatively, in the EMA network, the top two central symptoms were *cognitive restraint* and *drive for thinness*, both of which might be best addressed by Cognitive-Behavioral Therapy Enhanced (CBT-E), specifically modules on regular eating and thought challenging (Fairburn, Cooper, & Shafran, 2003). Finally, in the combined network (case conceptualization plus EMA data) the network was very similar to the EMA network, with drive for thinness and cognitive restraint as the top two central symptoms, which would again lead to similar treatment recommendations of CBT-E modules. However, we should note that *fear of weight gain* was the third most central symptom, also replicating most central symptoms from the clinician network (minus the *excessive exercise* symptom). As such, dependent on the model, treatment modules and ordering would vary.

8. Discussion

Current treatments for eating disorders are subpar, with only about 50% of adults responding to evidence-based treatments (Chesney et al., 2014; Deloitte Access Economics, 2020, p. 92; Walsh et al., 2021), and no treatments currently in existence for other specified feeding and eating disorders (the most common eating disorder) or for AN (Riesco et al., 2018). Part of the reason that treatment may not work effectively for a large subset of patients is that heterogeneity is extremely high in the eating disorders (e.g., Steinhausen, 2009). As such, personalized and evidence-based treatments are needed.

In this article, we compared different approaches to constructing and estimating personalized networks of eating disorder symptoms. We estimated networks based on clinician and patient case conceptualizations, networks estimated from patient EMA data, and networks that combine case conceptualizations and EMA data via Bayesian inference. Using two cases of patients with AN, we highlighted how using these different approaches can influence the results of subsequent centrality analyses, and therefore, potentially impact the choice of personalized treatment targets. We also demonstrated how clinicians might use each of these types of network to inform treatment selection. The current paper shows how to build personalized networks from intensive longitudinal data (collected via EMA), and how these can be integrated with case conceptualizations. This approach is especially important because the incorporation of both patient and clinician data into the models has the potential to provide more effective algorithms than patient data alone, and to help bridge the research-practice gap by encouraging clinician engagement with network models. Further, a specific benefit to *integrating* clinical and statistical models over using either of them alone is that the integration via Bayesian inference systematically weighs new evidence against the current case conceptualization. The systematic integration ties together the benefits of *clinical networks*, that are especially relevant in the early stages when insufficient EMA data are available to reliably estimate models, and the benefits of *statistical networks*, which may generate exploratory insight in later stages of the case conceptualization (von Klipstein, Riese, van der Veen, Servaas, & Schoevers, 2020; for a detailed discussion on the advantages of integrating clinical and statistical networks, see Burger et al., 2022). The Bayesian updating routine can stimulate a dialogue and reveal discrepancies between prior and posterior models that may suggest behavior or thought experiments (Burger et al., 2022).

Overall, the extent to which we observed discrepancies between which symptoms were most central for patients varied for the two cases. Specifically, for Patient A there was a somewhat large discrepancy in central symptoms, especially between the case conceptualization and EMA network, with patients and clinicians possibly overemphasizing the importance of excessive exercise behaviors. This difference is extremely interesting and may derive from the fact that traditional treatments for eating disorders very strongly emphasize problematic behaviors as key targets for intervention (e.g., Fairburn et al., 2003). However, recent research has suggested that cognitive-affective symptoms of eating disorders may be more important for the maintenance of active illness states (Levinson et al., 2018; 2021), which is a shift in the way in which treatments might be built and delivered. Future research is needed to identify not only which type of algorithm is most effective and most easily accepted by clinicians, but also why some models may have more or less overlap and what that overlap might mean for effective treatment.

There are many possible future clinical implications from this research. The ability to derive a personalized algorithm that identifies symptoms to target in treatment can lead to evidence-based personalized treatment for eating disorders, as well as additional psychiatric illnesses. Crucially, these types of algorithms need input from both clinicians and patients and these data demonstrate how to create such a model and how that type of model can be used to pinpoint treatment targets that can be matched with existing or novel evidence-based treatment modules. We provide an example of how we could match treatment targets such as fear of weight gain and drive for thinness in the results. Future research can turn these types of algorithms into clinician-friendly software to make an easy-to-use guidance system for clinicians.

8.1. Limitations

There are some limitations of this research. First and foremost, there were only two participants' data presented in the case-series design. However, we want to strongly emphasize that while we did not include many participants, the amount of data per person was large and consisted of intensive longitudinal data and clinician and patient

perspective data. With a shift to more personalized types of treatment, clinical researchers must also shift their viewpoint from considering that the size of the dataset refers to the number of observations per person, rather than the number of participants. In fact, "truly" idiographic research is not necessarily concerned with identifying generalizable features across individuals, but rather a model that works for a given patient, and should therefore focus on the length of time-series and not the number of individuals in a study. If clinical researchers want to build truly personalized evidence-based treatments, we must first develop and test the types of algorithms presented in the current study. We need this type of research, which develops algorithms with the potential to personalize and improve treatment, to build truly evidence-based personalized treatments.

Second, for the construction of the case conceptualization and combined networks, we used the average of the clinician and the patient perceived relations as a proxy for the *collaborative* case conceptualization. It could be argued, however, that establishing these case conceptualizations as a true collaborative effort between clinician and patient in conversation may yield more valid priors. For example, for patient A, for whom we observed large discrepancies between the case conceptualization network and the EMA/PREMISE network, there were also large differences between the individual clinician and patient networks (see Supplementary Fig. S2). In fact, the most central symptom in the clinician's prior network was drive for thinness, which was also highly central in the EMA network. In turn, the patient's prior network implied relatively high centrality for cognitive restraint, which was the most central symptom in the EMA network. While these important aspects get lost in the statistical averaging of the two networks, they could have been discussed and incorporated in a collaborative prior network. Indeed, it has been found that interactive reasoning ("explorative talk") improves judgment compared to individual results (Burger et al., 2022; Mercier & Sperber, 2018; Resnick, Salmon, Zeitz, Wathen, & Holowchak, 1993). More specifically, differences in the conceptualizations between clinician and patient could stimulate a dialogue and suggest thought and behavioral experiments to test relationships (Burger et al., 2022). Finally, such collaboration between clinician and patient aligns with the principles of case conceptualization, and additionally have other benefits, for example positive effects on the therapeutic relationship (Persons, 2012).

Third, it is currently unknown which statistical model best aligns with the type of relationships that clinician and patient specify in the case conceptualization networks. There are some preliminary guidelines for selecting a statistical model, for example by choosing a model that can capture the clinical phenomena of interest, and by asking for estimates of quantities that are intuitive for clinician and patient (Burger et al., 2022). In this paper we used the VAR model, which currently takes the most prominent role in the field of personalized networks, but is not without limitations (for an overview, see Bringmann, 2021; Haslbeck & Ryan, 2021). One particular limitation relates to the strong assumptions of the VAR model, such as stationarity. While we could show that the assumptions were largely met in the context of this data, there were some reasons for concern (the floor effects of *avoiding emotions* for patient B), calling for caution in interpreting effects with this variable. Further, we currently do not know if the provided clinical information are better used for the estimation of temporal or contemporaneous networks. In this paper, we opted for contemporaneous priors for two main reasons: First, most of the relationships between variables are better reflected on relatively short time scales. For example, it can be assumed that cognitive symptoms, such as self-criticism and body checking are interacting rather rapidly, and not on the lag-1 scales specified in the assessment of this data collection. Second, participants have undergone a training phase in which they were shown contemporaneous networks, and we therefore assumed that their estimates align with the notion of contemporaneous effects. However, there are also limitations to using contemporaneous networks, such as the fact that they do not only reflect contemporaneous effects but also model misspecification.

8.2. Future research

The approach used in this paper implies new areas of research, as it is truly a crucial first step in the personalization of evidence-based treatment for eating disorders. First, a randomized controlled trial is needed to test which type of algorithm leads to the most effective and efficient treatment or if there are comparable results regardless of type of algorithm. Taking this reasoning to the individual level, single case designs could reveal that different patients may benefit from different personalization approaches discussed in this paper. One hypothesis would be that patient groups with strong insight into their own pathological processes, or disorder groups with strong theoretical background, may benefit more from the case conceptualization network or the PREMISE approach, as these put more emphasis on theory, clinical expertise, and patient experience in deriving treatment targets. Patient (groups) with limited insight, or who only recently experienced symptom onset, and disorder groups with weaker theoretical background may in turn benefit more from a focus on data-driven modeling (i.e., the EMA networks presented in this paper). We suggest that these approaches could be implemented in a sequential within-person design, where the treatment implied by one personalization approach (e.g., targeting the most central symptom in the case conceptualization network) is used until no further (or no satisfactory) improvement can be achieved. The clinician can then resort to other personalization approaches, for example targeting the most central symptom in the PREMISE or EMA network. Such designs can be built around Bayes factor criteria (e.g., in the leapfrog design; Blackwell, Woud, Margraf, & Schönbrodt, 2019), formally indicating when a treatment switch may be appropriate, i.e., when no satisfactory improvement is achieved compared to the status-quo (either the control condition or the most successful treatment up until that point). In the future, implementing such designs in clinical practice could inform the administration of personalized treatments in real-time.

Second, this type of personalization should be extended to additional forms of psychiatric illness. While eating disorders are a very relevant example, given the lack of effective treatments (Chesney et al., 2014; Deloitte Access Economics, 2020, p. 92; Walsh et al., 2021), many psychiatric disorders are heterogeneous and have less than ideal treatment response, including but not limited to depression, post-traumatic stress disorder, and personality disorders (e.g., Hofmann, Asnaani, Vonk, Sawyer, & Fang, 2012). Of course, future research is also needed with larger sample sizes and with clinician-friendly software to test the ability to implement such algorithms in clinical practice. Future research integrating clinician input on using this type of model and how to best integrate these algorithms into clinical practice is needed.

Finally, there are several aspects of prior elicitation and statistical estimation that need further investigation. Next to the questions regarding the statistical models introduced above (see *Limitations*), one especially relevant question pertains to how strongly clinical priors should be weighed against EMA data. In this paper, we model prior information via an inverse-Wishart distribution, where the degrees of freedom reflect how strongly the model draws on the specified prior. Because we had no information on the confidence in the prior, we set the degrees of freedom to be 30, in line with the example analysis of the initial PREMISE paper (Burger et al., 2022). Given the amount of data available in this study, setting the degrees of freedom to 30 led to a reasonable balance between prior and posterior model. In the future, these settings could also be informed by eliciting how confident clinician and patient are in their priors. Future research should aim to develop anchors for setting these confidence estimates empirically, and incorporate confidence elicitation in the assessment of PREMISE.

9. Conclusion

In conclusion, we applied three different approaches for

personalizing eating disorder treatment and demonstrated these with data of two patients. We also provided examples of how these models can be used to inform clinical practice by matching evidence-based treatments to identified treatment targets. Overall, we found there were some patients who had similar treatment targets, regardless of type of algorithm, whereas for other patients' treatment targets varied. Future research is needed to continue to expand upon these work in additional eating disorder patients and in additional patient populations.

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Consent of human subjects statement

Informed consent was obtained for participation in the initial data collection.

CRediT authorship contribution statement

Julian Burger: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Christina Ralph-Nearman:** Conceptualization, Writing – original draft, Writing – review & editing, Data curation. **Cheri A. Levinson:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Validation, Investigation, Data curation, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that have been used are confidential.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.brat.2022.104221.

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