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CLINICAL VALIDITY AND UTILITY OF NETWORK ANALYSIS IN CLINICAL PRACTICE

Presentata da: Giovanbattista Andreoli

Coordinatore Dottorato	**Supervisori**	**Co-supervisore**
Prof.ssa Elisabetta Crocetti	Prof.ssa Giulia Casu	Prof.ssa Chiara Rafanelli
	Prof. Stefan G. Hofmann	

Esame finale anno 2025

To my family

"If you can keep your head when all about you
Are losing theirs and blaming it on you,
If you can trust yourself when all men doubt you,
But make allowance for their doubting too;
If you can wait and not be tired by waiting,
Or being lied about, don't deal in lies,
Or being hated, don't give way to hating,
And yet don't look too good, nor talk too wise:
(...)
If neither foes nor loving friends can hurt you,
If all men count with you, but none too much;
If you can fill the unforgiving minute
With sixty seconds' worth of distance run,
Yours is the Earth and everything that's in it,
And—which is more—you'll be a Man, my son!"
(Rudyard Kipling)

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advice, suspending judgment. And all those who have helped shape me into the professional and, above all, the person I am today. To all of you, I express my deepest gratitude.

Abstract

This dissertation aims to investigate the clinical validity and utility of fully idiographic network analysis (FINA) in clinical practice. Moving from an exploration of FINA empirical research using FINA to estimate person-specific networks in individuals with mental health conditions, it then explores FINA's potential in clinical practice. Chapter 1 presents an introduction on the importance of exploring the validity and utility of network analysis in clinical practice. Chapter 2 presents a systematic scoping review of studies applying FINA in mental health, highlighting common methodological practices and trends, while identifying areas for improvement. This review sets the stage for understanding how FINA has been applied to date and highlights further developments needed for its effective application in clinical research and practice. Chapter 3 describes an empirical study testing the clinical validity and utility of FINA by comparing empirical symptom networks, estimated on patient data using FINA, with clinician-predicted symptom networks in their ability to predict subsequent patient functioning. Additionally, the study explores both clinicians' and patients' perspectives on FINA's utility in routine clinical settings. Chapter 4 presents a general discussion on the clinical validity and utility of using NA to construct person-specific networks, with a focus on the findings, limitations, and implications of both the scoping review and empirical study, as well as directions for future research. The overarching goal of this dissertation is to advance personalized, data-driven approaches in clinical psychology by examining the clinical validity of FINA and evaluating its applicability in clinical practice. This work assesses FINA's potential as a tool for predicting patient functioning and improve treatment through support for more individualized interventions.

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Chapter 1

Why Exploring the Validity and Utility of Network Analysis in Clinical Practice?

Challenges in Clinical Interventions

Psychological clinical interventions, including psychotherapies, have proven effective in treating a wide range of psychological disorders (Goldberg et al., 2018; Grenon et al., 2019; Munder et al., 2019; Shepardson et al., 2018; Weitz et al., 2018). However, despite this evidence, several challenges persist in clinical psychology. For instance, cognitive-behavioral therapy (CBT), widely considered one of the most effective psychotherapies, still has a substantial portion of patients who do not respond to treatment. In the case of panic disorder, research has shown that patients with treatment resistance often experience minimal symptom improvement (Schwartz et al., 2019). For obsessive-compulsive disorder, about half of the patients show clinically significant improvement by the end of treatment, but only one in three achieves full remission of symptoms (McKay et al., 2015). Nearly 30% of patients with symptoms like anxiety and depression do not respond to CBT (Rozental et al., 2019). Furthermore, a meta-analysis indicates that while CBT can be effective for anxiety-related disorders at treatment completion and up to 12 months afterward, its effects tend to diminish with time (van Dis et al., 2020). In terms of efficacy, psychotherapy has made limited advancements in improving treatment outcomes, especially when compared to other health fields (Hayes & Hofmann, 2021). Recent evidence shows that the effect sizes of CBT for anxiety-related disorders in placebo-controlled trials have decreased compared to meta-analyses conducted five years earlier (Bhattacharya et al., 2023). Moreover, there is a growing need to enhance routine clinical practice by developing new methods for evaluating therapy outcomes, ensuring equal attention to all symptoms, and addressing the tendency for some symptoms to respond more effectively to treatment than others (McAleavey et al., 2019).

There are several potential explanations for the challenges in the efficacy of psychological treatments. One factor is the continued reliance on the medical illness model for defining and

classifying mental disorders. This model traditionally conceptualizes mental health issues as brain-based physical diseases, emphasizing biological treatments (Andreasen, 1985). Although the medical illness model was first challenged by the biopsychosocial model (Frazier, 2020), which underscores the interaction of biological, psychological, and social factors in shaping both well-being and illness, its influence remains strong in psychological treatment and therapy approaches (Cantú, 2023). For instance, this model assumes that symptoms reflect latent disease entities, which leads to an excessive focus on syndromes (Hofmann & Hayes, 2019). This perspective has also shaped the development of widely used diagnostic systems, such as the Diagnostic and Statistical Manual of Mental Disorders, 5th edition (DSM-5) (American Psychiatric Association, 2013), which primarily categorizes mental disorders into distinct entities and provides descriptive lists of symptoms to define each category.

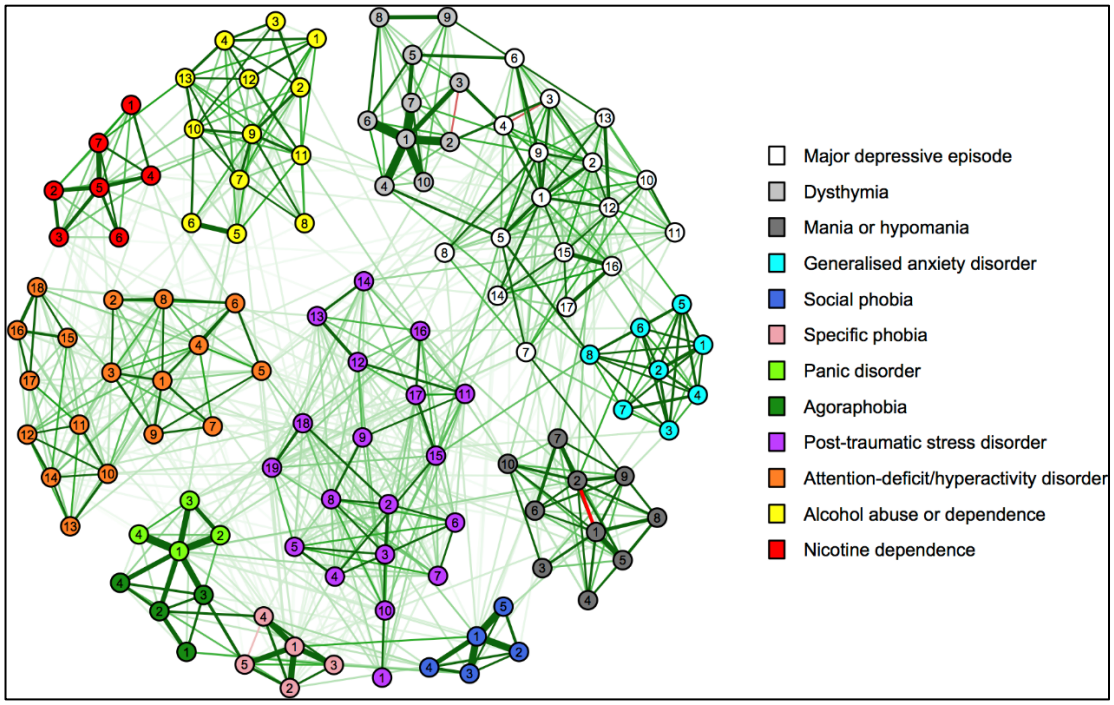
As a result, psychological interventions risk overlooking individual subjectivity and the unique differences of each patient by prioritizing symptom reduction as the primary measure of treatment success (Springer et al., 2018). This focus has led to the proliferation of protocolized treatments aimed primarily at reducing symptomatology, often at the expense of addressing the specific needs and goals of the individual. Such approaches risk turning psychological treatments into step-by-step "cookbooks" (Bakker, 2022) rather than adaptable interventions tailored to each patient’s unique characteristics. Furthermore, this perspective conflicts with the definition of evidence-based practice in psychotherapy, which emphasizes integrating the best research evidence with clinical expertise, all within the context of the patient’s individual characteristics, culture, and preferences (American Psychological Association Presidential Task Force on Evidence-Based Practice, 2005). To address this issue, a key solution is to identify treatments that are effective for various disorders while also respecting each patient’s unique characteristics (Lorenz-Artz et al., 2023). However, achieving this requires a well-described, valid, and useful representation of patient functioning.

Network Analysis as a Possible Solution

One of the most recent approaches to examining the complexity of individuals in relation to their symptoms is the network approach to psychopathology (Borsboom, 2017; Borsboom & Cramer, 2013). This approach suggests that psychopathology emerges from interactions among psychiatric symptoms, focusing on the symptoms themselves and their complex relationships (Borsboom, 2017; Hofmann et al., 2016). In doing so, it seeks to address the simplistic limitations of the medical illness model in mental health. The network approach introduces five key insights into the clinical field (Rief et al., 2023): (a) mental disorders are multifactorial, shaped by a complex interplay of biological, social, and environmental factors; (b) individuals with similar underlying factors may develop different issues, while those with different factors can experience the same problems; (c) individuals with the same diagnoses can vary widely in both the underlying factors and problems they face; (d) the problems individuals experience are often causally interconnected; and (e) mental disorders are inherently dynamic, fluctuating over time. In this way, the network approach introduces greater complexity and offers a more nuanced understanding of symptom overlap across different disorders, helping to explain comorbidity among various diagnostic conditions, such as those outlined in the DSM-5 (Figure 1).

Figure 1

Network Representing the Associations among Different Diagnostic Categories as Described in the DSM-5



Note. In this network, symptoms are represented as nodes (circles), and the associations between them are depicted as edges (lines). Node colors correspond to different diagnoses, while the numbers inside the nodes refer to specific symptoms as described in the DSM-5. Green edges indicate positive associations, and red edges indicate negative associations, with edge thickness representing the strength of the associations. The figure is adapted from Boschloo et al. (2015).

The success of the network approach to psychopathology has been greatly supported by the development of network analysis (NA). This analytical method enables the estimation of complex relationships among variables, allowing for the examination of network structures to uncover core features within the system. When applied to mental health variables, NA facilitates the creation of network models where symptoms are represented as nodes, and the relationships between them are depicted as edges (Borsboom & Cramer, 2013). These network models and NA techniques have

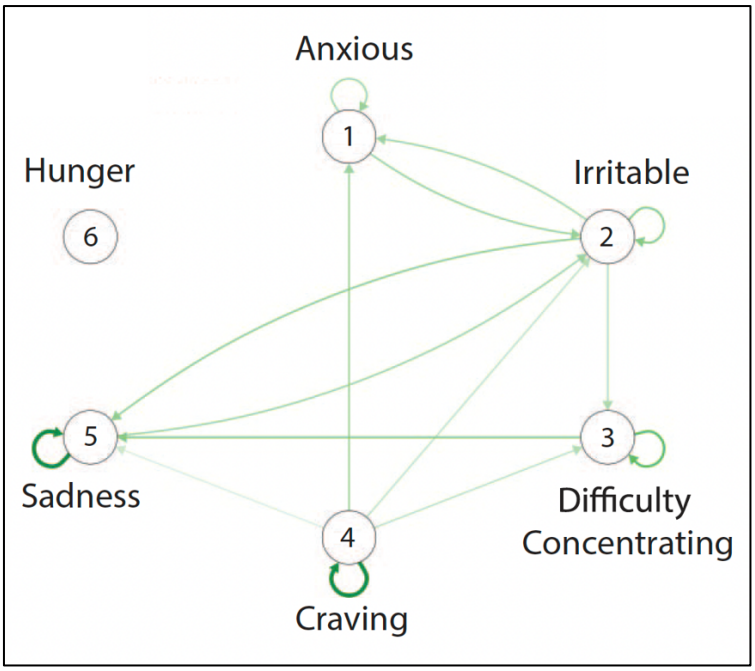
been effectively used to describe various mental disorders (Contreras et al., 2019) and to identify key targets for prevention and intervention strategies (Fried & Cramer, 2017).

NA can also be applied to intensively collected longitudinal data (Borsboom & Cramer, 2013) to explore how symptoms interact over time. Such data are often gathered using ambulatory assessment (AA; Trull & Ebner-Priemer, 2013), which includes methodologies like ecological momentary assessment (EMA; Shiffman et al., 2008). EMA enables the collection of real-time data on individuals' behaviors, thoughts, and emotions within their natural environments through repeated assessments over time. Recent advances in digital technology have facilitated the growing use of AA methods in psychology research, such as using smartphones to monitor psychological processes in daily life (Ellis, 2020).

Estimating networks from this type of data allows for the construction of longitudinal networks (Bringmann et al., 2022). These networks reveal how one symptom influences another over time, independent of changes in average symptom levels (Bringmann et al., 2013). Moreover, longitudinal networks can identify which symptoms are most predictive of others at later time points and which are most influenced by earlier symptoms. An example of a longitudinal network is shown in Figure 2, where the edge from node 3 (“Difficulty Concentrating”) to node 5 (“Sadness”) indicates that an increase in difficulties concentrating is predicted by an increase in sadness.

Figure 2

Example of Longitudinal Network



Note. A longitudinal network in which the nodes (circles) represent symptoms, and the edges represent the associations between symptoms from one measurement occasion to the next. Only green edges are observed in the network, indicating that the increase in one symptom tend to be associated with increases in other symptoms. The figure is adapted from Lydon-Staley et al. (2021).

The possibility to represent these associations among symptoms allows for a better understanding of the dynamics of psychological disorders over time (Borsboom & Cramer, 2013), which can inform treatment planning and the targeting of specific symptoms (Hofmann et al., 2016). However, it is important to emphasize that these networks are fundamentally statistical models representing conditional associations and, therefore, do not inherently indicate causal relationships (Ryan et al., 2022).

NA faces limitations in clinical psychology, particularly when it comes to incorporating this complexity at the individual level. To date, NA has predominantly been applied to estimate networks based on cross-sectional data, where symptoms are assessed across a group of individuals

at a single point in time (i.e., cross-sectional networks) (Burger et al., 2023). As a result, these cross-sectional networks cannot capture the dynamic relationships between symptoms or track their progression within individuals over time (Jordan et al., 2020). This limitation is important, especially considering that clinical psychology interventions are typically provided on an individual basis (Norcross & Wampold, 2011). Understanding the symptom dynamics of each person is essential for effective clinical practice.

From Network Analysis to Fully Idiographic Network Analysis

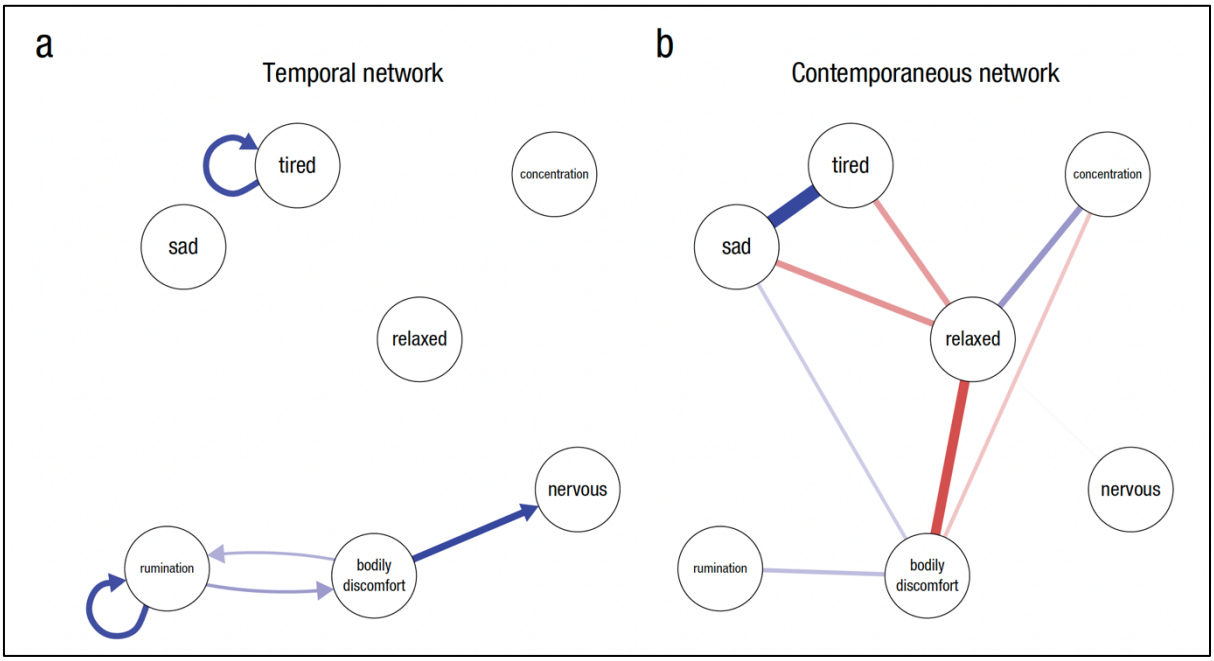
Given the limitations of group-level inferences (Uher, 2021), mental health research has increasingly shifted toward an idiographic perspective. Numerous studies have highlighted the importance of focusing on individuals rather than groups, prompting the development of methods to reach idiographic rather than nomothetic conclusions (Evans et al., 2023; Piccirillo & Rodebaugh, 2019; Piccirillo et al., 2019). This shift has led to a rise in studies employing single-case designs and personalized interventions (Miller et al., 2021; Nye et al., 2023; Rochat et al., 2018). Emphasize the individual is not new to clinical science (Molenaar, 2004) and is deeply rooted in the "therapist's dilemma", which refers to the challenge of treating a single individual based on group-level data (Levine et al., 1992).

In response to the limitations of cross-sectional data and the growing call for personalization in mental health research (Piccirillo & Rodebaugh, 2019), the network approach to psychopathology has increasingly adopted an idiographic perspective. In particular, person-centered research using time-series designs has given rise to a "fully idiographic" approach within the network framework. This approach examines the relationships between variables within a single individual over multiple time points (Piccirillo & Rodebaugh, 2019). Fully Idiographic Network Analysis (FINA) enables the estimation of person-specific networks by assessing dynamic interactions between symptoms and symptom progression over time. These person-specific networks can be either "temporal" or "contemporaneous," depending on the measurement window (Figure 3), as further detailed in Chapter 2 of this dissertation.

FINA offers a promising approach to exploring the complexity of symptoms within individuals and advancing clinical practice. However, a detailed description of its methodological characteristics and further information on its feasibility in clinical settings are still needed. This dissertation addresses these gaps by elaborating on the methodology of FINA and examining its practical applications in clinical settings.

Figure 3

An Example of Fully Idiographic Network Analysis



Note. Blue edges indicate positive relationships, and red edges indicate negative ones, with edge width and intensity reflecting the strength of the relationship. Panel (a) displays a temporal network, while Panel (b) shows a contemporaneous network. This figure is adapted from Epskamp, van Borkulo, et al. (2018).

Objectives of the Present Dissertation

This dissertation aims to investigate the clinical validity and utility of FINA in clinical practice. Moving from an exploration of FINA empirical research using FINA to estimate person-

specific networks in individuals with mental health conditions, it then explores FINA's potential in clinical practice.

Chapter 2 presents a systematic scoping review of studies applying FINA in mental health, highlighting common methodological practices and trends, while identifying areas for improvement. This review sets the stage for understanding how FINA has been applied to date and highlights further developments needed for its effective application in clinical research and practice.

Chapter 3 describes an empirical study testing the clinical validity and utility of FINA by comparing empirical symptom networks, estimated on patient data using FINA, with clinician-predicted symptom networks in their ability to predict subsequent patient functioning. Additionally, the study explores both clinicians' and patients' perspectives on FINA's utility in routine clinical settings.

Chapter 4 presents a general discussion on the clinical validity and utility of using NA to construct person-specific networks, with a focus on the findings, limitations, and implications of both the scoping review and empirical study, as well as directions for future research.

The overarching goal of this dissertation is to advance personalized, data-driven approaches in clinical psychology by examining the clinical validity of FINA and evaluating its applicability in clinical practice. This work assesses FINA's potential as a tool for predicting patient functioning and improve treatment through support for more individualized interventions.

Chapter 2

A Systematic Scoping Review of Fully Idiographic Network Analysis in Mental Health

Abstract

The network analysis (NA) approach is widely used in mental health research to describe a number of psychological conditions. NA has predominantly relied on cross-sectional data, to characterize the relationships between symptoms across individuals at a single time point. However, fully idiographic network analysis (FINA) allows for a more personalized perspective by estimating symptom networks at the individual level using intensive data collection. Because FINA is an analytical approach that started to emerge only in recent years, a comprehensive overview is needed of the methodological and analytical strategies employed in constructing person-specific networks. To map common practices and identify emerging trends and gaps, we conducted a scoping review of the scientific literature using FINA in mental health. We searched MEDLINE, PsycINFO, Scopus, and Web of Science for peer-reviewed journal articles (January 2011-March 2022). The initial search identified 7,422 resources, of which 23 were included in the review. Information was extracted on study and sample characteristics, data collection methods, and data analytic techniques. We observed high heterogeneity between the studies. However, commonly employed data collection methods included experience sampling and ecological momentary assessment, and the FINA model most frequently employed was graphical vector auto-regression. Most studies estimated both contemporaneous and temporal networks, and fewer than half shared their data in accordance with open science practices. We offer recommendations to guide researchers in planning, conducting, and reporting FINA studies, addressing current gaps and future directions in the rapidly expanding application of FINA in mental health research to help overcome methodological challenges.

Introduction

The nomothetic approach in psychological science focuses on examining interindividual differences to discover general laws that apply to the entire population (Lyon et al., 2017; Molenaar, 2004). Conversely, the idiographic approach examines intraindividual variation across time and contexts to make person-specific predictions (Lyon et al., 2017). Although traditional research practices in mental health are predominantly nomothetic and based on large groups of people, there is a growing recognition of the need for case-based, idiographic designs (Beltz et al., 2016; Piccirillo et al., 2019; Piccirillo & Rodebaugh, 2019) due to the awareness that psychology is fundamentally rooted in the study of individual processes (Molenaar, 2004). This shift is further driven by the primary goal in mental health settings to apply effective, personalized interventions tailored to individual patients (Howard et al., 1996). Nonetheless, the nomothetic–idiographic debate is still open. For instance, "the therapist's dilemma" – treating a single individual using group-level information (Levine et al., 1992) – is still a concern in the field of mental health (Piccirillo & Rodebaugh, 2019).

Despite its long tradition, nomothetic research has significant limitations (Fisher et al., 2017). For instance, psychological processes are nonergodic, therefore the results obtained from analyses of interindividual variation will not be the same as those obtained from analyses of intraindividual variation (Molenaar, 2004). Indeed, this is reflected in the substantial heterogeneity within diagnoses, as well as in symptom trajectories across individuals (Wright et al., 2015; Yaroslavsky et al., 2013). Consequently, the importance of conducting more single-case analyses has been highlighted (Smith, 2012). The nomothetic approach overlooks the dynamic and interconnected nature of symptoms within individuals across time (Fisher, 2015; Fisher et al., 2017). By relying on statistical methodologies that aggregate data across multiple individuals, it fails to capture the within-individual dynamics (Fisher et al., 2011). To adequately account for these idiographic, dynamic processes, it is essential to assess symptoms in single individuals over repeated occasions (Lyon et al., 2017).

Recently, the nomothetic-idiographic debate in mental health research has been intensified by the emergence of the network approach to psychopathology (Borsboom, 2017; Borsboom & Cramer, 2013). This approach conceptualizes mental disorders as complex networks of interconnected symptoms (Borsboom, 2017; Hofmann et al., 2016). The success of the network approach to psychopathology has been facilitated by the development of network analysis (NA) (Borsboom & Cramer, 2013). NA applied to symptom networks allows to estimate network models in which symptoms are nodes and connections between them are edges (Borsboom & Cramer, 2013). Within symptom networks, not all nodes are equally important. Centrality indices can help identify key nodes that may be more influential in the network. For instance, a central node might have strong direct connections with many nodes (strength centrality), be well connected to other nodes through direct or indirect paths (closeness centrality), or frequently lie on the shortest path between two other nodes (betweenness centrality) (Costantini et al., 2015). These indices have been proposed as measures of clinical relevance, to be used to guide the intervention by targeting the most central symptoms first (Fried et al., 2016). Network models and NA techniques have been successfully applied to describe a number of mental disorders (Contreras et al., 2019) and identify targets for prevention and intervention strategies (Fried & Cramer., 2017).

In clinical psychology, NA has predominantly been applied to estimate networks based on cross-sectional data, where symptoms are assessed from the entire sample at a single occasion (i.e., cross-sectional networks) (Burger et al., 2023). However, the shortcomings of the nomothetic approach are not overcome in cross-sectional networks, as they provide only a "snapshot" in describing psychopathology (Bystritsky et al., 2012). Furthermore, networks based on aggregated data reflect relationships observed at the group level, failing to account for potential differences in individual networks (Levinson et al., 2020). Inevitably, networks built using cross-sectional data cannot reveal dynamic relationships between symptoms or track symptom progression within individuals over time (Jordan et al., 2020). Yet, understanding individual symptom dynamics is crucial in clinical practice. For instance, depressive symptoms can rapidly shift from a healthy range

to severe impairment (Wichers et al., 2016), and individuals may transition between different psychiatric diagnoses over time (Garke et al., 2019).

Considering the call for personalization in mental health research (Piccirillo & Rodebaugh, 2019), the network approach to psychopathology has increasingly embraced an idiographic perspective. As part of this paradigm shift, NA has begun to be applied to intensive longitudinal data (Borsboom & Cramer, 2013), to investigate how symptoms interact over time (i.e., longitudinal networks) (Bringmann et al., 2022). Longitudinal networks allow to detect the influence of a symptom on another symptom from one time point to the next, independent of changes in the mean level of symptoms (Bringmann et al., 2013). Furthermore, longitudinal networks can identify which symptoms are most predictive of others at later time points and which are most influenced by symptoms at earlier time points (Jordan et al., 2020). This knowledge opens up significant opportunities for personalized intervention and case conceptualization, as it provides a clearer understanding of how a disorder originates and persists in a specific person (Borsboom & Cramer, 2013), informing treatment planning and the targeting of specific symptoms (Hofmann et al., 2016). However, these insights need further investigation, as these networks are statistical models that capture conditional association between variables. While they offer valuable information on symptom dynamics, they do not imply causal relationships (Ryan et al., 2022).

Particularly in person-centered research with time-series designs, a "fully idiographic" approach can be adopted within the network framework, which involves examining the relationships between variables within a single individual across multiple occasions (Piccirillo & Rodebaugh, 2019). This stands in contrast to other idiographic methodologies, such as multilevel network modeling, where individual networks are estimated considering within-person variability as pooled across individuals, rather than person-specific (Bringmann et al., 2013).

Fully Idiographic Network Analysis

Fully idiographic network analysis (FINA) allows to estimate person-specific networks by assessing dynamic relationships between symptoms and symptom progression within individuals

over time. Person-specific networks can be “temporal” or “contemporaneous” depending on the measurement window. Temporal networks represent predictive associations between symptoms, depicting how one node at a time *t* predicts itself or another node at the next window of measurement *t* + 1. In contrast, contemporaneous networks represent associations between symptoms within the same measurement window, showing how nodes are linked to one another at a single time point. In temporal networks, edges are directed, indicating which variables predict others at the subsequent time point. In contemporaneous networks, edges represent partial correlations between two nodes, controlling for all other nodes within the same measurement window as well as for temporal effects (Thonon et al., 2020). In FINA, various analytical models have been developed to estimate person-specific networks. One frequently used model is the graphical vector auto-regressive (gVAR) model (Epskamp, Waldorp, et al., 2018). This model extends the basic lag-1 VAR model, which estimates how variables at one time point predict variables at the next time point, by modeling the residuals within time points to estimate a partial contemporaneous network (Wild et al., 2010). However, an overview is lacking of the analytical techniques most commonly used to construct person-specific networks.

The application of FINA to obtain person-specific network requires intensive data collection. A number of intensive data collection methods are available. For instance, ambulatory assessment (AA; Trull & Ebner-Priemer, 2013) enables the gathering of data from individuals in their natural environments. AA includes methodologies such as experience sampling methods (ESM; Larson & Csikszentmihalyi, 1983), which traditionally focus on the intensive measurement of internal affective states, ecological momentary assessment (EMA; Shiffman et al., 2008), which typically also includes the monitoring of behaviors and physiological variables, and daily diary methods (Gunthert & Wenze, 2012). Recent advances in digital technologies and their accessibility have promoted an increasing use of AA methods in psychology research for the intensive monitoring of psychological processes in daily life (Ellis, 2020; Stange et al., 2019). However, there is no clear consensus on the best data collection method for conducting FINA.

Aims of the Present Study

Person-specific networks are increasingly used in psychological research, and significant efforts are being made for their implementation in mental health settings (Burger et al., 2020). Understanding the psychopathology of a single patient and its trajectories is crucial for a clinician. Therefore, FINA is regarded as a promising tool worthy of being disseminated and implemented in clinical practice.

Because FINA is an analytical approach that started to emerge only in recent years, no guidelines are available for its implementation. Studies that employed FINA to infer person-specific networks in mental health used different methodologies and analytic strategies to answer different research questions. Indeed, researchers who adopt an idiographic approach carefully consider individual differences. For instance, certain individuals may encounter challenges with intensive data collection methodologies, while some others may be more engaged. Additionally, some researchers may prioritize the dynamic evolution of symptoms within the patient over time, and some others the contemporaneous relationships between symptoms. An understanding of FINA research methods can contribute to improve its applications in mental health, addressing the disparity between clinical practice and clinical research. As a result, the current state of the field requires a comprehensive summary to address this variability and create a suitable framework for researchers interested in using FINA to construct person-specific networks.

Some reviews have been published on NA. For instance, Contreras et al. (2019) conducted a systematic review of empirical studies that applied NA to explore psychopathology. Robinaugh et al. (2019), in their review of the network approach literature, also considered theoretical and methodological contributions, in addition to empirical ones. More recently, Blanchard et al. (2023) offered an overview of data collection and analytical practices in research investigating temporal network dynamics of psychological variables at the group level. However, to our knowledge, no review has specifically focused on FINA in mental health.

Therefore, the purpose of this work is to review empirical research that estimated person-specific networks of psychological variables in individuals with a mental health condition, aiming to identify trends and gaps in the application of FINA methodologies in mental health research. We conducted a scoping review as it is especially suitable for mapping emerging and rapidly evolving research areas, and for synthesizing studies with different methodological approaches (Peterson et al., 2017). A scoping review is ideal when the aim is to identify common features across studies rather than answer specific questions (Munn et al., 2018). Accordingly, this review seeks to describe the practices employed in conducting FINA, highlight trends and pinpointing areas for improvement. The ultimate goal is to provide guidance for future researchers to make informed choices regarding study planning, data collection and analysis, and the reporting of relevant information.

Methods

Search Strategy

To conduct our scoping review, we followed the PRISMA extension for scoping reviews guidelines (PRISMA-ScR; Tricco et al., 2018).

Keywords searches were conducted in MEDLINE, PsycINFO, Scopus, and Web of Science, using a time restriction from January 2011 to March 2022. Variations of the following search string were used depending on the database: ((network*) AND (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*) AND (idiographic OR within subject* OR single subject* OR individual level* OR within person OR person centered OR person specific OR personalized)) OR ((idiographic) AND (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*)). The combination of the search terms was applied to title, abstract and keywords (Appendix A).

Inclusion and Exclusion Criteria

Research articles were included if they met the following characteristics: a) were original peer-reviewed research studies, b) were written in English, Spanish, or Italian, c) applied fully

idiographic (n = 1) analytical methods to time-series data to construct person-specific psychological networks, and d) involved participants with a mental health condition.

We excluded: a) non-original research articles (e.g., chapters, editorials, reviews, commentaries, study protocols), b) qualitative studies, c) validation studies, d) modelling/simulation studies without application in a real-world context, e) studies not involving humans, f) studies including participants without a mental health condition, g) studies that do not address psychological variables or use non-psychological networks (e.g., social NA, thematic NA, brain NA), h) studies with a cross-sectional design, i) studies applying NA methods without a fully idiographic approach (n > 1) (e.g., multilevel VAR; Bringmann et al., 2013), j) studies applying fully idiographic methods without a network approach (e.g., P-technique; Cattell, 1963), and k) studies not adopting a fully idiographic approach nor using NA methods (e.g., time-lagged hierarchical linear modeling; Bauer et al., 2006).

Study Selection Process

After removal of duplicates, the title and abstract of all identified records were screened by two independent reviewers. The same two reviewers then independently evaluated the full-text of the selected papers. Any disagreements were solved by discussion until consensus was reached.

Data Extraction

Following Blanchard et al. (2023), the information extracted from the selected studies included study and participant characteristics (i.e., reanalysis of pre-existing data, total sample size, number, age, gender, diagnosis of the individual(s) whose data were analyzed with FINA, setting of recruitment, compensation of participants), data collection (i.e., method and device used to collect intensive longitudinal data, timescale and length of data collection, sampling scheme, number and type of measured variables) and data analysis methods (i.e., missing data handling, testing of assumptions and correction for violations, treatment of overnight lag, testing for node overlap, analytical model and software used for FINA, variables used for node representation and number of nodes in the network, type of networks estimated, centrality indices, testing of network stability,

network comparison within and/or across individuals), and open science practices (i.e., study pre-registration, sharing of data and codes).

Two reviewers independently extracted the information from the selected studies and resolved any disagreements by consensus.

Results

Searches in the databases gave a total of 7,442 resources, which were reduced to 4,916 after removal of duplicates. After abstract and title screening, the full-text of 118 articles was assessed for eligibility, and 23 studies were selected for inclusion. Figure 1 shows the PRISMA flow diagram detailing the search and screening process and reasons for exclusion.

Study and Participants' Characteristics

Fifty-two percent of the included articles (n = 12) used data from open repositories or reanalyzed pre-existing data. The total sample size greatly varied between articles, ranging from 1 to 1,272 individuals. Twenty-two percent of the included articles (n = 5) were single-subject studies. The highest number of single individuals whose data were analyzed with FINA was 255 (M = 41.5, SD = 63.8). On average, 76.8% of the participants were included in FINA analyses. About 28% of studies with $n > 1$ (n = 5) reported the results of FINA (either in the main text, supplementary materials, or open science repositories) only for a subsample (10.4%, on average) of the individuals analyzed, primarily for illustrative purposes. The highest number of individuals analyzed with FINA whose FINA results were reported was 133 (M = 18.2, SD = 33.8). The mean age of participants analyzed with FINA ranged from 12 to 60.4, and the mean percentage of females was 68%. In 34.8% of the studies (n = 8), the most frequent diagnosis was depression. Participants were recruited from the community in 34.8% of studies (n = 8) and from outpatient settings in 26% of studies (n = 6). However, 26% of studies (n = 6) did not report the recruitment setting. Participants were compensated in 21.7% of studies (n = 5). An overview of participant characteristics is presented in Table 1. Detailed information is available in Appendix B.

Figure 1

PRISMA Flowchart Outlining the Study Selection Process

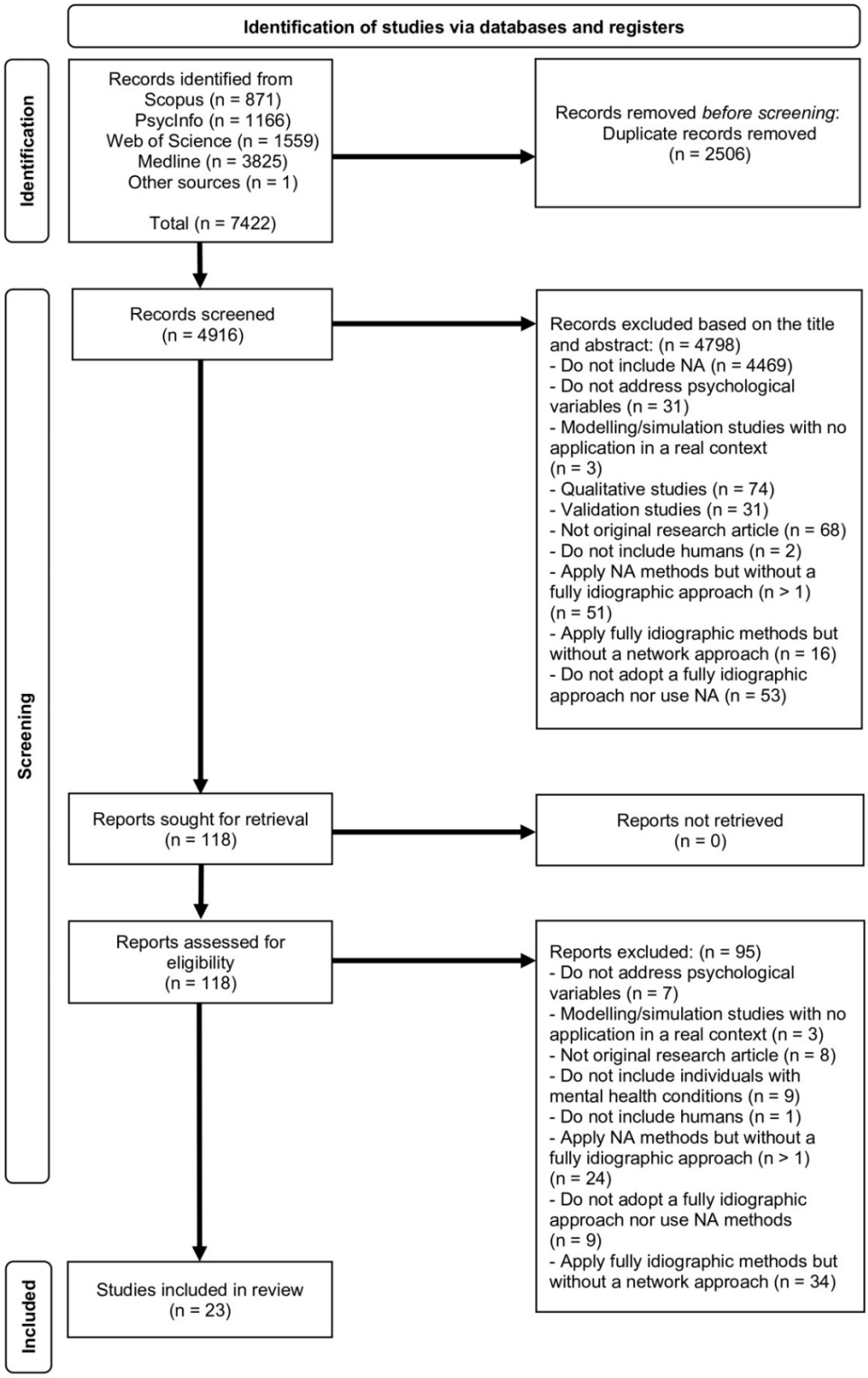


Table 1

Overview of Participants' Characteristics in the Selected Studies

Variable	*M*	*SD*	Median	Min	Max
Total number of participants	167.9	348	40	1	1,272
Participants analyzed with FINA					
n	41.5	63.8	12	1	255
%	76.8	40.9	100	0.2	100
Age (n = 17 studies)	36.2	13.7	34.4	12	60.4
Females (%) (n = 18 studies)	68	32.6	66	0	100
Diagnosis (%) (n = 21 studies)					
Depression	33.3	43.6	0	0	100
Comorbidity	23.1	38.6	0	0	100
Eating disorder	13.6	35.1	0	0	100
Obsessive-compulsive disorder	4.6	21.3	0	0	100
Personality disorder	4.6	21.3	0	0	100
Post-traumatic stress disorder	4.6	21.3	0	0	100
Schizophrenia	4.6	21.3	0	0	100
Tobacco withdrawal	4.6	21.3	0	0	100
Anxiety	3.4	11.24	0	0	51.1
Bipolar disorder	0.9	4	0	0	18.8
Adjustment disorder	0.4	1.8	0	0	8.3
Not reported	0.4	1.8	0	0	8.3
Participants analyzed with FINA whose FINA results are reported					
n	18.2	33.75	3	1	133
%	79.5	39.9	100	0.6	100
Age (n = 17 studies)	36.4	13.6	35	12	60.4
Females (%) (n = 17 studies)	71.8	35.2	91.2	0	100
Diagnosis (%) (n = 21 studies)					
Depression	34.1	46.1	0	0	100
Comorbidity	26.6	41.5	0	0	100
Eating disorder	14.3	35.9	0	0	100
Obsessive-compulsive disorder	4.8	21.8	0	0	100

Personality disorder	4.8	21.8	0	0	100
Post-traumatic stress disorder	4.8	21.8	0	0	100
Schizophrenia	4.8	21.8	0	0	100
Tobacco withdrawal	4.8	21.8	0	0	100
Adjustment disorder	0.4	1.8	0	0	8.3
Anxiety	0.4	1.8	0	0	8.3
Not reported	0.4	1.8	0	0	8.3

Data Collection Methods

EMA and ESM were used in 65% of studies (*n* = 15) to collect intensive longitudinal data, with electronic devices employed in 93.3% of cases (*n* = 14). Among these studies, four assessments per day were conducted in 40% (*n* = 6) and five assessments per day in 33.3% (*n* = 5). Assessment prompts were delivered at fixed intervals in 46.7% of cases (*n* = 7), and at pseudo-random times (i.e., prompts sent randomly within a fixed interval) in 33.3% (*n* = 5). Across all 23 studies, the frequency and length of assessment varied greatly: The frequency ranged from 10 assessments per day (4.3%) to 1 per month (4.3%), and the length from 7 days to 48 months. The maximum number of total timepoints ranged from 7 to 840, with a mean of 129.4 across studies. Ten studies (43.5%) reported the percentage of completed timepoints, which was, on average, 83.3%. Considering that in some studies (8.7%, *n* = 2) items were personalized and their number varied across participants, the mean maximum number of items administered at each assessment was 17.5. Items were rated on an ordinal scale in 47.8% of studies (*n* = 11), and on a continuous scale in 34.8% (*n* = 8). A summary of data collection methods is provided in Table 2, with further details available in Appendix B.

Table 2

Overview of Data Collection Methods in the Selected Studies

		Device				Timescale				Max *n* timepoints			Sampling scheme (*n* = 15)			Max *n* items at each timepoint (*n* = 22)			Type of items				
Method	***n* studies (%)**	**Electronic**	**Paper**	**Face to face/phone**	**NR**	**Daily**	**Multiple daily**	**Weekly**	**Monthly**	***M* (*SD*)**	**Median**	**Range**	**Fixed**	**Pseudo-random**	**NR**	***M* (*SD*)**	**Median**	**Range**	**O**	**C**	**OC**	**D**	**NR**
EMA	10 (45.4)	90	-	-	10	0	100	0	0	94.3 (35.7)	95	28-150	60	20	20	19.1 (15.7)	13	5-55	30	70	0	0	0
ESM	5 (22.7)	100	-	-	0	0	100	0	0	285.4 (321.4)	140	70-840	20	60	20	13.4 (5.1)	14	7-21	80	20	0	0	0
Interview	2 (9.1)	-	-	50	50	0	0	50	50	96.5 (68.6)	96.5	48-145	-	-	-	8 (0)	8	8	0	0	50	50	0
Self-report	3 (13)	0	66.7	0	50	66.7	0	33.3	0	91.3 (35.8)	100	52-122	-	-	-	26.5 (6.4)	26.5	22-31	50	0	33.3	0	50
ROM	2 (9.1)	50	0	0	50	0	0	100	0	20 (18.4)	20	7-33	-	-	-	21 (5.7)	21	17-25	100	0	0	0	0
Diary	1 (9.1)	100	0	0	0	100	0	0	0	100	-	-	-	-	-	16	-	-	100	0	0	0	0
Total	23 (100)	69.6	8.7	4.3	17.4	13	65.2	13	4.3	129.4 (164.8)	100	7-840	46.7	33.3	20	17.5 (11.7)	14	5-55	47.8	34.8	8.7	4.3	4.3

Note. Unless otherwise specified, percentages are reported. M = mean; SD = standard deviation; O = ordinal; C = continuous; OC = both ordinal and continuous; D = dichotomous; EMA = ecological momentary assessment; ESM = experience sampling method; ROM = routine outcome monitoring; NR = not reported.

Data Analysis

A summary of the data analysis methods used in the selected studies is presented in Table 3. Detailed information is available in Appendix B.

Data Preparation

Among the studies that were not single-subject designs (n = 18), 12 (66.7%) did not specify any criteria for excluding cases from statistical analyses due to missing timepoints, while 6 (33.3%) excluded cases based on the amount of missing timepoints. Specifically, 3 studies (50%) required a minimum response rate of 80% for inclusion in the analysis, one study (16.7%) set the threshold for inclusion at 71.7%, another study (16.7%) at 57.1%, and one (16.7%) required a 30% response rate for inclusion. Only one study (4.8%) reported checking the type of missing data, while information on missing data handling was provided in 61.9% of studies (n = 3). Most of these studies (30.8%, n = 4) applied multiple imputation methods. Among studies using FINA models that assumed a normal distribution of the data (87%, n = 20), only 2 studies (10%) checked this assumption (by means of skewness and/or kurtosis) and implemented corrective actions. Among studies using FINA models that assumed stationarity (i.e., stability of means, variances, and relationships of each variable with itself and others over time) (87%, n = 20), 45% (n = 9) reported the method used to check this assumption, mostly by testing for linear trends (44.4%, n = 4). Additionally, 60% (n = 12) reported the method used to correct for non-stationarity, with detrending procedures applied in 91.7% of cases (n = 11). Among EMA/ESM studies that reported treatment of overnight lag (93.3%, n = 14), removal of the lag (i.e., the first measurement of a day was not regressed on the last measurement of the previous day) was used in 78.6% of cases (n = 11). Among studies that used individual items for network construction (87%, n = 20), only four (20%) checked for node overlap, using correlation analyses.

Network Estimation

In the majority of studies (43.5%, n = 10), the model used to estimate FINA was gVAR. Other VAR models included principal component VAR (PC-VAR; 4.3%, n = 1), sparse VAR

(sVAR; 4.3%, *n* = 1), mixed VAR (mVAR; 4.3%, *n* = 1), Bayesian VAR (4.3%, *n* = 1) and time series latent variables gVAR (ts-lvgVAR; 4.3%, *n* = 1). Two studies (8.7%) used unified structural equation modeling (uSEM), two (8.7%) used dynamic time warp analysis (DTW), two (8.7%) used dynamic factor analysis (DFA), one (4.3%) used dynamic time series multiple linear regression (DTSMLR), and one (4.3%) used a contingency measure-based network (ConNEct). R was used for FINA estimation in 95.7% of studies (*n* = 22). Variables for node representation were exclusively individual items in 60.9% of studies (*n* = 14), and a mix of individual items and composites in 26.1% of studies (*n* = 6). Composites alone were used in studies that employed ts-lvgVAR and uSEM (13%, *n* = 3). The mean maximum number of nodes was 12.1.

Most studies (73.9%, *n* = 17) estimated both contemporaneous and temporal networks, with 17.6% (*n* = 3) combining them into a single plot. Centrality indices were estimated for both networks–strength for contemporaneous networks and instrength and outstrength for temporal networks–in 35.3% of these studies (*n* = 6). Only one study (4.3%) evaluated network stability (i.e., robustness to sampling error), using a data-dropping bootstrap method. A visual comparison of networks was conducted in 47.8% of studies (*n* = 11) across different participants, in 8.7% (*n* = 2) within participants, and in 17.4% (*n* = 4) both across and within participants. Edge density (i.e., number of edges) was the network characteristic most frequently compared across and/or within participants (65.2%, *n* = 15).

Table 3

Overview of Data Analytic Methods in the Selected Studies

		Data preparation								Network estimation											
Model used for FINA	***n* studies (%)**	**Report check for type of missing data**	**Report method of missing data handling**	**Report check for normality**	**Report method to correct for non-normality**	**Report check for stationarity**	**Report method to correct for non-stationarity**	**Report treatment of overnight lag (*n* = 15)**	**Report check for node overlap (*n* = 20)**	**Variable used for node representation**			**Max *n* of nodes**			**Type of network**			**Estimation of centrality indices**		**Report assessment of network stability**		**Software for FINA estimation (%)**
										II	**CS**	**II CS**	***M* (*SD*)**	**Median**	**Range**	**CN**	**TN**	**CN TN**	**CN (*n* = 21)**	**TN (*n* = 19)**	**CN (*n* = 21)**	**TN (*n* = 19)**	
gVAR	10 (43.5)	10	70	0	0	60	50	87.5	30	60	0	40	10.6 (3.1)	10.5	7-15	100	100	0	70	40	0	0	R (100)
PC-VAR	1 (4.3)	-	-	0	0	0	0	-	100	0	0	100	23	-	-	0	0	100	0	100	0	0	R (100)
sVAR	1 (4.3)	0	100	100	100	0	100	100	0	100	0	0	14	-	-	0	100	0	-	100	-	0	R (100)
mVAR	1 (4.3)	0	100	0	0	0	100	100	0	100	0	0	6	-	-	100	0	0	100	-	0	-	R (100)
BayesianVAR	1 (4.3)	0	100	0	0	0	100	100	0	100	0	0	5	-	-	100	100	0	0	0	0	0	R (100)
ts-lvgVAR	1 (4.3)	0	100	0	0	100	100	100	NA	0	100	0	5	-	-	100	100	0	100	100	100	100	R (100)
uSEM	2 (8.7)	0	0	50	50	0	50	50	NA	0	100	0	5 (1.4)	5	4-6	0	0	100	0	0	0	0	LISREL (50), R (50)
DTW	2 (8.7)	0	50	NA	-	NA	-	-	0	100	0	0	21 (5.7)	21	17-25	100	0	0	50	-	0	-	R (100)
DFA	2 (8.7)	0	50	0	0	50	100	100	0	50	0	50	20.5 (0.7)	20.5	20-21	100	100	0	100	100	0	0	LISREL and R (100)
DTSMLR	1 (4.3)	0	0	0	0	100	100	-	0	100	0	0	19	-	-	0	100	0	-	100	-	0	R (100)
ConNEcT	1 (4.3)	-	-	NA	-	NA	-	-	0	100	0	0	8	-	-	100	0	0	0	-	0	-	R (100)
Total	23 (100)	5	61.9	10	10	45	60	93.3	20	60.9	13	26.1	12.1 (6.3)	11	4-25	78.3	69.6	13	47.6	47.4	4.8	5.3	R (96), LISREL (13)

Note. Unless otherwise specified, percentages are reported. NA = not applicable; VAR = vector auto-regression; gVAR= graphical VAR; DTW = dynamic time warp analysis; DFA = dynamic factor analysis; uSEM = unified structural equation modeling; ts-lvgVAR = time series latent variables gVAR; sVAR = sparse VAR; PC-VAR = principal component-VAR; mVAR = mixed VAR; DTSMLR = dynamic time series multiple linear regression; ConNEcT = contingency measure-based network; II = individual items; CS = composite scores; IICS = both individual items and composite scores; CN = contemporaneous network; TN = temporal network; CNTN = both contemporaneous and temporal networks combined in a same plot.

Open Science Practices

Only 1 study (4.3%) was preregistered. Data were shared in eight studies (34.8%), and analysis code in 12 (52.2%), either in supplementary materials or open science repositories (see Appendix B).

Discussion

While reporting standards for cross-sectional NA have been established (Burger et al., 2023), to the best of our knowledge, no guidelines currently exist for NA of $n = 1$ time-series data. Therefore, this scoping review was conducted to overview data collection, analysis, and reporting practices in FINA for mental health research. The results highlight significant heterogeneity across studies, likely due to the absence of clear guidelines. Considering that the application of FINA is increasing at a rapid rate in mental health research, providing guidance for future studies on constructing person-specific networks is essential. Based on the results of this scoping review and relevant literature, we propose recommendations that focus on study planning, data collection, analysis, and reporting, while highlighting trends and gaps in the field. We provide these recommendations also in the form of a checklist in Appendix C, intended as a guide for reporting FINA studies. This checklist can also assist researchers in planning FINA studies and serve as a guide during the preregistration phase.

Study Planning

The decision to conduct FINA should align with research aims that focus on dynamic processes within single individuals, addressing research questions that are difficult to answer using aggregated group data. For instance, Fisher et al. (2017) investigated the idiographic temporal dynamics of mood and anxiety symptomatology, highlighting how individuals evolve over time–an aspect often missed in cross-sectional NA that examines average symptom associations within groups. FINA is also valuable for exploring differences between intraindividual and group-level networks as shown by Levinson, Vanzhula, et al. (2018) and

de Vos et al. (2017), who noted the limitations of generalizing group-level symptom connections to individuals.

Data Collection

About two thirds of the included studies used electronic devices to collect intensive data, primarily through EMA or ESM designs. Other methods, such as routine outcome monitoring (ROM), diaries, paper-and-pencil questionnaires, and interviews, were also used. A key difference among these methods is the timescale of assessments: EMA and ESM involve multiple daily assessments, while ROM, diaries, questionnaires, and interviews are typically conducted weekly or daily. Higher assessment frequency over extended periods can increase participant dropout, yet less intensive methods may miss short-term fluctuations. Recently, tools for intensive data collection have advanced, allowing for a more user-friendly and personalized subjective experience collection in mental health (Schick et al., 2023). Additionally, researchers can monitor subjective experiences during data collection (Kaur et al., 2021) and follow open-source guidelines to minimize burden and improve data quality (Myin-Germeys & Kuppens, 2022).

EMA and ESM designs are well-suited for gathering data from individuals in their natural environment, capturing recent states and overcoming recall biases associated with traditional self-report questionnaires (Shiffman et al., 2008). It is crucial to tailor the timescale to the variability of the clinical aspect being investigated. For example, Wright et al. (2015) used diaries over 100 days to assess behaviors related to personality pathology, while Epskamp, van Borkulo, et al. (2018) employed ESM over two weeks to monitor symptoms like sadness, tiredness, and rumination in a depressed patient, which fluctuate frequently throughout the day. In the reviewed studies, the maximum number of timepoints ranged from 7 to 840, with a median of 100, and the number of items per timepoint ranged from 3 to 55, with a median of 14. It is recommended to use at least 75 time points when

estimating a network with up to 6 nodes to ensure good sensitivity (i.e., the proportion of true correctly included in the network) (Mansueto et al., 2023). Although the absolute maximum number of timepoints for FINA is unclear, planning as many as feasible is advised, balancing participant burden with the need to capture temporal variation accurately. For instance, high daily assessment frequency can be manageable if the overall duration is kept short (Wrzus & Neubauer, 2023). When patients comply, intensive assessments can enhance the understanding of psychological processes. For example, Scholten et al., (2022) conducted three daily assessments over 30 days, with up to 35 items per assessment, achieving a completion rate of 87.2% of the timepoints. This high level of compliance enabled the estimation of person-specific networks for a better understanding of patients' functioning. Ensuring such compliance can be challenging but may be improved by using incentives (Wrzus & Neubauer, 2023) and personalized data collection applications (Pieritz et al., 2021), which help to maintain engagement over time.

Most EMA/ESM studies in this review used a fixed sampling scheme, where participants completed assessments at consistent intervals. In contrast, a random sampling scheme schedules assessments unpredictably throughout the day, which can result in uneven data distribution and may not accurately capture the entire day. Fixed sampling generally improves compliance (Vachon et al., 2019) and facilitates the collection of equidistant time-series data, a requirement for many FINA models, such as VAR (Janssens et al., 2018). A pseudo-random design, where assessments are conducted randomly within fixed intervals, also violates this assumption but may be acceptable if the variation between measurement points is minimal (Bringmann et al., 2013).

Finally, about half of the included studies measured variables exclusively on ordinal, Likert-type scales. However, continuous variables are recommended, as ordinal scales may limit variability in person-specific networks (Piccirillo & Rodebaugh, 2019).

Data Analysis

Missing Data

In most studies with $n > 1$, no specific criteria were defined for including cases in the analyses based on the amount of missing timepoints. However, among the few studies that did, a common criterion was the completion of at least 80% of timepoints for inclusion in FINA analyses. Following the recommendations of Mansueto et al. (2023), researchers should include participants who have completed a sufficient number of timepoints to ensure a high proportion of true edges accurately identified, for example, at least 75 timepoints for a network with up to 6 nodes, (Mansueto et al., 2023). Additionally, the minimum threshold of completed timepoints should be determined considering the characteristics of the study population, as compliance in longitudinal studies can be influenced by various factors such as specific psychological issues or low self-discipline (Schreuder et al., 2023). Only one study checked the type of missing data. The reviewed studies mostly handled missing data through multiple imputation or by omitting missing data point. For example, Piccirillo and Rodebaugh (2022) used random forest imputation (Stekhoven & Bühlmann, 2012), while gVAR handles missing data with the "beepvar" function, which removes pairs of nonconsecutive responses (e.g., Epskamp, van Borkulo, et al. 2018). It is recommended that researchers first assess the type of missing data to ensure compatibility with the chosen handling method, as different methods require specific assumptions (e.g. full-information maximum likelihood estimation assumes data are missing at random) (Cham et al., 2017). Planned missingness is also recommended, allowing certain items to be omitted at each measurement point to create data that are missing completely at random or missing at random, thereby mimicking item nonresponse while managing participant burden (Mansueto et al., 2023).

Normality

Many FINA models, such as those based on VAR, assume normality (Epskamp, Waldorp, et al., 2018). Among the reviewed studies, only 2 checked for normality using skewness and kurtosis, and took corrective actions. For example, de Vos et al. (2017) applied a normal quantile transformation to adjust the data. Various methods are available to address non-normality, and researchers should choose based on the statistical properties of their data (Pek et al., 2018). Noteworthy, while violations of normality can occur for various reasons, there is no clear consensus on how they impact the estimation of person-specific networks (Epskamp, 2020).

Stationarity

Stationarity is a key assumption in most FINA models, but it is rarely met in practice (Epskamp, 2020). Less than half of the reviewed studies using models that assumed stationarity checked for it, typically by plotting the data to visually inspect time trends or testing for significant linear trends. Decomposing time-series data to identify seasonal trends in mental health conditions is also possible (e.g., Beard et al., 2019). To correct for non-stationarity, most studies applied detrending, which involves regressing time-series data on time and using the residuals for further analysis. In some cases, researchers assume stationarity by selecting data from stable phases, such as post-assessment periods (Epskamp, 2020). However, detrending significant trends is generally recommended to avoid sensitivity issues in both contemporaneous and temporal networks (Epskamp, van Borkulo, et al., 2018).

Overnight Lag

Some models assume equidistant data points, an assumption that can be violated by overnight lag, where a larger time difference occurs between the last assessment of one day and the first of the next. Most EMA/ESM studies addressed this by removing overnight lag, not regressing the first measurement of the day on the last of the previous day. Alternatively,

some approaches ignore overnight lag, treating nighttime as equidistant with methods like cubic spline interpolation. Another strategy treats overnight lag as missing data, applying continuous time modelling (Ryan & Hamaker, 2022). Unconstrained models are recommended, as they allow the use of all these methods and enable testing overnight lag independently from daytime lag (Berkhout et al., 2024).

Node Overlap

When individual items are used as nodes in a network, some may measure the same construct and have similar associations with other nodes, a phenomenon known as topological overlap (Fried & Cramer, 2017). This was evaluated in only one fifth of the included studies that used individual items as nodes, by assessing inter-item correlations. To manage overlap, researchers can combine highly correlated variables into a composite score or exclude one of the variables (Piccirillo & Rodebaugh, 2022; Scholten et al., 2022). This data driven approach can be facilitated using tools like the Goldbricker function in the 'networktools' R package (Jones, 2017). Alternatively, a theoretical approach can be used, where experts select items representing unique symptoms before analysis (Levinson, Brosof, et al., 2018). It is recommended to start with a theoretical approach, followed by a data-driven one (Levinson, Brosof, et al., 2018).

Analytical Models

Various modeling approaches were used to estimate person-specific networks, with VAR models being the most common, especially gVAR, which was used in 43% of the reviewed studies. Other VAR models included PC-VAR, which applies principal component analysis before running VAR on the components (Bulteel et al., 2018). de Vos et al. (2017) employed sVAR, a model that uses regularization techniques to reduce spurious edges, while Burger, Epskamp et al. (2022) introduced PREMISE, which integrates clinician expertise with patient data using Bayesian VAR. Howe et al. (2020) applied the mVAR model, which

accommodates mixed data types (e.g., ordinal, binary) by allowing each variable to follow its own distribution, to clustered time points that were identified through latent profile analysis. VAR models, particularly gVAR, are widely used and recommended for person-specific networks (Jordan et al., 2020). However, a key limitation is that their results are dependent on the measurement window's duration. If this duration is shorter than the symptom dynamics, key patterns may not be captured. The optimal duration for these windows varies between individuals and remains uncertain (Epskamp, van Borkulo, et al., 2018). It is advisable to thoroughly understanding the relevant timescale for capturing the symptom dynamics of interest before using these models.

Besides VAR models, other methods were used to estimate FINA in the reviewed articles. DTW analysis (Booij et al., 2021; Hebbrecht et al., 2020) clusters symptoms based on the similarity of their dynamics: symptoms with similar severity trajectories exhibit smaller calculated distances, whereas those with independent trajectories show larger distances. These distances are then organized into a matrix, which can be visualized as a network. A key advantage of DWT is that it does not require fixed intervals between measurements nor does it assume normality and stationarity in the data. However, DTW is limited to identifying similarities between symptom trajectories and does not infer the direction of influence among symptoms.

Three studies integrated SEM with VAR models, with two using uSEM (Lydon-Staley et al., 2021; Wright et al., 2015) and one employing tslv-gVAR (Epskamp, 2020). Combining SEM with VAR models allows for the inclusion of both latent and observed variables, overcoming the limitation of relying solely on observed variables and assuming that all measurements are free of error. Both models also overcome SEM's constraints related to local independence (i.e., the assumption that variables are uncorrelated with each other after accounting for latent variables) (Epskamp et al., 2017). The main distinction between

uSEM and ts-lvgVAR lies in their treatment of contemporaneous effects. ts-lvgVAR models these relationships as partial correlations, without assuming any specific direction of influence. In contrast, uSEM treats contemporaneous relationships as directed effects, interpreting relationships between variables at the same time point as cause-and-effect. While uSEM enables the modeling of relationship directions within the same time point, determining the direction of these effects can be more challenging than working with the non-directional associations modeled by ts-lvgVAR (S. Epskamp, personal communication, October 3, 2024).

DFA was used in two studies (Fisher et al., 2017; Reeves & Fisher, 2020) to identify latent factors that influence observed variables over time. DFA combines elements of factor analysis with time series analysis, capturing both the structure and time-lagged relationships among latent factors. Unlike uSEM and ts-lvgVAR, which manage both observed and latent variables, DFA specifically focuses on modeling the dynamics of latent variables underlying time-series data. As a result, it does not prioritize the dynamics among observed variables, adhering to a latent variable approach, which is something network theory seeks to transcend.

David et al. (2018) estimated the partial correlation matrix of the network using a DTSMLR. This approach examines the association between individual outcomes and predictors separately, which differs from VAR models that analyze the mutual influence of multiple variables simultaneously over time. Although the step-by-step linear regression process of DTSMLR is more computationally demanding, it offers more detailed insights into the individual contributions of each predictor. Additionally, this approach proves particularly valuable in scenarios where VAR models are unsuitable due to the extent and pattern of missing data (David et al., 2018).

Finally, ConNEcT was used in one study (Bodner et al., 2022) to investigate symptom co-occurrence, offering a unique capability of handling dichotomous variables and operating

without the assumptions of normality, stationarity, or equidistant measurements. Furthermore, unlike VAR models, the bivariate relations modeled by ConNEct remain unchanged when a variable is added or excluded. However, ConNEcT describes symptoms co-occurrence without determining the directional influences between the symptoms.

Each model has its strengths and limitations, and model selection should align with the researcher goals in applying FINA. gVAR models are the most commonly used in the FINA studies reviewed, particularly with EMA and ESM data. Therefore, researchers have access to a substantial body of literature and widely cited software tools such as psychonetrics (Epskamp, 2021a) or graphicalVAR (Epskamp, 2021b) for applying these models. gVAR simultaneously provides contemporaneous and temporal networks, making it particularly useful for researchers interested in studying both types of effects. PC-VAR is suitable for researchers interested in studying components related to observable variables, particularly when dealing with a high number of variables and significant risk of multicollinearity. sVAR is advantageous for handling high-dimensional data, where applying methods including penalties becomes crucial to control network complexity and ensure that only the most relevant relationships between variables are included. For those exploring theoretical and data-driven combinations, Bayesian approaches may be more suitable, as they incorporate prior knowledge and inform clinical decision-making. Bayesian VAR allows starting with an informed understanding defined by the clinician and updates the prior knowledge with new data as it is collected. This approach ensures that the model reflects both empirical evidence and clinical expertise, making it highly adaptable for personalized care. mVAR is useful for handling datasets that include multiple types of variables, such as categorical and continuous data. This flexibility is particularly valuable in clinical settings, where different types of data, such as gender (categorical) and drug dosage (continuous), coexist and may influence outcomes (Haslbeck & Waldorp, 2020).

For studying latent factor dynamics, models such as uSEM, tslv-gVAR, and DFA are preferable. Specifically, uSEM and tslv-gVAR are particularly valuable if the research aims to include observed variables along with latent constructs and to gain insights into contemporaneous relationships. Furthermore, according to our review, tslv-gVAR is distinguished as the only model that provides a method for evaluating network stability, according to the framework described by Epskamp (2020). Within tslv-gVAR, researchers can test network stability using a bootstrap method, similar to the standard practice in cross-sectional networks where stability testing is a key component of network estimation (Epskamp, Borsboom, et al., 2018). DFA is recommended for examining dynamic relationships between latent constructs, particularly when working with short time-series data (Molenaar, 1985).

DWT and ConNEct are particularly suitable when the focus is on symptom co-occurrence rather than direct influences between symptoms. Both models rely on contemporaneous associations: DTW reveals how pairs of symptoms evolve similarly, while ConNEct is adept at studying pairwise associations in binary data. In addition, neither model requires adherence to common assumptions of normality, stationarity, and equidistant measures, which are often challenging to meet in clinical settings.

Finally, DTSMLR is particularly useful when more parsimonious statistical models are unsuitable due to the number of missing observations. For instance, in the study by David et al. (2018), DTSMLR was applied effectively with 26% of missing timepoints. This method's capability to handle incomplete data makes it a valuable option for analyses where traditional models might be constrained by missing data.

Variables and Number of Nodes

Most studies solely used individual items as nodes, averaging 12.1 nodes per network. Researchers should be aware that increasing the number of variables can raise the risk of

overfitting (Babyak, 2004) and reduce predictive accuracy in person-specific models (Lafit et al., 2022). It is therefore recommended to keep the network as simple as possible by reducing the number of nodes. To keep networks manageable, it is recommended to reduce the number of nodes by using composite scores (e.g., Frumkin et al., 2021) or preliminarily applying dimension reduction techniques (Bulteel et al., 2018).

Type of Networks

Most studies estimated both contemporaneous and temporal networks. Temporal networks capture relationships among variables over time, while contemporaneous networks reveal associations that occur more rapidly. Both are valuable in mental health research. For example, somatic arousal linked to the anticipation of a panic attack is captured in contemporaneous networks due to its immediacy, while the relationship between somatic arousal and avoidance behavior, which unfolds over time, is more likely to appear in temporal networks (Epskamp, van Borkulo, et al., 2018). The choice network type should align with the research question and the psychopathological processes of interest. However, using both network types can offer a more comprehensive view of mental health dynamics (e.g., Levinson et al., 2021), so models that estimate both are recommended.

Network Stability

Stability tests evaluate whether a network's structure remains consistent with fewer observations, focusing on edge accuracy and centrality indices (Epskamp, Borsboom, et al., 2018). While cross-sectional networks often use bootstrap methods for stability, longitudinal person-specific methods for stability assessment are still evolving (Reeves & Fisher, 2020). Of the reviewed studies, only one (Epskamp, 2020) used a data-dropping bootstrap, which removes blocks of data from a participant's dataset. This method is recommended for evaluating person-specific network stability. Stability can also be viewed in terms of resilience of highly connected nodes, where disturbances (e.g., external events) may

temporarily disrupt the network's equilibrium. For person-specific networks in mental health research, it is helpful to report connectivity levels, distinguishing between strongly stable (pathological) and weakly stable (healthy) networks (Hofmann et al., 2016).

Centrality Indices

Strength centrality (i.e., the sum of absolute edge weights connected to a node was the most commonly used index for contemporaneous networks, while instrength (i.e., the sum of incoming absolute edge weights to a node) and outstrength (i.e., the sum of outgoing absolute edge weights from a node) were the most frequently estimated indices for temporal networks. Selecting the appropriate centrality indices is crucial to accurately capture node importance (Bringmann et al., 2019), particularly in mental health intervention science where centrality indices can help identify personalized treatment targets (e.g., Levinson et al., 2020). Degree centrality, which measures the total number of edges connected to each node, is recommended for this purpose and should be re-estimated whenever a node is targeted in treatment to assess changes in its connectivity (Castro et al., 2024).

Network Comparison

About half of the reviewed studies compared networks across and/or within participants using visual inspection. However, this approach can overestimate network heterogeneity due to sampling variation or power limitations (Hoekstra et al., 2023). To address this, more rigorous methods for testing individual differences in person-specific networks are recommended. For example, Hoekstra et al. (2024) proposed the Individual Network Invariance Test, and Siepe et al. (2024) developed a Bayesian modeling approach for assessing network differences.

Reporting

To enhance transparency, reproducibility, and replicability, authors should report all relevant information. Most studies with $n > 1$ reported only the demographic and clinical

characteristics of the total sample, but researchers using FINA are encouraged to provide detailed characteristics of each individual analyzed. Given the intensive data collection required for FINA, it is important to detail the data collection methods, including the device used, sampling scheme, and variables measured–details often missing in the reviewed studies. Researchers can refer to guidelines on Ambulatory Assessment for comprehensive reporting (Trull & Ebner-Priemer, 2020). For data analysis, researchers should specify how missing data were checked and handled, using checklists where available (Sidi & Harel, 2018). It is also essential to document procedures for checking and correcting normality, stationarity, overnight lag, and node overlap, especially if required by the FINA model used. Detailed steps for network construction should also be reported. In the reviewed studies, centrality indices were often underreported despite being estimated, and network stability assessment was ignored in nearly all studies.

Open Science

Preregistration is rarely used in FINA research, with only one pre-registered study in this review (Scholten et al., 2022). Given that over half of the included studies reanalyzed data from previous research, it is important to note that specific guidelines have been made available for pre-registering studies that use existing data (Mertens & Krypotos, 2022; van den Akker et al., 2021). We strongly encourage researchers to preregister their research questions, hypothesis, data collection procedures, variables, and data analysis plans. A number of tools are available for study preregistration, such as AsPredicted and the Open Science Framework (Nosek et al., 2022). About two third of included articles shared their data, and over half shared their codes. Sharing data and code is crucial, especially in complex longitudinal approaches like EMA/ESM, as it enhances transparency, reproducibility, and collaboration, allowing researchers to validate findings, explore new questions, and build on

existing work, ultimately advancing the field. We recommend clearly specifying where data and code are available, such as on the Open Science Framework (OSF).

Limitations

Despite our efforts, some relevant studies may have been missed. The search keywords may not have been fully exhaustive (e.g., the keyword "dynamic*" often used in person-specific network analysis, was not included). Limiting the review to peer-reviewed studies may have introduced publication bias, overrepresenting positive findings or well-executed studies and overlooking less favorable or unpublished research that could provide a more balanced view of the field. We did not assess the quality of the included studies, which could have offered insights into their methodological rigor and reliability. Consistent with the scoping review approach, our focus was on mapping the existing literature rather than addressing specific research questions, which may have limited the depth of analysis to a broad descriptive overview of the studies.

Conclusion

This scoping review provided an overview of data collection and analysis methods used in studies applying FINA in mental health research. Future scoping reviews could investigate additional network analysis methods that assess dynamic relationships between symptoms within individuals, offering comparisons to fully idiographic approaches prevalent in clinical practice. One promising method is "idionomic networks" (Sanford et al., 2022), which model idiographic dynamics first and only incorporate nomothetic information from a population if it improves the idiographic model fit. A notable statistical model for estimating idionomic networks is Group Iterative Multiple Model Estimation (GIMME; Gates et al., 2017), which detects individual-level network edges and, if sufficiently common, models these edges at the group level.

Thorough reporting of FINA methodological details in mental health research can pave the way for future studies to accurately describe FINA, thereby promoting replicability and enabling evaluation of its clinical validity and utility. For instance, providing specifics on data collection, handling of missing data, and criteria for model selection can enhance the reproducibility of FINA studies. Detailed reporting also enables clinicians to evaluate whether the symptom networks estimated using FINA match the symptom patterns they observe in practice, such as the way one symptom affects another.

In conclusion, we hope this overview encourages rigorous planning and application of FINA to construct person-specific symptom networks, helping to bridge the gap between clinical practice and mental health research.

Chapter 3

Testing the Clinical Validity and Utility of Fully Idiographic Network Analysis

Abstract

Network analysis (NA) is increasingly being used in clinical psychology to represent psychopathological processes as complex systems in which symptoms affect each other. Fully Idiographic Network Analysis (FINA) estimates symptom networks at the individual level through intensive data collection. This study investigated the clinical validity and utility of FINA in 15 clinician-patient dyads. To assess clinical validity, a training-test approach was used to compare clinical models (i.e., symptom networks predicted by clinicians for their patient), empirical models (i.e., symptom networks estimated from patient data using FINA), and null models (which assume each symptom remains constant over time) in predicting patient functioning. To assess clinical utility, self-report questionnaires were administered to both clinicians and patients, focusing on FINA's applicability across different patients and settings, as well as its acceptability, ease of use and understanding, and cost. Results from mixed-effects models assessing clinical validity indicated that FINA outperformed both clinical models and null models in predicting patient functioning, suggesting that FINA offers greater predictive accuracy of symptom dynamics. Moreover, FINA's predictive accuracy improved as the volume of intensive data collected increased. Both clinicians and patients expressed a generally positive attitude toward the utility of FINA, with clinicians rating it more favorably in terms of global clinical utility, applicability across different patients and settings, ease of use and understanding, and perceived costs. Both clinicians and patients found FINA equally acceptable, as a tool that complements and supports clinical work. These findings underscore the validity of FINA in enhancing clinical assessments and its perceived utility in clinical setting. The study suggests important research and clinical implications,

offering pathways to expand FINA's use in clinical practice and further improve its effectiveness.

Introduction

A network is a model used to describe different phenomena, such as social relations (Freeman, 2004), brain functions (Bassett & Sporns, 2017), and biological structures (Brohée et al., 2008). Networks have also been applied to psychological phenomena, representing psychological and psychopathological processes as complex systems in which symptoms and other psychological variables influence one another (Schmittmann et al., 2013). In this context, networks depict relationships (i.e., edges) between variables such as feelings or symptoms (i.e., nodes) (Epskamp et al., 2012). Networks can be either "directed" or "undirected". In a directed network, relationships are asymmetrical (i.e., variable A influences B, but B does not influence A), whereas in an undirected network, relationships are reciprocal (i.e., variable A influences B, and B influences A) (Costantini et al., 2015).

Network analysis (NA), rooted in network theory, is an analytical tool applied to symptom networks to describe the connections and the dynamic influences among symptoms and other elements of mental disorders, contributing to a new theory in psychopathology (Borsboom, 2017). Psychological networks are currently employed to model both cross-sectional data from samples of more than one individual, where symptoms are assessed for the entire group at a single point in time, and time-series data from individuals, where symptoms are repeatedly measured over multiple occasions (Epskamp, van Borkulo, et al., 2018). This allows for the investigation of symptom interactions over time, leading to the estimation of longitudinal networks (Bringmann et al., 2022). Longitudinal networks allow to estimate the influence of one symptom on another from one time point to the next, independent of changes in the overall mean level of symptoms (Bringmann et al., 2013). Furthermore, longitudinal networks can identify which symptoms are most predictive of others at later time points and which are most influenced by symptoms at earlier time points (Jordan et al., 2020). Estimating longitudinal networks requires intensive repeated measures,

typically conducted over short time frames using ambulatory assessment (AA; Trull & Ebner-Priemer, 2013). AA encompasses various methodologies for collecting data from individuals in their natural environments, such as experience sampling methods (ESM; Larson & Csikszentmihalyi, 1983), which traditionally focus on the intensive measurement of internal affective states, and ecological momentary assessment (EMA; Shiffman et al., 2008), which often extends to monitoring behaviors and physiological variables. AA primarily relies on electronic devices, like smartphones, to collect data in a personalized and user-friendly manner (Ellis, 2020). Building on this intensive data collection, NA of time-series uses various modeling techniques, such as vector autoregressive models (VAR; Borsboom & Cramer, 2013), which estimate how well each variable predicts itself and other variables at the next time point.

In person-centered research using longitudinal networks and intensive repeated-measures designs, fully idiographic analytical approaches are used, where relationships between variables are examined within a single individual across many occasions (Piccirillo & Rodebaugh, 2019). This approach opens up significant opportunities for personalized intervention and case conceptualization, as it provides a clearer understanding of how a disorder originates and persists in a specific person (Borsboom & Cramer, 2013), thereby informing treatment planning and the targeting of specific symptoms (Hofmann et al., 2016). Fully idiographic network analysis (FINA) is a NA methodology applied to a single individual, assessed across repeated measures. FINA has demonstrated promising results as a tool for better understanding psychopathology at an individual level across various disorders, including obsessive-compulsive disorder (Burger, Epskamp et al., 2022), post-traumatic stress disorder (Reeves & Fisher, 2020), and depression (Epskamp, 2020). However, despite its potential, FINA remains under-utilized, with most NA research still focused on cross-sectional data, even as calls for constructing networks tailored to individuals and for greater

personalization in mental health research grow (Borsboom & Cramer, 2013; Piccirillo & Rodebaugh, 2019). For FINA to be effectively implemented in clinical practice, more evidence is needed to establish its clinical validity and utility (Contreras et al., 2019; Schumacher et al., 2021; Wright & Woods, 2020). This is particularly important given the growing interest in personalized approaches to psychopathology and the potential of network models to revolutionize mental health assessments.

Clinical Validity and Utility of FINA

Clinical validity refers to the extent to which an evaluation tool or method reinforces the validity of a clinician's judgments, while clinical utility is defined by how applicable the tool or method is across different populations and contexts, its acceptability, ease of use and understanding, and its cost-effectiveness in terms of time and effort (Haynes & Yoshioka, 2007).

FINA helps elucidate the temporal interplay between symptoms, offering a more nuanced understanding of mental disorders that can inform clinical judgments (Borsboom & Cramer, 2013). However, more methodological advancements are needed to fully establish the clinical validity of the network perspective for individual patients (Fried & Cramer, 2017) and to determine how accurately idiographic models reflect the unique clinical characteristics of each patient (Frumkin et al., 2021). Moreover, assessing FINA's validity in real-world clinical settings is essential to support its application in guiding intervention decisions (Klintwall et al., 2023) and complementing clinical judgment. This is particularly important in cases where clinicians, despite applying evidence-based interventions, must rely solely on their expertise when treatments prove ineffective (Levinson et al., 2024).

Turning to clinical utility, only a limited number of studies using idiographic models have considered both clinician and patient perspectives. Research suggests that while patients generally find FINA useful, clinicians tend to approach it with greater caution. For example,

patients often view FINA as valuable for helping clinicians gain a deeper understanding of their issues, but clinicians express skepticism about whether FINA's insights will meaningfully inform their clinical work with individual clients (Frumkin et al., 2021; Zimmermann et al., 2019). Additionally, the definition of clinical utility varies across existing studies, resulting in only a subset of utility indices being examined according to the definition adopted in the present study. For instance, clinical utility has been assessed in terms of perceived acceptability (e.g., providing new insights about the patient), ease of use and understanding (e.g., interpreting the network and applying it in clinical practice), and the cost in terms of time and effort (e.g., the burden of data collection required to estimate FINA) (Frumkin et al., 2021; Scholten et al., 2022; Zimmermann et al., 2019). To the best of our knowledge, no studies have thoroughly explored the clinical utility of FINA in terms of its applicability across different patient populations (e.g., patients with varying diagnoses) or its applicability across various settings (e.g., public or private practice).

The current evidence on the clinical utility of data collection methodologies for estimating FINA in clinical practice is inconclusive. Some studies indicate that methods commonly used in idiographic assessments, especially intensive and repeated measures, can be burdensome for patients (Stone et al., 2003; Vachon et al., 2019). However, this burden does not necessarily impact patient adherence (van Genugten et al., 2020). Other evidence suggests that AA methods are generally well-tolerated by patients (Shiffman et al., 2008). Nonetheless, clinician reluctance may hinder the implementation of AA, as many view daily questionnaires as an undue burden to place on their patients (Zimmerman et al., 2019).

In sum, further research is necessary to establish the clinical validity of FINA and clarify its potential utility in clinical practice.

The Present Study

This study aims to investigate the clinical validity and utility of FINA. Specifically, to integrate and clarify previous findings, we will assess the clinical validity and utility of FINA in clinical practice using a sample of clinicians and their patients.

Clinical validity will be evaluated using a training-test approach (Yarkoni & Westfall, 2017). In this approach, the clinician's expertise (i.e., the network of symptoms predicted by the clinician for their patient) and empirical data (i.e., the network derived from FINA based on a portion of data collected from their patient) will be compared in their relative ability to predict the patient's functioning. The clinical utility of FINA will be assessed by gathering clinicians' and patients' perspectives on its applicability, acceptability, ease of use and understanding, and cost using ad-hoc self-report questionnaires.

The following research questions will be addressed:

- Is FINA able to detect the relationships between a patient's symptoms in comparison to the clinician's expertise? In other words, is FINA clinically valid?
- Is FINA applicable across different patients and settings, acceptable and useful for comprehensive assessment, easy to use and understand, and not overly costly, based on clinicians' and patients' perceptions? In other words, is FINA clinically useful?

We aim to contribute to the evidence supporting the clinical validity and utility of FINA. Specifically, we seek to clarify whether the symptom network generated by FINA more accurately predicts patient functioning compared to clinician predictions, thus supporting the clinical validity of this network analysis method. If so, this would indicate that FINA is a valuable tool to support clinician's understanding of patient functioning and aid in intervention planning. Regarding clinical utility, we expect to offer valuable insights into whether and how FINA can be incorporated into clinical practice, informed by the perspectives of both patients and clinicians.

Methods

Participants and Procedures

Participants were dyads consisting of clinicians (psychologists and/or psychotherapists) in private practice and their patients. Clinicians were recruited through social media, personal contacts, and word of mouth. The scope of the study was explained to them and those interested in participating were asked to invite one of their current patients to join the study. Inclusion criteria for patients were: (a) being 18 years or older; (b) having access to a smartphone for data collection; (c) having attended at least eight clinical sessions with their current clinician; (d) being considered clinically stable by their clinician; and (e) not taking any psychotropic medication for at least one month nor planning to start such medication during the study. Criteria (c) and (d) were designed to avoid systematic changes in individual processes over time and to meet the assumption of stationarity (i.e., each variable maintains a similar mean, variance and relationship with other variables and itself during over time) required for some time-series analysis models (Bringmann, 2021). Indeed, recruiting patients at the very beginning of an intervention could bring rapid therapeutic change (Howard et al., 1996), whereas evidence suggests that stability in key clinical variables can be achieved relatively early in psychological interventions (Darnall et al., 2021; Sattel et al., 2012).

The study was organized into four distinct phases:

Phase 1 – Collection of Data from the Clinician ("Training Data" from the Clinician)

The clinician participated in a meeting with the researcher, following a structured script (Appendix D), during which they were guided through a three-step procedure based on Frumkin et al. (2021) to define their patient's symptom network:

1. The clinician was introduced to the concept of symptoms networks and their structure, specifically the roles of nodes and edges, using an adapted clinical case from Epskamp, Waldorp, et al. (2018).
2. The clinician was presented with five core items (depression, anxiety, stress, tiredness, and irritability experienced in the last hour) to be administered to the patient, with the option to add one or two additional items, either arbitrarily or from a provided list (Appendix E). The clinician ranked the symptoms by importance, identifying the patient's primary and secondary symptoms to develop an initial understanding of potential associations among them.
3. Using a shiny app (Chang et al., 2023), the clinician constructed the patient's network by using the items as nodes, predicting the associations of each symptom with itself and the other symptoms over the next three hours (i.e., the edges in the network). See the Measures section for more details.

Phase 2 – Collection of Data from the Patient (Collection of Wave 1, "Training Data" From the Patient)

The patient received detailed information about the study from their clinician and was provided with a leaflet that included detailed instructions on completing the pre-assessment questionnaires, downloading and using the Ethica (a.k.a. Avicenna) smartphone app for intensive data collection via EMA (https://avicennaresearch.com/), and understanding the data collection schedule (Appendix F). The pre-assessment questionnaire included a socio-demographic form and validated self-report measures of anxiety, depression, and general functioning. The patient then completed a two-week EMA, answering five to seven items (i.e., the five core items and up to two personalized items from Phase 1) five times daily at fixed three-hour intervals (10 a.m., 1 p.m., 4 p.m., 7 p.m., 10 p.m.), following prompts from the smartphone app.

Phase 3 – Subsequent Functioning of the Patient (Collection of Wave 2, "Test Data" from the Patient)

After a one-week break, the patient completed a second, one-week EMA with the same features as in Phase 2. This was followed by a post-assessment questionnaire, which included the same self-report measures as the pre-assessment questionnaire.

Phase 4 – Perceived Utility of FINA

Both the clinician and the patient were provided with the graphical representation and a descriptive interpretation of the patient's temporal network estimated from the Phase 2 data. They were then asked to complete a self-report questionnaire to gather their perceptions of the clinical utility of this network and of FINA overall. The questionnaire focused on its applicability across different patients and settings, acceptability, ease of use and understanding, and the perceived cost in terms of time and effort required for its application.

Before participating in the study, both clinicians and patients signed an informed consent and data privacy form. Participation was entirely voluntary for both clinicians and patients, and no incentives were provided. All procedures related to participant enrollment and the study phases were approved by the Bioethics Committee of the University of Bologna (protocol number 0001230, January 4, 2023).

Measures

Data Collected from the Clinician

Sociodemographic and Practice-Related Information. During the initial meeting, the following sociodemographic and practice-related information was collected from the clinician (Appendix D): (a) gender; (b) age; (c) professional qualification (psychologist or psychotherapist); (d) year of registration with the regional professional board of psychologists; (e) if the clinician was a psychotherapist, their practice orientation (e.g., psychodynamic, cognitive-behavioral); (f) number of sessions completed with the enrolled

patient; (g) most recent session frequency with the enrolled patient; (h) duration of the intervention with the enrolled patient; (i) the motivation prompting the patient to seek the clinician's help; and (j) the clinician's diagnostic hypothesis for the enrolled patient.

Shiny App. To assist clinicians in defining their patient's symptom network, we used a Shiny app (Chang et al., 2023) adapted from a previous study (Schumacher et al., 2021). This tool allowed clinicians to evaluate the relationships among all possible pairs of the five to seven symptoms identified in Phase 1. For each potential relationship in the network, the clinician rated the strength of the connection on an 11-point scale from -1 (Perfectly negative connection) to 1 (Perfectly positive connection) (see Figure 2 in Appendix D). As the clinician entered each relationship, the resulting network was displayed in real time. The app then generated a matrix containing the edge values specified by the clinician.

Clinician Clinical Utility Questionnaire. An ad-hoc self-report questionnaire was designed to assess clinician's perceptions of the clinical utility of FINA (Appendix G), including questions on its applicability across different patients and settings, acceptability, ease of use and understanding, and perceived cost in terms of time and effort required for its application. Items were developed based on operational definitions derived from the literature (Haynes & Yoshioka, 2007) and previous research on the perceived utility of idiographic network models (Frumkin et al., 2021) and feedback from experts in the field. The resulting questionnaire included 32 items measuring the following aspects of FINA's utility: applicability to different patients, defined as the extent to which FINA can be applied to all patients regardless of psychopathology, presenting issues, biographical characteristics, cognitive development, or cultural background, while adequately reflecting individual differences (5 items; e.g., "The network of relationships between symptoms could be used with all my patients"); applicability across different settings, defined as the extent to which FINA can adapt to private practice, structured environments with multi-professional

collaboration, any stage of clinical work (beginning, treatment, conclusion, follow-up), and non-clinical contexts (6 items; e.g., “The network of relationships between symptoms would be easily usable in private practice”); acceptability, defined as the extent to which FINA can be a valuable tool that complements the clinician’s usual methods and expertise, enhancing the therapeutic process without creating obstacles in the clinician-patient relationship (9 items; e.g., “The network of relationships between symptoms will be useful in the clinical work I am doing with my patient”); ease of use and understanding, defined as the clarity of the network’s meaning, ease of use in clinical practice with individual patients, ease with which clinicians can explain the results to patients, and the simplicity and readability of the graphical layout (5 items; e.g., “It was easy to understand the graphical representation of the network of relationships between my patient’s symptoms”); and cost in terms of time and effort, defined as the extent to which FINA requires minimal time, energy, and material resources to learn and apply, representing more of a benefit than a burden for both clinician and patient (7 items; e.g., “Using the network of relationships between symptoms in my clinical work with my patient would take a lot of time”, reverse-scored). The respondent rated each item on a 7-point scale, ranging from 1 (Strongly disagree) to 7 (Strongly agree). For each dimension, a mean score was computed. Higher scores in each dimension indicated greater perceived utility, such as wider applicability, higher acceptability, greater ease of use and understanding, or lower perceived costs in terms of time and effort. A total score was also computed, reflecting overall perceived utility by averaging the scores across all dimensions. To improve internal consistency reliability, two items (item #1 and item #6) were removed from the ease of use and understanding dimension, and three items (item #3, item #13, and item #29) were discarded from the costs dimension. Cronbach’s alpha coefficients were .76 for applicability to different patients, .89 for applicability across

different settings, .90 for acceptability, .69 for ease of use and understanding, .70 for cost in terms of time and effort, and .93 for the total scale.

Data Collected from the Patient

Pre-Post Assessment Questionnaires. A socio-demographic form was included in the pre-assessment questionnaire to collect information on gender, age, education, marital status, and employment status. Three self-report measures were included in both the pre- and post-assessment questionnaires, administered at the beginning of Phase 2 and at the end of Phase 3, respectively.

General Anxiety Disorder Scale-7 (GAD-7; Spitzer et al., 2006). The GAD-7 is a brief, 7-item self-report measure designed to assess the diagnostic criteria for GAD over the past two weeks, as outlined in the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV; American Psychiatric Association, 1994). Each item (e.g., "Feeling nervous, anxious or on edge") is rated on a 4-point scale ranging from 0 (Not at all) to 3 (Nearly every day), resulting in a total score ranging from 0 to 21, with higher scores indicating greater severity of anxiety. The internal consistency of the GAD-7 has been reported as Cronbach's alpha = .92 (Spitzer et al., 2006). In the present study, Cronbach's alpha was .82 at pre-assessment and .71 at post-assessment.

Patient Health Questionnaire-9 (PHQ-9; Kroenke et al., 2001). The PHQ-9 is a 9-item self-report measure designed to assess the severity of depression. Each item (e.g., "Feeling down, depressed, or hopeless") is rated on a 4-point scale from 0 (Not at all) to 3 (Nearly every day), resulting in a total score range from 0 to 27, with higher scores indicating greater severity of depression. The internal consistency of the PHQ-9 has been reported as higher than .80 (Cronbach's alpha) (Kroenke et al., 2001). In the present study, Cronbach's alpha was .71 at pre-assessment and .65 at post-assessment.

Work and Social Adjustment Scale (WSAS; Mundt et al., 2002). The WSAS is a brief, 5-item self-report measure used to assess functional impairment across work, social, and family domains. Each item is rated on a 9-point scale, ranging from 0 (Not at all impaired) to 8 (Very severely impaired), resulting in a total score range of 0 to 40, with higher scores indicating greater impairment. The internal consistency has been reported as Cronbach's alpha ranging from .79 to .94 (Mundt et al., 2002). In the present study, Cronbach's alpha was .81 at pre-assessment and .74 at post-assessment.

EMA Survey. The EMA survey included a total of up to seven items. Five items were core EMA items, common to all participating patients, and assessed transdiagnostic factors such as depression, anxiety, stress, tiredness, and irritability (Kirtley et al., 2019; Bullis et al., 2019). Up to two additional items were personalized, selected by the clinician. For each item, patients rated their current experience on a scale from 1 (Not at all) to 10 (A lot). Participants were prompted five times daily at fixed three-hour intervals (10 a.m., 1 p.m., 4 p.m., 7 p.m., and 10 p.m.), following smartphone alerts, to report on their emotional experience during the past hour (e.g., "How down have you felt in the last hour?").

Patient Clinical Utility Questionnaire. The patient version of the clinical utility questionnaire was an adaptation of the clinician version. Items originally developed for clinicians were modified to ensure relevance for patients, with only those items deemed applicable to patients included (Appendix G). The questionnaire included 28 items measuring applicability to different patients (5 items; e.g., "The network of relationships between symptoms should be used with all patients who consult a psychologist"), applicability across different settings (5 items; e.g., "The network of relationships between symptoms should also be used in structured settings (e.g., hospitals or clinics)"), acceptability (8 items; e.g., "The network of relationships between symptoms has made me more aware of my condition"), ease of use and understanding (5 items; e.g., "It was easy to understand the graphical

representation of the network of relationships between my symptoms"), and cost in terms of time and effort (5 items; e.g., "Understanding the network of relationships between my symptoms required a lot of time", reverse-scored). The patient rated each item on a 7-point scale, ranging from 1 (Strongly disagree) to 7 (Strongly agree). For each dimension, a mean score was computed, with higher scores indicating greater perceived utility, such as wider applicability, higher acceptability, greater ease of use and understanding, or lower perceived costs in terms of time and effort. A total score was also computed by averaging the scores across all dimensions, reflecting the overall perceived utility. Cronbach's alpha coefficients were .89 for applicability to different patients, .91 for applicability across different settings, .92 for acceptability, .83 for ease of use and understanding, .82 for cost in terms of time and effort, and .97 for the total scale.

Data Analysis

Descriptive statistics were used to outline the characteristics of the clinician-patient dyads. To evaluate changes in self-reported levels of anxiety (GAD-7), depression (PHQ-9), and functional impairment (WSAS), repeated measures ANOVAs were conducted. Interpretation of effect size was based on Cohen's *d*, using the following thresholds: 0.2 small, 0.5 medium, and 0.8 large (Cohen, 1988).

Clinical Validity

To evaluate clinical validity, we used a training-test approach (Yarkoni & Westfall, 2017), a method from machine learning designed to assess the predictive accuracy of a model – specifically, how well the model predicts independent data. This accuracy is determined by calculating the model's prediction error, typically through cross-validation. Cross-validation involves training a model on one dataset and then testing it on a separate, independent dataset (Browne, 2000). A simple way to implement this is by splitting the original dataset into two sets: a training set and a test set. The training set is used to fit the model, while the test set is

used to evaluate the model's performance by measuring its prediction error (Yarkoni & Westfall, 2017). Lower prediction error (or higher predictive accuracy) when tested on the test set indicates greater validity.

In the present study, we evaluated the predictive accuracy of three distinct models in predicting Wave 2 data collected during Phase 3 (i.e., test data from the patient): a clinical model, an empirical model, and a null model. The clinical model represents the clinician-predicted network, constructed by the clinician during Phase 1 (i.e., training data from the clinician). The empirical model represents the network estimated using FINA on Wave 1 data collected from the patient during Phase 2 (i.e., training data from the patient). Finally, the null model assumes that each symptom remains constant over time, and rely solely on the mean of each symptom from the patient's training data. This model serves a basic benchmark for predictive accuracy. By comparing both the clinical and empirical models to this baseline model, we could determine whether they offer meaningful improvements over the simplistic assumption that symptoms do not change over time.

The analysis followed five distinct steps. All analyses were conducted using the software R, version 4.4.1 (R Core Team, 2024), and the script used is provided in Appendix H.

Step 1: Using Training Data from the Patient to Estimate the Empirical Model. FINA was applied to the Phase 2 data, estimating a temporal network using gVAR (Epskamp, Waldorp et al., 2018) with the R package *psychonetrics* (Epskamp, 2020). Missing data were handled using full information maximum likelihood. To ensure equidistant measures and treat overnight lag, as required by VAR models (Janssens et al., 2018), we used the "dayvar" argument, which removed the influence of the first measurement of a day being regressed on the last measurement of the previous day. Notably, the empirical model was estimated using FINA without statistically checking or correcting for stationarity, despite the use of VAR to

model time-series data. Consequently, no detrending procedures were applied. This approach was adopted for consistency with the clinical model, which also did not include statistical checks or corrections for stationarity. It would be impractical to ask clinicians to consider time effects and apply detrending adjustments while constructing the clinical model. By maintaining the same assumptions for both models, we ensured a fair and straightforward comparison of their predictive accuracy. Additionally, comparability between the models was further ensured by transposing and rounding the edge values in the matrix of the empirical model to one decimal place, consistent with the one-decimal format used in the Shiny app matrix.

Step 2: Handling Missingness from Test Data and Applying Standardization. Phase 3 data were cleaned by removing incomplete prompts. The remaining data were then standardized using the means and standard deviations from the data collected during Phase 2 (i.e., training data from the patient).

Step 3: Generating Predictions Based on Standardized Test Data. We used the three models (clinical, empirical, null) to predict Phase 3 data by regressing the standardized Phase 3 data collected at each timepoint (t+1) on the data from the previous timepoint (t), but only when the timepoints were consecutive and within the same day. If timepoints were not consecutive, missing timepoints were inserted in the predicted test data. This was done using the autoregressive and cross-lagged regression coefficients from (a) the clinical model, (b) the empirical model, or (c) the null model. Notably, because the null model is based on the mean of each variable from the training data, its standardized coefficients equal zero. Thus, the null model consistently predicted zero for all variable values. Additionally, since the original observed data were bounded between 1 and 10, we adjusted the predicted values from both the clinical and empirical models to remain within these limits. Predicted values that fell outside this range were recoded to the nearest boundary value, using the standardized

versions of the boundary limits for consistency. Step 3 generated three predicted values for each dyad, timepoint, and variable in the Phase 3 data: one from the clinical model, one from the empirical model, and one from the null model.

Step 4: Calculation of Absolute Residuals. Absolute residuals were computed by subtracting the predicted values (from the clinical, empirical, and null models) from the observed values in the standardized Phase 3 data. This calculation was performed for each timepoint across all symptoms, for every dyad. Missing timepoints were removed from the residuals for all models.

Step 5: Comparison of the Predictive Accuracy of Each Model Using Mixed-Effects Models. We compared the predictive accuracy of the clinical, empirical, and null models using two mixed-effects models. In the first mixed-effects model, the predictor variable was the model type (clinical, empirical, or null), and the outcome variable was the absolute residuals. To account for the fact that certain data points belonged to the same group (dyad or symptom), random intercepts were included for each dyad and each symptom, allowing both groups to have their own baseline level of residuals. In the second mixed-effects model, we examined the role of the number of unique observations collected during Phase 2, based on the hypothesis that empirical models with higher predictive accuracy would be obtained from patients who provided more data during Phase 2. The number of unique observations differs from the total number of timepoints collected in Phase 2 because it counts actual data points (non-missing entries) across all timepoints and symptoms, reflecting the true quantity of usable data. If a timepoint was only partially completed (i.e., with some symptoms recorded and others missing), counting timepoints would overestimate the amount of available data. The second mixed-effects model included the same features as the first, but the predictor variables were the model type (clinical, empirical, or null), the number of unique observations, and their interaction. The number of unique observations was

standardized to improve interpretability. In both mixed-effects models, ANOVA followed by a post hoc test with Holm correction for multiple comparisons, was used to identify statistically significant differences between the clinical, empirical, and null models in predictive accuracy. Finally, three separate linear mixed-effects models were conducted to analyze the influence of the number of unique observations on predictive accuracy within each model individually.

Clinical Utility

To assess FINA's clinical utility, descriptive statistics (mean and standard deviation) were used to summarize clinicians' and patients' responses to the clinical utility questionnaires. Repeated measure ANOVA was used to compare clinicians' and patients' scores, with effect size interpretation based on Cohen's *d*. The patient's temporal network, which both the clinician and the patient evaluated for clinical utility, was estimated using the same procedures as those applied for the empirical model used to assess FINA's clinical validity. However, preliminary analyses were conducted on the Phase 2 data prior to estimating this temporal network. Specifically, the assumption of stationarity was checked and corrected if necessary. Each symptom in the time series was visually inspected for linear trends (Burger, Hoekstra et al., 2022), which were then statistically tested by regressing each symptom on time. When significant linear trends were identified, the residuals were used in place of the original scores for further analysis.

Results

Clinician and Patient Characteristics

A total of 132 clinicians were invited to participate in the study through personal and professional contacts. Of these, 40 clinicians (30.3%) expressed interest in participating and in presenting the study to one of their patients. However, 12 clinicians (30%) were unable to identify an eligible patient, and 10 (25%) chose not to participate for personal reasons.

Eighteen clinicians provided signed consent forms for both themselves and their patients. While two clinician-patient dyads withdrew after Phase 1 for personal reasons, 16 dyads completed all study phases. However, one dyad was excluded due to a lack of variability in Phase 3 data, resulting in a total of 15 dyads were included in the study (Figure 1).

Seventy-three percent of clinicians were female, and 73.3% reported a cognitive-behavioral orientation. All clinicians were either licensed psychotherapists or psychologists currently in training to become certified psychotherapists. The number of sessions completed with the enrolled patient ranged from 13 to 98 (M = 31.5, SD = 22.2), with the majority (40%) meeting on a weekly basis. One-third of clinicians had been working with their patient for over 12 months, another one-third for 6 to 12 months, and the remaining one-third for less than 6 months. The years since the registration with the professional board ranged from 1 to 34 (M = 9.1, SD = 7.8). Most clinicians (46.7%) indicated that their patient sought help for relationship and/or work-related issues. The most frequently reported diagnostic hypotheses was generalized anxiety disorder (26.7%).

One patient's pre-assessment questionnaire, which included socio-demographic information, was lost due to technical issues. However, we were able to recover the participant's gender and age from details provided in the informed consent form and from information supplied by the clinician during the Phase 1 meeting. Sixty percent of patients were females, with ages ranging from 19 to 65 (M = 31.9 years, SD = 12.0). Among the 14 patients who provided complete sociodemographic information, the majority had a high school diploma (42.9%) and were employed (64.3%), whereas 28.6% were married or living with a partner. The repeated measures ANOVAs revealed only small, nonsignificant changes from pre- to post-assessment in GAD-7, $F(1, 13) = 0.08$, $p = .78$, $d = 0.08$, PHQ-9, $F(1, 13) = 1.56$, $p = .23$, $d = 0.31$, and WSAS, $F(1, 13) = 0.88$, $p = .37$, $d = 0.18$. Table 1 displays the

socio-demographic and practice-related information collected from patients and clinicians. Dyad-specific information is included in Appendix I.

Across Phase 2 and Phase 3, the overall average percentage of timepoints completed by patients was 73.3%. Specifically, the average completion rate was 77% for Phase 2 (Wave 1) and 33.9% for Phase 3 (Wave 2).

Figure 1.

Flow Chart of Study Participation

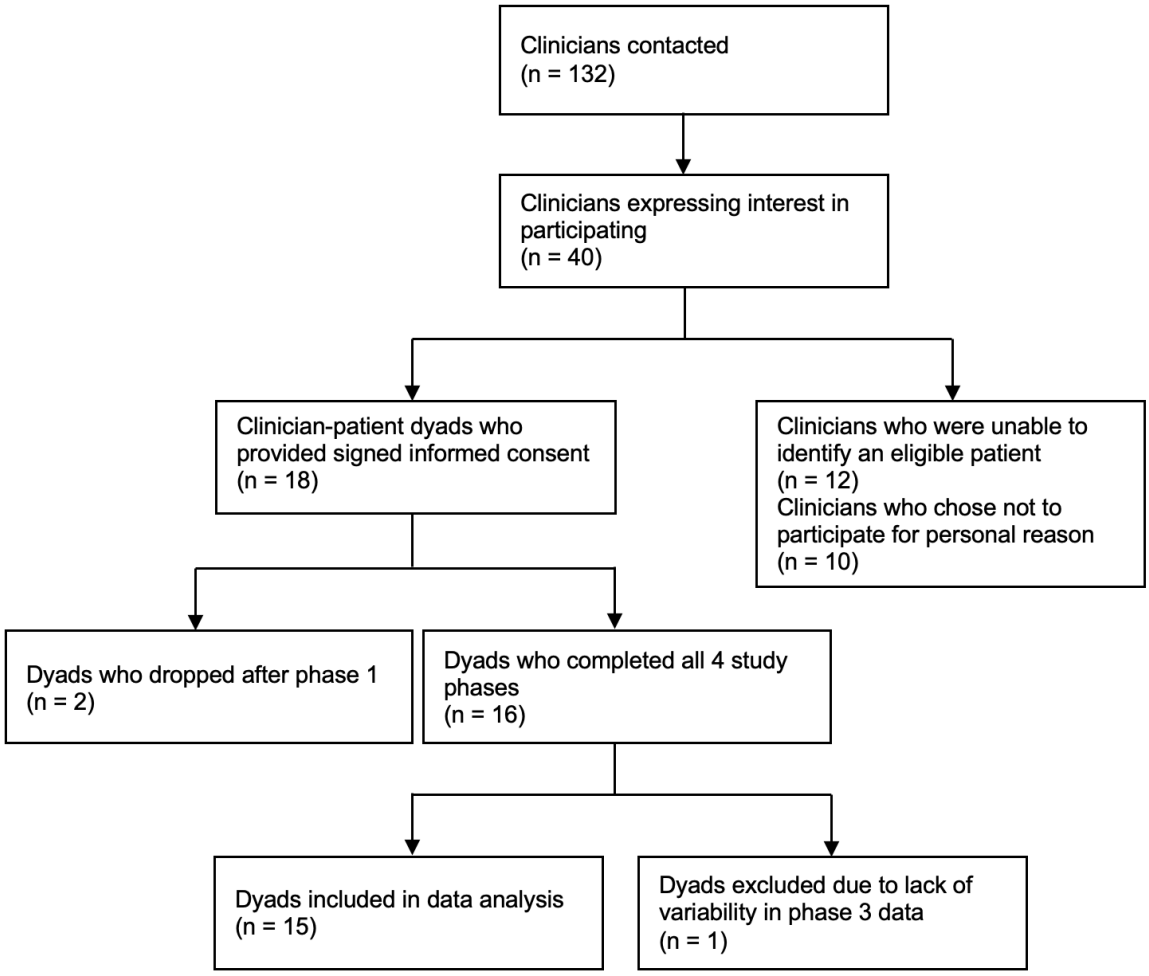


Table 1.

Sociodemographic and Practice-Related Information Collected from Clinicians and Patients

Clinicians (n = 15)		Patients (n = 14)	
	n (%)		n (%)
Gender		Gender[a]	
Female	11 (73.3)	Female	9 (60.0)
Male	4 (26.7)	Male	6 (40.0)
Age, *M* (*SD*)	36.2 (9.6)	Age, *M* (*SD*)[a]	31.9 (12.0)
Years since registration, *M* (*SD*)	9.1 (7.8)	Education	
Practice orientation		Up to high school	7 (50.0)
Cognitive-behavioral	11 (73.3)	Bachelor	2 (14.3)
Systemic	2 (13.3)	Master	4 (28.6)
Constructivist	1 (6.7)	Post-graduate	1 (7.1)
Integrative	1 (6.7)	Marital status	
n sessions conducted, *M* (*SD*)	31.5 (22.2)	Married/cohabiting	4 (28.6)
Session frequency		Single	10 (71.4)
1 per week	6 (40.0)	Employment status	
1 per 2 weeks	4 (26.7)	Student	5 (35.7)
1 per month	2 (13.3)	Employee	6 (42.9)
other	3 (20.0)	Freelancer	3 (21.4)
Duration of the intervention		GAD-7 pre, *M* (*SD*)	9.3 (3.9)
> 12 months	5 (33.3)	GAD-7 post, *M* (*SD*)	9.6 (3.5)
6-12 months	5 (33.3)	PHQ-9 pre, *M* (*SD*)	9.4 (4.0)
< 6	5 (33.3)	PHQ-9 post, *M* (*SD*)	10.6 (3.8)
Patient's motivation to seek help		WSAS pre, *M* (*SD*)	20.6 (8.7)
Relationship and/or work-related issues	7 (46.7)	WSAS post, *M* (*SD*)	19.1 (7.8)
Anxiety, OCD, and/or related issues	5 (33.3)		
Low mood, sense of being stucked, and/or related issues	3 (20.0)		
Diagnostic hypothesis			

GAD	4 (26.7)	
Dysthymia	3 (20.0)	
MDD	2 (13.3)	
SAD	3 (20.0)	
OCPD	2 (13.3)	
OCD	1 (6.7)	

Note. GAD-7 = General Anxiety Disorder Questionnaire-7, PHQ-9 = Patient Health Questionnaire-9, WSAS = Work and Social Anxiety Scale, GAD = General Anxiety Disorder, MDD = Major Depressive Disorder, SAD = Social Anxiety Disorder, OCPD = Obsessive-Compulsive Personality Disorder, OCD = Obsessive-Compulsive Disorder.

[a] $n = 15$.

Clinical Validity

Sample Dyad

We selected one dyad (ID 7) as an example to describe the clinical and empirical models used to examine FINA's clinical validity, alongside the null model. We begin by presenting background information collected on both the clinician and patient in this dyad, followed by a description of the clinical and empirical models estimated from them. Appendix J presents the clinical and empirical models and the corresponding matrices for all 15 dyads.

Dyad's Characteristics. The clinician, a 33-year-old female cognitive-behavioral psychotherapist, reported that her patient, a 31-year-old female with a diagnosis of social anxiety disorder, sought psychotherapy to address challenges in work and relationships. The clinician had conducted approximately 60 sessions with this patient, with a recent frequency of one session per week, and had been treating her for over a year at the time of enrollment in this study. She had been registered with the professional board of psychologists for seven years.

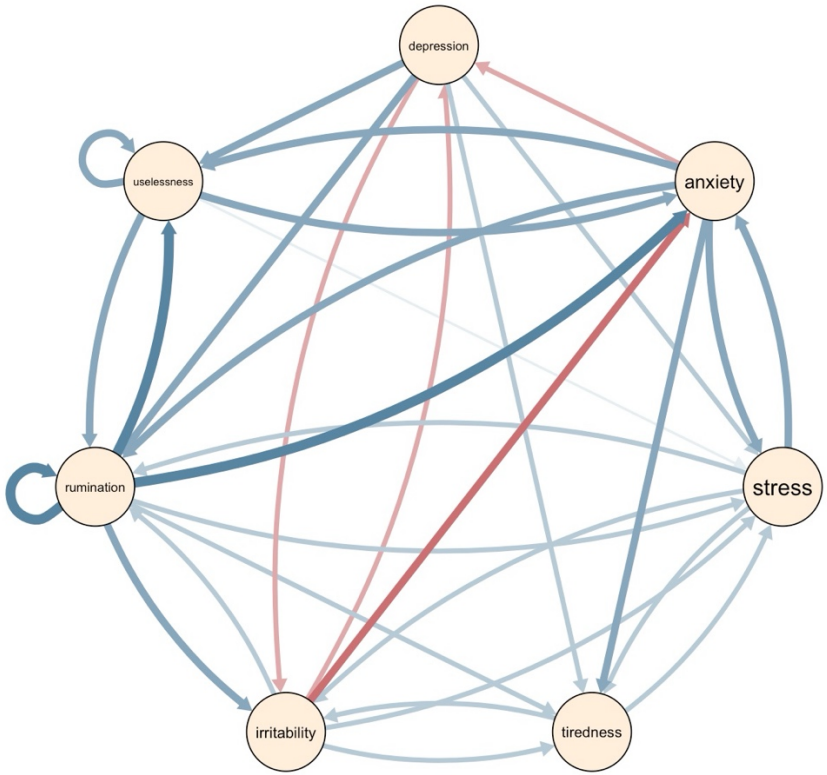
Clinical Model. In addition to the five core items (depression, anxiety, stress, tiredness, and irritability), the clinician selected two more symptoms: rumination and feelings of uselessness. In

the clinical model constructed in Phase 1 (Figure 2, Panel A), depression had strong positive connections with rumination and uselessness, moderate positive connections with stress and tiredness, and a moderate negative connection with irritability. Anxiety had strong positive connections with stress, tiredness, rumination, and feelings of uselessness, and a moderate negative connection with depression. Stress had a strong positive connection with anxiety and moderate positive connections with tiredness, irritability, and rumination. Tiredness had moderate positive connections with stress and irritability. Irritability had strong negative connections with anxiety, moderate negative connections with depression, and moderate positive connections with stress, tiredness, and rumination. Rumination had strong positive connections with irritability, and especially with anxiety, feelings of uselessness, and itself, along with moderate positive connections with stress and tiredness. Finally, feelings of uselessness had strong positive connections with anxiety, rumination, and itself, as well as a weak positive connection with stress. The edge values in the clinical model are displayed in Table 2.

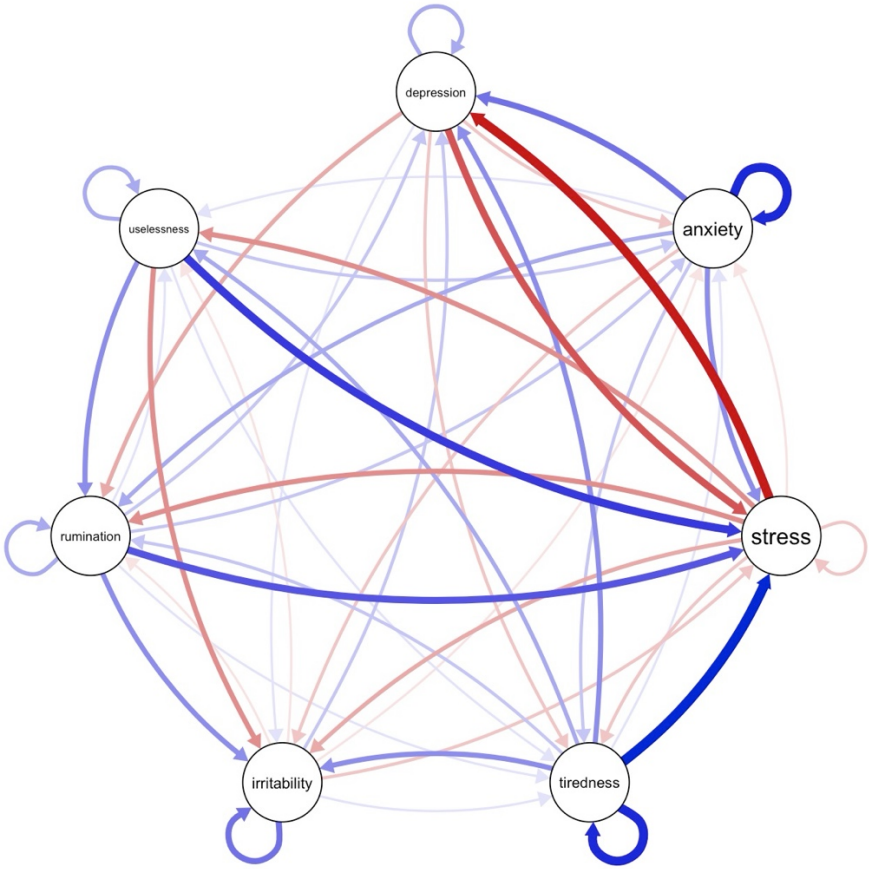
Figure 2.

Clinical Model Constructed in Phase 1 (A) and Empirical Model Estimated from Phase 2 Data Using FINA (B)

A



B



Note. Blue links indicate positive relationships, red links indicate negative relationships, and the width and saturation of the link indicates the strength of the relationship.

Table 2.

Edge Values in the Clinical and Empirical Models

	Clinical Model						
	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**	**Uselessness**
Depression	0	0	.3	.3	-.3	.5	.5
Anxiety	-.3	0	.5	.5	0	.5	.5
Stress	0	.5	0	.3	.3	.3	0
Tiredness	0	0	.3	0	.3	0	0
Irritability	-.3	-.5	.3	.3	0	.3	0
Rumination	0	.7	.3	.3	.5	.7	.7
Uselessness	0	.5	.1	0	0	.5	.5
	Empirical Model						
	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**	**Uselessness**
Depression	.3	-.2	-.6	-.2	.1	-.3	0
Anxiety	.5	.8	.4	.2	-.2	.3	.1
Stress	-.8	-.1	-.2	-.2	-.3	-.4	-.4
Tiredness	.4	.1	.9	.8	.4	.2	.3
Irritability	.2	-.1	-.2	.1	.5	-.1	-.1
Rumination	.2	.2	.6	.1	.4	.3	.1
Uselessness	0	.2	.7	.1	-.4	.4	.3

Empirical Model. During Phase 2, the patient responded to 58 out 70 notifications (82.9%) prompted by Ethica (a.k.a. Avicenna). Figure 2 (Panel B) shows the empirical model estimated from this data, with edge values displayed in Table 2. Depression had a strong negative connection with stress, a moderate positive connection with itself, a moderate negative connection with rumination, weak negative connections with anxiety and tiredness,

and a weak positive connection with irritability. Anxiety had strong positive connections with depression and especially with itself, moderate positive connections with stress and rumination, weak positive connections with tiredness and feelings of uselessness, and a weak negative connection with irritability. Stress had a strong negative connection with depression, moderate negative connections with irritability, rumination, and feelings of uselessness, and weak positive connections with anxiety, tiredness, and itself. Tiredness had strong positive connections with stress and itself, moderate positive connections with depression, irritability, and feelings of uselessness, and weak positive connections with anxiety and rumination. Irritability had a strong positive connection with itself, weak positive connections with depression and tiredness, and weak negative connections with anxiety, stress, rumination, and feelings of uselessness. Rumination had a strong positive connection with stress, moderate positive connections with irritability and itself, and weak positive connections with depression, anxiety, tiredness, and feelings of uselessness. Finally, feelings of uselessness had a strong positive connection with stress, a moderate negative connection with irritability, moderate positive connections with rumination and itself, and weak positive connections with anxiety and tiredness.

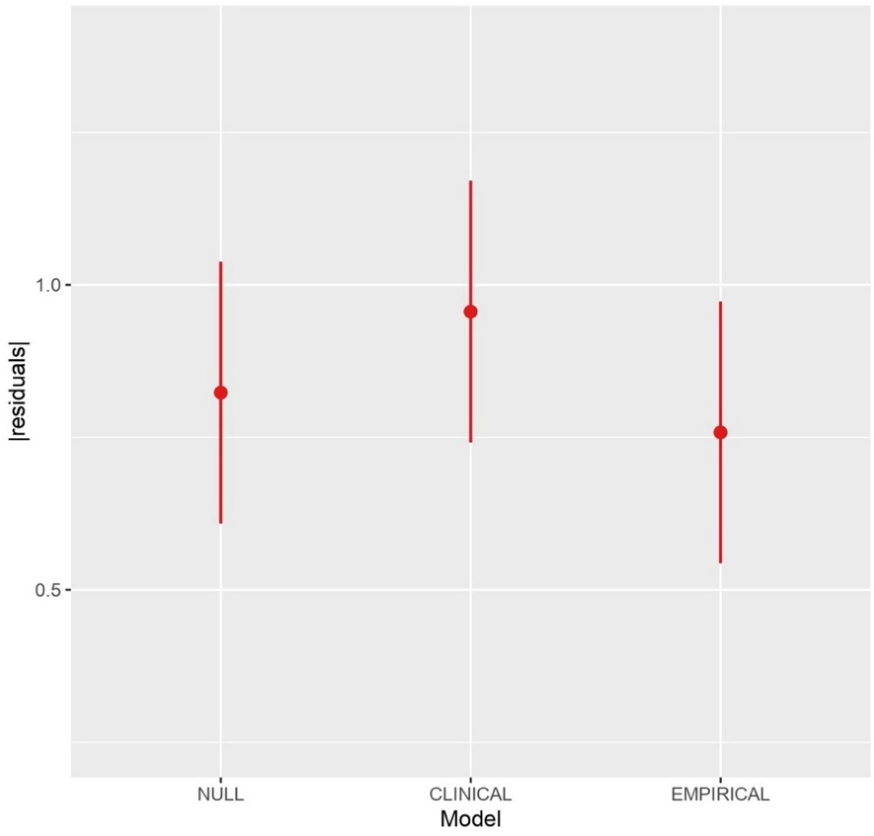
Mixed-Effects Models

The calculation of absolute residuals from the predicted scores, which served as the outcome variable in both the first and second mixed-effects models, resulted in a total of 3,957 residuals (1,320 per model), accounting for each timepoint and symptom across the 15 dyads. The number of unique observations, used as a predictor variable along with model type (clinical, empirical, or null) and their interaction in the second mixed-effects model, ranged from 216 to 476 (M = 356.6, SD = 80.8), indicating substantial variability in the amount of data provided by each patient in the Phase 2 dataset.

First Mixed-Effects Model. The results of the ANOVA indicated that the model used to predict Phase 3 data significantly affected the marginal means of absolute residuals, $F(2, 3899.4) = 21.04$, $p < .001$. Specifically, the empirical model had the smallest marginal mean of absolute residuals ($M = 0.76$, 95% CI [0.54, 0.97]), followed by the null model ($M = 0.82$, 95% CI [0.61, 1.04]), while the clinical model had the largest marginal mean of residuals ($M = 0.96$, 95% CI [0.74, 1.17]). A post-hoc analysis with Holm correction showed that all differences in marginal means of absolute residuals between the models were statistically significant: The empirical model outperformed both the clinical model, $\chi^2(1) = 40.52$, $p < .001$, and the null model, $\chi^2(1) = 4.40$, $p = .036$. Additionally, the null model outperformed the clinician model, $\chi^2(1) = 18.21$, $p < .001$ (Figure 3).

Figure 3.

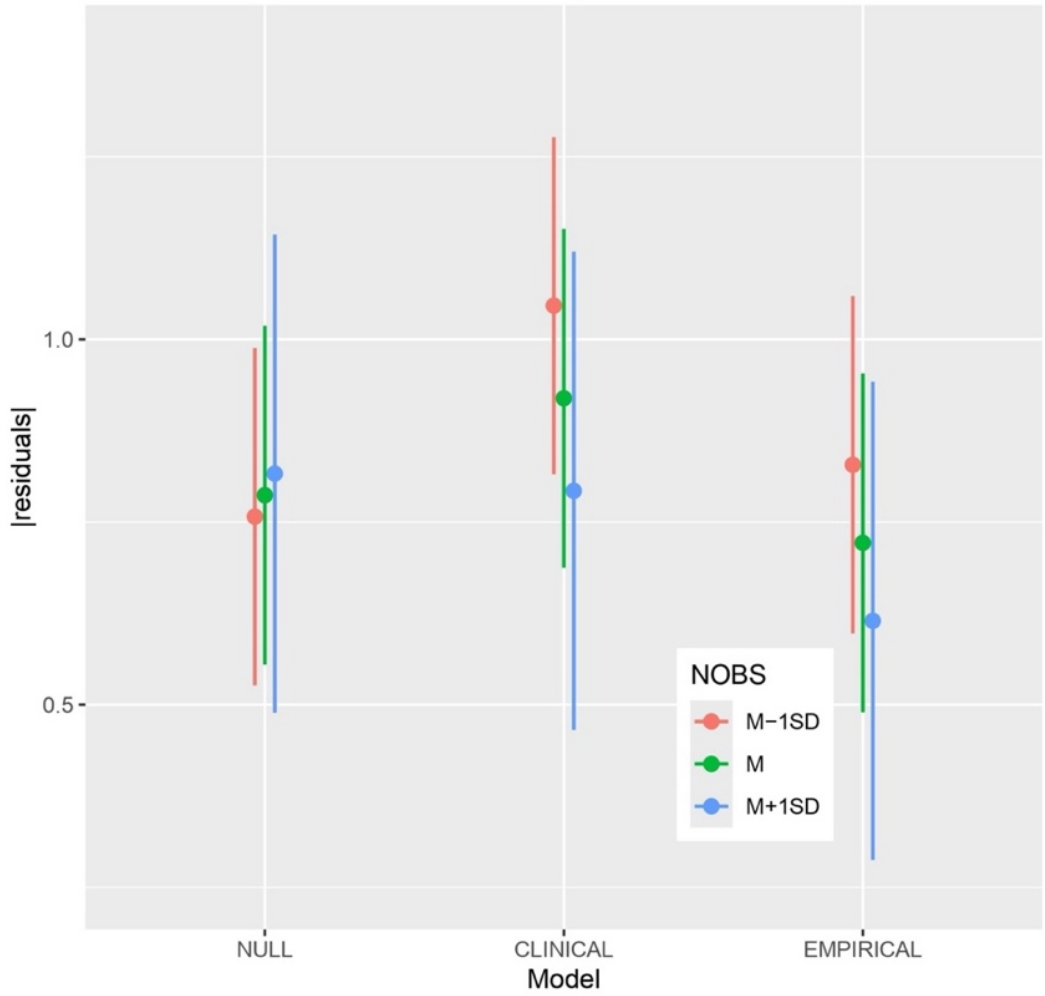
Marginal Means of Absolute Residuals Across Null, Clinical, and Empirical Models



Second Mixed-Effects Model. The results of the ANOVA indicated a significant main effect of model type on the marginal means of absolute residuals, $F(2, 3897.6) = 21.19$, $p < .001$, no significant effect of the number of unique observations, $F(1, 12.8) = 0.71$, $p = .416$, and a significant interaction effect between model type and number of unique observations, $F(2, 3897.6) = 15.06$, $p < .001$. Specifically, when the number of unique observations was low (M - 1SD), the marginal means of absolute residuals were 1.05 (95% CI [0.82, 1.28]) for the clinical model, 0.83 (95% CI [0.60, 1.06]) for the empirical model, and 0.76 (95% CI [0.53, 0.99]) for the null model. At the mean level of the number of unique observations, the marginal means of absolute residuals were 0.92 (95% CI [0.69, 1.15]) for the clinical model, 0.72 (95% CI [0.49, 0.95]) for the empirical model, and 0.79 (95% CI [0.55, 1.02]) for the null model. When the number of unique observations was high (M + 1SD), the marginal means of absolute residuals were 0.79 (95% CI [0.47, 1.12]) for the clinical model, 0.61 (95% CI [0.29, 0.94]) for the empirical model, and 0.82 (95% CI [0.49, 1.14]) for the null model (Figure 4). Finally, linear mixed-effects models conducted on each individual model showed that a larger number of unique observations marginally improved the predictive accuracy of the empirical model, $\beta = -0.095$, $SE = 0.05$, $p = .058$. However, the number of unique observations did not significantly affect the predictive accuracy of the clinical model, $\beta = -0.147$, SE = .18, $p = .420$, nor the null model, $\beta = .002$, $SE = .051$, $p = .97$.

Figure 4.

Marginal Means of Absolute Residuals across Null, Clinical, and Empirical Models According to Number of Unique Observations



Note. NOBS = number of unique observations.

Clinical Utility

Sample Dyad

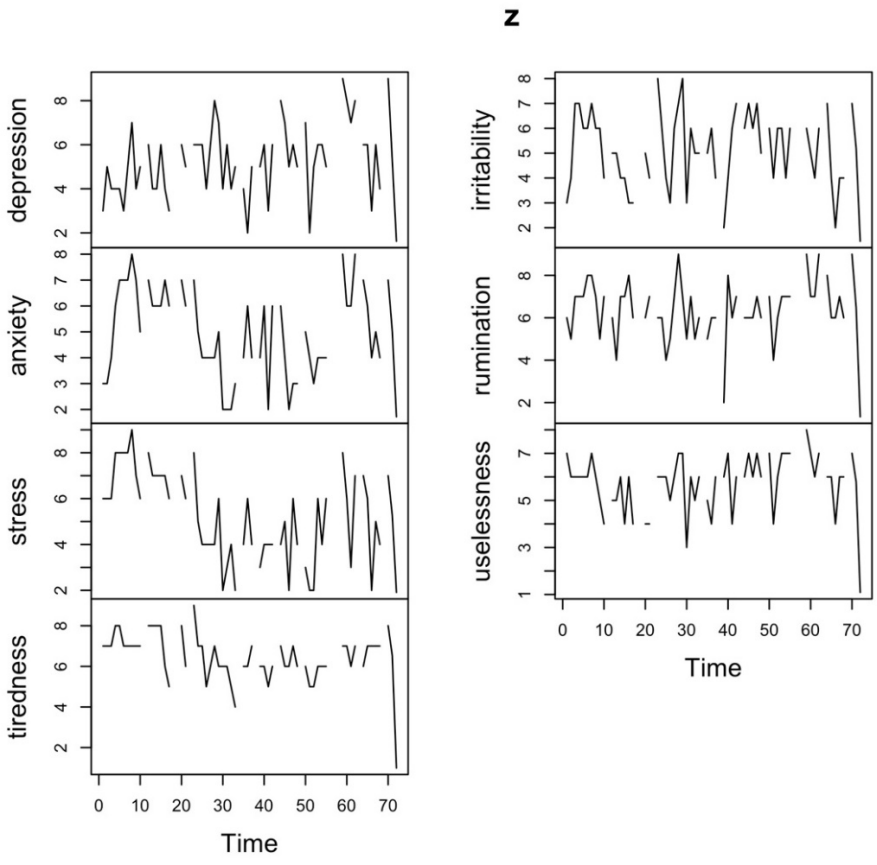
For FINA clinical utility, as with clinical validity, we use dyad # 7 as an illustrative example to describe the patient's temporal network that was shared with both the clinician and the patient, along with its descriptive interpretation, before they completed the clinical

utility questionnaire. We begin by presenting the preliminary analysis conducted on the Phase 2 data from the patient of this dyad, followed by a description of the patient's temporal network. We then report the clinician's and patient's evaluations of the utility of this network in terms of acceptability, applicability, ease of use and understandings, and cost. Finally, we report the overall clinical utility results, summarizing clinician and patient perceptions of the clinical utility of the shared networks from all 15 dyads.

Preliminary Analysis. Visual inspection indicated possible linear trends in each of the seven symptoms collected during Phase 2 (Figure 5). Significant linear trends were found for depression ($p = .047$), stress ($p < .001$), and tiredness ($p = .005$). To meet the stationarity assumption, these three symptoms were detrended using their residuals in the FINA analysis.

Figure 5.

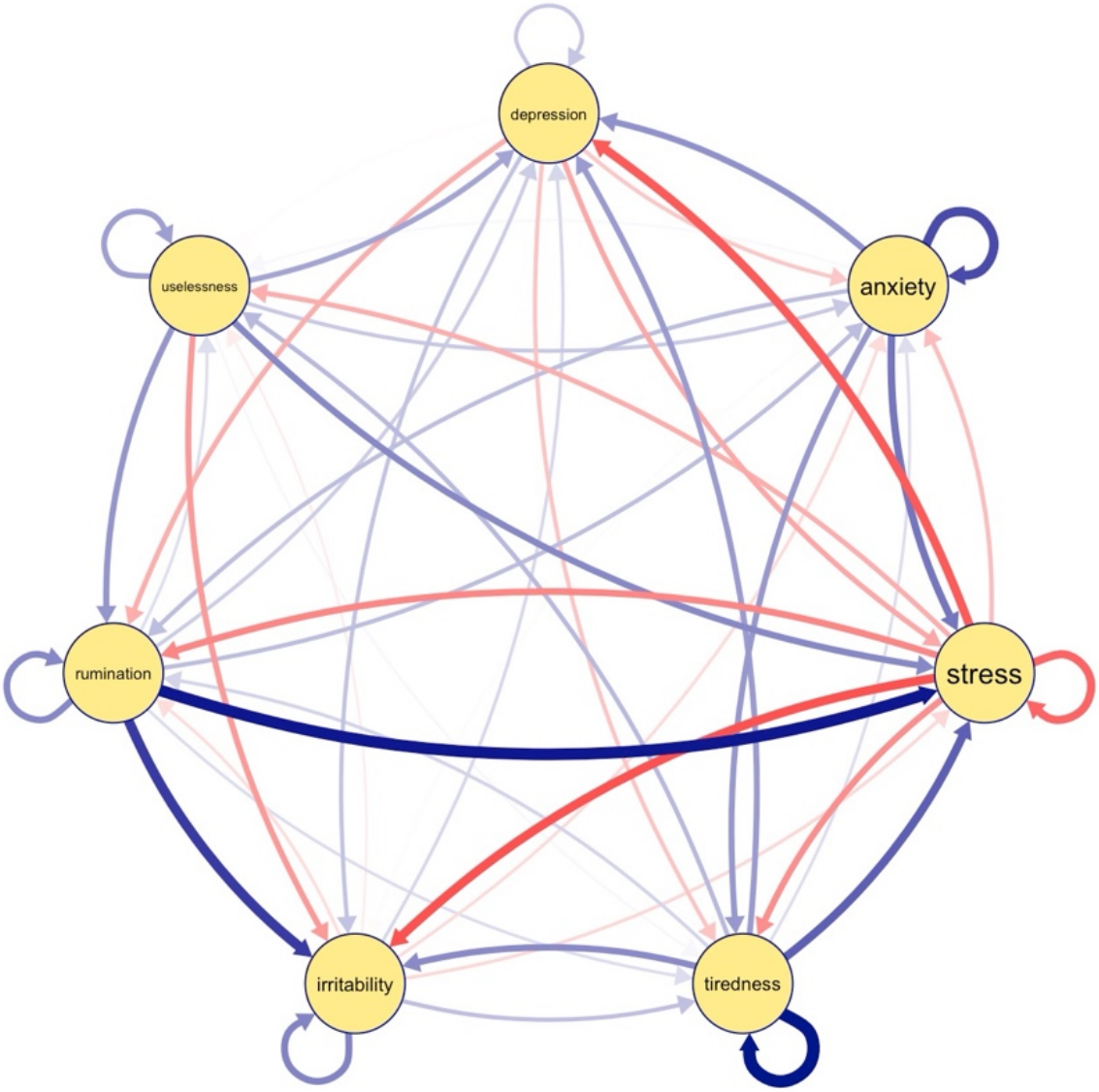
Graphical Representation of Time Trends



Patient's Temporal Network. Figure 6 shows the patient's temporal network estimated from the Phase 2 data, with edge values displayed in Table 3. Depression had weak positive connections with irritability and itself, and weak negative connections with anxiety, stress, tiredness, and rumination. Anxiety had moderate positive connections with stress and itself, and weak positive connections with depression, tiredness, and rumination. Stress had moderate negative connections with depression, irritability, and itself, and weak negative connections with anxiety, tiredness, rumination, and feelings of uselessness. Tiredness had a strong positive connection with itself, a moderate positive connection with stress, and weak positive connections with depression, anxiety, irritability, rumination, and feelings of uselessness. Irritability had weak positive connections with depression, tiredness, and itself, and weak negative connections with anxiety, stress, and rumination. Rumination had a strong positive connection with stress, a moderate positive connection with irritability, and weak positive connections with depression, anxiety, tiredness, feelings of uselessness, and itself. Finally, feelings of uselessness had weak positive connections with depression, anxiety, stress, rumination, and itself, and a weak negative connection with irritability. Appendix K presents the patient's temporal network along with the corresponding matrix and its descriptive interpretation for each dyad.

Figure 6.

Patient's Temporal Network Estimated on Phase 2 Detrended Data



Note. Blue links indicate positive relationships, red links indicate negative relationships, and the width and saturation of the link indicates the strength of the relationship.

Table 3.

Edge Values in the Patient's Temporal Network

	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**	**Uselessness**
Depression	.110	-.107	-.169	-.115	.116	-.160	-.003
Anxiety	.213	.350	.265	.199	-.005	.127	.014
Stress	-.320	-.129	-.301	-.221	-.336	-.236	-.157
Tiredness	.194	.063	.311	.497	.226	.084	.136
Irritability	.076	-.069	-.075	.122	.242	-.066	-.032
Rumination	.097	.126	.465	.065	.382	.233	.062
Uselessness	.175	.105	.229	.015	-.199	.206	.188

Clinician's and Patient's Perceptions of Clinical Utility. Table 4 shows the average utility scores of FINA based on the perceptions of both the clinician and the patient. Both parties found the graphical representation of the patient's symptom network to be equally applicable across different settings. Global utility perception scores were also comparable between the clinician and the patient. However, the clinician rated FINA as poorly applicable across different patients, in contrast to the patient, whose mean score was above the midpoint of the response scale. The clinician also rated FINA as more acceptable and easier to use and understand than the patient, though both had mean scores above the midpoint. These differences may be due to several factors. The clinician's higher level of psychological expertise and familiarity with symptom dynamics, combined with her cognitive-behavioral orientation, may have contributed to a greater appreciation of FINA's utility in tracking specific symptom patterns. Additionally, with approximately 60 sessions conducted, the clinician's extensive familiarity with the patient's history and treatment progress likely made FINA's insights feel more intuitive and manageable to her than to the patient.

The perceived costs of FINA in terms of the time and effort required to understand the graphical representation of the patient's symptom network, as well as the data collection procedure involved, were rated higher by the patient than by the clinician. For the patient, completing the intensive repeated assessments and interpreting the symptom network output felt more burdensome than it did for the clinician. Despite this, the patient's high completion rate of assessments considering both Wave 1 and Wave 2 (84.8%) indicates strong engagement with the frequent assessments.

Table 4.

Mean FINA Clinical Utility Dimension and Total Scores for Clinician-Patient Dyad #7

	Applicability to different patients	Applicability across different settings	Acceptability	Ease of use and understanding	Cost for its application	Total clinical utility
Clinician	2.00	4.67	5.56	5.33	5.75	4.66
Patient	4.60	4.60	4.63	4.60	3.80	4.44

Note. Scores for each dimension and the total score ranged from 1 to 7.

Perceived FINA Clinical Utility from Clinicians and Patients across All Dyads

Table 5 presents the average utility of FINA as perceived by all clinicians and patients. Overall, clinicians found FINA significantly and largely more applicable across different patients, $F(1, 14) = 4.79$, $p = .046$, $d = 0.76$. Although differences were nonsignificant, clinicians rated FINA as slightly more applicable across different settings, $F(1, 14) = 1.90$, $p = .19$, $d = 0.35$, and moderately easier to use and understand, $F(1, 14) = 2.94$, $p = .11$, $d = 0.49$, and less costly, $F(1, 14) = 2.18$, $p = .16$, $d = 0.52$, than did patients. Global perceived clinical utility was also moderately higher among clinicians than patients, with the difference approaching significance, $F(1, 14) = 4.09$, $p = .06$, $d = 0.51$. Notably,

mean ratings of acceptability were identical across clinicians and patients, $F(1, 14) = 0.01$, $p = .94$, $d = 0.02$.

Table 5.

Descriptive Statistics (Means and SD) of FINA Clinical Utility Dimension and Total Scores Across Clinicians and Patients

	Applicability to different patients	Applicability across different settings	Acceptability	Ease of use and understanding	Cost for its application	Total clinical utility
Clinician	5.00 (1.24)	4.77 (1.42)	4.58 (1.36)	5.24 (1.03)	5.43 (0.83)	5.00 (0.86)
Patient	3.95 (1.52)	4.28 (1.37)	4.55 (1.26)	4.69 (1.21)	4.87 (1.29)	4.47 (1.18)

Note. Scores for each dimension and the total score ranged from 1 to 7.

Discussion

In recent years, NA has proven to be a valuable tool for investigating the complex interplay of psychological symptoms. Unlike approaches that aggregate data across individuals, FINA offers a person-centered method that can reveal unique symptom dynamics within individual patients, potentially informing more personalized intervention strategies (Piccirillo & Rodebaugh, 2019). Given the powerful potential of FINA for highly personalized patient care, this study ambitiously aimed to rigorously evaluate its clinical validity and real-world utility within authentic clinical practice environments. More specifically, our research sought to determine, through a robust training-test approach, whether networks estimated using FINA could accurately and effectively predict patient functioning. We also explored whether both clinicians and patients perceived FINA as broadly applicable across varied patient profiles and settings, acceptable and user-friendly, easily understandable, and, importantly, cost-effective.

For clinical validity, the findings suggest that FINA is a valid predictive tool for the functioning of the patient. When comparing the FINA-derived empirical model against both a clinician-derived model and a null model built on symptom means, we observed significant differences in predictive accuracy. Specifically, FINA exhibited the highest predictive accuracy in forecasting patient functioning, outperforming both the clinical and null models. Furthermore, the clinical model produced significantly less accurate predictions than the null model. These findings suggest that FINA may offer a more accurate representation of individual symptom dynamics than clinicians' conceptualizations. However, the superior performance of empirical models over clinical models, and the lower performance of clinical models relative to null models, should be interpreted within the framework of fully idiographic analyses, which focus on intraindividual variations estimated through intensive, repeated-measures data collection (Piccirillo & Rodebaugh, 2019). Indeed, our results align with previous research in psychopathology, which has demonstrated that data-driven models can capture dynamic symptom fluctuations with a level of precision that traditional clinical assessments may lack, suggesting that empirical data-based models may enhance clinicians' treatment strategies (Burger, Epskamp et al., 2022; Frumkin et al., 2021; Lutz et al., 2024). The advantage of the empirical model over the clinician model supports the notion that systematic, data-driven methods may deepen the understanding of patient-specific patterns. While clinician insights are valuable, they can sometimes be limited and, as a result, outperformed by data-driven approaches (Fernandez et al., 2017). Consequently, clinical judgment may be enhanced when combined with idiographic assessments that emphasize temporal patterns and symptom interactions (Burger et al., 2020). Additionally, data-driven methods highlight limitations in traditional clinical practice related to the infrequent timing of patient assessments. Clinicians typically rely on weekly sessions to evaluate patient functioning (Brattland et al., 2018), which contrasts with the intensive data collection

provided by EMA. Therefore, it is unsurprising that the clinician model may not perform as effectively as models constructed through intensive EMA data collection. The difference in data collection intensity between clinician-derived and empirical models, highlights FINA's potential role in providing real-time insights that clinicians alone may not have the capacity to gather. FINA also mitigates limitations related to recall bias (i.e., the tendency to alter past experiences when recalling them) by allowing patients to give more accurate and realistic evaluations of their symptoms through brief, multiple daily assessments (Shiffman et al., 2008).

The superior performance of the null model, which assumes symptoms remain constant and independent of each other, over the clinical model may be attributed to several factors. For instance, when the time window is relatively short, it may not fully capture the dynamic interrelationships between symptoms (Epskamp, van Borkulo et al., 2018), allowing the null model's assumption of symptom constancy to yield better predictions. Moreover, clinicians may introduce biases or overestimate connections between symptoms based on theoretical orientations or personal clinical experience, rather than real-time data patterns (Bowes et al., 2020; Vally et al., 2023). This can diminish the predictive accuracy of the clinical model compared to the straightforward assumptions of the null model.

The significant interaction effect between model type and number of observations in the second mixed-effects model indicated that, as the number of observations increased, predictive accuracy varied depending on model type, with the empirical model showing improved accuracy at higher data volumes. This suggests that FINA's effectiveness in representing an individual's symptom network may rely on a high data intensity. This finding aligns with previous research indicating that data density is essential for capturing nuanced, person-specific symptom interactions (Mansueto et al., 2023; Piccirillo & Rodebaugh, 2019). Minimizing missing data is therefore critical when estimating networks with FINA. One

statistical approach involves adopting planned missingness (Mansueto et al., 2023), where certain items are intentionally omitted at each measurement point to create data that are missing completely at random or missing at random, thus balancing participant burden with data completeness. Another strategy to reduce missing data in intensive assessments is improving patient compliance through incentives (Wrzus & Neubauer, 2023) or by personalizing data collection tools to be more user-friendly, promoting better engagement and adherence (Pieritz et al., 2021).

Turning to FINA's clinical utility, both clinicians and patients found the graphical representation of the patient's symptom network to be an acceptable tool that complements and supports the clinical work, enhancing rather than hindering the therapeutic relationship. Clinicians rated FINA as more applicable across different patients and settings, easier to use and understand, and less costly. These findings suggest that, while FINA holds considerable promise for clinicians, patient perspectives should be carefully considered to optimize its utility in clinical practice, particularly in terms of ease of use and understanding, and the time and effort required for its application.

Regarding ease of use and understanding, as well as the time and effort required for patients to grasp the graphical representation of their symptom network, the results highlight the importance of presenting the symptom network output in a way that is accessible to patients. This involves using clear, tailored language that makes the information approachable for individuals without a clinical or statistical background, allowing them to better understand their own functioning and identify practical steps for addressing psychological concerns. This approach aligns with research suggesting that, when presenting information to a patient, it is important to consider factors like the patient's ability to understand healthcare information accurately and their emotional responses to feedback (Russo et al., 2019). Additionally, reports for patients should be more comprehensive. Rather

than simply presenting a graphical network and a list of symptom connections, they could include explanations on how multiple symptoms interact to shape the patient's difficulties, thereby enhancing patient insight (Kroeze et al., 2017). Furthermore, the time and effort required for the intensive data collection procedure is an important consideration. The two-week period with five daily prompts used in this study, while effective for data collection, may benefit for adaptation to improve the patient experience and reduce any sense of burden. Research suggests that intensive EMA can be challenging for patients unless tailored to individual needs (Fritz et al., 2024; Meglio et al., 2024). Although intensive data collection has been shown to be less intrusive in non-clinical settings (Perski et al., 2022), careful planning is essential in mental health settings. This involves considering the patient's specific issues and adjusting technical aspects of EMA, such as prompt frequency and duration, to enhance its utility while ensuring reliable data collection (Yang et al., 2019).

Our results align with previous studies on both clinician and patient perspectives regarding clinical utility (Frumkin et al., 2021; Zimmermann et al., 2019). Like these studies, we found that clinicians tend to evaluate methods like FINA more favorably across multiple dimensions of utility, whereas patients, though generally receptive to these approaches, report somewhat lower scores. Both clinicians and patients in our study demonstrated a generally positive attitude toward FINA, with scores above the midpoint of the response scale across all utility dimensions for clinicians and nearly all dimensions for patients, as well as for global utility for both parties. This is consistent with other research showing that idiographic models, particularly those estimating patient-specific symptom dynamics, are valued by clinicians and patients alike in therapeutic contexts (Andreasson et al., 2023; Ralph-Nearman et al., 2024).

The present study has some limitations that should be acknowledged. First, FINA was estimated using a model (gVAR) that requires stationarity, meaning that the patient's

symptoms remain consistent over time. To address this, we included patients deemed clinically stable by their clinicians, following previous FINA studies that selected individuals not in relapse (Burger, Epskamp et al., 2022) or with stable medication regimens to ensure symptom stability (Epskamp, 2020). However, prioritizing stable patients may not fully reflect the goals of clinical practice and research, where addressing symptom instability is key (Epskamp, 2020). Future research could employ statistical models that do not assume stationarity, such as dynamic time warp analysis (Booij et al., 2021), and include patients with symptom instability, enabling broader comparisons in predictive accuracy and providing more relevant insights for typical clinical settings (Piccirillo & Rodebaugh, 2019).

Second, the three-hour window applied uniformly across symptoms in the EMA schedule may have overlooked the possibility that shorter or longer windows might better capture specific symptom patterns. Although the optimal duration for these windows likely varies across individuals and remains uncertain (Epskamp, van Borkulo, et al., 2018), evaluating the relevant timescale for each symptom before finalizing EMA measurements could ensure a more accurate reflection of individual symptom fluctuations.

Third, clinicians in our study may have faced challenges in defining the clinical model, particularly in estimating partial correlations. Partial correlations - a key statistical measure in psychological networks - is straightforward for statistical models to calculate but challenging for clinicians to conceptualize and apply. Research shows that clinicians tend to assess symptom relationships based on direct correlations (unconditional relationships) rather than partial correlations, which control for other variables (Schumacher et al., 2021). Additionally, defining symptom relationships over a three-hour time window, as required during the construction of the clinical model, may have added complexity, potentially impacting the clinical models' accuracy. Future studies could involve clinicians with research

experience who are better equipped to navigate both the research and clinical aspects of such models, rather than relying solely on clinical expertise (Bager-Charleson & McBeath, 2021).

Fourth, the clinicians in our study predominantly adhered to a cognitive-behavioral orientation, which may have influenced their positive evaluation of FINA's utility. Cognitive-behavioral approaches emphasize understanding symptom interconnections and prioritizing key symptoms (Ruggiero et al., 2021). This alignment with the network approach to psychopathology may have predisposed these clinicians to view FINA more favorably. Future studies should include clinicians from a broader range of therapeutic orientations.

Fifth, the FINA-derived empirical networks are statistical models representing conditional association between variables and do not inherently imply causal relationships. In contrast, clinician-predicted symptom networks are informed by clinical expertise and may incorporate causal assumptions based on theoretical knowledge. Determining how data-driven networks can integrate causal information remains a challenge, and future studies should explore methods to infer causal structures from empirical networks (Ryan et al., 2022).

Finally, we used a clinical utility questionnaire specifically developed for this research. While its internal consistency was adequate, evidence of validity has yet to be established. Although the questionnaire was designed based on prior literature (Frumkin et al., 2021, Haynes & Yoshioka, 2007) and expert feedback, this limitation may impact the robustness of findings related to FINA's clinical utility. Future studies should evaluate the questionnaire's psychometric properties in larger samples to ensure a valid and reliable assessment.

Despite these limitations, the findings of this study open new avenues for research and present important clinical implications. By providing evidence for FINA's validity, this study reinforces the potential for data-informed methods like FINA to effectively complement

clinicians' expertise, especially in understanding individual symptom dynamics. For example, symptoms network could be applied in clinical practice to identify personalized treatment targets within a patient's symptom profile (Levinson et al., 2021; Ong et al., 2022), allowing clinicians to tailor interventions more effectively by prioritizing the most impactful symptoms.

Additionally, FINA can strengthen the accuracy of clinicians' judgments by improving case conceptualization in daily practice. For instance, FINA helps clarify relationships between key clinical variables, promoting a more individualized approach to case formulation rather than relying solely on diagnosis-driven models (Tolchinsky, 2024; van den Bergh et al., 2024). FINA can also facilitate alignment of therapeutic goals between clinicians and patients. When patients feel misunderstood by the clinician or perceive a misalignment with their clinician, this can lead to early therapy termination (Alfonsson et al., 2024; Kealy et al., 2022). By serving as a "map" to clarify the patient's symptom dynamics and anticipated progress, FINA can help both parties assess whether they are working toward shared objectives and foster a more nuanced understanding of the patient's experiences and challenges. Expanding the validity and utility of FINA across diverse clinical populations is another important direction for future research. For example, it would be valuable to examine how FINA performs within specific mental disorders, as symptom dynamics can vary substantially among individuals with the same diagnosis (Roefs et al., 2022). Beyond diagnostic contexts, assessing FINA within different cultural, socioeconomic, and age groups could further reveal whether and how its idiographic approach can adapt to diverse patient populations.

A further key area for future research involves examining the long-term impact of FINA on patient outcomes. While this study primarily focused on predictive accuracy, future studies could investigate whether integrating FINA into treatment leads to improvements in

patient functioning over time. This could be assessed through randomized controlled trials, comparing improvements for patients receiving traditional care versus those whose treatment is informed by FINA-derived insights.

To improve FINA's clinical utility for both clinicians and patients, efforts could focus on enhancing how FINA, and idiographic data-driven methods in general, are perceived as valuable in clinical practice. Although FINA was generally viewed as clinically useful by both clinicians and patients, there is certainly room for improvement. One approach could involve refining how intensive data collection is structured and conducted in clinical settings. For example, EMA and ESM designs could be implemented in ways that minimize patient burden, considering that high-frequency daily assessments can be manageable, if the overall duration is kept short (Wrzus & Neubauer, 2023).

On the clinician side, further education is needed on how intensive data collection, such as EMA, can support clinical practice and provide compelling reasons to adopt it. Addressing factors that obscure the immediate benefits of EMA for practitioners is crucial. For instance, EMA may sometimes be viewed as burdensome or even as a potential cause of symptom worsening, and clinicians often place greater trust in traditional resources for outcome monitoring, such as semi-structured diagnostic interviews or consultations with supervisors (Bos et al., 2019; Ellison, 2021). Emphasizing the role of clinicians' expertise in contributing with patient-specific insights can enhance the data collection process and increase their comfort with EMA (Burger, Epskamp et al., 2022). Another strategy could involve designing EMA collaboratively with patients (Soyster & Fisher, 2019), allowing for greater personalization and fostering active engagement from both clinicians and patients in understanding the patient's functioning. Ultimately, improving FINA's clinical utility will require not only technological advancements but also shifts in mental health professional training. Introducing clinicians to fully idiographic network models and intensive data

collection should be integrated into clinical training programs, following a structured implementation process (Wensing & Grol, 2019). This training could include case studies that illustrate the practical application of FINA, workshops on interpreting network models, and guidance on using patient data to inform treatment planning.

Conclusion

This research contributed to the growing body of literature on idiographic assessments in mental health, aiming to improve clinical practices tailored to individual patients. Our findings indicate that FINA is a valid methodology to complement traditional assessment and support clinicians in understanding symptom dynamics, with both clinicians and patients generally endorsing its clinical utility. To build on these findings and address the noted limitations, further research is needed to strengthen FINA's application in clinical practice, particularly across diverse patient populations and therapeutic orientations.

In conclusion, our study offers preliminary insights into FINA's potential as a valid and useful tool in clinical settings, paving the way for more individualized approaches to understanding and treating mental health disorders. While data-driven methods will not replace clinicians in their daily work with patients, they can serve as powerful aids to enhance therapy effectiveness and ultimately contribute to improved psychological well-being for patients.

Chapter 4

Final Reflections on the Clinical Validity and Utility of Network Analysis

General Discussion

The primary aim of this dissertation was to explore the clinical validity and utility of network analysis (NA) in clinical practice, with a specific focus on Fully Idiographic Network Analysis (FINA). FINA is a NA approach applied at the individual level, designed to estimate person-specific networks by assessing dynamic relationships between symptoms and tracking symptom progression over time through intensive data collection. The fully idiographic focus of this research was grounded in the unresolved "therapist's dilemma" (Levine et al., 1992): how could therapists plan and conduct therapy tailored to the individual when clinical psychology research is predominantly conducted at a nomothetic level? How could general principles derived from group-level research be effectively adapted to address the specific needs of an individual in a one-to-one clinical setting? This dissertation aimed to address this dilemma by investigating FINA's potential for enhancing clinical assessment and treatment planning in real-world settings.

To determine whether FINA is a suitable tool for clinical use, establishing its validity is essential, as current evidence is limited regarding its ability to reinforce and support the accuracy of clinicians' judgments in practice (Contreras et al., 2019; Schumacher et al., 2021; Wright & Woods, 2020). At the same time, previous research (Frumkin et al., 2021; Zimmermann et al., 2019) has not comprehensively examined all aspects of FINA's utility, including its applicability across different populations and settings, acceptability, ease of use and understanding, and time and effort costs (Haynes & Yoshioka, 2007). To address these objectives, two studies were conducted and reported in this dissertation.

The first study, reported in Chapter 2, was a systematic scoping review of empirical research that applied FINA in mental health. Its purpose was to identify common practices, trends, and gaps in the field (Peterson et al., 2015) to provide guidance for studies focused on constructing person-specific networks. The ultimate goal was to equip future researchers with the information needed to make informed decisions about study planning, data collection, analysis, and reporting. For example, we sought to clarify which analytical models are best suited for estimating person-specific networks and the types of data necessary for accurate estimation. The scoping review revealed considerable heterogeneity among studies using FINA, which, while presenting certain challenges, also offers a broad range of options for data collection and analysis in FINA research within mental health. As a result, researchers can now draw on the findings and guidelines from our review to apply FINA more effectively in investigating dynamic processes within individuals.

The second study, reported in Chapter 3, empirically tested FINA's clinical validity and utility using data from 15 clinicians and their patients. Clinical validity was assessed by comparing FINA-derived statistical models with clinician-derived models based on clinical expertise to evaluate their relative accuracy in predicting patient functioning. Clinical utility was assessed using ad-hoc questionnaires to capture clinicians' and patients' perceptions of FINA's applicability across different populations and settings, acceptability, ease of use and understanding, and cost. The findings showed that FINA-derived models outperformed clinician-derived models in predicting patient functioning, with FINA's predictive accuracy increasing as the number of data points grew. This suggests that FINA offers a more precise representation of symptom dynamics than clinician judgement alone, underscoring the importance of a high data volume for accurately capturing patient functioning. Both clinicians and patients generally supported the clinical utility of FINA, although clinicians reported higher perceived utility in some areas.

Findings from both studies lead to two complementary conclusions, one emphasizing theoretical aspects and the other focusing on practical applications. First, the findings from the scoping review underscore the importance of detailed reporting of FINA's methodological features in mental health research, laying the groundwork for future studies to apply this approach accurately. This includes addressing essential elements such as data collection, analysis, and the selection of appropriate statistical models. Second, the empirical study demonstrated the practical potential of FINA as a valid and useful tool in clinical settings, enabling more personalized approaches to mental health care. These individualized methods can be tailored to the unique symptom patterns and therapeutic goals of each patient, making interventions more precise and effective.

General Limitations

Despite efforts to provide a comprehensive scoping review of FINA and to test its validity and utility in mental health settings, both studies have limitations, as discussed in the previous chapters of this dissertation. Additional limitations arise when considering the broader conclusions of both studies.

First, both studies are limited by low specificity in the included samples, which may complicate the application of findings to specific clinical populations. While this promotes heterogeneity and may support broader applicability, it also complicates drawing precise conclusions for particular patient groups. Although both studies focused on a mental health context, FINA's clinical validity and utility remain unexplored within specific diagnoses, cultural backgrounds, and demographic subgroups. Future research should address this limitation by considering more narrowly defined populations to provide insights that can better inform individualized clinical applications.

Another limitation is the limited exploration of FINA’s long-term application, in both the scoping review and the empirical research. In the scoping review, only four studies

(Bodner et al., 2022; Hebbrecht et al., 2020; Levinson et al., 2020; Mariotti et al., 2021) assessed patients over a period of one year or more, while most studies, including the empirical research here, focused on short-term assessments lasting only a few weeks. This shorter timeframe may limit FINA's applicability for clinicians interested in evaluating patient functioning over the long term. Long-term assessment is particularly relevant in psychotherapeutic approaches, such as psychoanalysis, which prioritize understanding enduring patterns in a patient's psychological functioning. Without sufficient exploration of long-term dynamics, valuable insights that could improve FINA's practical application, particularly in therapies where symptom shifts occur gradually may be overlooked. Future research should address this gap by incorporating extended assessment periods to evaluate the clinical validity and utility of FINA in a way that better aligns with clinical practice. An interesting area for exploration would be whether clinician-derived models could outperform FINA over the long term, as FINA may excel at short-term predictions (e.g., over two weeks), while clinician models, informed by insights from ongoing therapy, might demonstrate superior performance over extended periods.

Finally, despite the insights gained from the scoping review and empirical study, it is important to acknowledge that NA is a relatively new and evolving statistical model, particularly within the idiographic approach. FINA represents an emerging methodology in clinical psychology, but several key aspects of network analysis in this context still require further exploration. For example, the use of node centrality indices, which measure the importance of specific symptoms within a network, is debated. While some researchers argue that these indices can guide interventions by identifying critical symptoms (Hofmann & Curtiss, 2018), others question their practical relevance in clinical settings (Bringmann et al., 2019). As the theoretical framework of idiographic network models continues to evolve,

more research is needed to determine which features of network analysis are truly essential for applying FINA in mental health contexts.

General Implications and Conclusion

The implications of this dissertation primarily concern the clinical validity and utility of network analysis in mental health. The findings from Chapter 2 and Chapter 3 make a significant contribution to both empirical research and clinical practice by addressing current gaps and outlining future directions for FINA. Additionally, they provide empirical support for FINA's potential to enhance the accuracy of clinicians' judgments, underscoring both research and clinical implications.

In terms of research implications, this dissertation offers researchers a clearer understanding of the available methodologies for constructing person-specific networks. The scoping review serves as a map, guiding researchers through the methodological and analytical strategies used in FINA, with insights into data collection methods, missing data handling, and criteria for model selection. Future research using FINA can build on this foundation by exploring underutilized models, especially those that do not assume stationarity, to broaden FINA’s applicability across diverse clinical populations.

Moreover, the scoping review in Chapter 2 and the empirical application of FINA in Chapter 3 lay the groundwork for establishing best practices in testing the clinical validity and utility of other models that, while not fully idiographic, may still hold value in clinical settings. An example of this is the potential testing of idionomic networks (Sanford et al., 2022), which model idiographic dynamics first and incorporate nomothetic data from larger populations only when it enhances the fit of the idiographic model. Building on the approach outlined in this dissertation, researchers could begin by conducting a scoping review to map the methodologies used in idionomic networks, identifying common practices and areas for improvement. Researchers could then test the clinical validity of idionomic models by

comparing them with FINA-derived models and clinician-based models to determine which approach is more suitable for clinical practice. Evaluating the clinical validity and utility of various statistical models could ultimately enhance the integration of data-driven methods in mental health.

In terms of clinical implications, this dissertation contributes to establishing a foundation for clinical interventions based on NA, offering both a guideline for selecting appropriate statistical models to estimate person-specific networks and evidence of NA's validity and utility in clinical practice. In recent years, clinical interventions using the network approach have started to emerge, exemplified by Process-Based Therapy (PBT) (Hofmann & Hayes, 2019; Moskow et al., 2023). PBT represents a shift from diagnosis-driven treatments to a more dynamic, process-oriented approach to mental health issues. By prioritizing idiographic and functional analysis over nomothetic, diagnosis-based approaches, PBT provides a framework for integrating FINA into clinical practice.

In PBT, a network approach is used to estimate an individual's symptoms network, guiding the therapist in selecting evidence-based interventions based on the network structure (e.g., addressing edges with the highest values). This approach allows PBT to adapt flexibly to each patient's unique symptoms network rather than relying on one-size-fits-all diagnoses. While PBT studies have often utilized models such as Group Iterative Multiple Model Estimation (GIMME) (Ong et al., 2022), FINA offers additional modeling options. For example, a clinician aiming to understand both fast-acting symptoms of a patient's anxiety, like those seen in panic attacks, and slower symptoms such as rumination, could use FINA with gVAR modeling within the PBT framework. In this setup, contemporaneous effects in gVAR, modeled with shorter intervals (e.g., three-hour windows), capture rapid symptom fluctuations, while temporal effects are suited to track more gradual symptom dynamics. Integrating FINA into PBT could enable clinicians to develop more targeted and personalized

interventions, focusing on dynamic processes that are meaningful for both clinician and patient, collaboratively addressing these processes across different phases of therapy.

In conclusion, this dissertation represents a first successful step in exploring the clinical validity and utility of network analysis in clinical practice. FINA offers a promising approach to bridging the gap between clinical practice and mental health research, addressing the therapist's dilemma. Furthermore, it has the potential to enhance clinical psychological interventions by tailoring them to each patient's unique characteristics and helping to achieve personalized therapeutic goals.

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Appendix A

Search Strings

MEDLINE

(("network*"[Title/Abstract] AND ("analys*"[Title/Abstract] OR "statistic*"[Title/Abstract] OR "model*"[Title/Abstract] OR "approach*"[Title/Abstract] OR "psycho*"[Title/Abstract] OR "symptom*"[Title/Abstract] OR "method*"[Title/Abstract]) AND ("idiographic"[Title/Abstract] OR "within subject*"[Title/Abstract] OR "single subject*"[Title/Abstract] OR "individual level*"[Title/Abstract] OR "within person"[Title/Abstract] OR "person centered"[Title/Abstract] OR "person centred"[Title/Abstract] OR "person specific"[Title/Abstract] OR "personalized"[Title/Abstract] OR "personalised"[Title/Abstract])) OR ("idiographic"[Title/Abstract] AND ("analys*"[Title/Abstract] OR "statistic*"[Title/Abstract] OR "model*"[Title/Abstract] OR "approach*"[Title/Abstract] OR "psycho*"[Title/Abstract] OR "symptom*"[Title/Abstract] OR "method*"[Title/Abstract]))) AND (("clinical trial"[Publication Type] OR "controlled clinical trial"[Publication Type] OR "journal article"[Publication Type] OR "meta analysis"[Publication Type] OR "observational study"[Publication Type] OR "randomized controlled trial"[Publication Type] OR "review"[Publication Type] OR "systematic review"[Filter]) AND ("english"[Language] OR "italian"[Language] OR "spanish"[Language] OR "humans"[MeSH Terms]) AND 2010/01/01:2021/12/31[Date - Publication]) AND "medline"[Filter]

PsycINFO

(TI (network*) AND TI (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*) AND TI (idiographic OR within-subject* OR single-subject* OR individual-level* OR within-person OR person-centered OR person-centred OR person-specific OR personalized OR personalised)) OR (TI (idiographic) AND TI (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*)) OR (AB (network*) AND AB (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*) AND AB (idiographic OR within-subject* OR single-subject* OR individual-level* OR within-person OR person-centered OR person-centred OR person-specific OR personalized OR personalised)) OR (AB (idiographic) AND AB (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*)) OR (KW (network*) AND KW (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*) AND KW (idiographic OR within-subject* OR single-subject* OR individual-level* OR within-person OR person-centered OR person-centred OR person-specific OR personalized OR personalised)) OR (KW (idiographic) AND KW (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*))

Scopus

(TITLE-ABS-KEY (network*) AND (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*) AND (idiographic OR within subject* OR single subject* OR individual level* OR within person OR person centered OR person centred OR person specific OR personalized OR personalised)) OR (TITLE-ABS-KEY (idiographic) AND (analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*)) AND (LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014) OR LIMIT-TO (PUBYEAR , 2013) OR LIMIT-TO (PUBYEAR , 2012) OR LIMIT-TO (PUBYEAR , 2011) OR LIMIT-TO (PUBYEAR , 2010)) AND (LIMIT-TO (LANGUAGE , "English") OR LIMIT-TO (LANGUAGE , "Italian") OR LIMIT-TO (LANGUAGE , “Spanish”)) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "re"))

Web of Science

(((TI= (network*)) AND (TI=(analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*)) AND (TI=(idiographic OR within-subject* OR single-subject* OR individual-level* OR within-person OR person-centered OR person-centred OR person-specific OR personalized OR personalised))) OR ((TI=(idiographic)) AND (TI=(analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*))) OR ((AB= (network*)) AND (AB=(analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*)) AND (AB=(idiographic OR within-subject* OR single-subject* OR individual-level* OR within-person OR person-centered OR person-centred OR person-specific OR personalized OR personalised))) OR ((AB=(idiographic)) AND (AB=(analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*))) OR ((KP= (network*)) AND (KP=(analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*)) AND (KP=(idiographic OR within-subject* OR single-subject* OR individual-level* OR within-person OR person-centered OR person-centred OR person-specific OR personalized OR personalised))) OR ((KP=(idiographic)) AND (KP=(analys* OR statistic* OR model* OR approach* OR psycho* OR symptom* OR method*))))

Appendix B

Data Extracted from Included Studies

1st author last name (Year)	Is the study part of a larger project or an analysis of already published/preexisting data (i.e., secondary analysis)?	Total sample size	Characteristics of the total sample (NR = not reported)			N (%) individuals analyzed with FINA	Characteristics of individuals analyzed with FINA (NR = not reported)		
			Age	%F	Diagnosis		Age	%F	Diagnosis
Bodner (2022)	YES	267	42.8 (11.3)	65	Depression (100%)	158 (59.2%)	NR	NR	Depression (100%)
Booij (2021)	NO	133	60.4 (15.1)	64.7	Depression (100%)	133 (100%)	60.4 (15.1)	64.7	Depression (100%)
Bulteel (2018)	YES	204	101 younger (25.6 (2.7)) and 103 older adults (71.3 (4.1))	101 younger (51.5% women) and 103 older adults (49.5% women)	NR	1 (0.5%)	21	100	Depression (potential diagnosis) (100%)
Burger (2022)	YES	1	31	100	Obsessive-compulsive disorder (100%)	1 (100%)	31	100	Obsessive-compulsive disorder (100%)
David (2018)	YES	1	44	100	Comorbidity (100%)	1 (100%)	44	100	Comorbidity (100%)
de Vos (2017)	YES	54 (27 MDD patients and 27 healthy controls)	34.7 (9.9) (MDD group); 34.0 (9.0) (healty group)	74.1 (MDD group); 74.1 (healthy group)	Depression (50%)	54 (100%)	34.7 (9.9) (MDD group); 34 (9) (healty group)	74.1 (MDD group); 74.1 (healthy group)	Depression (50%)
Epskamp (2018)	NO	1	53	100	Depression (100%)	1 (100%)	53	100	Depression (100%)
Epskamp (2020)	YES	1	57	0	Depression (100%)	1 (100%)	57	0	Depression (100%)
Fisher (2017)	YES	40	18 to 65	65	Generalised anxiety disorder (15%), major depressive disorder (10%), comorbidity (75%)	40 (100%)	18 to 65	65	Generalised anxiety disorder (15%), major depressive disorder (10%), comorbidity (75%)
Frumkin (2021)	NO	12	33.7 (12.1)	58.3	Comorbidity (75%), adjustment disorder (8.33%), general anxiety disorder (8.33%), not available (8.33%)	12 (100%)	33.7 (12.1)	58.3	Comorbidity (75%), adjustment disorder (8,3%), general anxiety disorder (8,3%), not available (8.3%)
Hebbrecht (2020)	YES	255	50.9 (15.4)	64.7	Depression (81.2%); bipolar disorder (18.8%)	255 (100%)	50.9 (15.4)	64.7	Depression (81.2%); bipolar disorder (18.8%)
Howe (2020)	YES	45	37.6 (13.4)	65.2	Generalised anxiety disorder (51.1%), major depressive disorder (24.4%), comorbidity (24.4%)	45 (100%)	37.6 (13.4)	65.2	Generalised anxiety disorder (51.1%), major depressive disorder (24.4%), comorbidity (24.4%)
Levinson (2018)	NO	66	25 (7.3)	97	Eating disorders (100%)	3 (4.6%)	NR	NR	Anorexia nervosa (100%)
Levinson (2020)	YES	1272	18.5 (4.2)	100	Eating disorder or at-risk of eating disorder (100%)	50 (3.9%)	18.3 (5.1)	100	NR
Levinson (2021)	NO	34	34.5 (11.1)	91.2	Eating disorder (100%)	34 (100%)	34.5 (11.1)	91.2	Eating disorder (100%)
Levinson (2022)	NO	102	29.6 (9.3)	94.1	Eating disorder (100%)	97 (95.1%)	NR	NR	Eating disorder (100%)
Lydon-Staley (2021)	YES	1210	NR	58.4	Tobacco withdrawal (100%)	2 (0.2%)	NR	NR	Tobacco withdrawal (100%)
Mariotti (2021)	NO	1	12	0	Comorbidity (100%)	1 (100%)	12	0	Comorbidity (100%)
Piccirillo (2022)	NO	35	21.4 (5.2)	100	Comorbidity (100%)	35 (100%)	21.4 (5.2)	100	Comorbidity (100%)
Reeves (2020)	NO	20	38.4 (12.5)	40	Post-traumatic stress disorder (100%)	20 (100%)	38.4 (12.5)	40	Post-traumatic stress disorder (100%)
Scholten (2022)	NO	3	33 (9.7)	33.3	Depression (66.7%) and comorbidity (33.3%)	3 (100%)	33 (9.7)	33.3	Depression (66.7%) and comorbididity (33.3%)
Thonon (2020)	NO	3	34 (5)	66.7	Schizophrenia (100%)	3 (100%)	34 (5)	66.7	Schizophrenia (100%)
Wright (2015)	YES	101	44.9 (13.3)	65.3	Personality disorders (100%)	4 (4%)	NR	NR	Personality disorders (100%)

1st author last name (Year)	N (%) individuals analyzed with FINA whose FINA results are reported (in either the main text, supplementary material or open science repositories)	Characteristics of individuals analyzed with FINA whose FINA results are reported (in either the main text, supplementary material or open science repositories) (NR = not reported)			Setting of recruitment (NR = not reported)	Compensation (NR = not reported)	Method used to collect data	Device used to collect data (NR = not reported)
		Age	%F	Diagnosis				
Bodner (2022)	1 (0.6%)	NR	NR	Depression (100%)	Outpatient	NR	Interview	Telephone
Booij (2021)	133 (100%)	60.4 (15.1)	64.7	Depression (100%)	Inpatient	NR	Routine Outcome Monitoring (ROM)	NR
Bulteel (2018)	1 (100%)	21	100	Depression (potential diagnosis) (100%)	Community	NR	Self-report questionnaire	NR
Burger (2022)	1 (100%)	31	100	Obsessive-compulsive disorder (100%)	NR	NR	EMA	Electronic device - smartphone
David (2018)	1 (100%)	44	100	Comorbidity (100%)	NR	NR	Self-report questionnaire	Paper and pencil
de Vos (2017)	8 (14.8%)	NR	NR	NR	NR	NR	ESM	Electronic device (PsyMate)
Epskamp (2018)	1 (100%)	53	100	Depression (100%)	Outpatient	NR	ESM	Electronic device - smartphone
Epskamp (2020)	1 (100%)	57	0	Depression (100%)	NR	NR	ESM	Electronic device (PsyMate)
Fisher (2017)	3 (7.5%)	36	66.7	Comorbidity (100%)	Community	NR	ESM	Electronic device - smartphone
Frumkin (2021)	12 (100%)	33.7 (12.1)	58.3	Comorbidity (75%), adjustment disorder (8.3%), general anxiety disorder (8.3%), not available (8.3%)	Outpatient	YES	EMA	Electronic device - smartphone
Hebbrecht (2020)	2 (0.8%)	46.5 (12)	100	Depression (100%)	Inpatient	NR	Routine Outcome Monitoring (ROM)	Electronic device - computer (except for the first face-to-face assessment)
Howe (2020)	2 (4.4%)	44.5 (16.3)	100	Major depressive disorder (50%), comorbidity (50%)	Community	NR	EMA	Electronic device - smartphone
Levinson (2018)	3 (100%)	NR	NR	Anorexia nervosa (100%)	Inpatient and outpatients	YES	EMA	Electronic device - smartphone
Levinson (2020)	50 (100%)	18.3 (5.1)	100	NR	Community	NR	Interview	NR
Levinson (2021)	34 (100%)	34.5 (11.1)	91.2	Eating disorder (100%)	NR	NR	EMA	Electronic device - smartphone
Levinson (2022)	97 (100%)	NR	NR	Eating disorder (100%)	Community	NR	EMA	Electronic device - smartphone
Lydon-Staley (2021)	2 (100%)	NR	NR	Tobacco withdrawal (100%)	Community	NR	EMA	NR
Mariotti (2021)	1 (100%)	12	0	Comorbidity (100%)	Outpatient	NR	Self-report questionnaire	Paper and pencil
Piccirillo (2022)	35 (100%)	21.4 (5.2)	100	Comorbidity (100%)	Community	YES	EMA	Electronic device - smartphone
Reeves (2020)	20 (100%)	38.4 (12.5)	40	Post-traumatic stress disorder (100%)	Community	YES	EMA	Electronic device - smartphone
Scholten (2022)	3 (100%)	33 (9.7)	33.3	Depression (66.7%) and comorbidity (33.3%)	Outpatient	NR	EMA	Electronic device - smartphone
Thonon (2020)	3 (100%)	34 (5)	66.7	Schizophrenia (100%)	Outpatient	NR	ESM	Electronic device - smartphone
Wright (2015)	4 (100%)	NR	NR	Personality disorders (100%)	NR	YES	Diary	Electronic device - smartphone/computer

1st author last name (Year)	Length of data collection	Timescale	Maximum n of timepoints (i.e. timescale * lenght of data collection)	Mean number of completed timepoints / Percentage of completed timepoints (NR = not reported)	Sampling scheme (only for EMA/ESM studies) (NR = not reported)	Measures
Bodner (2022)	1015 days	1 per week	145	100 (percentage of completed timepoints)	-	Depression section of the Composite International Diagnostic Interview (CIDI) version 2.1
Booij (2021)	28-42 days (depending on the participant)	1 per week	7	6.2 (mean number of completed timepoints)	-	Comprehensive Psychopathological Rating Scale (CPRS) abbreviated version
Bulteel (2018)	78 days (78 observations were selected that were exactly 1day apart)	1 per day	100	100 (percentage of completed timepoints)	-	Positive and Negative Affect Schedule and 11 ad hoc items of depression-related symptoms
Burger (2022)	28 days (selected from a data collection period of almost 1 year)	3 per day	84	63.1 (percentage of completed timepoints)	Fixed	Ad hoc items
David (2018)	122 days	1 per day	122	73.8 (percentage of completed timepoints)	-	Items adapted from the Mood and Anxiety Symptoms Questionnaire
de Vos (2017)	30 days	3 per day	90	91.8 (MDD group); 93.2 (healthy group) (percentage of completed timepoints)	NR	Items adapted from a previous study
Epskamp (2018)	2 weeks	5 per day	70	93 (percentage of completed timepoints)	Fixed	Ad hoc items
Epskamp (2020)	84 days	10 per day	840	78.6 (percentage of completed timepoints)	Pseudo-random	Ad hoc items
Fisher (2017)	29-35 days (depending on the participant)	4 per day	140	130.4 (mean number of completed timepoints)	Pseudo-random	10 items based on the extant symptoms of the DSM-5 criteria for GAD and MDD and 11 ad hoc items
Frumkin (2021)	21-24 days (depending on the participant) for each wave (2 waves)	5 per day	120 for each wave (2 waves)	94 (mean number of completed timepoints)	Fixed	Ad hoc items
Hebbrecht (2020)	2 weeks-16 months (depending on the participant)	1 per 2 weeks	33	5.8 (mean number of completed timepoints)	-	Hamilton Rating Scale for Depression
Howe (2020)	30 days	4 per day	120	NR	Pseudo-random	Ad hoc items
Levinson (2018)	7 days	4 per day	28	23.3 (mean number of completed timepoints)	Fixed	Items drawn from the Eating Disorder Inventory-2, Eating Pathology Symptoms Inventory and Eating Disorder Examination-Questionnaire
Levinson (2020)	48 months	1 per month	48	NR	-	Items from the semi-structured Eating Disorder Diagnostic Interview
Levinson (2021)	15 days	5 per day	75	72.8 (percentage of completed timepoints)	NR	Ad hoc items
Levinson (2022)	25 days	4 per day	100	73 (percentage of completed timepoints)	Pseudo-random	Daily Habits Questionnaire
Lydon-Staley (2021)	14 days	4 per day	56	27.9 (mean number of completed timepoints) [calculated on the total sample]	NR	Items from the Wisconsin Smoking Withdrawal Scale and the Questionnaire of Smoking Urges
Mariotti (2021)	1 year (approximately)	1 per week (parent-ratings); 1 per 2 weeks (parent- and child-ratings)	52 (approximately)	NR	-	DSM–5 Level 2 Cross-Cutting Symptom Measures, Parent/Guardian-Rated and Child-Rated
Piccirillo (2022)	30 days	5 per day	150	125.4 (mean number of completed timepoints)	Fixed	Ad hoc items
Reeves (2020)	30 days (approximately)	4 per day	120 (approximately)	126.2 (mean number of completed timepoints)	Fixed	Items adapted from the Post-traumatic stress disorder Checklist for DSM-5
Scholten (2022)	30 days	3 per day	90	87.2 (percentage of completed timepoints)	Fixed	Items ad hoc or adapted from previous studies
Thonon (2020)	2 weeks in the baseline and follow-up phases, 7 weeks in the intervention phase	5 per day (baseline and follow-up phases), 3 per day (intervention phase)	287	NR	Pseudo-random	Ad hoc items
Wright (2015)	100 days	1 per day	100	89.5 (mean number of completed timepoints)	-	Ad hoc items

1st author last name (Year)	N of items/questions at each time point (NR = not reported)	Response scale	Exclusion of participants from statistical analyses based on missing timepoints (NR = not reported)	Check type of missing data (NR = not reported)	Method(s) used to handle missing data (NR = not reported)	Method(s) used to check for normality (NA = not applicable; NR = not reported)	Method(s) used to correct for non-normality (NR = not reported)
Bodner (2022)	8 (subset of items selected for the study)	Dichotomous	YES (participants with ≥ 71.7% of complete assessments were included in the analyses).	-	No missing data	NA	-
Booij (2021)	25	Ordinal (7-point Likert scale)	YES (participants with ≥ 57.1% of complete assessments were included in the analyses).	NR	Omitting missing data points	NA	-
Bulteel (2018)	31	Ordinal (8- and 4-point Likert scale)	NR	-	No missing data	NR	NR
Burger (2022)	5	Continuos (0-100)	NA	NR	Full information maximum likelihood	NR	NR
David (2018)	22 (subset of items selected for the study)	NR	NA	NR	NR	NR	NR
de Vos (2017)	14	Ordinal (7-point Likert scale)	NR	NR	Multiple imputation by expectation maximization with bootstrapping	Skewness	Normal quantile transformation of items
Epskamp (2018)	7 (subset of items selected for the study)	Ordinal (7-point Likert scale)	NA	NR	Omitting missing data points	NR	NR
Epskamp (2020)	14 (subset of items selected for the study)	Ordinal (7-point Likert scale)	NA	NR	Full information maximum likelihood	Theoretically assumed	-
Fisher (2017)	21	Continuos (0-100)	YES (participants with ≥ 80% of complete assessments were included in the analyses).	NR	Imputation (missing time differences replaced with zero)	NR	NR
Frumkin (2021)	9-11 (depending on the participant (8 fixed items + up to 3 perzonalized items))	Continuous (1-10)	NR	NR	Omitting missing data points	Theoretically assumed	-
Hebbrecht (2020)	17 (subset of items selected for the study)	Ordinal (5- and 3-point Likert scale)	NR	NR	NR	NA	-
Howe (2020)	6 (subset of items selected for the study)	Continuous (0-100)	NR	NR	Omitting missing data points	NR	NR
Levinson (2018)	11	Ordinal (6-point Likert scale)	NR	NR	Single imputation by Kalman filter	NR	NR
Levinson (2020)	8 (subset of items selected for the study)	Continuous (0-30 and 0-84) and ordinal (7-point Likert scale)	NR	NR	Multiple imputation by chained equations	NR	NR
Levinson (2021)	55	Continuous (0-100)	NR	NR	Multiple imputation by chained equations	NR	NR
Levinson (2022)	13	Ordinal (6-point Likert scale)	NR	NR	Single imputation by Kalman filter	NR	NR
Lydon-Staley (2021)	13	Continuous (0-10)	NR	NR	NR	NR	NR
Mariotti (2021)	NR	Continuos (dependently by the number of target behaviors) and ordinal (5-point Likert scale)	NA	NR	NR	NR	NR
Piccirillo (2022)	14	Continuous (0-10)	NR	NR	Multiple imputation by random forest	NR	NR
Reeves (2020)	28 (subset of items selected for the study)	Continuous (0-100)	YES (participants with ≥ 80% of complete assessments were included in the analyses).	NR	NR	NR	NR
Scholten (2022)	25-35 (depending on the participant)	Ordinal (5- and 6-point Likert scale)	YES (participants with ≥ 80% of complete assessments were included in the analyses).	YES	NR	NR	NR
Thonon (2020)	11 (subset of items usable for NA)	Ordinal (7-point Likert scale)	NR	NR	NR	NR	NR
Wright (2015)	16	Ordinal (8-point Likert scale)	YES (participants with ≥ 30% of complete assessments were included in the analyses).	NR	NR	Skewness and kurtosis	Robust WLSM and polychoric correlation matrix in multilevel CFAs

1st author last name (Year)	Method(s) used to check for stationarity (NA = not applicable; NR = not reported)	Method(s) used to correct for non-stationarity (NR = not reported)	Treatment of overnight lag (only for EMA/ESM studies) (NR = not reported)	Method(s) used to check for overlap between nodes (NA = not applicable; NC = not checked)	Methods used to handle overlap between nodes	Model used to estimate the networks	Variable used for node representation
Bodner (2022)	NA	-	-	NC	-	Contingency measure-based networks (ConNEcT)	Individual item score
Booij (2021)	NA	-	-	NC	-	Dynamic Time Warp (DTW) analysis	Individual item score
Bulteel (2018)	Theoretically assumed	-	-	Correlation analyses	Dimension reduction using Principal Component Analysis	Principal Component VAR (PC-VAR)	Individual item score, composite score
Burger (2022)	NR	Selection of a sample of the data without clinical relapses; detrending[a]	Removed[b]	NC	-	Bayesian VAR (PREMISE approach)	Individual item score
David (2018)	Portmanteau Q-test and Lagrange multiplier test	Detrending[a]	-	NC	-	Dynamic time series multiple linear regression	Individual item score
de Vos (2017)	NR	Detrending[a]	Ignored (it is assumed that the overnight lag has the same duration as the in-day time lags)	NC	-	Sparse VAR (sVAR)	Individual item score
Epskamp (2018)	Test of significance of linear trends	Detrending[a]	Removed[b]	NC	-	gVAR	Individual item score
Epskamp (2020)	Test of significance of linear trends	Detrending[a]	Removed[b]	NA (nodes are composite scores)	-	time series - latent variables gVAR (ts-lvgVAR)	Composite score
Fisher (2017)	Test of significance of linear trends	Detrending[a]	Ignored (cubic spline interpolation)	NC	-	Dynamic factor analysis	Individual item score
Frumkin (2021)	Correlations between study items and day and survey number	Detrending[a]	Removed[b]	Correlation analyses	Creation of composites using equally-weighted averages at each time point	gVAR	Individual item score, composite score
Hebbrecht (2020)	NA	-	-	NC	-	Dynamic Time Warp (DTW) analysis	Individual item score
Howe (2020)	NR	Latent Profile Analysis (applied to individual time series)	Removed[b]	NC	-	Latent profile analysis (applied to individual time series) and mixed VAR (mVAR)	Individual item score
Levinson (2018)	NR	NR	NR	NC	-	gVAR	Individual item score
Levinson (2020)	Inspection of time trends	No correction necessary	-	NC	-	gVAR	Individual item score
Levinson (2021)	NR	NR	Removed[b]	NC	-	gVAR	Individual item score
Levinson (2022)	NR	NR	Removed[b]	NC	-	gVAR	Individual item score
Lydon-Staley (2021)	NR	Detrending[a]	Removed[b]	NA (nodes are composite scores)	-	Unified SEM (uSEM)	Composite score
Mariotti (2021)	NR	NR	-	NC	-	gVAR	Individual item score, composite score
Piccirillo (2022)	Inspection of time trends	Detrending[a]	Removed[b]	Correlation analyses	Creation of an average composite between strongly correlated items	gVAR	Individual item score, composite score
Reeves (2020)	NR	Detrending[a]	Ignored (cubic spline interpolation)	NC	-	Dynamic factor analysis	Individual item score, composite score
Scholten (2022)	Test of significance of linear trends	Detrending[a]	Removed[b]	Correlation analyses	Selection of the variable with the larger variance in case of a large bivariate correlation	gVAR	Individual item score
Thonon (2020)	Computation of rolling means	NR	Removed[b]	NC	-	gVAR	Individual item score, composite score
Wright (2015)	NR	NR	-	NA (nodes are composite scores)	-	Unified SEM (uSEM)	Composite score

Note. [a] replacement of scores with the residuals; [b] the first measurement of a day is not regressed on the last measurement of the previous day

1st author last name (Year)	N of nodes in the estimated network(s)	Estimation of contemporaneous network(s)	Estimation of temporal network(s)	Centrality indices in the contemporaneous network (NR = not reported; NE = not estimated)	Centrality indices in the temporal network (NR = not reported; NE = not estimated)	Method(s) to evaluate network stability in the contemporaneous network (NR = not reported; NA = not applicable)	Method(s) to evaluate network stability in the temporal network (NR = not reported; NC = not checked)
Bodner (2022)	8	YES	NO	NE	-	NA	-
Booij (2021)	6-25 (depending on the participant)	YES	NO	Strength	-	NA	-
Bulteel (2018)	23 in the PANAS network, 14 in the depression network	YES (contemporaneous and lagged relationships combined in a single figure)	YES (contemporaneous and lagged relationships combined in a single figure)	NE	Outstrength	NR	NR
Burger (2022)	5	YES	YES	NE	NE	NR	NR
David (2018)	19	NO	YES	-	Outdegree, indegree, betweenness	NR	NR
de Vos (2017)	14	NO	YES	-	Instrength, outstrength	Skewness	NR
Epskamp (2018)	7	YES	YES	NE	NE	NR	NR
Epskamp (2020)	5	YES	YES	NR	NR	Theoretically assumed	Case-drop bootstrap (25%)
Fisher (2017)	21	YES	YES	Strength	Instrength, outstrength	NR	NR
Frumkin (2021)	9-11 (depending on the participant)	YES	YES	Strength	Instrength, outstrength	Theoretically assumed	NR
Hebbrecht (2020)	Up to 17 (depending on the participant; items that consistently scored 0 were excluded)	YES	NO	NE	-	NA	-
Howe (2020)	6	YES	NO	NR	-	NR	-
Levinson (2018)	6-10 (depending on the participant)	YES	YES	Strenght	NE	NR	NR
Levinson (2020)	3-8 (depending on the participant)	YES	YES	Strenght	Instrenght, outstrenght	NR	NR
Levinson (2021)	15 and 8 (items with the top 15 or 8 highest individual means were selected for inclusion in two different networks per participant)	YES	YES	Strenght	Instrenght, outstrenght	NR	NR
Levinson (2022)	2-13 (depending on the participant)	YES	YES	Strenght	Instrenght, outstrenght	NR	NR
Lydon-Staley (2021)	6	YES (contemporaneous and lagged relationships combined in a single figure)	YES (contemporaneous and lagged relationships combined in a single figure)	NE	NE	NR	NR
Mariotti (2021)	7	YES	YES	NE	NE	NR	NR
Piccirillo (2022)	12	YES	YES	One-step expected influence, predictability	NE	NR	NR
Reeves (2020)	20	YES	YES	Strenght	Instrenght, outstrenght	NR	NC
Scholten (2022)	5-15 (depending on the participant) (separate networks were estimated for each component yielded by the PCA; items with SD ≤ 0.10 were excluded)	YES	YES	Strenght	NE	NR	NR
Thonon (2020)	8	YES	YES	NE	NE	NR	NR
Wright (2015)	4	YES (contemporaneous and lagged relationships combined in a single figure)	YES (contemporaneous and lagged relationships combined in a single figure)	NE	NE	Skewness and kurtosis	NR

1st author last name (Year)	Software used to estimate/plot the networks (package)	Comparison between networks	Method(s) to perform any comparison between networks	Network characteristics compared	Preregistered study	Openly shared data	Openly shared codes
Bodner (2022)	R (qgraph, ConNEcT)	YES (across participants)	Hierarchical classes analysis (HICLAS), followed by visual inspection	Edges (density)	NO	YES	YES
Booij (2021)	R (dtw, parallelDist, DistatisR, qgraph, networktools)	YES (across participants)	Visual inspection	Edges (density)	NO	NO	NO
Bulteel (2018)	R (qgraph, ctsem)	NO	-	-	NO	NO	NO
Burger (2022)	R (qgraph, psychonetrics)	YES (within participants)	Visual inspection	Edges (density)	NO	YES	YES
David (2018)	R (qgraph)	-	-	-	NO	NO	NO
de Vos (2017)	R (package not reported)	YES (across participants)	Visual inspection	Edges (density)	NO	NO	NO
Epskamp (2018)	R (graphicalVAR)	YES (within participants)	Visual inspection	Edges (density; comparison made across contemporaneous and temporal networks)	NO	YES	YES
Epskamp (2020)	R (Psychonetrics)	NO	-	-	NO	YES	YES
Fisher (2017)	LISREL, R (qgraph)	YES (across participants)	Visual inspection; normalization of centrality indices	Edges (density), nodes (centrality indices)	NO	YES	YES
Frumkin (2021)	R (graphicalVAR, qgraph)	YES (across participants and within participants)	Visual inspection; correlational analyses between predicted and empirical models; standardization of centrality indices	Edges (density), nodes (centrality indices)	NO	YES	YES
Hebbrecht (2020)	R (dtw, parallelDist, qgraph, pheatmap)	YES (across participants)	Visual inspection	Edges (density)	NO	NO	YES
Howe (2020)	R (mclust, mgm, qgraph)	YES (across participants and within participants)	Visual inspection; post hoc t test	Edges (density)	NO	YES	YES
Levinson (2018)	R (graphicalVAR, qgraph)	YES (across participants)	Visual inspection	Edges (density), nodes (centrality indices)	NO	NO	NO
Levinson (2020)	R (graphicalVAR, qgraph)	YES (across participants)	Visual inspection	Edges (density; comparisons made both across contemporaneous and temporal networks (within-participants) and for contemporaneous and temporal networks (across participants)), nodes (centrality indices)	NO	NO	NO
Levinson (2021)	R (graphicalVAR, qgraph)	YES (across participants and within participants)	Visual inspection	Nodes (centrality indices; comparisons made both across contemporaneous and temporal networks (within-participants) and for contemporaneous and temporal networks (across participants))	NO (retrospectively registered)	NO	YES
Levinson (2022)	R (graphicalVAR, qgraph)	YES (across participants and within participants)	Visual inspection	Nodes (centrality indices; comparisons made both across contemporaneous and temporal networks (within-participants) and for contemporaneous and temporal networks (across participants))	NO	NO	YES
Lydon-Staley (2021)	R (pompom)	YES (across participants)	Visual inspection	Edges (density)	NO	NO	NO
Mariotti (2021)	R (graphicalVAR)	-	-	-	NO	NO	NO
Piccirillo (2022)	R (graphicalVAR, mgm, qgraph)	YES (across participants)	Visual inspection	Edges (density), nodes (centrality indices)	NO	NO	NO
Reeves (2020)	LISREL, R (qgraph)	YES (across participants)	Within-participant normalization of centrality indices	Nodes (centrality indices)	NO	YES	YES
Scholten (2022)	R (psych, lavaan, graphicalVAR, qgraph)	NO	-	-	YES	NO	NO
Thonon (2020)	R (graphicalVAR, qgraph)	YES (across participants and within participants)	Descriptive comparison of partial correlations	Edges (density; comparisons made both across contemporaneous and temporal networks (within-participants) and for contemporaneous and temporal networks (across participants))	NO (retrospectively registered)	NO	NO
Wright (2015)	LISREL	YES (across participants)	Visual inspection	Edges (density; comparisons made for contemporaneous and temporal networks across participants), nodes (centrality indices)	NO	NO	YES

Appendix C

Checklist for Fully Idiographic Network Analysis (FINA) in Mental Health Research

This checklist is designed to guide researchers in reporting FINA studies, addressing key considerations such as study aim, participant(s), procedures, data collection, measures, data analysis, and results. Additionally, it can aid researchers in planning FINA studies and also serve as a resource during the preregistration phase.

Study aim

☐ Rationale for FINA: Motivations for choosing FINA over other approaches are clearly described.

Note: FINA should be preferred in studies aimed to explore dynamic intraindividual processes that are not addressed by group-level analyses (Fisher et al., 2017).

Participant(s)

☐ Participants' characteristics: Age, gender and diagnosis are reported both for the total sample (in case of n > 1 studies) and for each individual analyzed using FINA.

Procedures

☐ Setting of recruitment: The setting where participants were recruited (e.g., inpatient, outpatient, community) is clearly indicated.

☐ Incentives: If incentives were provided to participants (e.g., monetary), this has been acknowledged. It is specified whether they were given based on a percentage of participation (e.g., completing 50% of timepoints).

Data collection

☐ Data collection method: The method (e.g., Ecological Momentary Assessment - EMA, Experience Sampling Method - ESM) and the device used for data collection (e.g., smartphone, paper and pencil) are clearly specified.

☐ Length of data collection: The duration of data collection is clearly stated. If the length of data collection varies among participants, the individual-specific duration is indicated.

☐ Timescale: The timescale of data collection (i.e., the frequency and number of assessments, such as per day or per week) is provided.

Note. The timescale should match the variability of the clinical aspect under study (e.g., symptoms fluctuating daily or hourly) (Kasanova et al., 2020; Ram et al., 2017)*, and data collection frequency should be balanced to minimize participant burden* (Burke et al., 2017).

☐ Number of timepoints: The maximum possible number of timepoints is indicated.

Note. The number of timepoints should be sufficient to ensure good sensitivity, meaning that a high proportion of true edges are accurately identified in the network (e.g., at least 75 timepoints for a network with up to 6 nodes) (Mansueto et al., 2023).

☐ Sampling scheme: In the case of using EMA/ESM to collect data, the sampling scheme (i.e., fixed, random, or pseudo-random) is indicated and justified.

Note. A fixed design should be prioritized to facilitate equidistant data in case of using a model assuming that (e.g., VAR) (Janssens et al., 2018), *and to improve participant compliance* (Dejonckheere & Erbas, 2022).

Measures

☐ Measures used: The measures administered are specified, indicating whether they are pre-existing, drawn from an item repository, or created specifically for the study.

☐ Number of items: The number of items or questions asked at each timepoint is specified.

☐ Response scale: The response scale for the administered items (e.g., ordinal, continuous) is indicated.

Data analysis

☐ Missing data: The percentage of missing data is reported, the type of missing data (i.e., completely random, random, not random) is assessed, and the method for handling missing data (e.g., multiple imputation) is described. If participants are excluded due to missing timepoints, the minimum percentage of missingness for exclusion is stated.

☐ Normality: If applicable, data normality is checked, and the adopted corrective measures (e.g., data transformations or robust estimation methods) are reported in case of non-normality.

☐ Stationarity: If applicable, stationarity is checked, and the adopted corrective measures (e.g., detrending) are reported in case of non-stationarity.

☐ Overnight lag: In the case of using EMA/ESM to collect data, treatment of overnight lag (e.g., removed, ignored) is detailed.

☐ Node overlap: Node overlap is assessed (e.g., via correlation analyses), and methods used to handle overlap (e.g., creation of composites) are clearly indicated.

☐ Model selection: The model used to estimate the networks (e.g., VAR, uSEM, DTW) is reported.

Note. The choice of a model should be clearly justified by explaining how it can help answer the research question based on data characteristics (e.g., sampling scheme, type of variables) (Bringmann, 2021).

☐ Network construction: The type of variables used for node representation (i.e., individual item or composite scores) and the number of nodes in the network are clearly indicated.

Note. The type of variables used for node representation and the number of nodes included in the network should be selected considering to balance the amount of information and network simplicity (Lafit et al., 2022; Mansueto et al., 2023).

☐ Type of networks: It is indicated whether temporal and/or contemporaneous networks are estimated.

Note: The decision to estimate temporal or contemporaneous networks (or both) should be justified based on the type of information they provide (Epskamp, et al., 2018).

☐ Centrality indices: The estimated centrality indices (e.g., strength, instrength, outstrength, degree) are specified.

☐ Network stability: The method used to assess network stability (e.g., data-dropping bootstrap) is reported, or the lack of assessment is justified.

☐ Software used: The software and relevant packages used to estimate and plot the network are specified.

☐ Network comparison: If more than one network is estimated, the networks are compared within participants and/or across participants, and the method used for network comparison is clearly described.

Results

☐ Number of timepoints completed: The number or percentage of timepoints completed by participant(s) is reported.

☐ Node overlap: The number of overlapping nodes and the statistics for their overlap (e.g., correlation indices) are provided.

☐ Type of networks: All networks estimated, whether temporal, contemporaneous, or both, are reported in the results. If both types are estimated, details for each are provided.

☐ Centrality indices: Values for all estimated centrality indices are reported.

☐ Network comparison: If networks are compared, either within or across participants, the results detailing the differences and similarities between the networks are provided

☐ Individual-level description: Detailed results are provided for each individual analyzed with FINA.

Open Science

☐ Preregistration: Research questions, hypotheses, data collection methods, variables and analysis plans are preregistered (e.g., on the Open Science Framework or AsPredicted).

☐ Data and code sharing: Anonymized data and analysis scripts are made publicly available for replication and further exploration.

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Appendix D

Step-by-step Script to Collect Data from the Clinician

"Thank you very much for agreeing to take part in the study. Is everything clear so far, or do you have any questions about the material I sent you?"

Address any questions and verify the presence of the following characteristics of the patient: being 18 or older; having access to a smartphone; not taking any psychotropic medication for at least one month nor planning on starting psychotropic medication during the course of the study; having symptom stability (clarify that stability does not mean absence of symptoms but the presence of symptoms that do not change over time). Also, collect the following data:

☐ Name of the clinician

☐ Gender of the clinician

☐ Age of the clinician

☐ Professional qualification (psychologist or psychotherapist)

☐ Year of registration with the regional professional board of psychologists

☐ Practice orientation (e.g., psychodynamic, cognitive-behavioral) (if the clinician is a psychotherapist)

☐ Number of sessions conducted so far with the enrolled patient (if the clinician does not remember the exact number of sessions, an approximate number will be asked)

☐ Most recent sessions frequency with the enrolled patient

☐ Time since the start of the intervention with the enrolled patient:

- More than 12 months
- Between 6 and 12 months
- Less than 6 months

☐ Motivation that prompted the patient to seek the clinician's help

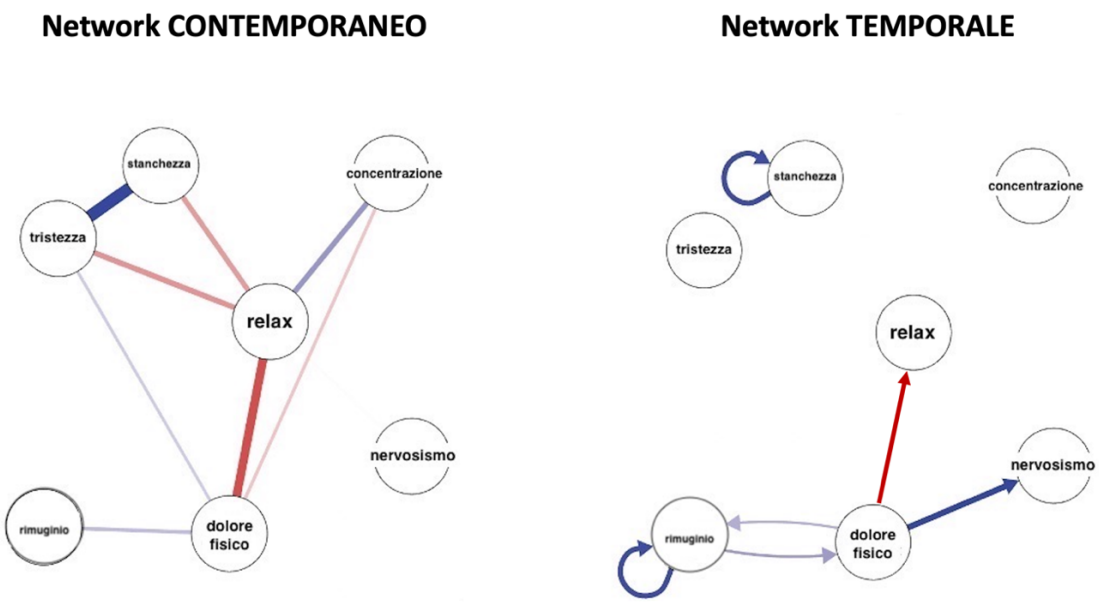
☐ Diagnostic hypothesis based on the patient's clinical profile (it is required to refer to a diagnostic system of reference: DSM or ICD, or any psychological test administered to the patient).

"During today's session, which will last about an hour, we will design the symptom network of your patient":

Show the example of the network below

Figure 1.

Examples of Contemporaneous (Left) and Temporal (Right) Network Illustrated to the Clinician



Note. The figure is an adaptation of Fig. 1 in Epskamp, S., van Borkulo, C. D., van der Veen, D. C., Servaas, M. N., Isvoranu, A. M., Riese, H., & Cramer, A. O. (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

"Here you can see examples of Network Analysis built on a single patient: it is a 40-year-old man diagnosed with hypochondria. A network consists of 'circles' representing different symptoms, such as sadness or rumination. Additionally, there are 'lines' or 'arrows' between one symptom and another, showing the connections between the symptoms. These connections can be either positive or negative. For example, let's observe the network on the left. Relaxation and concentration are connected through a positive connection, shown in blue: this means they increase and decrease together. This patient, when more relaxed, also feels more focused on performing his daily activities, and conversely, when this patient feels more focused, he also feels more relaxed at the same time. Now let's look at relaxation and physical pain, which are in a negative connection, shown in red. This means that when this patient is more relaxed, he simultaneously feels less physical pain. Conversely, when this patient feels less physical pain, he also feels more relaxed at the same time. Symptoms may also not be connected: in this patient, nervousness is not related to any other symptom. For example, there is no connection between the physical pain the patient feels at a certain moment and how nervous he feels at the same time. To summarize, connections between symptoms in a network can be positive, negative, or absent. Blue lines or arrows indicate positive connections. Red lines or arrows indicate negative connections. If two symptoms are not connected by any line or arrow, there is no connection between them. The thicker and more intense the color of the lines or arrows, the stronger and more important the connection between the symptoms. With Network Analysis, it is possible to identify two different networks for each patient: a contemporaneous network (here on the left) and a temporal network (on the right). For the session we are doing now, the temporal network is what interests us the most. In the contemporaneous network, which we have just looked at together, it is not possible to define a causal connection between one symptom and another and therefore say which symptom causes which. However, if we consider the temporal

network here on the right, the situation changes. The temporal network allows us to understand how variables are related (or not!) over time. Now, instead of lines, we have arrows that connect the symptoms. these arrows represent effects, predictions. Let's consider the arrow from physical pain to nervousness: this blue arrow indicates a positive prediction. That is, if the patient is experiencing physical pain now, in 3 hours they will feel more nervous. If we consider the red arrow from physical pain to relaxation, this indicates a negative prediction: if the patient is experiencing physical pain now, in 3 hours they will feel less relaxed. Let's look at the two arrows between physical pain and rumination: they indicate that if the patient experiences physical pain now, in 3 hours they will ruminate more, which will then cause an increase in physical pain 3 hours later. And so on, creating a vicious cycle. Moreover, symptoms can also predict themselves. For example, rumination predicts itself: in this specific patient, ruminating now predicts that they will ruminate more in 3 hours. Alternatively, there may also be no temporal connection between two symptoms. For instance, how relaxed this patient feels now does not predict how focused they will be in 3 hours. How were these networks built? This patient answered a questionnaire administered via smartphone every 3 hours, 5 times a day for two weeks. Each circle you see corresponds to a question in the questionnaire. For example, one question in the questionnaire was: 'How much physical pain did you feel in the last hour?' rated on a scale from 1 to 10. The same thing will be done by your patient. Now I will show you the items your patient will respond to."

Show the clinician the five fixed items, reading them aloud

"We chose these 5 items because they are transdiagnostic. Your patient will receive five notifications a day inviting them to complete a short questionnaire about their psychological state based on these questions. The application will send notifications for completing the questionnaire within the time range of 10:00 AM – 10:00 PM. After each notification, the

patient will have 1 hour to complete the questionnaire. If you wish, you can add one or two items to these 5. For example, if you think there is a symptom in your patient's clinical picture that is not represented among these 5 but you believe it would be worth assessing five times a day, we can add it. If you need some idea, I have a non-exhaustive list of items from which you can choose."

Share the EMA item list* (Appendix E) *with the clinician, selecting a maximum of 2 additional items together or confirming the standard 5 items

"Great. Now I ask you to rank the items for your patient in order of importance. That is, considering ***Read the final symptoms***, what is their order of importance in understanding your patient? Note that by 'importance,' we mean 'severity,' which refers to how much the symptom impacts the patient's subjective discomfort."

Note the order, following what the clinician says

"So, if we were to create a ranking of importance, this is what you're saying:"

List the symptoms in the order given and ask for confirmation

"Now that you've ranked the symptoms by importance, I ask you: thinking about your patient overall, do you consider one or more of these symptoms to be secondary to one or more primary symptoms?"

Record the clinician's response

"Good. Now that we've chosen the items your patient will respond to using their smartphone, I ask you to 'draw' the network with the connections between the symptoms. Remember that each item corresponds to a symptom in the network. The idea is to draw how you think, based on your knowledge of the patient, these symptoms are connected to one another. To do this, we'll use a program I've developed for network drawing. I'll show it to you now."

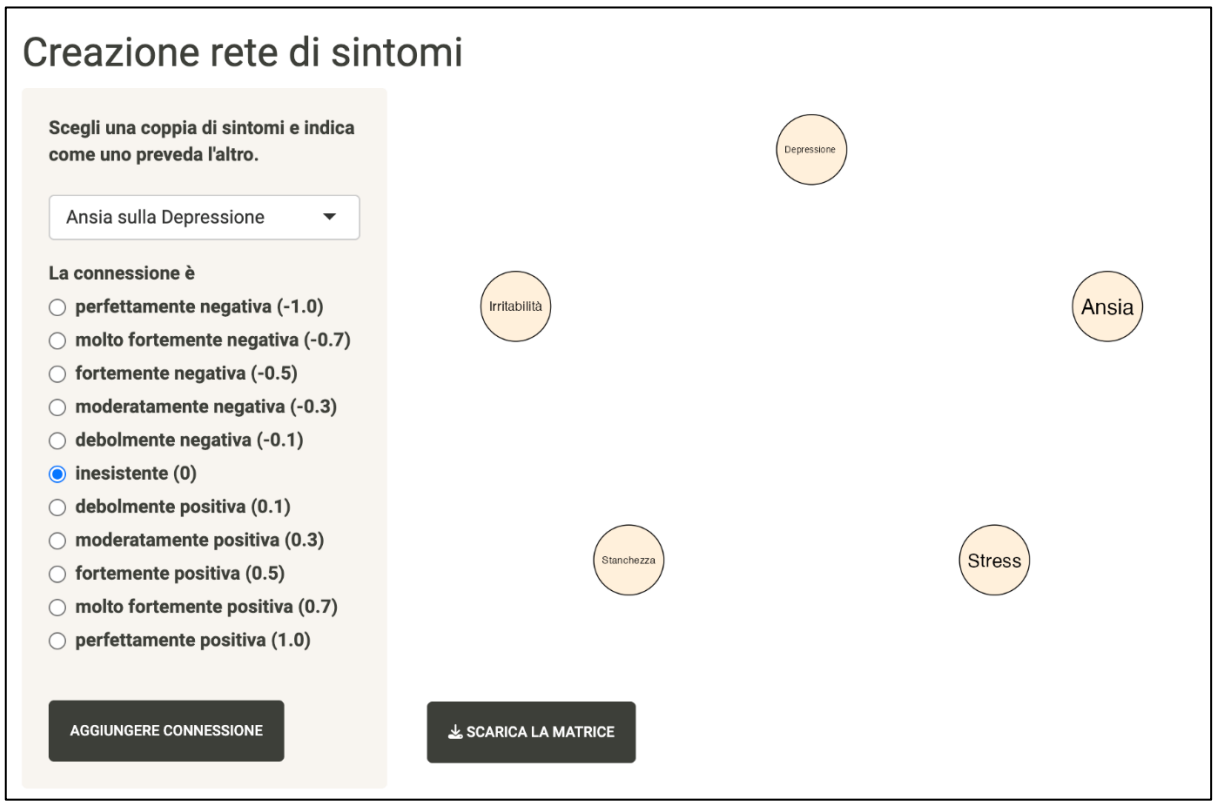
At this point, the actual network drawing phase will begin. Open and share the virtual form (i.e., Shiny app) for building the network, which will display the 5-7 circles

representing the items chosen by the clinician for their patient. While guiding the clinician through the network drawing, the researcher will input the connections between the symptoms, as indicated by the clinician, into the Shiny app*

Below is the interface of the Shiny app with only 5 symptoms.

Figure 2.

Shiny App Interface with Five Symptoms



Note. On the right side, the symptoms chosen by the clinician are presented. On the left side, you can see the list of these same symptoms and the possible values of the connections between the symptoms. The labels of the connections between symptoms are perfectly positive (1.0), very strongly positive (.7), strongly positive (.5), moderately positive (.3), weakly positive (.1), not existing (0), weakly negative (-.1), moderately negative (-.3), strongly negative (-.5), very strongly negative (-.7), perfectly negative (-1.0).

"Now, we will build only the temporal network of your patient together. To do this, you will need to imagine the effect of one symptom on another. Whether and how one symptom predicts another, whether and how it predicts itself, and don't forget the 'loop' ***Mimic a circle with your finger***: a symptom can predict another symptom and in turn be predicted by that same symptom. Try to describe how each connection exists (or does not exist) while also considering the presence of other symptoms. In other words, think pair by pair, considering how the two symptoms in each pair might be connected independently of all the others. Let's start with the symptom you consider the most important in the ranking we created together earlier ***For example, if the clinician has ranked DEPRESSION as the most important symptom, we will proceed as follows***, in your case, DEPRESSION. In your opinion, based on your knowledge of your patient, does DEPRESSION predict the other symptoms of your patient? For example, does your patient's level of DEPRESSION at this moment predict their level of ***Read the second symptom in the ranking, in order of importance, for example, ANXIETY*** ANXIETY at a later time?"

Based on the clinician's response, choose one of the following steps

If the clinician responds "NO": "Ok, so you're telling me that there is no arrow going from DEPRESSION to ANXIETY. Therefore, you're saying there's no connection between how depressed this patient feels right now and how anxious they will feel 3 hours later."

At this point, select the symptom pair "Depression to Anxiety" in the Shiny app and choose "non-existent (0)" from the possible connection values

If the clinician responds "YES": "Ok, so you're telling me there's an arrow going from DEPRESSION to ANXIETY. How do you see this effect of DEPRESSION on ANXIETY, or this prediction? Positive or negative?"

***Based on the clinician's response, follow the next steps*:**

***→ If the clinician responds "NEGATIVE"*:**

"Ok: So you're telling me that the more depressed this patient feels right now, the less anxious they will feel 3 hours later. Is that correct? So how depressed they are now predicts how much less anxious they will be in 3 hours."

***→ If the clinician responds "POSITIVE"*:**

"Ok: So you're telling me that the more depressed this patient feels right now, the more anxious they will feel 3 hours later. Is that correct? So how depressed they are now predicts how much more anxious they will be in 3 hours."

"Very good. When you hypothesize an arrow between symptoms, remember that there are also other symptoms, and other connections and arrows between the other symptoms, in the network. So, remember to think about each connection (arrow) independently of all the others. Actually, it's easier than it sounds. You just need to keep in mind how you believe your patient functions. Now, this connection that you said is ***Report the clinician's response: POSITIVE or NEGATIVE***, how strong do you think this connection is? That is, from ***Read the extremes of the connections: 'perfectly positive' to 'weakly positive' / 'perfectly negative' to 'weakly negative'***, how would you define it?"

Once the clinician has responded, select the symptom pair "Depression to Anxiety" in the Shiny app and choose the connection value selected by the clinician

***The drawing of the remaining connections with the first symptom (in our example: DEPRESSION) proceeds more quickly, as described below. When moving from one symptom to another, follow the order of the symptom ranking made by the clinician*.**

"Ok, now let's consider ***Read the third symptom from the ranking***. If your patient is experiencing DEPRESSION now, what happens to ***Name of the third symptom from the ranking*** in 3 hours? Does it increase, decrease, or is there no connection between depression now and ***Name of the third symptom from the ranking*** in 3 hours? Finally, does how depressed your patient is now predict how depressed they will be in 3 hours?"

Once this procedure is completed, summarize for the clinician what has been drawn for that specific symptom (in our example, DEPRESSION)

"In summary, you said that how depressed your patient is now very strongly predicts how anxious they will be in 3 hours, and that it weakly predicts how ***Name of the third symptom from the ranking*** will be in 3 hours. Additionally… ***Continue listing all the connections for DEPRESSION, along with their intensity, including the prediction of DEPRESSION itself***. Is there anything you'd like to change? Or does it look good as is?"

Make any adjustments to the drawing if requested by the clinician. Then, restart the procedure for each of the remaining symptoms (which at this point will number between 4 and 6), always following the ranking order given by the clinician until all the connections between the symptoms have been defined

"Great, thank you for your work. Now we have the symptom network corresponding to the patient you had in mind! I remind you that, at the end of this session, you will receive an email containing the leaflet (Appendix F) to give to your patient the first time you see them, with instructions on how to install the app and begin the data collection phases."

Finally, ask if there are any questions and remain available for further clarifications

Appendix E

List of EMA Optional Items

"How _____ have you felt in the last hour?"

A
- Abandoned
- Accepted
- Alert
- Alone
- Anxious
- Apathetic
- Ashamed
- Assured
- At ease
- Attentive
- Awkward

B
- Balanced
- Bored
- Busy

C
- Calm
- Capable of facing things
- Centered
- Comfortable
- Confident
- Confused
- Conscious
- Criticized
- Curious

D
- Disappointed
- Disappointed by others
- Disappointed in yourself
- Discouraged
- Disgusted
- Disinterested
- Dissociated
- Distracted
- Distressed
- Disturbed

E
- Energetic
- Enthusiastic
- Euphoric
- Excited
- Excluded

F
- Focused
- Frustrated
- Fulfilled

G
- Grateful
- Guilty

H
- Helpless
- Hopeful

I
- Important
- Indifferent
- Insecure
- Isolated

M
- Mindful
- Misunderstood
- Motivated

N
- Nervous
- Numb

O
- Open
- Overwhelmed

P
- Peaceful
- Powerless
- Proud

R
- Reassured
- Rejected
- Rejuvenated
- Relaxed
- Relieved
- Restless

S
- Safe
- Satisfied
- Secure
- Settled
- Shaken
- Sleepy
- Stable
- Stressed
- Supported

T
- Tense
- Thoughtful
- Tired
- Tranquil
- Troubled
- Trusting

U
- Uncertain
- Uncomfortable
- Unsupported
- Unwell

V
- Vulnerable

Appendix F

Leaflet

Dear [name of the patient]

Thank you for deciding to participate in this study. In this leaflet you will find all the steps you need to follow to start your participation in the first part of the study.

Remember that for any need or difficulty you can contact the researcher at the following contacts:

Tel: xxx xxx xxxx

Email: giovanbatti.andreol2@unibo.it

Below you will find your **personal code:**

XY1234JK

Transcribe it and keep it safe. You will need it at different times of your participation in this study.

Step 1

First, we ask you to answer an online questionnaire, which you can find at the following link:

https://forms.office.com/e/W77QK2NCAg

Step 2

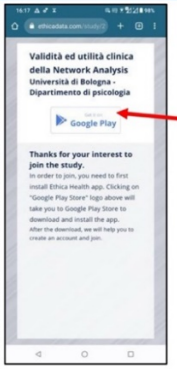
Install the "Ethica» (Avicenna) application on your smartphone, that you will need to take part in the study.

To find the "Ethica" (Avicenna) application click on the following link from your smartphone:

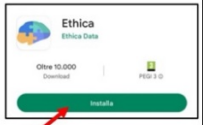
https://ethicadata.com/study/2897/

You will see the following introductory screen. Click on **"PARTICIPATE"**

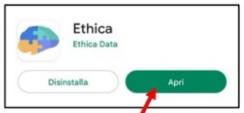
Step 3



If you have an Android device, **click on "Get it on Google Play"**

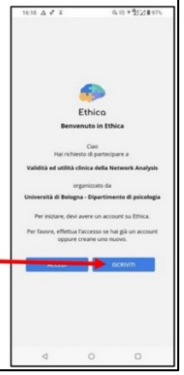


Download "Ethica» (Avicenna) by clicking on **"Install"** if you have an Android device or on the **iCloud icon** if you have an iOS device



After installation, **click on "Open"**

If you have an Android device, you will see the "Ethica" welcome screen. Click on **"SIGN UP"**



Step 4

To sign up, choose a name, enter your email address and create your password. Write down this information somewhere, so that you can retrieve it in case of need. Then click on **"SIGN-UP"**.

If you see the screen here on the right, the sign-up process was successful. Now click on **"Next»**.

These screens will appear. For each click on **"Next"**. Finally, click on **"Get Started»**.

Step 4 (continue)

You will see the welcome screen of this studio. Click on **"REGISTER"** to confirm your registration for this study.

Now you are enrolled in the study!

Now make sure that **notifications** from the "Ethica" (Avicenna) application are **allowed** on your device. Usually in the smartphone this can be verified by opening the "Settings" menu and looking for the item "Applications" and then "Ethica» (Avicenna). Also make sure that notifications are **not** set to **silent**!

Then click on **"Let's get started!"** to select your personal code and confirm that you are ready to get started.
Important: This step is required in order to start your participation in the study.

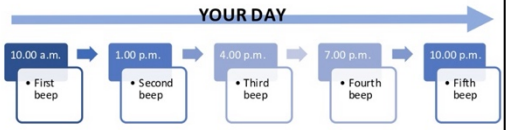
NOTE: You may see a warning at the top of the screen, like the red box in the image on the side. You can ignore this warning – **you don't need** to click "CONTINUE".

Now the "Ethica" (Avicenna) application is set up for your participation! From **tomorrow morning** you will start receiving notifications from "Ethica» (Avicenna).

Important: if tomorrow you don't receive any notifications, make sure you have completed the "Let's get started!" step. Notifications will begin receiving from 10 a.m. on the day after that this step is completed.

Summary of your participation in this first part of the study

In this graph you will find the schematic illustration of your 5 notifications (beeps) throughout the day.



Every day you will receive 5 notifications. The notification invites you to fill out a short questionnaire about your psychological state. The time you receive the notifications is always the same, with a **three-hour** interval between one notification and the next. The possibility to fill out the questionnaire will expire **60 minutes** after receiving each notification.

"In this chart, you will find the diagram of the two detection phases planned for this first part of the study."

IMPORTANT: once the first detection phase has been completed, do not uninstall "Ethica" (Avicenna). You will need it a week later for the second phase of detection.

Appendix G

Clinical Utility Questionnaires

Clinician Questionnaire

We would like to understand how you perceive the usefulness of the networks of relationships between symptoms in clinical work. Please answer as sincerely as possible, indicating your level of agreement with each of the statements below.

We ask you to first consider the network of relationships between the symptoms of the patient involved in this study, which was provided to you along with an interpretive description.

	Strongly disagree						**Strongly agree**
1. It was easy to understand the graphical representation of the network of relationships between my patient's symptoms.	1	2	3	4	5	6	7
2. The interpretative reading provided helped me better understand the graphical representation of the network of relationships between symptoms.	1	2	3	4	5	6	7
3. Understanding the network of relationships between my patient's symptoms required a lot of time.	1	2	3	4	5	6	7
4. The network of relationships between symptoms accurately describes my patient's condition.	1	2	3	4	5	6	7

5. The network of relationships between symptoms revealed unexpected information about my patient's condition.	1	2	3	4	5	6	7
6. The procedure required for my patient to obtain the network of relationships between their symptoms is complex.	1	2	3	4	5	6	7
7. The network of relationships between symptoms will be useful in the clinical work I am doing with my patient.	1	2	3	4	5	6	7
8. The network of relationships between symptoms will help us decide what to focus on in the clinical work with my patient.	1	2	3	4	5	6	7
9. I would like to use the network of relationships between symptoms in my clinical work with my patient.	1	2	3	4	5	6	7
10. It is likely that I will use the network of relationships between symptoms in my clinical work with my patient.	1	2	3	4	5	6	7
11. Using the network of relationships between symptoms would make it easier to explain the patient's issue to them.	1	2	3	4	5	6	7
12. The network of relationships between symptoms would be useful at any point during my clinical work with my patient.	1	2	3	4	5	6	7
13. Using the network of relationships between symptoms would speed up my clinical work with my patient.	1	2	3	4	5	6	7
14. The network of relationships between symptoms would be useful for describing my patient's condition to their family members.	1	2	3	4	5	6	7

15. The network of relationships between symptoms would be useful for describing my patient's condition to other health professionals.	1	2	3	4	5	6	7
16. The network of relationships between symptoms would allow any psychologist to understand my patient's condition.	1	2	3	4	5	6	7
17. Using the network of relationships between symptoms in my clinical work with my patient would be burdensome.	1	2	3	4	5	6	7
18. Using the network of relationships between symptoms in my clinical work with my patient would take a lot of time.	1	2	3	4	5	6	7
19. In my clinical work with my patient, we have already represented the relationships between their symptoms as a network.	1	2	3	4	5	6	7

Now we ask you to think more in general about using the network of relationships between symptoms in clinical practice.

	Strongly disagree						**Strongly agree**
20. The network of relationships between symptoms could be used with all my patients.	1	2	3	4	5	6	7

21. Properly understanding the network of relationships between my patients' symptoms would require a lot of time.	1	2	3	4	5	6	7
22. It would be easy to use the network of relationships between symptoms in my clinical work to conceptualize the case and plan the intervention.	1	2	3	4	5	6	7
23. The network of relationships between symptoms would be applicable only to my patients with mild psychological issues.	1	2	3	4	5	6	7
24. The network of relationships between symptoms would be applicable only to patients I have been following for a long time.	1	2	3	4	5	6	7
25. I would like to use a network of relationships between symptoms, like the one I received, in my clinical work.	1	2	3	4	5	6	7
26. All my patients would benefit from using the network of relationships between symptoms.	1	2	3	4	5	6	7
27. The network of relationships between symptoms would be easily usable in private practice.	1	2	3	4	5	6	7
28. The network of relationships between symptoms would be usable at any stage of my clinical work (initial sessions, central sessions, final sessions, follow-up).	1	2	3	4	5	6	7
29. Using the network of relationships between symptoms would make my clinical work easier.	1	2	3	4	5	6	7

30. The network of relationships between symptoms would be easily usable in structured work settings (e.g., hospitals or clinics).	1	2	3	4	5	6	7
31. Explaining the network of relationships between symptoms to my patients would take a lot of time.	1	2	3	4	5	6	7
32. In my clinical work, I am used to representing my patients' symptom relationships as a network.	1	2	3	4	5	6	7

Dimension	**Items**
Applicability across different patients	16, 20, 23, 24, 26
Applicability across different settings	12, 14, 15, 27, 28, 30
Acceptability	4, 5, 7, 8, 9, 10, 19, 25, 32
Ease of use and understanding	1, 2, 6, 11, 22
Cost in terms of time and effort for its application	3, 13, 17, 18, 21, 29, 31

Note. Items # 3, 6, 17, 18, 21, 23, 24, and 31 are reverse items.

Patient Questionnaire

We would like to understand how useful you believe the networks of relationships between symptoms could be within a psychological treatment process. Please consider the network of relationships between your symptoms that was provided to you along with its description. Please answer as sincerely as possible, indicating your level of agreement with each of the statements below.

	Strongly disagree						**Strongly agree**
1. It was easy to understand the graphical representation of the network of relationships between my symptoms.	1	2	3	4	5	6	7
2. The interpretative reading provided helped me better understand the graphical representation of the network of relationships between my symptoms.	1	2	3	4	5	6	7
3. Understanding the network of relationships between my symptoms required a lot of time.	1	2	3	4	5	6	7
4. The network of relationships between my symptoms accurately describes my condition.	1	2	3	4	5	6	7
5. The network of relationships between my symptoms will help my psychologist better understand my difficulties.	1	2	3	4	5	6	7
6. The procedure required to obtain the network of relationships between my symptoms was complex for me.	1	2	3	4	5	6	7

7. The network of relationships between my symptoms will be useful to my psychologist in the clinical work they are doing with me.	1	2	3	4	5	6	7
8. The network of relationships between my symptoms will help us decide what to focus on in my work with my psychologist.	1	2	3	4	5	6	7
9. I would like to use the network of relationships between my symptoms during my work with my psychologist.	1	2	3	4	5	6	7
10. I would like my psychologist to use the network of relationships between my symptoms.	1	2	3	4	5	6	7
11. The network of relationships between symptoms helped me better understand my difficulties.	1	2	3	4	5	6	7
12. The network of relationships between my symptoms will be useful at any time during my work with my psychologist.	1	2	3	4	5	6	7
13. Using the network of relationships between my symptoms would make my work with my psychologist faster.	1	2	3	4	5	6	7
14. The network of relationships between my symptoms would be useful for describing my condition to my family members.	1	2	3	4	5	6	7
15. The network of relationships between my symptoms would be useful for describing my condition to other health professionals (e.g., my general practitioner).	1	2	3	4	5	6	7

16. The network of relationships between my symptoms would allow any psychologist to understand my condition.	1	2	3	4	5	6	7
17. The procedure required to obtain the network of relationships between my symptoms was burdensome for me.	1	2	3	4	5	6	7
18. The procedure required to obtain the network of relationships between my symptoms took a lot of my time.	1	2	3	4	5	6	7
19. In my work with my current psychologist, we have already represented the relationships between my symptoms as a network.	1	2	3	4	5	6	7
20. Being able to visualize the network of relationships between my symptoms made me feel better.	1	2	3	4	5	6	7
21. The procedure required to obtain the network of relationships between my symptoms was costly for me.	1	2	3	4	5	6	7
22. The network of relationships between symptoms has made me more aware of my condition.	1	2	3	4	5	6	7
23. I would be able to use the network of relationships between my symptoms to understand the steps needed to best address my difficulties.	1	2	3	4	5	6	7
24. The network of relationships between my symptoms would allow a psychologist who has recently started working with me to understand my condition.	1	2	3	4	5	6	7

25. The network of relationships between symptoms should be used with all patients who consult a psychologist.	1	2	3	4	5	6	7
26. All patients who consult a psychologist would benefit from using the network of relationships between symptoms.	1	2	3	4	5	6	7
27. The network of relationships between symptoms should be used by all psychologists in their private practice.	1	2	3	4	5	6	7
28. The network of relationships between symptoms should also be used in structured settings (e.g., hospitals or clinics).	1	2	3	4	5	6	7

Dimension	**Items**
Applicability across different patients	16, 20, 24, 25, 26
Applicability across different settings	12, 14, 15, 27, 28
Acceptability	4, 5, 7, 8, 9, 10, 19, 22
Ease of use and understanding	1, 2, 6, 11, 23
Cost in terms of energy and time for its application	3, 13, 17, 18, 21

Note. Items # 3, 6, 17, 18, and 21 are reverse items.

Appendix H

R Script Used for Clinical Validity Analysis

```
# Install packages
pacman::p_load("readxl", "dplyr", "qgraph", "graphicalVAR",
               "bootnet", "psychonetrics", "ez", "emmeans",
               "stringr", "reshape2",
               "lme4", "lmerTest", "sjPlot",
               "phia")

# Define the number of datasets
num_datasets <- 15

# Initialize lists to store datasets
all_netClin <- list()
all_dt_train <- list()
all_dt_test <- list()
all_vars <- list()
all_max <- list()
all_min <- list()

# Store clinicians and patients datasets, exctracting the variables of interest
for (i in 1:num_datasets) {
  # Construct filenames
  clinician_filename <- paste0(i, "_Matrix_Clinician.xlsx")
  patient_filename <- paste0(i, "_dt_EMA_Patient.xlsx")

  # Read the clinician dataset
  netClin <- read_excel(clinician_filename, sheet = "labels")
  netClin <- as.matrix(netClin)
```

```
  # Read the patient datasets
  dt_train <- read_excel(patient_filename, sheet = "Training")
  dt_test <- read_excel(patient_filename, sheet = "Test")

  # Exclude the first three columns and extract the remaining column names as variables of interest
  vars_train <- colnames(dt_train)[-c(1:3)]
  vars_test <- colnames(dt_test)[-c(1:3)]

  # Check that there are the same variables in the training and test data
  if(any(vars_train != vars_test) | any(vars_train != colnames(netClin)))
    break

  # Remove unwanted characters from variable names
  vars <- vars_train
  vars <- str_replace_all(vars, "-", ".")
  vars <- str_replace_all(vars, " ", ".")

  rownames(netClin) <- colnames(netClin) <-
    names(dt_train)[-c(1:3)] <-
    names(dt_test)[-c(1:3)] <- vars

  # Store the datasets and variables of interest in the lists
  all_netClin[[i]] <- netClin
  all_dt_train[[i]] <- dt_train
  all_dt_test[[i]] <- dt_test
  all_vars[[i]] <- vars
}

# Estimate nonregularized models with psychonetrics for each dt_train dataset
```

```
all_models <- list()

for (i in 1:num_datasets) {
  dt_train <- all_dt_train[[i]]
  vars <- all_vars[[i]]

  # Estimate the nonregularized models
  mdl_gv <- gvar(dt_train, beepvar = "beep", dayvar = "day", vars = vars, estimator = "FIML")
  fit_gv <- runmodel(mdl_gv)

  # Store the models in the list
  all_models[[i]] <- fit_gv

}

# Extract and round beta matrices from each method
all_beta_matrices <- list()

for (i in 1:num_datasets) {
  fit_gv <- all_models[[i]]
  vars <- all_vars[[i]]

  # Extract the beta matrices, transpose it, and set column and row names
  beta <- getmatrix(fit_gv, "beta") %>% t()
  colnames(beta) <- rownames(beta) <- vars

  # Round the beta matrices
  beta <- round(beta, 1)

  # Store the rounded beta matrices in the list
```

```
  all_beta_matrices[[i]] <- beta

  # Print the rounded beta matrices
  print(beta)
}

# Remove missing values and standardize the test data for each dataset using means and sds of train data
for (i in 1:num_datasets) {
  dt_train <- all_dt_train[[i]]
  dt_test <- all_dt_test[[i]]
  vars <- all_vars[[i]]

  # Determine the indices of the variables to standardize
  var_indices <- (4:(3 + length(vars)))

  # Remove missing values from the test data
  dt_test_std <- dt_test[rowSums(is.na(dt_test[, var_indices])) == 0,]

  # Calculate means and standard deviations from the training data
  means <- colMeans(dt_train[, var_indices], na.rm = TRUE)
  sds <- apply(dt_train[, var_indices], 2, sd, na.rm = TRUE)

  # Create matrices of means and standard deviations
  Mean_mat <- matrix(means, nrow = nrow(dt_test_std), ncol = length(vars), byrow = TRUE)
  SD_mat <- matrix(sds, nrow = nrow(dt_test_std), ncol = length(vars), byrow = TRUE)

  # Standardize the test data
  dt_test_std[, var_indices] <- (dt_test_std[, var_indices] - Mean_mat) / SD_mat

  # Store the standardized test data back in the list
```

```
  all_dt_test[[i]] <- dt_test_std

  # Also store the minimum and maximum possible predicted value, given the
  # bounded nature of the data (1-10). all_min and all_max include
  # the standardized values corresponding to 1 and 10 respectively
  all_min[[i]] <- (1-means)/sds
  all_max[[i]] <- (10-means)/sds
}

# For each timepoint in the test data, generate predictions from previous one based on the estimated network
all_PRED_NULL <- list()
all_PRED_EMP <- list()
all_PRED_CLIN <- list()

# Generate predictions
for (i in 1:num_datasets) {
  dt_test_std <- all_dt_test[[i]]
  vars <- all_vars[[i]]
  beta <- all_beta_matrices[[i]]
  netClin <- all_netClin[[i]]

  # Initialize prediction dataframes
  PRED_NULL <- PRED_EMP <- PRED_CLIN <- dt_test_std

  # Set the variables of interest to NA
  PRED_NULL[, vars] <- PRED_EMP[, vars] <- PRED_CLIN[, vars] <- NA

  # Loop through the test data to generate predictions
  for (j in 2:nrow(dt_test_std)) {
    if (
```

```
    # Only proceed if the day is the same
    (dt_test_std[j, "day"] == dt_test_std[j - 1, "day"]) &
    # Only proceed if the beeps are consecutive
    (dt_test_std[j, "beep"] == dt_test_std[j - 1, "beep"] + 1)
   ) {
    # Generate predictions from empirical network
    predictor <- dt_test_std[j - 1, vars] %>% as.matrix
    PRED_EMP[j, vars] <- predictor %*% beta
    # Generate predictions from the network of the clinician
    PRED_CLIN[j, vars] <- predictor %*% netClin
   }
  }

  # The null method consists in predicting each timepoint simply
  # using the means of the training set. Since the data are standardized using
  # those means, this amounts to predicting zero for all values.
  PRED_NULL[,vars] <- 0

  # Store the prediction results in the lists
  all_PRED_EMP[[i]] <- data.frame(PRED_EMP)
  all_PRED_CLIN[[i]] <- data.frame(PRED_CLIN)
  all_PRED_NULL[[i]] <- data.frame(PRED_NULL)
}

# Ensure that all predictions are within the boundaries of the data
# (i.e., the standardized versions of 1 and 10)

for(i in 1:num_datasets)
{
  for(j in 1:length(all_vars[[i]]))
```

```
  {
    var <- all_vars[[i]][j]
    min_var <- all_min[[i]][var]
    max_var <- all_max[[i]][var]

    all_PRED_EMP[i][[1]][,var][!is.na(all_PRED_EMP[i][[1]][,var]) &
                               all_PRED_EMP[i][[1]][,var] < min_var] <-
      min_var
    all_PRED_EMP[i][[1]][,var][!is.na(all_PRED_EMP[i][[1]][,var]) &
                               all_PRED_EMP[i][[1]][,var] > max_var] <-
      max_var

    all_PRED_CLIN[i][[1]][,var][!is.na(all_PRED_CLIN[i][[1]][,var]) &
                                all_PRED_CLIN[i][[1]][,var] < min_var] <-
      min_var
    all_PRED_CLIN[i][[1]][,var][!is.na(all_PRED_CLIN[i][[1]][,var]) &
                                all_PRED_CLIN[i][[1]][,var] > max_var] <-
      max_var
  }
}

# Estimate observed and predicted values
all_RES_NULL <- list()
all_RES_EMP <- list()
all_RES_CLIN <- list()

# Calculate residuals
for (i in 1:num_datasets) {
  dt_test_std <- all_dt_test[[i]]
  vars <- all_vars[[i]]
```

```
  PRED_NULL <- all_PRED_NULL[[i]]
  PRED_EMP <- all_PRED_EMP[[i]]
  PRED_CLIN <- all_PRED_CLIN[[i]]

  RES_NULL <- dt_test_std[, vars] - PRED_NULL[, vars]
  RES_EMP <- dt_test_std[, vars] - PRED_EMP[, vars]
  RES_CLIN <- dt_test_std[, vars] - PRED_CLIN[, vars]

  # Remove rows with NA
  RES_NULL <- RES_NULL[rowSums(is.na(PRED_CLIN[, vars])) == 0, vars]
  RES_EMP <- RES_EMP[rowSums(is.na(PRED_CLIN[, vars])) == 0, vars]
  RES_CLIN <- RES_CLIN[rowSums(is.na(PRED_CLIN[, vars])) == 0, vars]
  PRED_EMP <- PRED_EMP[rowSums(is.na(PRED_CLIN[, vars])) == 0, vars]
  PRED_CLIN <- PRED_CLIN[rowSums(is.na(PRED_CLIN[, vars])) == 0, vars]
  PRED_NULL <-  PRED_NULL[rowSums(is.na(PRED_CLIN[, vars])) == 0, vars]

  # Store the residuals in the lists
  all_RES_NULL[[i]] <- RES_NULL
  all_RES_EMP[[i]] <- RES_EMP
  all_RES_CLIN[[i]] <- RES_CLIN

  # Store the cleaned predictions back in the lists
  all_PRED_EMP[[i]] <- PRED_EMP
  all_PRED_CLIN[[i]] <- PRED_CLIN
  all_PRED_NULL[[i]] <- PRED_NULL
}

# Mixed model approach to error analysis - analysis across dyads

# Count number of train datapoints (number of observations) in each dyad
```

```
Nobs <- data.frame(ID = 1:num_datasets,
                   Nobs = sapply(all_dt_train, function(x) sum(!is.na(x[,-c(1:3)]))))

mean(Nobs$Nobs)
sd(Nobs$Nobs)
range(Nobs$Nobs)

# Create a dataframe of errors across all method types
all_RES_NULL_mlt <- lapply(all_RES_NULL, melt)
all_RES_EMP_mlt <- lapply(all_RES_EMP, melt)
all_RES_CLIN_mlt <- lapply(all_RES_CLIN, melt)

for(i in 1:num_datasets)
{
  all_RES_NULL_mlt[[i]]$ID <- i
  all_RES_CLIN_mlt[[i]]$ID <- i
  all_RES_EMP_mlt[[i]]$ID <- i
}

all_RES_NULL_mlt <- bind_rows(all_RES_NULL_mlt)
all_RES_EMP_mlt <- bind_rows(all_RES_EMP_mlt)
all_RES_CLIN_mlt <- bind_rows(all_RES_CLIN_mlt)

all_RES_NULL_mlt$method <- "NULL"
all_RES_EMP_mlt$method <- "EMP"
all_RES_CLIN_mlt$method <- "CLIN"

all_RES <- bind_rows(all_RES_NULL_mlt, all_RES_EMP_mlt, all_RES_CLIN_mlt)

all_RES <- merge(all_RES, Nobs, by = "ID")
```

```
all_RES$abs_residual <- abs(all_RES$value)
all_RES$method <- as.factor(all_RES$method)
all_RES$method <- relevel(all_RES$method, "NULL")
all_RES$Nobs <- scale(all_RES$Nobs)

# First mixed model analysis
fit1 <- lmer(abs_residual ~ method + (1|ID) + (1|variable),
        data = filter(all_RES))

anova(fit1)
testInteractions(fit1, pairwise = "method")
pm1 <- sjPlot::plot_model(fit1, type = "emm", terms = c("method"),
                  axis.lim = c(.25, 1.4),
                  axis.title = "|residuals|") +
 scale_x_discrete(name = "Model", limits = c("NULL", "CLINICAL", "EMPIRICAL")) +
 theme(axis.text.x = element_text(angle = 0, hjust = 0.5)) +
 ggtitle(NULL)

pm1$data

# Second mixed model analysis
fit2 <- lmer(abs_residual ~ method * Nobs + (1|ID) + (1|variable),
        data = filter(all_RES))
anova(fit2)
testInteractions(fit2, pairwise = "method")

pm2 <- sjPlot::plot_model(fit2, type = "emm", terms = c("method", "Nobs"),
              axis.lim = c(.25, 1.4),
              title = NULL,
              axis.title = "|residuals|") +
```

```
  scale_x_discrete(name = "Model", limits = c("NULL", "CLINICAL", "EMPIRICAL")) +
  theme(axis.text.x = element_text(angle = 0, hjust = 0.5)) +
  ggtitle(NULL)

pm2 <- pm2 +
  scale_colour_discrete(name = "NOBS", labels = c("M-1SD", "M", "M+1SD")) +
  theme(legend.position = c(0.7, 0.2))

pm2$data

fit2_null <- lmer(abs_residual ~ Nobs + (1|ID) + (1|variable),
          data = filter(all_RES, method == "NULL"))
summary(fit2_null)



fit2_clin <- lmer(abs_residual ~ Nobs + (1|ID) + (1|variable),
          data = filter(all_RES, method == "CLIN"))
summary(fit2_clin)

fit2_emp <- lmer(abs_residual ~ Nobs + (1|ID) + (1|variable),
          data = filter(all_RES, method == "EMP"))
summary(fit2_emp)

pdf("figure_mixed_model.pdf", width = 6, height = 6)
pm1
pm2
dev.off()
```

Appendix I

Information Collected among Clinicians and Patients

ID	Gender of clinician	Age of clinician	Gender of patient	Age of patient	Orientation of the intervention (NA = not applicable)	Completed sessions (approx.)
1	M	33	M	25	Cognitive-Behavioural	98
2	F	35	F	50	Cognitive-Behavioural	14
3	M	36	M	32	Cognitive-Behavioural	13
4	F	29	F	26	Cognitive-Behavioural	27
5	M	32	F	37	Cognitive-Behavioural	35
6	F	42	F	24	Cognitive-Behavioural	20
7	F	33	F	31	Cognitive-Behavioural	60
8	F	36	F	65	Systemic	15
9	F	34	M	19	Cognitive-Behavioural	24
10	F	31	F	21	Cognitive-Behavioural	32
11	F	34	M	26	Integrative	22
12	F	31	F	31	Systemic	36
13	M	36	M	27	Cognitive-Behavioural	17
14	F	69	M	38	Cognitive-Behavioural	19
15	F	32	F	27	Cognitive-Costructivist	40

ID	Most recent frequency of the sessions	Duration of the intervention	Year of inscription to professional board	Motivation for contact	Diagnostic hypothesis
1	1 per month	More than 12 months	2016	Relationship problems	GAD
2	1 per 3 weeks	Less than 6 months	2015	Relationship problems	Dysthymia
3	1 per 10 days	Less than 6 months	2016	Working problems	MDD
4	1 per 3 weeks	More than 12 months	2021	Anxiety and relationship problems	OCPD
5	1 per week	More than 12 months	2018	Working and relationship problems	GAD
6	1 per month	Between 6 and 12 months	2006	Obsessions and compulsions	OCD
7	1 per week	More than 12 months	2017	Working and relationship problems	SAD
8	1 per 2 weeks	Between 6 and 12 months	2013	Anxiety related to family problems	GAD
9	1 per week	Less than 6 months	2015	Social anxiety and panic attacks	SAD
10	1 per week	Between 6 and 12 months	2018	Anxiety	OCPD
11	1 per week	Less than 6 months	2023	Relationship problems	SAD
12	1 per 2 weeks	Between 6 and 12 months	2014	Low self-esteem and sadness	Dysthymia
13	1 per 2 weeks	Between 6 and 12 months	2015	Low satisfaction about life	Dysthymia
14	1 per week	Less than 6 months	1990	Relationship problems	MDD
15	1 per 2 weeks	More than 12 months	2018	Feeling of being stucked in life	GAD

Appendix J

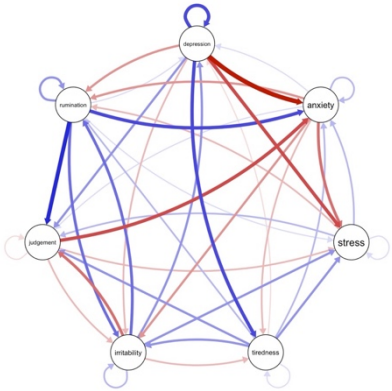
Clinical and Empirical Models: Graphical Representation and Corresponding Matrices

Dyad 1

Clinical Model

	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Judgement**	**Rumination**
Depression	0.1	0.1	0	0	0	0	.1
Anxiety	.1	0.1	.1	0	0	.1	.1
Stress	0	0	0	.3	0	0	.1
Tiredness	0	0	.1	0	0	0	0
Irritability	0	0	.5	.1	0	0	.1
Judgement	.3	.1	.1	0	.3	.1	.5
Rumination	.3	.5	.1	0	.1	.3	.3

Empirical Model



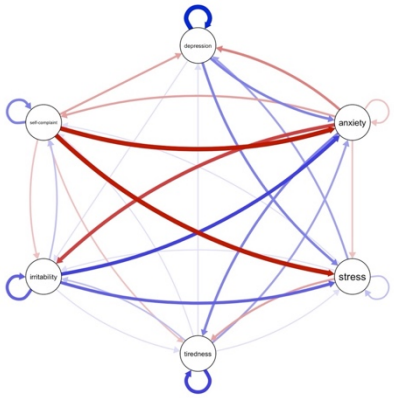
	Y variable						
X variable	**Depressio**	**Anxiety**	**Stres**	**Tirednes**	**Irritability**	**Judgement**	**Rumination**
Depression	.5	-.7	-.5	.5	-.2	.3	-.3
Anxiety	.1	.2	-.4	-.2	-.3	.1	-.3
Stress	0	.2	.1	0	0	.2	-.2
Tiredness	-.1	.2	.3	.1	.3	.3	.2
Irritability	.3	0	.3	-.2	.2	-.4	.4
Judgement	0	-.5	-.2	0	-.2	-.1	0
Rumination	.1	.5	.1	0	.4	.6	.3

Dyad 2

Clinical Model

	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-complaint**
Depression	0	0	0	.1	.5	.3
Anxiety	0	0	.3	0	0	0
Stress	0	.3	0	.1	.1	0
Tiredness	.1	0	0	.1	.1	0
Irritability	.3	0	0	0	.1	0
Self-complaint	.3	0	.1	.1	.3	0

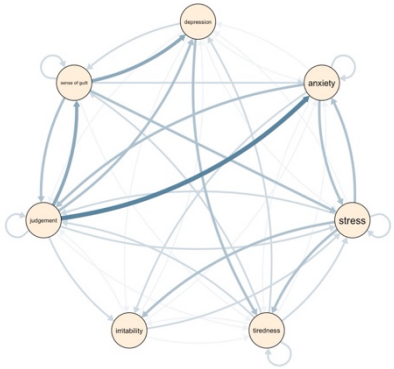
Empirical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-complaint**
Depression	.8	.4	.4	0	.1	0
Anxiety	-.4	-.2	-.2	.4	-.6	-.3
Stress	.3	0	.2	-.3	.1	.1
Tiredness	.1	.3	.1	.6	.2	.1
Irritability	0	.6	.5	.1	.5	.2
Self-complaint	-.3	-.8	-.8	-.2	-.2	.4

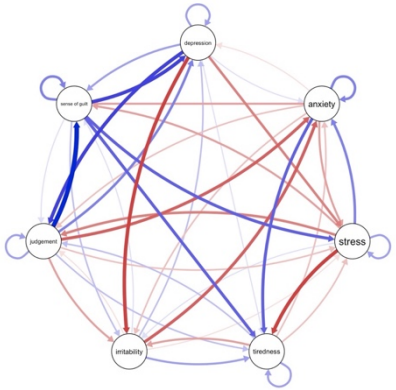
Dyad 3

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Judgement**	**Sense of guilt**
Depression	0	.1	.1	.5	.1	.1	.3
Anxiety	.1	.3	.5	.1	.3	.5	0
Stress	.1	.5	.3	.5	.5	.3	0
Tiredness	.3	.1	.3	.3	.1	.3	.3
Irritability	.1	.1	.3	.1	0	.1	0
Judgement	.5	1	.3	.1	.3	.3	.7
Sense of guilt	.7	.3	.5	.1	0	.5	.3

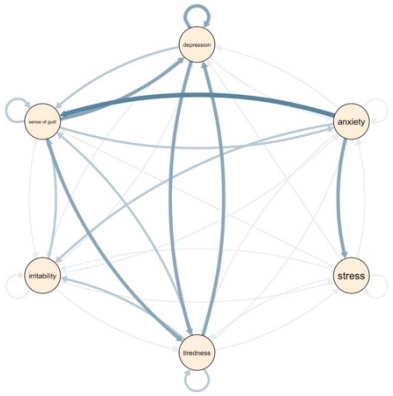
Empirical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Judgement**	**Sense of guilt**
Depression	.3	.1	-.4	.1	-.6	.6	.3
Anxiety	-.1	.4	-.3	.5	-.2	-.2	-.3
Stress	0	.4	.3	-.6	.1	-.4	-.3
Tiredness	0	-.2	-.2	.3	-.3	.2	0
Irritability	.2	-.5	-.1	.3	0	-.1	.1
Judgement	.4	-.5	-.2	.2	-.3	.3	.8
Sense of guilt	.6	0	.5	.5	.2	.1	.4

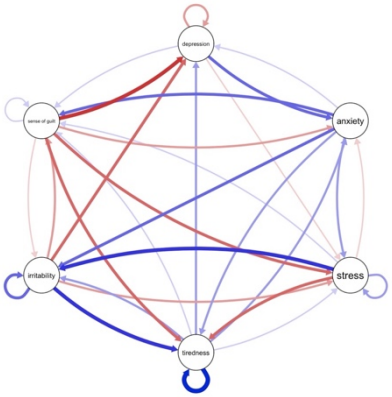
Dyad 4

Clinical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Sense of guilt**
Depression	.5	.1	0	.5	.1	.3
Anxiety	.1	.1	.5	.1	.3	.7
Stress	.1	.1	.1	.1	.1	.1
Tiredness	.5	.1	.1	.3	.3	.3
Irritability	.1	.1	.1	.1	-.1	.3
Sense of guilt	.5	.3	0	.5	.1	.3

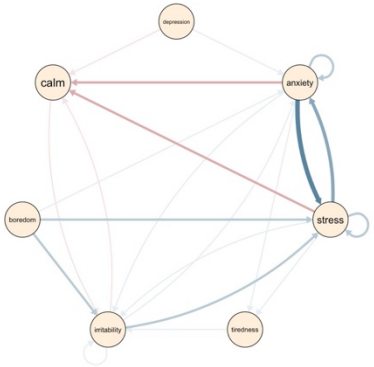
Empirical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Sens of guilt**
Depression	-.2	.3	-.1	0	0	.1
Anxiety	.1	0	.2	.2	.3	.3
Stress	0	-.1	.2	-.3	.4	.1
Tiredness	.2	.2	.1	.5	.2	.1
Irritability	-.3	0	-.2	.4	.3	-.2
Sens of guilt	-.4	-.2	-.3	-.3	-.1	.1

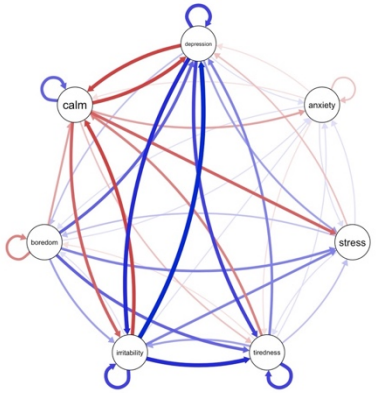
Dyad 5

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Boredom**	**Calm**
Depression	0	.1	0	0	0	0	-.1
Anxiety	0	.3	.7	.1	.1	0	-.3
Stress	0	.5	.3	.1	.1	0	-.3
Tiredness	0	0	0	0	.1	0	0
Irritability	0	.1	.3	0	.1	0	-.1
Boredom	0	.1	.3	0	.3	0	0
Calm	0	0	0	0	-.1	0	0

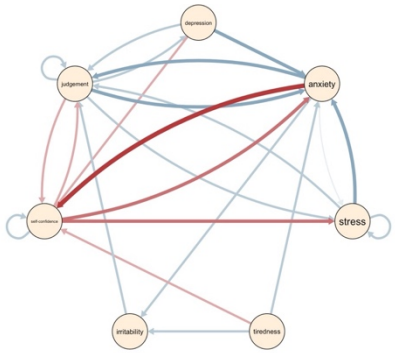
Empirical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Boredom**	**Calm**
Depression	.6	.1	.3	.6	.7	.2	-.6
Anxiety	-.1	-.2	.1	-.1	0	.1	-.1
Stress	-.2	.1	0	.1	0	.2	0
Tiredness	.4	.1	.2	.6	.3	-.1	-.4
Irritability	.8	.1	.4	.7	.6	.1	-.6
Boredom	.5	.1	.4	.5	.3	-.4	-.3
Calm	-.6	-.3	-.5	-.2	-.5	0	.5

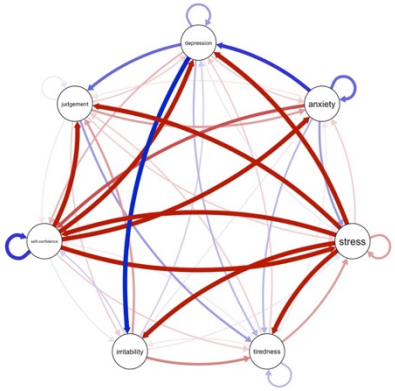
Dyad 6

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-confidence**	**Judgement**
Depression	0	.5	0	0	0	-.3	.3
Anxiety	0	0	.1	0	.3	-.7	.5
Stress	0	.5	.3	0	0	0	.3
Tiredness	0	.3	0	0	.3	-.3	0
Irritability	0	0	0	0	0	0	.3
Self-confidence	0	-.5	-.5	0	0	.3	-.3
Judgement	.3	.5	.3	0	0	-.3	.3

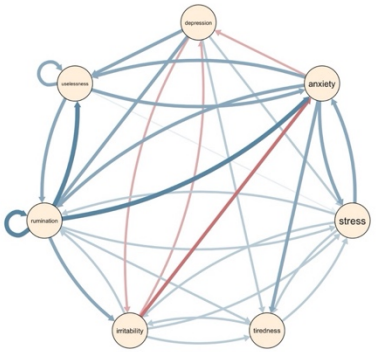
Empirical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-confidence**	**Judgement**
Depression	.4	-.2	.1	.3	1	-.3	.6
Anxiety	.8	.6	.4	.3	.1	-.7	-.1
Stress	-1	-.2	-.4	-1	-1	1	-1
Tiredness	-.2	-.1	-.4	.3	-.1	-.1	-.2
Irritability	.2	0	.1	-.5	0	.2	-.4
Self-confidence	-1	-1	-1.2	-.2	.1	.8	-1
Judgement	-.2	-.4	-.2	.4	-.2	-.1	.1

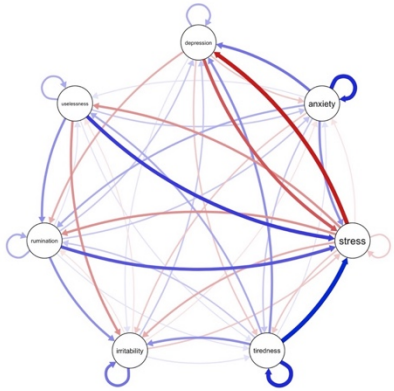
Dyad 7

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**	**Uselessness**
Depression	0	0	.3	.3	-.3	.5	.5
Anxiety	-.3	0	.5	.5	0	.5	.5
Stress	0	.5	0	.3	.3	.3	0
Tiredness	0	0	.3	0	.3	0	0
Irritability	-.3	-.5	.3	.3	0	.3	0
Rumination	0	.7	.3	.3	.5	.7	.7
Uselessness	0	.5	.1	0	0	.5	.5

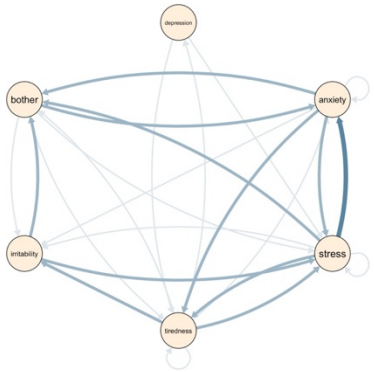
Empirical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**	**Uselessness**
Depression	.3	-.2	-.6	-.2	.1	-.3	0
Anxiety	.5	.8	.4	.2	-.2	.3	.1
Stress	-.8	-.1	-.2	-.2	-.3	-.4	-.4
Tiredness	.4	.1	.9	.8	.4	.2	.3
Irritability	.2	-.1	-.2	.1	.5	-.1	-.1
Rumination	.2	.2	.6	.1	.4	.3	.1
Uselessness	0	.2	.7	.1	-.4	.4	.3

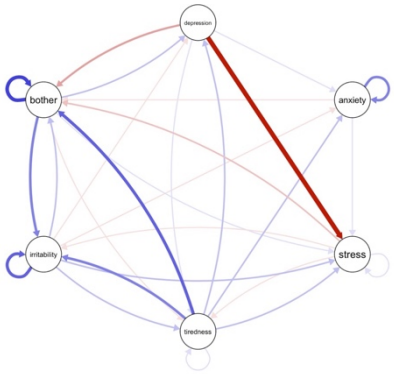
Dyad 8

Clinical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Bother**
Depression	0	0	.1	.1	0	0
Anxiety	0	.1	.3	.3	.1	.3
Stress	0	.5	.1	.3	.1	.3
Tiredness	.1	.1	.3	.1	.3	.1
Irritability	0	0	.3	0	0	.3
Bother	0	.3	.1	.1	.1	0

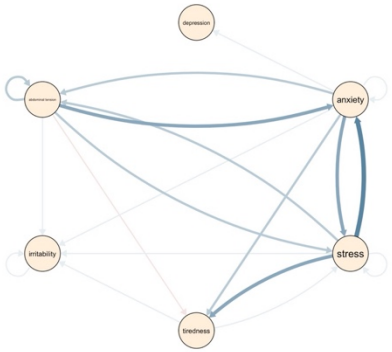
Empirical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Bother**
Depression	0	.1	-.8	.1	0	-.3
Anxiety	0	.4	.1	0	0	-.1
Stress	0	0	.1	-.1	-.1	-.2
Tiredness	.2	.2	.2	.1	.4	.5
Irritability	-.1	-.1	.2	.2	.5	.2
Bother	.2	0	.1	-.1	.4	.6

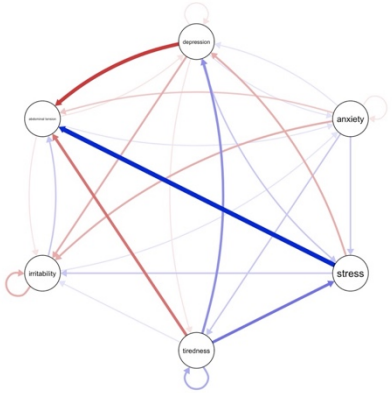
Dyad 9

Clinical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Abdominal tension**
Depression	0	0	0	0	0	0
Anxiety	.1	.1	.5	.3	.1	.3
Stress	0	.7	.1	.5	.1	.3
Tiredness	0	0	.1	0	.1	0
Irritability	0	0	0	0	.1	0
Abdominal tension	0	.5	.3	-.1	.1	.3

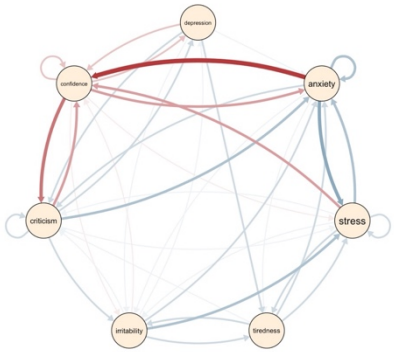
Empirical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Abdominal tension**
Depression	-.1	.1	.2	-.1	-.3	-.7
Anxiety	.1	-.1	.2	.2	-.3	-.2
Stress	-.3	0	0	0	.2	.9
Tiredness	.4	0	.5	.3	.1	-.5
Irritability	0	.1	0	0	-.3	.2
Abdominal tension	-.1	.1	0	0	-.1	0

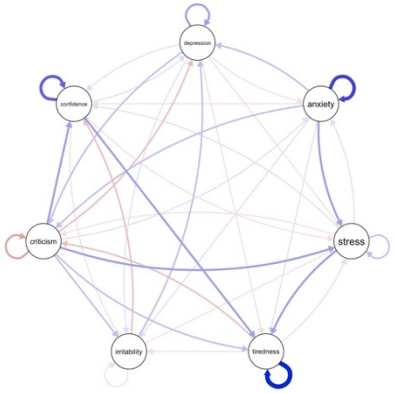
Dyad 10

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Criticism**	**Confidence**
Depression	0	.1	0	.3	.1	.3	-.3
Anxiety	0	.5	.7	.1	.1	.3	-1
Stress	0	.5	.3	.3	.1	.1	-.5
Tiredness	0	.3	.3	0	.3	.1	0
Irritability	.1	.3	.5	.3	0	.1	-.1
Criticism	.3	.5	.1	0	.3	.3	-.5
Confidence	-.3	-.5	-.1	0	-.1	-.7	-.3

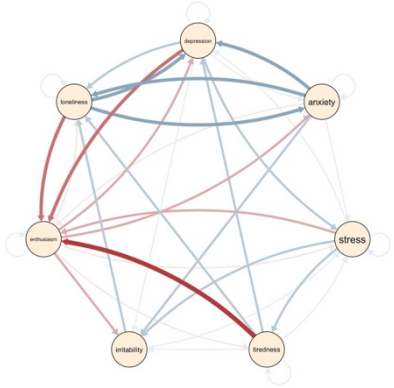
Empirical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Criticism**	**Confidence**
Depression	.3	-.1	-.1	-.1	.1	.2	.1
Anxiety	.2	.6	.3	.1	.1	.2	-.1
Stress	0	.1	.2	.3	0	-.1	.1
Tiredness	0	0	.1	.8	-.1	-.2	0
Irritability	.2	0	-.1	0	-.1	0	-.2
Criticism	-.2	.1	.3	.2	.2	-.3	.3
Confidence	.1	0	-.1	.3	-.1	0	.5

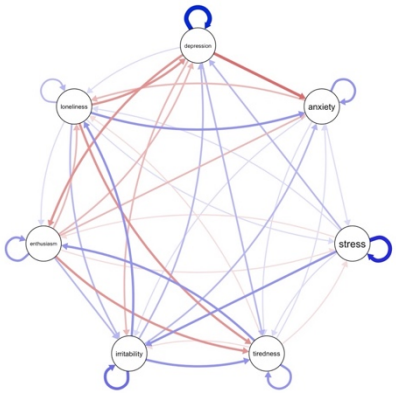
Dyad 11

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Enthusiasm**	**Loneliness**
Depression	.1	.1	.3	0	.1	-.5	.3
Anxiety	.5	.1	.1	0	.3	-.1	.5
Stress	.1	0	.1	.3	.3	-.3	0
Tiredness	.3	0	.1	.1	.1	-.7	.3
Irritability	0	0	.1	0	0	0	.3
Enthusiasm	-.3	-.3	-.1	-.1	-.3	.1	-.1
Loneliness	.5	.5	0	0	0	-.5	.1

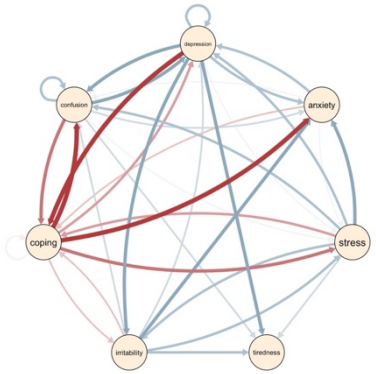
Empirical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Enthusiasm**	**Loneliness**
Depression	.7	-.4	0	.2	-.2	-.3	.1
Anxiety	0	.3	.1	.1	.1	0	-.2
Stress	.2	0	.6	.1	.3	-.1	.1
Tiredness	0	.1	-.1	.3	-.1	.3	-.1
Irritability	.2	.2	0	.3	.4	0	.3
Enthusiasm	-.2	-.2	-.1	-.3	.2	.3	-.2
Loneliness	-.3	.3	.1	-.3	.2	.1	.2

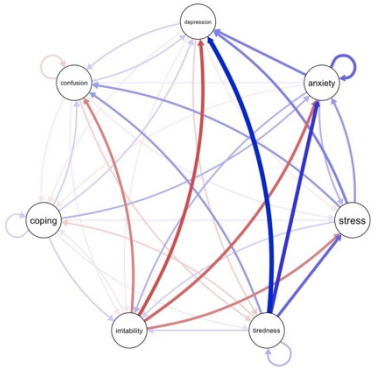
Dyad 12

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Coping**	**Confusion**
Depression	.5	.5	.1	.7	.7	-1	.7
Anxiety	.5	0	.1	0	0	-.3	.1
Stress	.5	.7	0	.3	.5	-.5	.5
Tiredness	0	0	0	0	0	0	0
Irritability	.3	.7	.5	.5	0	-.3	.3
Coping	-.5	-1	-.7	0	-.3	-.1	-1
Confusion	.7	.3	.1	.3	0	-.7	.5

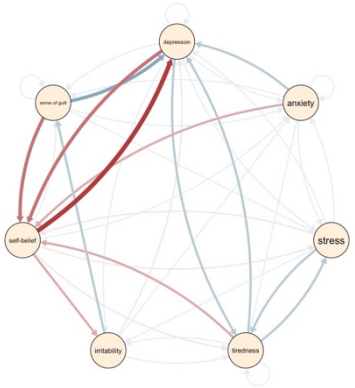
Empirical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Coping**	**Confusion**
Depression	0	0	-.1	-.2	-.1	-.1	.2
Anxiety	.5	.6	.3	0	.3	-.1	.1
Stress	.5	.4	0	0	.2	0	.4
Tiredness	1	.8	.6	.3	.2	-.2	.4
Irritability	-.7	-.6	-.5	0	0	.1	-.5
Coping	.2	.3	.1	.1	.2	.2	.2
Confusion	.2	0	.1	-.2	-.1	-.1	-.2

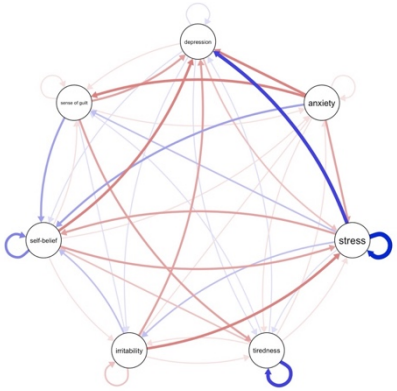
Dyad 13

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-belief**	**Sense of guilt**
Depression	.1	.1	.1	.3	.1	-.5	.1
Anxiety	.3	.1	.1	.1	0	-.3	.1
Stress	.1	.1	0	.3	.1	-.1	0
Tiredness	.3	0	.3	.1	.1	-.3	0
Irritability	-.1	.1	0	.1	0	0	.3
Self-belief	-.7	.1	-.1	-.1	-.3	0	.1
Sense of guilt	.5	.1	.1	0	0	-.5	.1

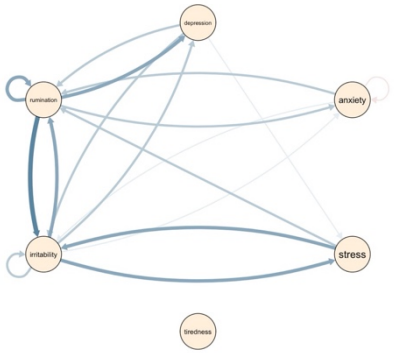
Empirical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-belief**	**Sense of guilt**
Depression	.1	0	-.2	.1	.1	.1	-.1
Anxiety	-.4	-.1	-.3	-.1	-.1	.3	-.4
Stress	.6	0	.8	.1	.2	-.3	.2
Tiredness	.1	-.1	-.1	.6	-.1	-.2	.1
Irritability	-.3	0	-.4	-.1	-.2	.2	0
Self-belief	-.4	-.1	-.3	0	-.1	.4	-.1
Sense of guilt	-.3	-.1	0	-.3	.1	.3	-.1

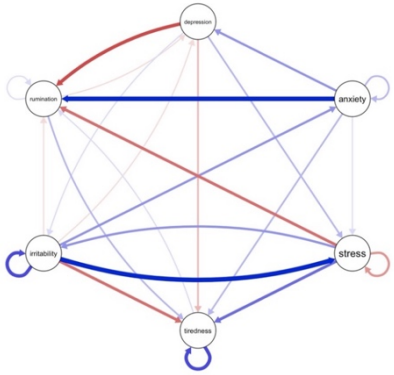
Dyad 14

Clinical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**
Depression	0	0	.1	0	.3	.3
Anxiety	0	-.1	0	0	.1	.3
Stress	0	0	0	0	.5	.3
Tiredness	0	0	0	0	0	0
Irritability	.3	.1	.5	0	.3	.5
Rumination	.5	.3	0	0	.7	.5

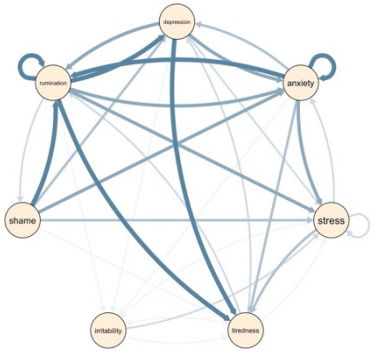
Empirical Model



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**
Depression	0	0	.2	-.2	.1	-.5
Anxiety	.3	.2	.1	.2	0	.7
Stress	0	0	-.3	.4	.3	-.4
Tiredness	0	0	0	.5	0	.1
Irritability	-.1	.3	.7	-.4	.5	-.1
Rumination	-.1	0	0	.2	0	.1

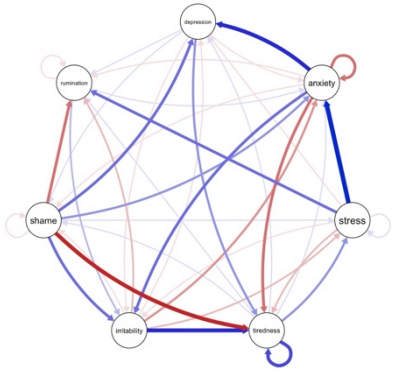
Dyad 15

Clinical Model



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Shame**	**Rumination**
Depression	0	.7	.3	1	.1	0	.7
Anxiety	.5	1	.7	.5	.1	0	1
Stress	0	.3	.3	.5	.1	0	0
Tiredness	.3	0	.1	0	.1	0	.3
Irritability	0	0	.3	.1	0	0	0
Shame	.5	.7	.5	.1	0	0	1
Rumination	1	.7	.7	1	.1	.3	1

Empirical Model

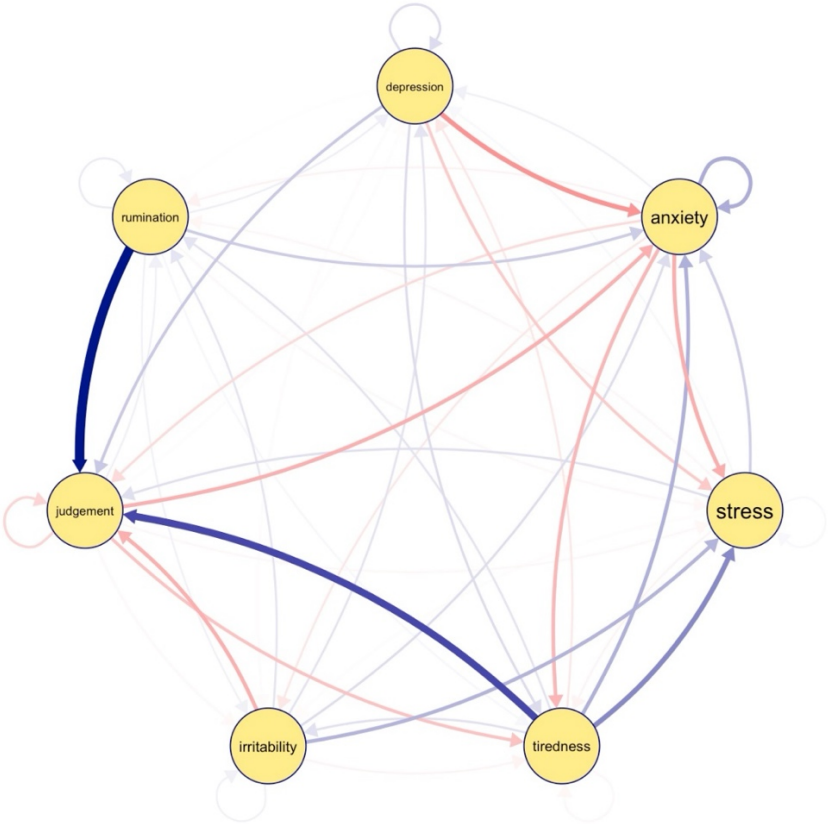


	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Shame**	**Rumination**
Depression	0	-.1	0	.3	-.1	.1	.1
Anxiety	.6	-.4	0	-.4	.4	-.1	-.1
Stress	-.1	.7	.1	-.2	-.1	0	.4
Tiredness	.1	.1	.3	.5	0	.1	.1
Irritability	-.1	-.3	-.2	.6	0	-.1	-.2
Shame	.4	.3	.1	-.6	.4	-.1	-.4
Rumination	0	.1	0	0	.2	0	-.1

Appendix K

Patient's Temporal Network: Graphical Representation, Corresponding Matrix, and Descriptive Interpretation

Dyad 1



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Judgement**	**Rumination**
Depression	.017	-.053	-.026	.017	-.002	.026	-.001
Anxiety	.007	.041	-.041	-.036	-.011	-.018	-.007
Stress	.003	.023	.003	-.006	-.002	.015	-.004
Tiredness	-.011	.039	.058	-.004	.015	.091	.013
Irritability	.013	.016	.037	-.006	.006	-.039	.012
Judgement	-.002	-.039	-.004	-.030	-.003	-.021	.007
Rumination	.008	.025	-.004	.004	.006	.127	.010

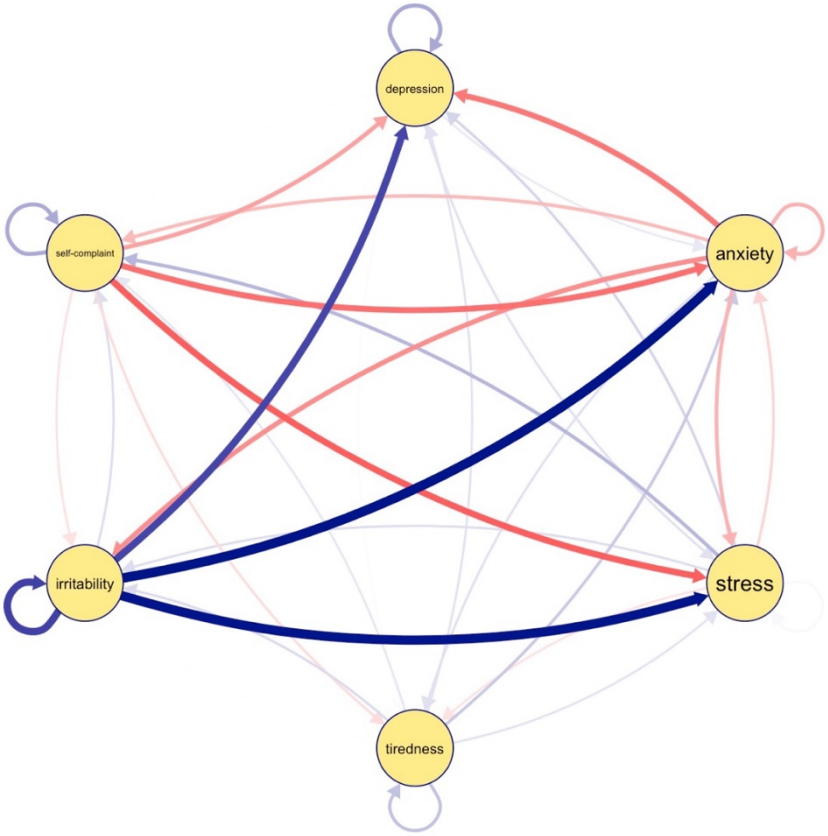
Descriptive interpretation

 2 weak positive relationships:

- Rumination and judgment (.13) - The more the patient feels they are ruminating at a given moment, the more they will feel judged 3 hours later.
- Tiredness and judgment (.09) - The more the patient feels tired at a given moment, the more they will feel judged 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 2



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-complaint**
Depression	.207	.051	.071	.006	.003	-.002
Anxiety	-.327	-.187	-.184	.074	-.272	-.163
Stress	.101	-.100	.016	-.065	.079	.173
Tiredness	.067	.126	.065	.146	.086	.060
Irritability	.450	.623	.606	-.003	.459	.078
Self-complaint	-.227	-.347	-.389	-.082	-.069	.205

Descriptive interpretation

- **4 strong positive relationships**:
  - Irritability and anxiety (.62) - The more the patient feels irritable at a given moment, the more they will feel anxious 3 hours later.
  - Irritability and stress (.61) - The more the patient feels irritable at a given moment, the more they will feel stressed 3 hours later.
  - Irritability and irritability itself (.46) - When the patient feels irritable at a given moment, it is likely that they will feel the same 3 hours later.
  - Irritability and depression (.45) - The more the patient feels irritable at a given moment, the more they will feel depressed 3 hours later.
- **4 moderate negative relationships**:
  - Self-complaint and stress (-.39) - The more the patient feels self-critical at a given moment, the less they will feel stressed 3 hours later.
  - Self-complaint and anxiety (-.35) - The more the patient feels self-critical at a given moment, the less they will feel anxious 3 hours later.
  - Anxiety and depression (-.33) - The more the patient feels anxious at a given moment, the less they will feel depressed 3 hours later.
  - Anxiety and irritability (-.27) - The more the patient feels anxious at a given moment, the less they will feel irritable 3 hours later.
- **6 weak positive relationships**:
  - Depression and depression itself (.21) - When the patient feels depressed at a given moment, it is likely that they will feel the same 3 hours later.
  - Self-complaint and self-complaint itself (.21) - When the patient feels self-critical at a given moment, it is likely that they will feel the same 3 hours later.

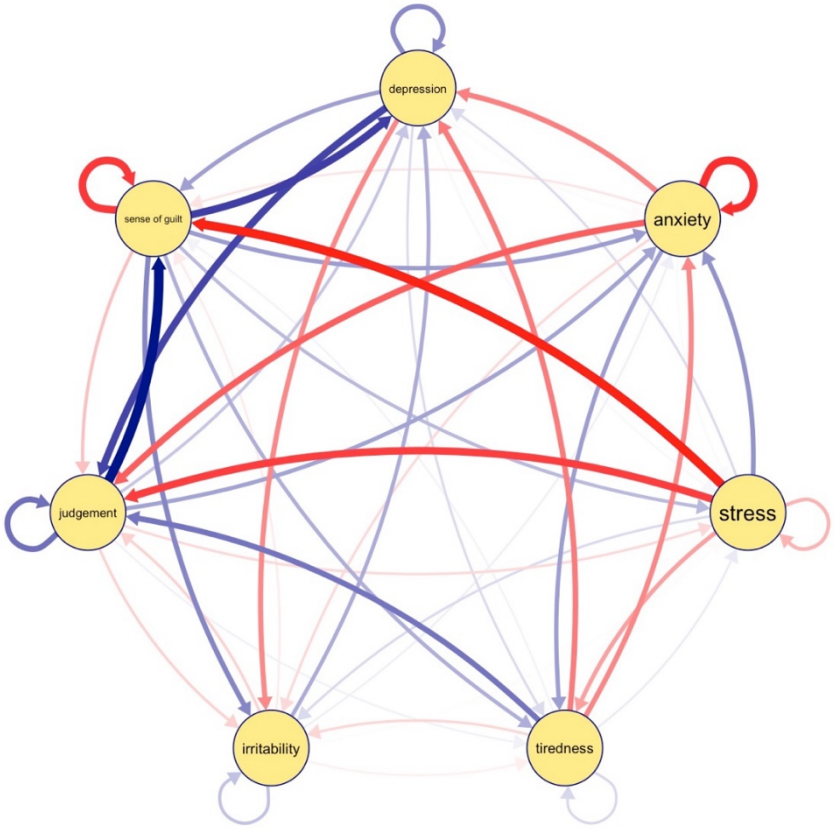
- Stress and self-complaint (.17) - The more the patient feels stressed at a given moment, the more they will feel self-critical 3 hours later.
- Tiredness and tiredness itself (.15) - When the patient feels fatigued at a given moment, it is likely that they will feel the same 3 hours later.
- Tiredness and anxiety (.13) - The more the patient feels fatigued at a given moment, the more they will feel anxious 3 hours later.
- Stress and depression (.10) - The more the patient feels stressed at a given moment, the more they will feel depressed 3 hours later.

 6 weak negative relationships:

- Self-complaint and depression (-.23) - The more the patient feels self-critical at a given moment, the less they will feel depressed 3 hours later.
- Anxiety and anxiety itself (-.19) - The more the patient feels anxious at a given moment, the less they will feel the same 3 hours later.
- Anxiety and stress (-.18) - The more the patient feels anxious at a given moment, the less they will feel stressed 3 hours later.
- Anxiety and self-complaint (-.16) - The more the patient feels anxious at a given moment, the less they will feel self-critical 3 hours later.
- Stress and anxiety (-.10) - The more the patient feels stressed at a given moment, the less they will feel anxious 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 3



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Judgement**	**Sense of guilt**
Depression	.165	-.008	.009	.050	-.169	.266	.135
Anxiety	-.181	-.299	.007	.138	-.053	-.228	-.037
Stress	.050	.154	-.106	-.135	.052	-.277	-.336
Tiredness	-.189	-.172	.029	.055	-.056	.196	.017
Irritability	.118	.021	-.005	-.020	.086	-.063	-.028
Judgement	.080	.130	-.053	.018	-.063	.205	.367
Sense of guilt	.275	.140	.098	.114	.172	-.087	-.283

Descriptive interpretation

- **3 moderate positive relationships**:
  - Judgment and sense of guilt (.37) - The more the patient feels judged at a given moment, the more they will feel guilty 3 hours later.
  - Sense of guilt and depression (.28) - The more the patient feels guilty at a given moment, the more they will feel depressed 3 hours later.
  - Depression and judgment (.27) - The more the patient feels depressed at a given moment, the more they will feel judged 3 hours later.
- **4 moderate negative relationships**:
  - Stress and sense of guilt (-.34) - The more the patient feels stressed at a given moment, the less guilty they will feel 3 hours later.
  - Anxiety and anxiety itself (-.30) - The more anxious the patient feels at a given moment, the less anxious they will feel 3 hours later.
  - Stress and judgment (-.28) - The more stressed the patient feels at a given moment, the less judged they will feel 3 hours later.
  - Sense of guilt and sense of guilt itself (-.28) - The guiltier the patient feels at a given moment, the less guilty they will feel 3 hours later.
- **15 weak positive relationships**:
  - Tiredness and judgment (.20) - The more tired the patient feels at a given moment, the more they will feel judged 3 hours later.
  - Judgment and judgment itself (.20) - When the patient feels judged at a given moment, it is likely they will feel judged again 3 hours later.
  - Depression and depression itself (.17) - When the patient feels depressed at a given moment, it is likely they will feel depressed again 3 hours later.

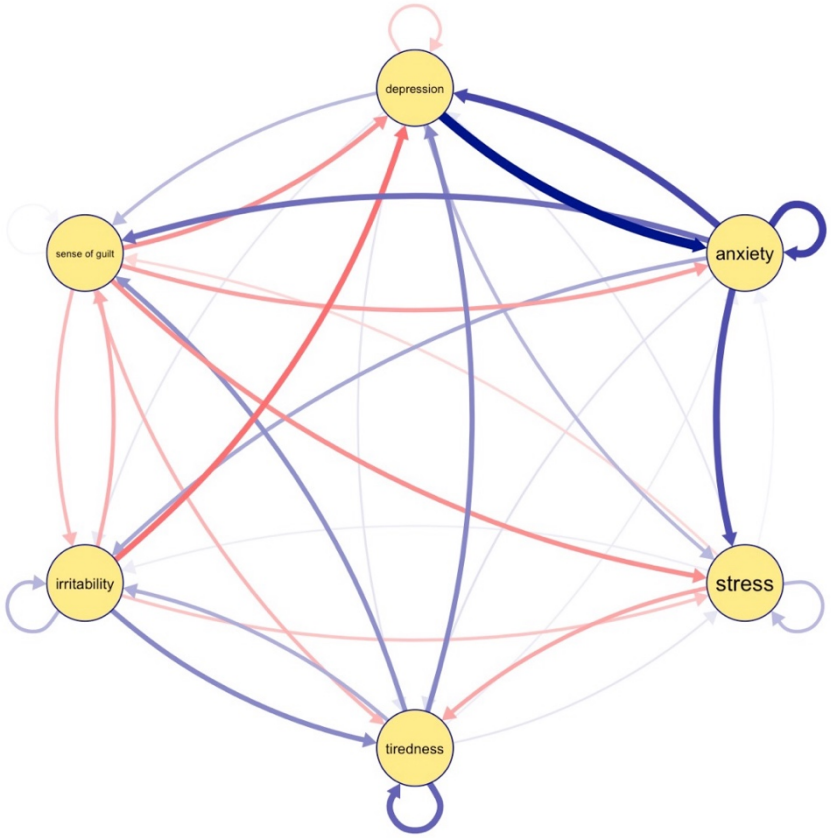
- Sense of guilt and irritability (.17) - The guiltier the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Stress and anxiety (.15) - The more stressed the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Depression and guilt (.14) - The more depressed the patient feels at a given moment, the guiltier they will feel 3 hours later.
- Anxiety and tiredness (.14) - The more anxious the patient feels at a given moment, the more tired they will feel 3 hours later.
- Sense of guilt and anxiety (.14) - The guiltier the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Judgment and anxiety (.13) - The more judged the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Irritability and depression (.12) - The more irritable the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Sense of guilt and tiredness (.11) - The guiltier the patient feels at a given moment, the more tired they will feel 3 hours later.
- Depression and tiredness (.10) - The more depressed the patient feels at a given moment, the more tired they will feel 3 hours later.
- Sense of guilt and stress (.10) - The guiltier the patient feels at a given moment, the more stressed they will feel 3 hours later.
- Irritability and irritability itself (.09) - When the patient feels irritable at a given moment, it is likely they will feel irritable again 3 hours later.
- Judgment and depression (.08) - The more judged the patient feels at a given moment, the more depressed they will feel 3 hours later.

 8 weak negative relationships:

- Anxiety and judgment (-.23) - The more anxious the patient feels at a given moment, the less judged they will feel 3 hours later.
- Tiredness and depression (-.19) - The more tired the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Anxiety and depression (-.18) - The more anxious the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Depression and irritability (-.17) - The more depressed the patient feels at a given moment, the less irritable they will feel 3 hours later.
- Tiredness and anxiety (-.17) - The more tired the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Stress and tiredness (-.14) - The more stressed the patient feels at a given moment, the less tired they will feel 3 hours later.
- Stress and stress itself (-.11) - The more stressed the patient feels at a given moment, the less stressed they will feel 3 hours later.
- Sense of guilt and judgment (-.09) - The guiltier the patient feels at a given moment, the less judged they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 4



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Sense of guilt**
Depression	-.105	.512	.141	.051	.045	.138
Anxiety	.370	.379	.348	.056	.172	.289
Stress	.046	.021	.138	-.176	.034	-.081
Tiredness	.239	.033	.049	.313	.162	.219
Irritability	-.283	-.001	-.117	.236	.148	-.167
Sense of guilt	-.217	-.190	-.222	-.147	-.143	.016

Descriptive interpretation

- **1 strong positive relationship**:
  - Depression and anxiety (.51) – The more the patient feels depressed at a given moment, the more they will feel anxious 3 hours later.
- **5 moderate positive relationships**:
  - Anxiety and anxiety itself (.38) – When the patient feels anxious at a given moment, it is likely they will feel anxious again 3 hours later.
  - Anxiety and depression (.37) – The more the patient feels anxious at a given moment, the more they will feel depressed 3 hours later.
  - Anxiety and stress (.35) – The more the patient feels anxious at a given moment, the more they will feel stressed 3 hours later.
  - Tiredness and tiredness itself (.31) – When the patient feels tired at a given moment, it is likely they will feel tired again 3 hours later.
  - Anxiety and sense of guilt (.29) – The more the patient feels anxious at a given moment, the more they will feel guilty 3 hours later.
- **1 moderate negative relationship**:
  - Irritability and depression (-.28) – The more the patient feels irritable at a given moment, the less they will feel depressed 3 hours later.
- **9 weak positive relationships**:
  - Irritability and tiredness (.24) – The more the patient feels irritable at a given moment, the more they will feel tired 3 hours later.
  - Tiredness and depression (.24) – The more the patient feels tired at a given moment, the more they will feel depressed 3 hours later.
  - Tiredness and sense of guilt (.22) – The more the patient feels tired at a given moment, the more they will feel guilty 3 hours later.

- Anxiety and irritability (.17) – The more the patient feels anxious at a given moment, the more they will feel irritable 3 hours later.
- Tiredness and irritability (.16) – The more the patient feels tired at a given moment, the more they will feel irritable 3 hours later.
- Irritability and irritability itself (.15) – When the patient feels irritable at a given moment, it is likely they will feel irritable again 3 hours later.
- Depression and stress (.14) – The more the patient feels depressed at a given moment, the more they will feel stressed 3 hours later.
- Depression and sense of guilt (.14) – The more the patient feels depressed at a given moment, the more they will feel guilty 3 hours later.
- Stress and stress itself (.14) – When the patient feels stressed at a given moment, it is likely they will feel stressed again 3 hours later.

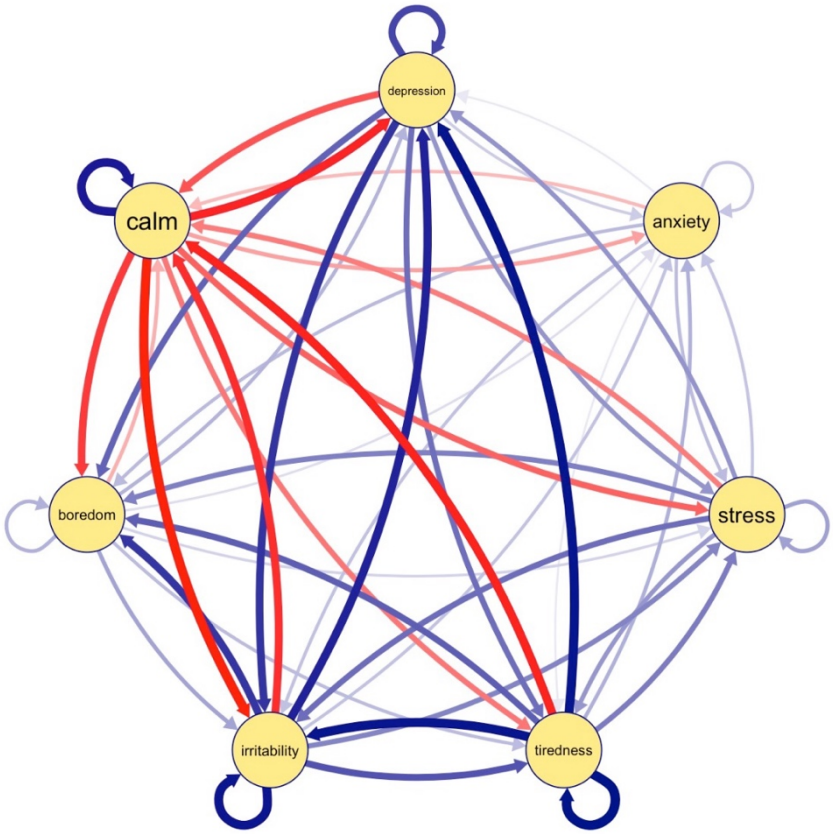
 10 weak negative relationships:

- Sense of guilt and stress (-.22) – The more the patient feels guilty at a given moment, the less they will feel stressed 3 hours later.
- Sense of guilt and depression (-.22) – The more the patient feels guilty at a given moment, the less they will feel depressed 3 hours later.
- Sense of guilt and anxiety (-.19) – The more the patient feels guilty at a given moment, the less they will feel anxious 3 hours later.
- Stress and tiredness (-.18) – The more the patient feels stressed at a given moment, the less they will feel tired 3 hours later.
- Irritability and guilt (-.17) – The more the patient feels irritable at a given moment, the less they will feel guilty 3 hours later.
- Sense of guilt and tiredness (-.15) – The more the patient feels guilty at a given moment, the less they will feel tired 3 hours later.

- Sense of guilt and irritability (-.14) – The more the patient feels guilty at a given moment, the less they will feel irritable 3 hours later.
- Irritability and stress (-.12) – The more the patient feels irritable at a given moment, the less they will feel stressed 3 hours later.
- Depression and depression itself (-.11) – The more the patient feels depressed at a given moment, the less they will feel depressed 3 hours later.
- Stress and sense of guilt (-.08) – The more the patient feels stressed at a given moment, the less they will feel guilty 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 5



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Boredom**	**Calm**
Depression	.096	.026	.055	.075	.105	.081	-.089
Anxiety	.011	.030	.034	.011	.032	.036	-.036
Stress	.055	.030	.048	.053	.075	.066	-.068
Tiredness	.128	.041	.067	.133	.128	.083	-.118
Irritability	.114	.032	.064	.089	.125	.104	-.108
Boredom	.039	.017	.023	.035	.047	.040	-.041
Calm	-.114	-.049	-.081	-.071	-.129	-.102	.119

Descriptive interpretation

- **12 weak positive relationships**:
  - Tiredness and depression (.13) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.
  - Tiredness and tiredness itself (.13) - When the patient feels tired at a given moment, they are likely to feel tired again 3 hours later.
  - Tiredness and irritability (.13) - The more tired the patient feels at a given moment, the more irritable they will feel 3 hours later.
  - Irritability and irritability itself (.12) - When the patient feels irritable at a given moment, they are likely to feel irritable again 3 hours later.
  - Calm and calm itself (.12) - When the patient feels calm at a given moment, they are likely to feel calm again 3 hours later.
  - Irritability and depression (.11) - The more irritable the patient feels at a given moment, the more depressed they will feel 3 hours later.
  - Depression and irritability (.11) - The more depressed the patient feels at a given moment, the more irritable they will feel 3 hours later.
  - Irritability and boredom (.10) - The more irritable the patient feels at a given moment, the more bored they will feel 3 hours later.
  - Depression and depression itself (.10) - When the patient feels depressed at a given moment, they are likely to feel depressed again 3 hours later.
  - Irritability and tiredness (.09) - The more irritable the patient feels at a given moment, the more tired they will feel 3 hours later.
  - Depression and boredom (.08) - The more depressed the patient feels at a given moment, the more bored they will feel 3 hours later.

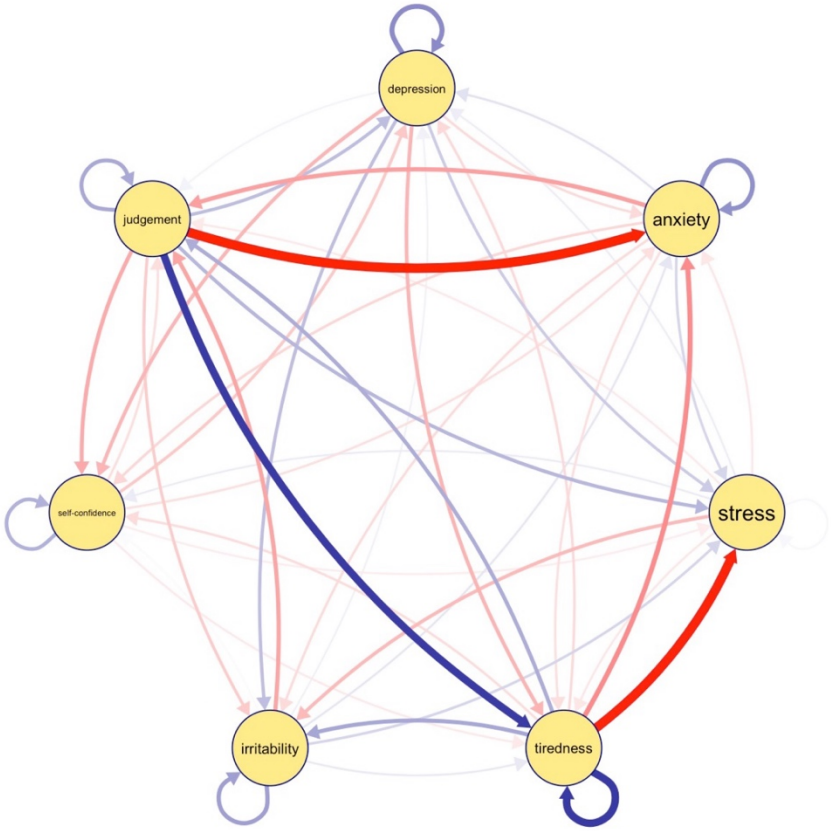
- Tiredness and boredom (.08) - The more tired the patient feels at a given moment, the more bored they will feel 3 hours later.

 7 weak negative relationships:

- Calm and irritability (-.13) - The calmer the patient feels at a given moment, the less irritable they will feel 3 hours later.
- Tiredness and calm (-.12) - The more tired the patient feels at a given moment, the less calm they will feel 3 hours later.
- Irritability and calm (-.11) - The more irritable the patient feels at a given moment, the less calm they will feel 3 hours later.
- Calm and depression (-.11) - The calmer the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Calm and boredom (-.10) - The calmer the patient feels at a given moment, the less bored they will feel 3 hours later.
- Depression and calm (-.09) - The more depressed the patient feels at a given moment, the less calm they will feel 3 hours later.
- Calm and stress (-.08) - The calmer the patient feels at a given moment, the less stressed they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 6



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-confidence**	**Judgement**
Depression	.073	-.023	.032	-.047	.040	-.046	.007
Anxiety	.018	.069	.025	-.020	-.023	-.026	-.060
Stress	.011	-.015	.005	-.015	-.044	.011	-.013
Tiredness	-.024	-.073	-.158	.125	.055	-.022	.052
Irritability	.008	.016	.026	.014	.060	.002	-.057
Self-confidence	-.034	-.019	-.012	-.013	.001	.049	-.020
Judgement	.041	-.163	.045	.124	-.032	-.053	.054

Descriptive interpretation

 2 weak positive relationships:

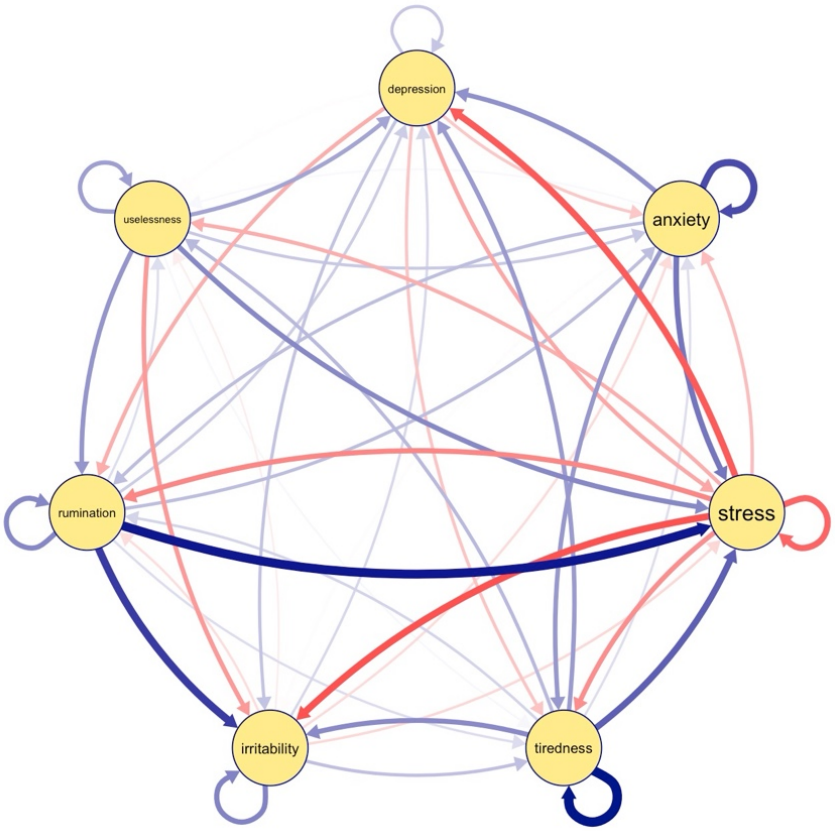
- Tiredness and tiredness itself (.13) - When the patient feels tired at a given moment, they are likely to feel tired again 3 hours later.
- Judgment and tiredness (.12) - The more judged the patient feels at a given moment, the more tired they will feel 3 hours later.

 2 weak negative relationships:

- Tiredness and stress (-.16) - The more tired the patient feels at a given moment, the less stressed they will feel 3 hours later.
- Judgment and anxiety (-.16) - The more judged the patient feels at a given moment, the less anxious they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 7



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**	**Uselessness**
Depression	.110	-.107	-.169	-.115	.116	-.160	-.003
Anxiety	.213	.350	.265	.199	-.005	.127	.014
Stress	-.320	-.129	-.301	-.221	-.336	-.236	-.157
Tiredness	.194	.063	.311	.497	.226	.084	.136
Irritability	.076	-.069	-.075	.122	.242	-.066	-.032
Rumination	.097	.126	.465	.065	.382	.233	.062
Uselessness	.175	.105	.229	.015	-.199	.206	.188

Descriptive interpretation

- **2 strong positive relationships**:
  - Tiredness and tiredness itself (.50) - When the patient feels tired at a given moment, they are likely to feel tired again 3 hours later.
  - Rumination and stress (.47) - The more the patient feels they are ruminating at a given moment, the more stressed they will feel 3 hours later.
- **4 moderate positive relationships**:
  - Anxiety and anxiety itself (.35) - When the patient feels anxious at a given moment, they are likely to feel anxious again 3 hours later.
  - Tiredness and stress (.31) - The more tired the patient feels at a given moment, the more stressed they will feel 3 hours later.
  - Anxiety and stress (.27) - The more anxious the patient feels at a given moment, the more stressed they will feel 3 hours later.
  - Rumination and irritability (.17) - The more the patient feels they are ruminating at a given moment, the more irritable they will feel 3 hours later.
- **3 moderate negative relationships**:
  - Stress and irritability (-.34) - The more stressed the patient feels at a given moment, the less irritable they will feel 3 hours later.
  - Stress and depression (-.32) - The more stressed the patient feels at a given moment, the less depressed they will feel 3 hours later.
  - Stress and stress itself (-.30) - The more stressed the patient feels at a given moment, the less stressed they will feel 3 hours later.
- **21 weak positive relationships**:
  - Irritability and irritability itself (.24) - When the patient feels irritable at a given moment, they are likely to feel irritable again 3 hours later.

- Irritability and irritability itself (.24) - When the patient feels irritable at a given moment, they are likely to feel irritable again 3 hours later.
- Judgment and stress (.23) - The more judged the patient feels at a given moment, the more stressed they will feel 3 hours later.
- Rumination and rumination itself (.23) - When the patient feels they are ruminating at a given moment, they are likely to feel the same 3 hours later.
- Tiredness and irritability (.23) - The more tired the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Anxiety and depression (.21) - The more anxious the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Judgment and rumination (.21) - The more judged the patient feels at a given moment, the more they will ruminate 3 hours later.
- Anxiety and tiredness (.20) - The more anxious the patient feels at a given moment, the more tired they will feel 3 hours later.
- Tiredness and depression (.19) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Judgment and depression (.18) - The more judged the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Judgment and depression (.18) - The more judged the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Tiredness and judgment (.14) - The more tired the patient feels at a given moment, the more judged they will feel 3 hours later.
- Anxiety and rumination (.13) - The more anxious the patient feels at a given moment, the more they will ruminate 3 hours later.

- Rumination and anxiety (.13) - The more the patient feels they are ruminating at a given moment, the more anxious they will feel 3 hours later.
- Depression and irritability (.12) - The more depressed the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Irritability and tiredness (.12) - The more irritable the patient feels at a given moment, the more tired they will feel 3 hours later.
- Depression and depression itself (.11) - When the patient feels depressed at a given moment, they are likely to feel depressed again 3 hours later.
- Rumination and depression (.10) - The more the patient feels they are ruminating at a given moment, the more depressed they will feel 3 hours later.
- Judgment and anxiety (.10) - The more judged the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Tiredness and rumination (.08) - The more tired the patient feels at a given moment, the more they will ruminate 3 hours later.
- Irritability and depression (.08) - The more irritable the patient feels at a given moment, the more depressed they will feel 3 hours later.

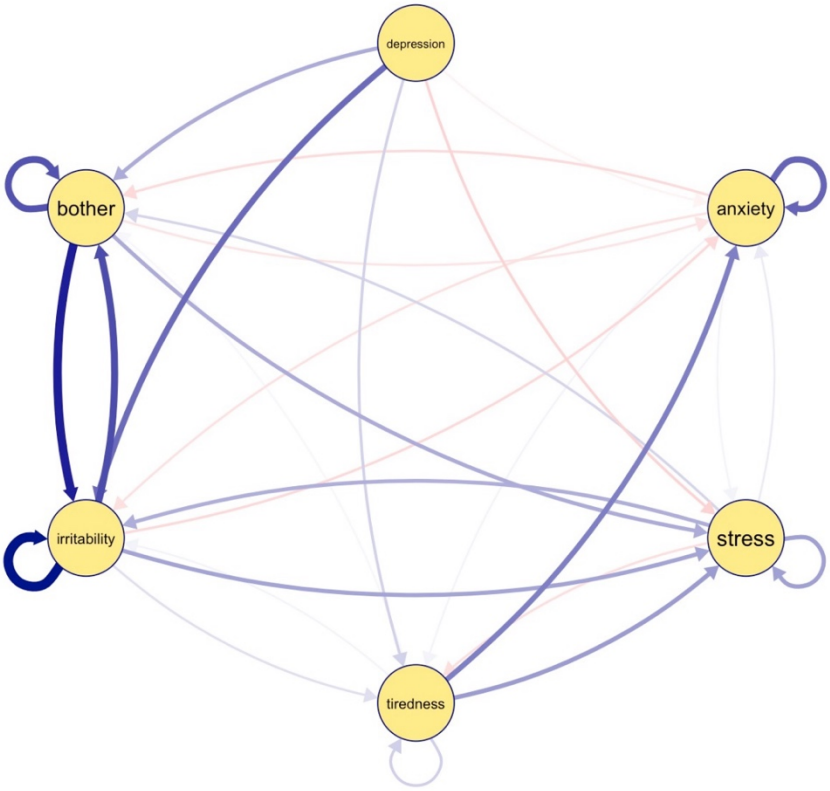
 10 weak negative relationships:

- Stress and rumination (-.24) - The more stressed the patient feels at a given moment, the less they will ruminate 3 hours later.
- Judgment and irritability (-.24) - The more judged the patient feels at a given moment, the less irritable they will feel 3 hours later.
- Stress and tiredness (-.22) - The more stressed the patient feels at a given moment, the less tired they will feel 3 hours later.
- Depression and stress (-.17) - The more depressed the patient feels at a given moment, the less stressed they will feel 3 hours later.

- Stress and judgment (-.16) - The more stressed the patient feels at a given moment, the less judged they will feel 3 hours later.
- Depression and rumination (-.16) - The more depressed the patient feels at a given moment, the less they will ruminate 3 hours later.
- Stress and anxiety (-.13) - The more stressed the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Depression and tiredness (-.12) - The more depressed the patient feels at a given moment, the less tired they will feel 3 hours later.
- Depression and anxiety (-.11) - The more depressed the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Irritability and stress (-.08) - The more irritable the patient feels at a given moment, the less stressed they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 8



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Bother**
Depression	0	-.011	-.039	.041	.134	.076
Anxiety	0	.141	.010	.010	-.026	-.033
Stress	0	.018	.085	-.028	.072	.037
Tiredness	0	.116	.090	.042	.009	.007
Irritability	0	-.033	.082	.028	.235	.163
Bother	0	-.025	.075	-.000	.207	.156

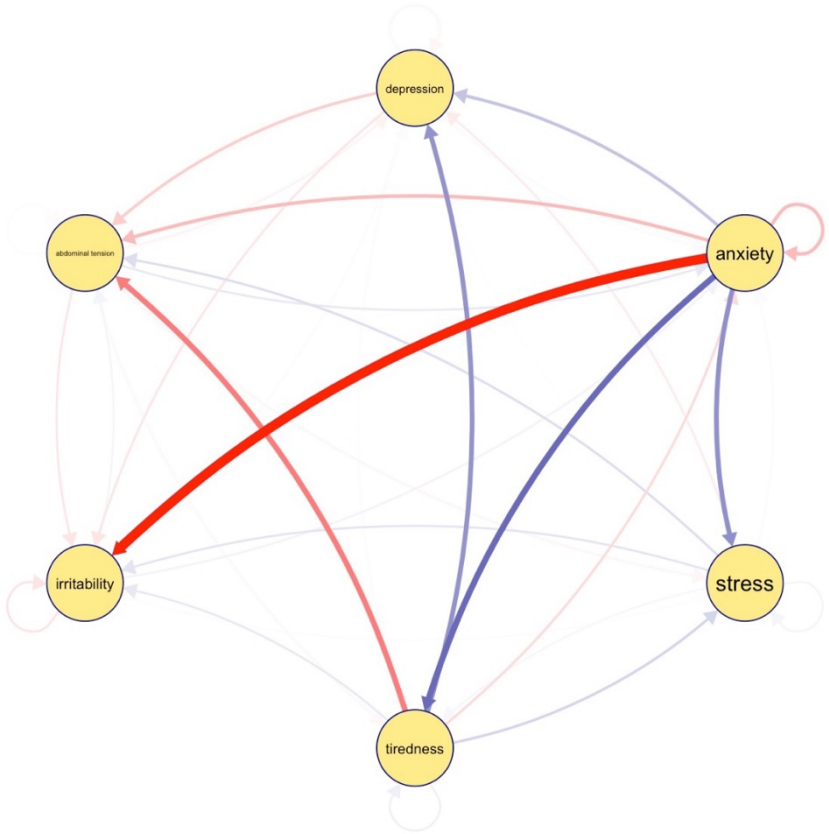
Descriptive interpretation

 11 weak positive relationships:

- Irritability and irritability itself (.24) - When the patient feels irritable at a given moment, they are likely to feel irritable again 3 hours later.
- Bother and irritability (.21) - The more bothered the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Irritability and bother (.16) - The more irritable the patient feels at a given moment, the more bothered they will feel 3 hours later.
- Bother and bother itself (.16) - When the patient feels bothered at a given moment, they are likely to feel bothered again 3 hours later.
- Anxiety and anxiety itself (.14) - When the patient feels anxious at a given moment, they are likely to feel anxious again 3 hours later.
- Depression and irritability (.13) - The more depressed the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Depression and bother (.13) - The more depressed the patient feels at a given moment, the more bothered they will feel 3 hours later.
- Tiredness and anxiety (.12) - The more tired the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Tiredness and stress (.09) - The more tired the patient feels at a given moment, the more stressed they will feel 3 hours later.
- Irritability and stress (.08) - The more irritable the patient feels at a given moment, the more stressed they will feel 3 hours later.
- Bother and stress (.08) - The more bothered the patient feels at a given moment, the more stressed they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 9



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Abdominal tension**
Depression	-.009	.004	-.002	-.005	-.026	-.053
Anxiety	.064	-.073	.121	.161	-.280	-.073
Stress	-.021	.005	.011	.009	.028	.036
Tiredness	.117	-.039	.045	.017	.025	-.142
Irritability	.003	.013	.002	.000	-.028	.011
Abdominal tension	-.013	.024	-.010	-.008	-.027	-.003

Descriptive interpretation

 1 moderate negative relationship:

- Anxiety and irritability (-.28) - The more anxious the patient feels at a given moment, the less irritable they will feel 3 hours later.

 3 weak positive relationships:

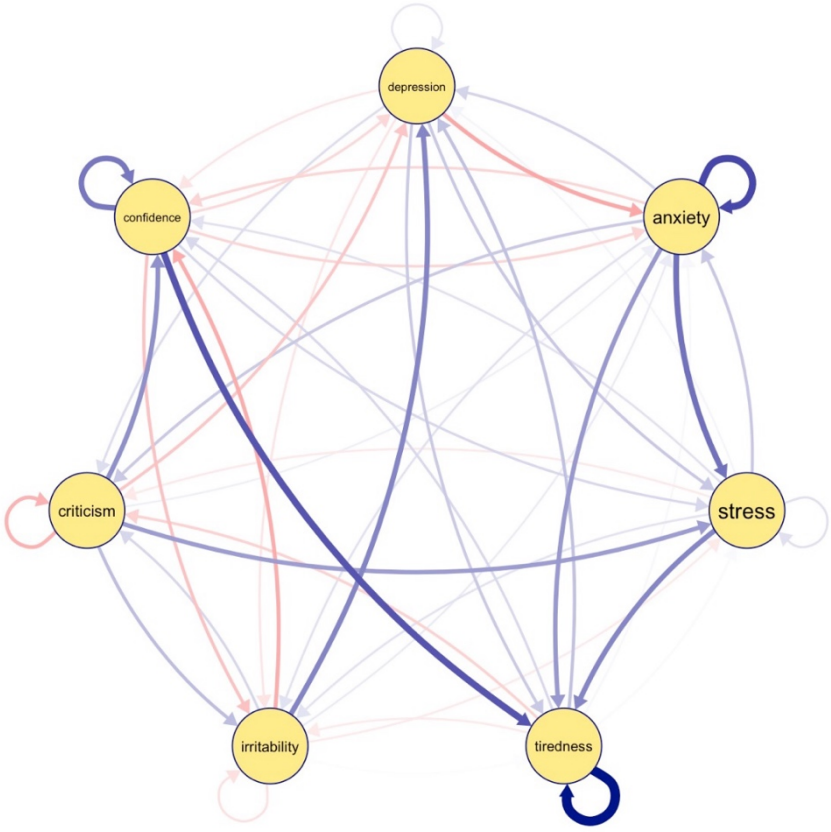
- Anxiety and tiredness (.16) - The more anxious the patient feels at a given moment, the more tired they will feel 3 hours later.
- Anxiety and stress (.12) - The more anxious the patient feels at a given moment, the more stressed they will feel 3 hours later.
- Tiredness and depression (.12) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.

 1 weak negative relationship:

- Tiredness and abdominal tension (-.14) - The more tired the patient feels at a given moment, the less abdominal tension they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 10



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Criticism**	**Confidence**
Depression	.050	-.176	.109	.106	-.053	.066	-.051
Anxiety	.086	.372	.287	.208	.058	.107	-.084
Stress	.021	.111	.062	.245	.056	-.044	.059
Tiredness	.125	.017	.011	.522	-.041	-.091	.076
Irritability	.248	.039	-.041	.004	-.059	.079	-.167
Criticism	-.114	.031	.199	.002	.131	-.153	.223
Confidence	-.078	-.084	.077	.345	-.123	.003	.273

Descriptive interpretation

- **1 strong positive relationship**:
  - Tiredness and tiredness itself (.52) - The more tired the patient feels at a given moment, the more tired they will feel 3 hours later.
- **6 moderate positive relationships**:
  - Anxiety and anxiety itself (.37) - When the patient feels anxious at a given moment, they are likely to feel anxious again 3 hours later.
  - Confidence and tiredness (.34) - The more confident the patient feels at a given moment, the more tired they will feel 3 hours later.
  - Anxiety and stress (.29) - The more anxious the patient feels at a given moment, the more stressed they will feel 3 hours later.
  - Confidence and confidence itself (.27) - When the patient feels confident at a given moment, they are likely to feel confident again 3 hours later.
  - Stress and tiredness (.25) - The more stressed the patient feels at a given moment, the more tired they will feel 3 hours later.
  - Irritability and depression (.25) - The more irritable the patient feels at a given moment, the more depressed they will feel 3 hours later.
- **13 weak positive relationships**:
  - Criticism and confidence (.22) - The more criticized the patient feels at a given moment, the more confident they will feel 3 hours later.
  - Anxiety and tiredness (.21) - The more anxious the patient feels at a given moment, the more tired they will feel 3 hours later.
  - Criticism and stress (.20) - The more criticized the patient feels at a given moment, the more stressed they will feel 3 hours later.

- Criticism and irritability (.13) - The more criticized the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Tiredness and depression (.12) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Depression and stress (.11) - The more depressed the patient feels at a given moment, the more stressed they will feel 3 hours later.
- Depression and tiredness (.11) - The more depressed the patient feels at a given moment, the more tired they will feel 3 hours later.
- Anxiety and criticism (.11) - The more anxious the patient feels at a given moment, the more criticized they will feel 3 hours later.
- Stress and anxiety (.11) - The more stressed the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Anxiety and depression (.09) - The more anxious the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Tiredness and confidence (.08) - The more tired the patient feels at a given moment, the more confident they will feel 3 hours later.
- Irritability and criticism (.08) - The more irritable the patient feels at a given moment, the more criticized they will feel 3 hours later.
- Confidence and stress (.08) - The more confident the patient feels at a given moment, the more stressed they will feel 3 hours later.

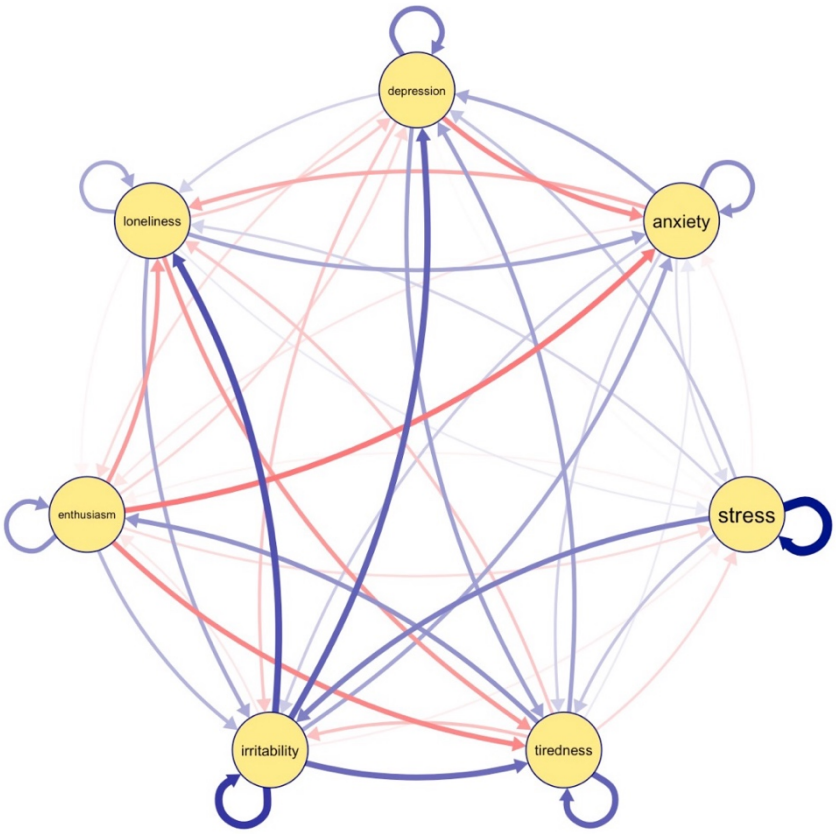
 9 weak negative relationships:

- Depression and anxiety (-.18) - The more depressed the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Irritability and confidence (-.17) - The more irritable the patient feels at a given moment, the less confident they will feel 3 hours later.

- Criticism and criticism itself (-.15) - The more criticized the patient feels at a given moment, the less criticized they will feel 3 hours later.
- Confidence and irritability (-.12) - The more confident the patient feels at a given moment, the less irritable they will feel 3 hours later.
- Criticism and depression (-.11) - The more criticized the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Tiredness and criticism (-.09) - The more tired the patient feels at a given moment, the less criticized they will feel 3 hours later.
- Confidence and anxiety (-.08) - The more confident the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Confidence and depression (-.08) - The more confident the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Anxiety and confidence (-.08) - The more anxious the patient feels at a given moment, the less confident they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 11



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Enthusiasm**	**Loneliness**
Depression	.219	-.193	-.008	.157	-.095	-.059	.075
Anxiety	.147	.191	.056	.078	.086	-.040	-.144
Stress	.100	-.022	.431	.096	.213	-.019	.072
Tiredness	.157	.035	-.065	.265	-.105	.181	-.095
Irritability	.264	.149	-.026	.248	.336	-.038	.291
Enthusiasm	-.066	-.224	-.060	-.201	.124	.190	-.165
Loneliness	-.087	.149	.034	-.169	.143	-.015	.147

Descriptive interpretation

- **6 moderate positive relationships**:
  - Stress and stress itself (.43) - When the patient feels stressed at a given moment, they are likely to feel stressed again 3 hours later.
  - Irritability and irritability itself (.34) - When the patient feels irritable at a given moment, they are likely to feel irritable again 3 hours later.
  - Irritability and loneliness (.29) - The more irritable the patient feels at a given moment, the lonelier they will feel 3 hours later.
  - Tiredness and tiredness itself (.27) - When the patient feels tired at a given moment, they are likely to feel tired again 3 hours later.
  - Irritability and depression (.26) - The more irritable the patient feels at a given moment, the more depressed they will feel 3 hours later.
  - Irritability and tiredness (.25) - The more irritable the patient feels at a given moment, the more tired they will feel 3 hours later.
- **17 weak positive relationships**:
  - Depression and depression itself (.22) - When the patient feels depressed at a given moment, they are likely to feel depressed again 3 hours later.
  - Stress and irritability (.21) - The more stressed the patient feels at a given moment, the more irritable they will feel 3 hours later.
  - Enthusiasm and enthusiasm itself (.19) - When the patient feels enthusiastic at a given moment, they are likely to feel enthusiastic again 3 hours later.
  - Anxiety and anxiety itself (.19) - When the patient feels anxious at a given moment, they are likely to feel anxious again 3 hours later.
  - Tiredness and enthusiasm (.18) - The more tired the patient feels at a given moment, the more enthusiastic they will feel 3 hours later.

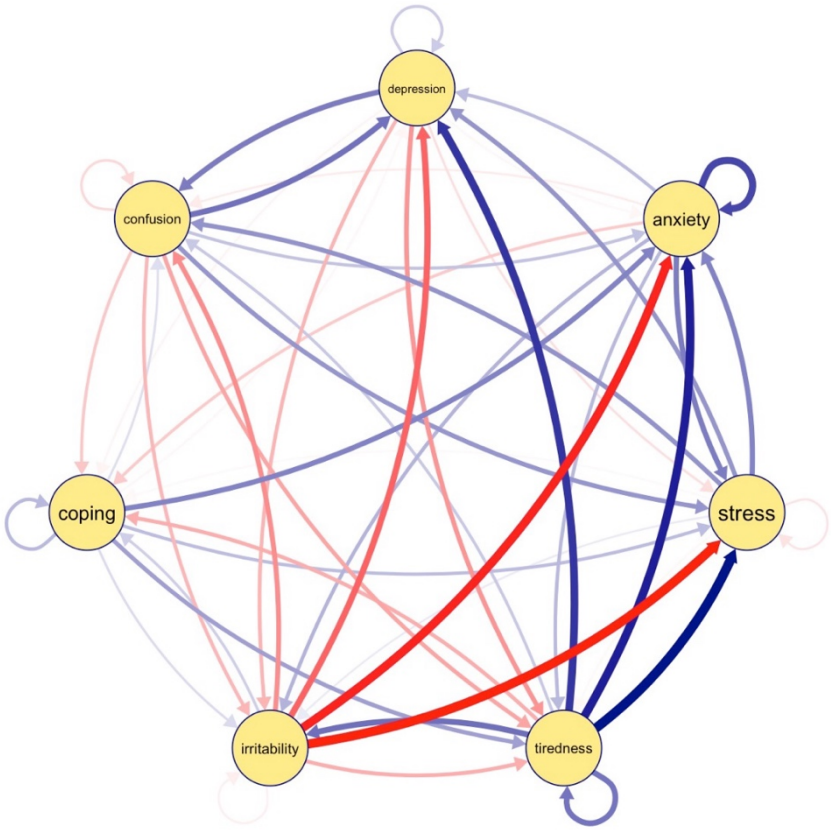
- Tiredness and depression (.16) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Depression and tiredness (.16) - The more depressed the patient feels at a given moment, the more tired they will feel 3 hours later.
- Irritability and anxiety (.15) - The more irritable the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Loneliness and loneliness itself (.15) - When the patient feels lonely at a given moment, they are likely to feel lonely again 3 hours later.
- Loneliness and anxiety (.15) - The lonelier the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Anxiety and depression (.15) - The more anxious the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Loneliness and irritability (.14) - The lonelier the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Enthusiasm and irritability (.12) - The more enthusiastic the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Stress and depression (.10) - The more stressed the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Stress and tiredness (.10) - The more stressed the patient feels at a given moment, the more tired they will feel 3 hours later.
- Anxiety and irritability (.09) - The more anxious the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Anxiety and tiredness (.08) - The more anxious the patient feels at a given moment, the more tired they will feel 3 hours later.

 10 weak negative relationships:

- Enthusiasm and anxiety (-.22) - The more enthusiastic the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Enthusiasm and tiredness (-.20) - The more enthusiastic the patient feels at a given moment, the less tired they will feel 3 hours later.
- Depression and anxiety (-.19) - The more depressed the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Loneliness and tiredness (-.17) - The lonelier the patient feels at a given moment, the less tired they will feel 3 hours later.
- Enthusiasm and loneliness (-.16) - The more enthusiastic the patient feels at a given moment, the less lonely they will feel 3 hours later.
- Anxiety and loneliness (-.14) - The more anxious the patient feels at a given moment, the less lonely they will feel 3 hours later.
- Tiredness and irritability (-.10) - The more tired the patient feels at a given moment, the less irritable they will feel 3 hours later.
- Tiredness and loneliness (-.10) - The more tired the patient feels at a given moment, the less lonely they will feel 3 hours later.
- Depression and irritability (-.09) - The more depressed the patient feels at a given moment, the less irritable they will feel 3 hours later.
- Loneliness and depression (-.09) - The lonelier the patient feels at a given moment, the less depressed they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 12



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Coping**	**Confusion**
Depression	.097	-.015	-.06	-.202	-.141	-.02	.247
Anxiety	.126	.35	.245	.133	.142	-.102	-.036
Stress	.2	.235	-.052	-.013	.039	-.01	.205
Tiredness	.384	.427	.489	.262	.272	-.153	.103
Irritability	-.297	-.429	-.469	-.153	-.031	.09	-.216
Coping	-.015	.235	.123	.18	.067	.132	.06
Confusion	.268	.113	.199	-.17	-.136	-.105	-.072

Descriptive interpretation

- **1 strong positive relationship**:
  - Tiredness and stress (.49) - The more tired the patient feels at a given moment, the more stressed they will feel 3 hours later.
- **1 strong negative relationship**:
  - Irritability and stress (-.47) - The more irritable the patient feels at a given moment, the less stressed they will feel 3 hours later.
- **8 moderate positive relationships**:
  - Tiredness and anxiety (.43) - The more tired the patient feels at a given moment, the more anxious they will feel 3 hours later.
  - Tiredness and depression (.38) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.
  - Anxiety and anxiety itself (.35) - When the patient feels anxious at a given moment, they are likely to feel anxious again 3 hours later.
  - Tiredness and irritability (.27) - The more tired the patient feels at a given moment, the more irritable they will feel 3 hours later.
  - Confusion and depression (.27) - The more confused the patient feels at a given moment, the more depressed they will feel 3 hours later.
  - Tiredness and tiredness itself (.26) - When the patient feels tired at a given moment, they are likely to feel tired again 3 hours later.
  - Anxiety and stress (.25) - The more anxious the patient feels at a given moment, the more stressed they will feel 3 hours later.
  - Depression and confusion (.25) - The more depressed the patient feels at a given moment, the more confused they will feel 3 hours later.
- **2 moderate negative relationships**:

- Irritability and anxiety (-.43) - The more irritable the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Irritability and depression (-.30) - The more irritable the patient feels at a given moment, the less depressed they will feel 3 hours later.

 15 weak positive relationships:

- Stress and anxiety (.24) - The more stressed the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Coping and anxiety (.24) - The more capable the patient feels of coping at a given moment, the more anxious they will feel 3 hours later.
- Stress and confusion (.21) - The more stressed the patient feels at a given moment, the more confused they will feel 3 hours later.
- Confusion and stress (.20) - The more confused the patient feels at a given moment, the more stressed they will feel 3 hours later.
- Stress and depression (.20) - The more stressed the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Coping and tiredness (.18) - The more capable the patient feels of coping at a given moment, the more tired they will feel 3 hours later.
- Anxiety and irritability (.14) - The more anxious the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Anxiety and depression (.13) - The more anxious the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Anxiety and tiredness (.13) - The more anxious the patient feels at a given moment, the more tired they will feel 3 hours later.
- Coping and coping itself (.13) - When the patient feels capable of coping at a given moment, they are likely to feel the same 3 hours later.

- Coping and stress (.12) - The more capable the patient feels of coping at a given moment, the more stressed they will feel 3 hours later.
- Confusion and anxiety (.11) - The more confused the patient feels at a given moment, the more anxious they will feel 3 hours later.
- Depression and depression itself (.10) - When the patient feels depressed at a given moment, they are likely to feel depressed again 3 hours later.
- Tiredness and confusion (.10) - The more tired the patient feels at a given moment, the more confused they will feel 3 hours later.
- Irritability and coping (.09) - The more irritable the patient feels at a given moment, the more capable they will feel of coping 3 hours later.

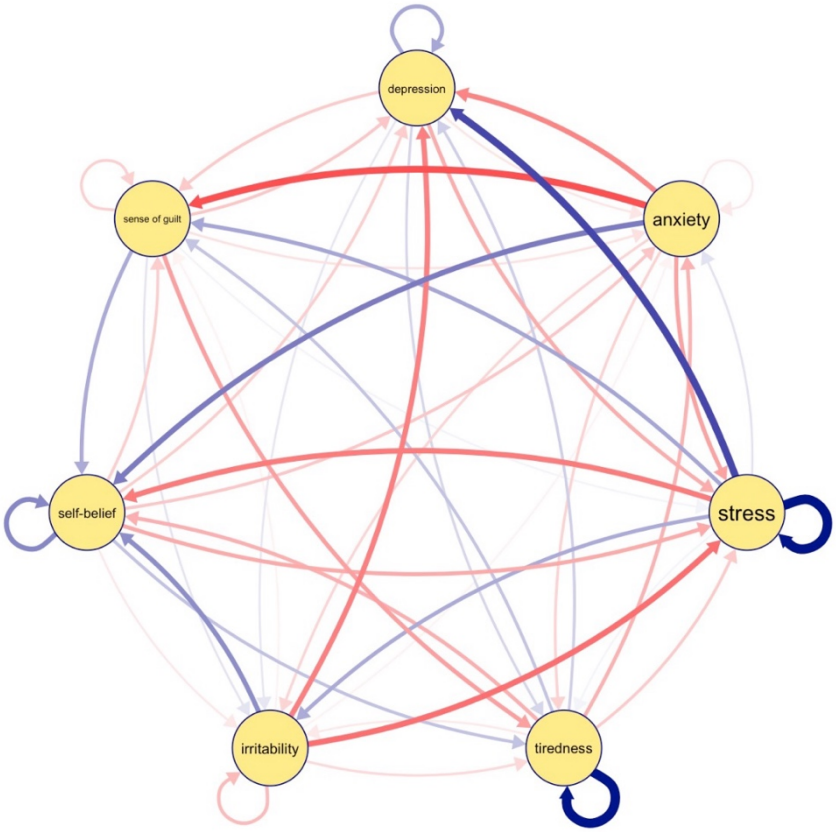
 9 weak negative relationships:

- Irritability and confusion (-.22) - The more irritable the patient feels at a given moment, the less confused they will feel 3 hours later.
- Depression and tiredness (-.20) - The more depressed the patient feels at a given moment, the less tired they will feel 3 hours later.
- Confusion and tiredness (-.17) - The more confused the patient feels at a given moment, the less tired they will feel 3 hours later.
- Tiredness and coping (-.15) - The more tired the patient feels at a given moment, the less capable they will feel of coping 3 hours later.
- Irritability and tiredness (-.15) - The more irritable the patient feels at a given moment, the less tired they will feel 3 hours later.
- Confusion and irritability (-.14) - The more confused the patient feels at a given moment, the less irritable they will feel 3 hours later.
- Depression and irritability (-.14) - The more depressed the patient feels at a given moment, the less irritable they will feel 3 hours later.

- Confusion and coping (-.11) - The more confused the patient feels at a given moment, the less capable they will feel of coping 3 hours later.
- Anxiety and coping (-.10) - The more anxious the patient feels at a given moment, the less capable they will feel of coping 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 13



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Self-belief**	**Sense of guilt**
Depression	.151	-.042	-.142	.070	.042	.001	-.093
Anxiety	-.211	-.038	-.160	-.077	-.071	.227	-.301
Stress	.320	.049	.447	.018	.145	-.228	.152
Tiredness	.082	-.134	-.091	.443	-.036	-.136	.102
Irritability	-.219	-.020	-.248	-.064	-.118	.195	-.021
Self-belief	-.085	-.099	-.147	.106	-.038	.207	-.085
Sense of guilt	-.096	-.051	.019	-.165	.045	.145	-.080

Descriptive interpretation

- **1 strong positive relationship**:
  - Stress and stress itself (.45) - When the patient feels stressed at a given moment, they are likely to feel stressed again 3 hours later.
- **2 moderate positive relationships**:
  - Tiredness and tiredness itself (.44) - When the patient feels tired at a given moment, they are likely to feel tired again 3 hours later.
  - Stress and depression (.32) - The more stressed the patient feels at a given moment, the more depressed they will feel 3 hours later.
- **2 moderate negative relationships**:
  - Anxiety and sense of guilt (-.30) - The more anxious the patient feels at a given moment, the less guilty they will feel 3 hours later.
  - Irritability and stress (-.25) - The more irritable the patient feels at a given moment, the less stressed they will feel 3 hours later.
- **10 weak positive relationships**:
  - Anxiety and self-belief (.23) - The more anxious the patient feels at a given moment, the more they will believe in themselves 3 hours later.
  - Self-belief and self-belief itself (.21) - When the patient feels a sense of self-belief at a given moment, they are likely to feel the same 3 hours later.
  - Irritability and self-belief (.19) - The more irritable the patient feels at a given moment, the more they will believe in themselves 3 hours later.
  - Stress and guilt (.15) - The more stressed the patient feels at a given moment, the guiltier they will feel 3 hours later.
  - Sense of guilt and self-belief (.15) - The guiltier the patient feels at a given moment, the more they will believe in themselves 3 hours later.

- Depression and depression itself (.15) - When the patient feels depressed at a given moment, they are likely to feel depressed again 3 hours later.
- Stress and irritability (.14) - The more stressed the patient feels at a given moment, the more irritable they will feel 3 hours later.
- Self-belief and tiredness (.11) - The more the patient believes in themselves at a given moment, the more tired they will feel 3 hours later.
- Tiredness and sense of guilt (.10) - The more tired the patient feels at a given moment, the guiltier they will feel 3 hours later.
- Tiredness and depression (.08) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.

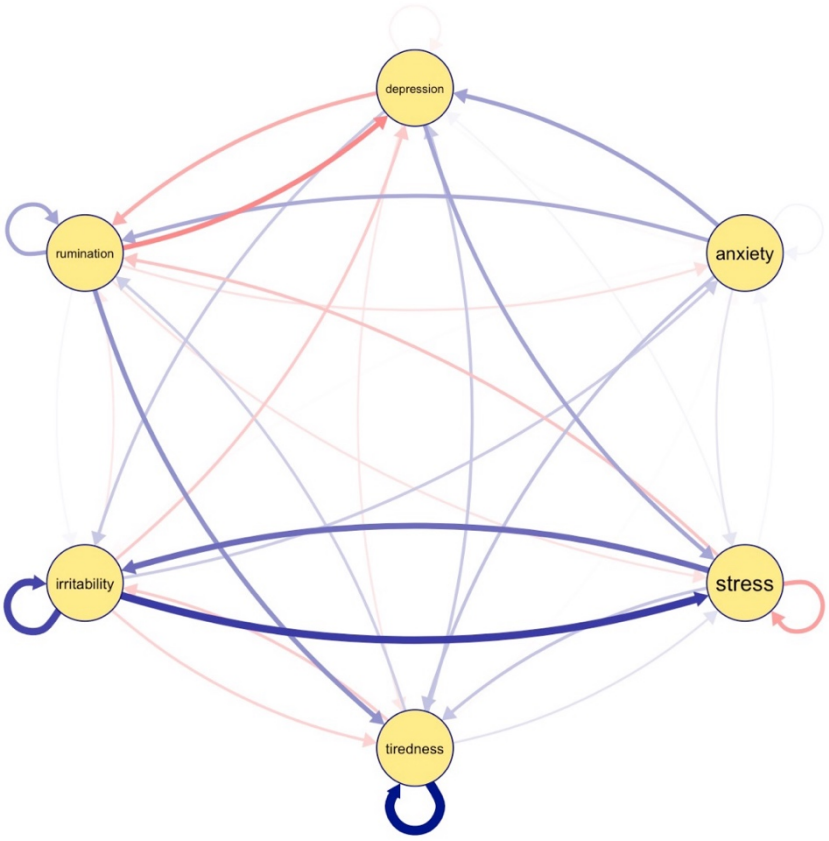
 18 weak negative relationships:

- Stress and self-belief (-.23) - The more stressed the patient feels at a given moment, the less they will believe in themselves 3 hours later.
- Irritability and depression (-.22) - The more irritable the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Anxiety and depression (-.21) - The more anxious the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Sense of guilt and depression (-.17) - The guiltier the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Anxiety and stress (-.16) - The more anxious the patient feels at a given moment, the less stressed they will feel 3 hours later.
- Self-belief and stress (-.15) - The more the patient believes in themselves at a given moment, the less stressed they will feel 3 hours later.
- Tiredness and self-belief (-.14) - The more tired the patient feels at a given moment, the less they will believe in themselves 3 hours later.

- Depression and stress (-.14) - The more depressed the patient feels at a given moment, the less stressed they will feel 3 hours later.
- Tiredness and anxiety (-.13) - The more tired the patient feels at a given moment, the less anxious they will feel 3 hours later.
- Irritability and irritability itself (-.12) - The more irritable the patient feels at a given moment, the less irritable they will feel 3 hours later.
- Sense of guilt and depression (-.10) - The guiltier the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Self-belief and anxiety (-.10) - The more the patient believes in themselves at a given moment, the less anxious they will feel 3 hours later.
- Tiredness and stress (-.09) - The more tired the patient feels at a given moment, the less stressed they will feel 3 hours later.
- Depression and sense of guilt (-.09) - The more depressed the patient feels at a given moment, the less guilty they will feel 3 hours later.
- Self-belief and sense of guilt (-.09) - The more the patient believes in themselves at a given moment, the less guilty they will feel 3 hours later.
- Self-belief and depression (-.09) - The more the patient believes in themselves at a given moment, the less depressed they will feel 3 hours later.
- Anxiety and tiredness (-.08) - The more anxious the patient feels at a given moment, the less tired they will feel 3 hours later.
- Sense of guilt and sense of guilt itself (-.08) - The guiltier the patient feels at a given moment, the less guilty they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 14



	Y variable					
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Rumination**
Depression	-.020	-.008	.144	-.038	.090	-.135
Anxiety	.153	.017	.042	.101	-.007	.139
Stress	.015	.013	-.157	.094	.239	-.096
Tiredness	.090	-.007	.045	.418	-.083	.079
Irritability	-.087	.084	.318	-.073	.303	-.035
Rumination	-.193	-.050	-.046	.177	.013	.146

Descriptive interpretation

- **3 moderate positive relationships**:
  - Tiredness and tiredness itself (.42) - When the patient feels tired at a given moment, they are likely to feel tired again 3 hours later.
  - Irritability and irritability itself (.42) - When the patient feels irritable at a given moment, they are likely to feel irritable again 3 hours later.
  - Irritability and stress (.32) - The more irritable the patient feels at a given moment, the more stressed they will feel 3 hours later.
- **12 weak positive relationships**:
  - Stress and irritability (.24) - The more stressed the patient feels at a given moment, the more irritable they will feel 3 hours later.
  - Rumination and tiredness (.18) - The more the patient feels they are ruminating at a given moment, the more tired they will feel 3 hours later.
  - Anxiety and depression (.15) - The more anxious the patient feels at a given moment, the more depressed they will feel 3 hours later.
  - Rumination and rumination itself (.15) - When the patient feels they are ruminating at a given moment, they are likely to feel the same 3 hours later.
  - Anxiety and rumination (.14) - The more anxious the patient feels at a given moment, the more they will ruminate 3 hours later.
  - Depression and stress (.14) - The more depressed the patient feels at a given moment, the more stressed they will feel 3 hours later.
  - Anxiety and tiredness (.10) - The more anxious the patient feels at a given moment, the more tired they will feel 3 hours later.
  - Depression and irritability (.09) - The more depressed the patient feels at a given moment, the more irritable they will feel 3 hours later.

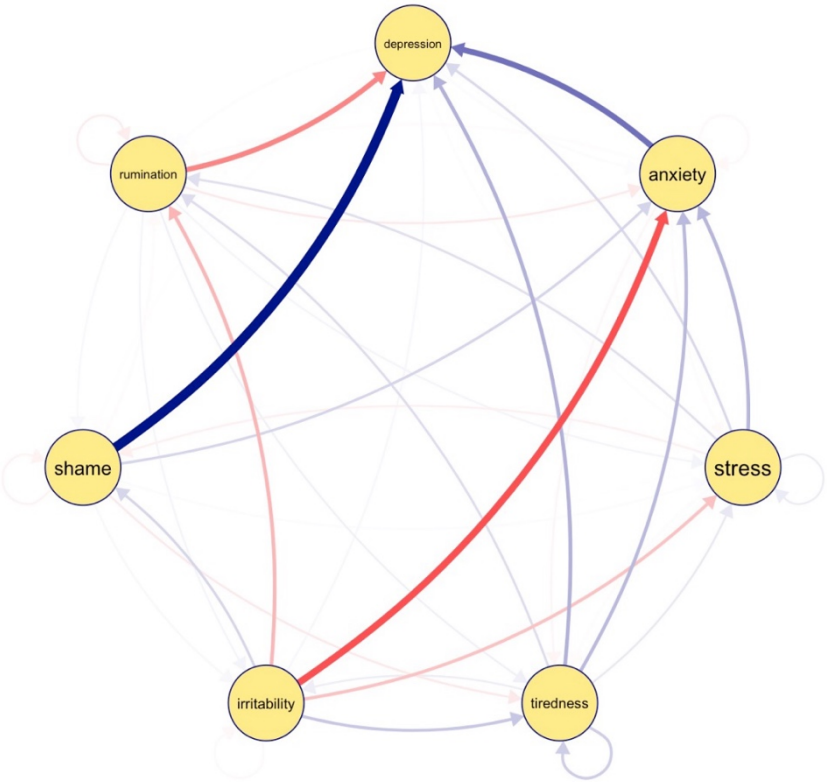
- Stress and tiredness (.09) - The more stressed the patient feels at a given moment, the more tired they will feel 3 hours later.
- Tiredness and depression (.09) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.
- Tiredness and rumination (.08) - The more tired the patient feels at a given moment, the more they will ruminate 3 hours later.
- Irritability and anxiety (.08) - The more irritable the patient feels at a given moment, the more anxious they will feel 3 hours later.

 7 weak negative relationships:

- Rumination and depression (-.19) - The more the patient ruminates at a given moment, the less depressed they will feel 3 hours later.
- Stress and stress itself (-.16) - The more stressed the patient feels at a given moment, the less stressed they will feel 3 hours later.
- Depression and rumination (-.14) - The more depressed the patient feels at a given moment, the less they will ruminate 3 hours later.
- Stress and rumination (-.10) - The more stressed the patient feels at a given moment, the less they will ruminate 3 hours later.
- Irritability and depression (-.09) - The more irritable the patient feels at a given moment, the less depressed they will feel 3 hours later.
- Tiredness and irritability (-.08) - The more tired the patient feels at a given moment, the less irritable they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.

Dyad 15



	Y variable						
X variable	**Depression**	**Anxiety**	**Stress**	**Tiredness**	**Irritability**	**Shame**	**Rumination**
Depression	0	.004	.002	.001	0	-.003	.003
Anxiety	.242	-.012	-.008	-.014	.001	0	-.007
Stress	.064	.123	.031	-.007	0	-.025	.053
Tiredness	.131	.116	.037	.083	.028	0	.056
Irritability	.013	-.296	-.103	.093	-.011	.069	-.124
Shame	.439	.071	.005	-.035	.01	-.021	-.008
Rumination	-.207	-.035	.017	.024	.016	.012	-.031

Descriptive interpretation

- **1 moderate positive relationship**:
  - Shame and depression (.44) - The more the patient feels ashamed at a given moment, the more depressed they will feel 3 hours later.
- **1 moderate negative relationship**:
  - Irritability and anxiety (-.30) - The more irritable the patient feels at a given moment, the less anxious they will feel 3 hours later.
- **6 weak positive relationships**:
  - Anxiety and depression (.24) - The more anxious the patient feels at a given moment, the more depressed they will feel 3 hours later.
  - Tiredness and depression (.13) - The more tired the patient feels at a given moment, the more depressed they will feel 3 hours later.
  - Stress and anxiety (.12) - The more stressed the patient feels at a given moment, the more anxious they will feel 3 hours later.
  - Tiredness and anxiety (.12) - The more tired the patient feels at a given moment, the more anxious they will feel 3 hours later.
  - Irritability and tiredness (.09) - The more irritable the patient feels at a given moment, the more tired they will feel 3 hours later.
  - Tiredness and tiredness itself (.08) - When the patient feels tired at a given moment, they are likely to feel tired again 3 hours later.
- **3 weak negative relationships**:
  - Rumination and depression (-.21) - The more the patient ruminates at a given moment, the less depressed they will feel 3 hours later.
  - Irritability and rumination (-.12) - The more irritable the patient feels at a given moment, the less they will ruminate 3 hours later.

- Irritability and stress (-.10) - The more irritable the patient feels at a given moment, the less stressed they will feel 3 hours later.

The other relationships in the network are very weak, and thus poorly representative of the patient's functioning.