Personalized Assessment and Network Model Feedback: An Empirically-Based Approach to Personalizing Psychotherapy

Dissertation zur Erlangung des Doktorgrades des Fachbereichs Humanwissenschaften der Universität Osnabrück

vorgelegt von
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aus
Luxemburg, Luxemburg

Osnabrück, 2023

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Tag der mündlichen Prüfung:

12.06.2023

Betreuer der Doktorarbeit: Prof. Dr. Julian Rubel

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Dissertation in Fulfilment of the Requirements of the Doctoral Degree in the Faculty of Humanities of Osnabrück University

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Osnabrück, 2023

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12.06.2023

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Funding & Ethics Statement

The present dissertation and the associated TheraNet Project is supported by the Luxembourg National Research Fund (Project #14590366). The project was conducted at and approved by the ethics commission of the Department of Psychology at the University of Giessen (#2021-0002).

Luxembourg National Research Fund

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Artikel	Individuelle Beiträge
Study 1: A systematic review of momentary assessment designs for mood and anxiety symptoms *Autor*innen:* - **Mila Hall (MH)** - Paloma V. Scherner (PVS) - Yannic Kreidel (YK) - Julian A. Rubel (JAR)	*Konzeption:* **MH**, JAR *Datenanalyse:* **MH**, PVS, YK *Verfassen des Artikels:* **MH** *Kritische Revision des Artikels:* **MH**, PVS, JAR *Finale Zustimmung zur Veröffentlichung:* **MH**, PVS, YK, JAR
Study 2: Using personalized assessment and network model feedback in psychotherapy: Proof of principle for the TheraNet project *Autor*innen:* - **Mila Hall (MH)** - Annika A. Wagner (AAW) - Paloma V. Scherner (PVS) - Katharina L. Michael (KLM) - Glenn Lawyer (GL) - Wolfgang Lutz (WL) - Julian A. Rubel (JAR)	*Konzeption:* **MH**, WL, JAR *Entwicklung der Datenerhebungsplattform:* GL, **MH**, JAR *Datenanalyse:* **MH**, AAW, PVS, KLM *Verfassen des Artikels:* **MH** *Kritische Revision des Artikels:* **MH**, GL, WL, JAR *Finale Zustimmung zur Veröffentlichung:* **MH**, AAW, PVS, KLM, GL, WL, JAR

Study 3:
If you give a therapist a network: A qualitative analysis of therapists' reactions to their patients' EMA-based network models

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Verfassen des Artikels:
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Kritische Revision des Artikels:
MH, JAR
Finale Zustimmung zur Veröffentlichung:
AAW, **MH**, PVS, JAR

Study 4:
To use or not to use: Exploring therapists' experiences with pre-treatment EMA-based personalized feedback in the TheraNet Project.

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MH, JAR
Kritische Revision des Artikels:
MH, JAR
Finale Zustimmung zur Veröffentlichung:
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Osnabrück, 03.04.2023 ………..

Overall Abstract

Background Network modeling has become an increasingly popular method of data analysis within psychology. The appeal of visually displaying relationships between psychological variables (i.e., individual symptoms) may be explained by its potentials for use in clinical practice. Most network model studies suggest that future research could have relevant clinical implications. What that means, concretely, has not been explored in much depth. One potential avenue towards integrating network models into clinical practice constitutes providing treating psychotherapists with their patients' networks, in the form of feedback. The research of feedback in psychotherapy shows that providing psychotherapists with more information about their patients most often leads to improved therapeutic outcomes (i.e., faster and greater reduction of symptomatology). In order to create these patient-level networks, intensive data collection schedules (e.g., Ecological Momentary Assessment; EMA), can be used. **Methods** Providing therapists with their patients' EMA-based network models, exploring how these models were utilized, and measuring to what extent this form of feedback beneficially impacts therapeutic outcomes are the foci of the TheraNet Project. This dissertation provides first insights into how the TheraNet Project was developed (Study 1), implemented (Study 2), and perceived by participating therapists (Studies 3 and 4). In Study 1, an overview of existing EMA methodologies were explored in an effort to provide guidance for the EMA design within TheraNet. Study 2 provided detailed information about the finalized design of TheraNet, and included two examples of patient feedback and their treating therapists' reactions thereto. Study 3 focused on the therapists' first reactions to their first TheraNet patients' feedback in the context of an interpretation workshop. Lastly, Study 4 analyzed retrospective focus groups with therapists who had been participating for a longer amount of time, as a way to understand their use of the feedback over time/across patients and to gain more insights into potential obstacles to use. **Results** Findings indicate that networks may hold value as clinical feedback tools for therapists, though several suggestions for the networks' clinical optimization were made too. Other contextual factors also significantly contributed to the use or non-use of the network feedback, which should be considered in future research. **Conclusions** Networks can be useful in clinical practice, though contextual/systemic barriers may cause problems in the implementation of these kinds of studies. Quantitative, session-to-session measurement of therapeutic progress and outcomes within the TheraNet Project are still ongoing and will need to be interpreted within the context of the results described here.

Allgemeiner Abstrakt

Hintergrund Netzwerk Analysen haben sich zu einer immer beliebteren Methode der Datenanalyse entwickelt, besonders innerhalb der Psychologie. Die Attraktivität der visuellen Darstellung von Beziehungen zwischen psychologischen Variablen (z.B., einzelnen Symptomen), lässt sich zum Teil durch ihr Potenzial für den Einsatz in der klinischen Praxis erklären. Die meisten Studien zu psychologischen Netzwerkmodellen deuten darauf hin, dass künftige Forschung relevante klinische Nutzen haben könnten. Was das konkret bedeutet, wurde bisher noch nicht eingehend erforscht. Eine Möglichkeit zur Anwendung von Netzwerkmodellen in der klinischen Praxis besteht darin, den/der behandelnden Psychotherapeut*in die Netzwerke ihrer Patient*innen in Form von Feedback zur Verfügung zu stellen. Die Forschung zu Psychotherapie Feedback zeigt, dass die Bereitstellung von mehr Informationen über die Patient*innen für Psychotherapeut*innen in den meisten Fällen zu besseren therapeutischen Ergebnissen führt (d.h. zu einer schnelleren und stärkeren Reduzierung der Symptomatik). Um diese Netzwerke auf Patient*innenebene zu erstellen, können intensive Datenerfassungspläne (z.B,. Ecological Momentary Assessment; EMA) verwendet werden. **Methoden** Therapeut*innen die EMA-basierten Netzwerkmodelle ihrer Patient*innen zur Verfügung zu stellen, zu erforschen, wie diese Modelle genutzt wurden, und zu messen, inwieweit diese Form des Feedbacks die therapeutischen Ergebnisse positiv beeinflusst, sind die Schwerpunkte des TheraNet-Projekts. Diese Dissertation gibt erste Einblicke, wie das TheraNet-Projekt entwickelt (Studie 1), umgesetzt (Studie 2) und von den teilnehmenden Therapeut*innen wahrgenommen wurde (Studien 3 und 4). In Studie 1 wurde ein Überblick über bestehende EMA-Methoden gegeben, um eine Orientierung für das EMA-Design innerhalb von TheraNet zu erhalten. Studie 2 lieferte detaillierte Informationen über das endgültige Design von TheraNet und enthielt zwei Beispiele von Patient*innenfeedback und die Reaktionen der behandelnden Therapeut*innen darauf. Studie 3 konzentrierte sich auf die ersten Reaktionen der Therapeut*innen auf das Feedback ihrer ersten TheraNet-Patient*innen im Rahmen eines Interpretationsworkshops. Studie 4 analysierte schließlich retrospektive Fokusgruppen mit Therapeut*innen, die bereits seit längerer Zeit an der Studie teilgenommen hatten, um zu verstehen, wie sie das Feedback im Laufe der Zeit bzw. über mehrere Patient*innen hinweg nutzen und um mehr Einblicke in mögliche Hindernisse bei der Nutzung zu erhalten. **Ergebnisse** Die Ergebnisse deuten darauf hin, dass Netzwerke als klinische Feedbackinstrumente für Therapeut*innen wertvoll sein können, obwohl auch mehrere

Vorschläge zur klinischen Optimierung der Netzwerke gemacht wurden. Andere kontextbezogene Faktoren trugen ebenfalls signifikant zur Nutzung oder Nichtnutzung des Netzwerkfeedbacks bei, was in zukünftigen Untersuchungen berücksichtigt werden sollte. **Schlussfolgerungen** Netzwerke können in der klinischen Praxis nützlich sein, obwohl kontextuelle/systemische Barrieren Probleme bei der Durchführung dieser Art von Studien verursachen können. Quantitative, sitzungsbezogene Messungen des therapeutischen Fortschritts und der Ergebnisse im Rahmen des TheraNet-Projekts sind noch nicht abgeschlossen und müssen im Zusammenhang mit den hier beschriebenen Ergebnissen interpretiert werden.

1 Theoretical Background

Psychotherapy has been shown to be an effective treatment for a variety of mental health disorders (Barkham et al., 2021), but some patients still don't benefit (Hofmann et al., 2012). Some patients even deteriorate as a result of psychotherapy (Hansen et al., 2002; Strauss et al., 2021), which therapists are not always able to recognize (Hannan et al., 2005). In the last 50 years, very little has been identified as potential remedies for these gaps in treatment effectiveness.

One reason for differences in the effectiveness of psychotherapy among patients, as well the surprising number of patients who do not benefit from psychotherapy (Hansen et al., 2002; Strauss et al., 2021), could be that patients differ so greatly from one another. The most prominent approach to grouping patients remains using diagnostic categories, such as those in the Diagnostic and Statistical Manual of Mental Disorders (DSM; American Psychiatric Association [APA], 2013). The diagnostic categories presented in the DSM cluster patients into discrete but still incredibly heterogeneous groups.

Galatzer-Levy and Bryant showed in their 2013 paper, how many symptom combinations could result in a post-traumatic stress disorder (PTSD) diagnosis, with over half a million possible symptom constellations as the answer. This exploration took place based entirely on the diagnostic criteria listed in different editions of DSM (APA, 2013). In other words, several other extremely relevant variables that would be relevant to a treating therapist (i.e., sociodemographic background, mental health history in the family) were not considered in these analyses, and would undoubtedly lead to much more variability within the identified 630,000+ unique PTSD symptom profiles.

These findings of extreme variability within seemingly discrete diagnostic categories are supported by more subjective reports from practicing psychotherapists. Several studies show that clinicians inherently know that individual diagnostic categories are incredibly diverse, and that providing quality mental health care for patients requires more information than just their diagnosis (Hatfield & Ogles, 2007; Jensen-Doss & Hawley, 2010; 2011). In other words, therapists establish internal "rules" for how they treat their patients in psychotherapy (Cook et al., 2010). Quantifying and testing these "rules" has been attempted, but has largely fallen short given its ever-changing and therefore difficult to measure nature (Barkham et al., 2021). Nonetheless, this intuitive, learned "rule-following" and "-adjusting" could be reconceptualized as a personalization process, wherein the therapist continually adjusts their expectations and treatment plans based on their view of the patient. These processes undoubtedly also differ depending on the training and supervision experiences of the therapists, though one study showed that a majority of therapists asked worked integratively and across therapeutic schools (Cook et al., 2010).

1.1 Psychotherapists' Achilles heel

This highly complex personalization procedure appears to work well for many cases, although there are still a large number of cases that do not benefit from psychotherapy (Barkham et al., 2021). Some patients' mental health even deteriorates as a result of psychotherapy (Strauss et al., 2021). For this reason, the detection and prediction of negative developments within psychotherapy have been thought of as a potential blind spot for psychotherapists, or their proverbial Achilles heel.

This Achilles heel can be seen in the work of Walfish and colleagues (2012), wherein therapists were interviewed about their perceptions of their work, and found a sizable self-assessment bias. Therapists in the Walfish sample estimated, on average, that 85% of their patients benefit from psychotherapy. Additionally, 90% of the therapists surveyed reported believing that they belonged to the top 25% of their peers. None of the therapists reported believing that their patients' outcomes were below average (Walfish et al., 2012). Of course, this is not a bias unique to the psychotherapist profession, but a normal human flaw (Bass & Yammarino, 1991; Dunning et al., 2004; Karpen, 2018).

Not being able to perceive negative developments in psychotherapy represents a problem, since it does not allow for "course correction" on behalf of the therapist (Bystedt et al., 2014; Strauss et al., 2021). If problematic developments or reactions are not perceived by the treating therapist or are not mentioned directly by the patient, the opportunity to resolve the situation is lost. In this way, a therapist's blind spot or Achilles heel hinders their therapeutic effectiveness. Psychotherapy has been shown, at the group-level and across all patients, to be better than no mental health treatment, though these effects change when individual differences and the patient-level is observed (Cook et al., 2010). In fact, at the individual level, approximately 35-40% of patient do not benefit from psychotherapy, with 5-10% of patients' symptoms worsening (Cook et al., 2010). Given that not all patients benefit from psychotherapy and that self-assessment bias often hinders psychotherapists from perceiving non-favorable developments in their patients' progress, providing therapists with additional information about their patients is a logical next step.

1.2 Feedback as a solution

Providing additional information about individual patients to a treating therapist is one definition of so-called “psychotherapy feedback” (Barkham et al, 2021). There are several different approaches to feedback, including what kinds of data are included, how it is analyzed, and subsequently presented.

Broadly speaking, there are two main strategies to generating patient-level feedback on an empirical basis (Lutz, Neu, & Rubel, 2019). The first and more well-researched option is to make use of data sets from patients who have already been treated to predict new patients’ outcomes, so-called “Big Data”. The other strategy consists of collecting, analyzing, and presenting intensive time series data from individual patients and subsequently using or basing predictions on their own data.

Though the latter approach was used in the present dissertation, patient-level intensive time series data, the vast majority of feedback research is conducted using the “Big Data” methodology, and is therefore relevant for discussion and contextualization. Within this “Big Data” approach, there are several analytic methods that can be used, with one of the more commonly used approaches being the Nearest Neighbors (NN) approach (Lutz et al., 2005). The NN method originated in avalanche research and was used to predict the likelihood of an avalanche occurring, based on how similar conditions (i.e., humidity, wind speed, temperature) were to other days when an avalanche occurred. In essence, the NN approach for avalanches responds to the question “how many times did an avalanche occur on the 50 most similar days in the past?” (Buser, 1983).

Transferring this knowledge to psychology and the psychotherapy context, the NN approach explores how similar a patient is to other previously treated patients (i.e., in age, sociodemographic variables, initial symptom severity). With that information, NN can then be used to explore a variety of questions, such as how often did the 50 most similar patients drop out of therapy, which approaches were used to successfully treat the 50 most similar patients, and much more (Bennemann et al., 2022; Lutz et al., 2005; Lutz et al., 2015; Rubel et al., 2020). Using NN and other similar machine learning approaches can effectively predict patient outcomes (Chekroud et al., 2021). However, several studies also show that similar complex models do not always outperform simpler regression-based models (Christodoulou et al., 2019; Espel-Huynh et al., 2021).

The other option, besides “Big Data” approaches, like NN, are the patient-level intensive longitudinal data sets. These kinds of data sets can be adapted to suit a variety of different time frames, including data collection multiple times a day or on a weekly basis, prior to therapy appointments. The first option, with multiple data collection time points per day, can be measured with methods like ecological momentary assessment (EMA; Hehlmann et al., 2021; Trull & Ebner-Priemer, 2009), which will be explained in more detail in Section 1.3.1.

1.2.1 Routine outcome monitoring as feedback

When discussing feedback, it becomes necessary to discuss when that feedback is provided to therapists. There seem to be two different options: at the beginning of therapy, and/or throughout therapy (Lambert et al., 2003; 2005; Lutz, Neu, & Rubel, 2019). Providing feedback after therapy has concluded may be interesting as well, but does little to improve the therapeutic outcomes of that particular patient. Pre-treatment feedback will be discussed in more detail in Section 1.2.2, but the majority of the existing literature is based on feedback provided on a rolling basis throughout therapy. This format is often called routine outcome monitoring (ROM; Lambert et al., 2003; 2005).

Lambert and colleagues (2003; 2005; 2018) pioneered these kinds of ROM-based feedback systems in the United States, focusing primarily on the use of the Outcome Questionnaire-45 (OQ-45; Lambert et al., 2004). The OQ-45 remained unchanged for untreated individuals and showed fluctuations in individuals receiving psychotherapy (Lambert et al., 2004). Based on this data, the Outcome Questionnaire System was developed (Lambert et al., 2010), which allowed therapists to receive information about how their patients were progressing throughout therapy in comparison to other similar patients.

Since then, a similar system was established in Germany as well, where ROM is regularly provided to therapists. This system is implemented at the University of Trier, in the form of their Trier Treatment Navigator (TTN; Lutz, Rubel, et al., 2019). The TTN allows therapists to view their patients' individual trajectories from session-to-session throughout therapy (Lutz, Rubel, et al., 2019). Included in the TTN is also a prediction of the expected symptom trajectory throughout the course of therapy and a "critical threshold" indicating that a patient is significantly deviating from the expected course of symptom development (Lutz, Rubel, et al., 2019). In this way, therapists are able to monitor, with the guidance through this critical threshold, whether their patients are "on track" (OT) or "not on track" (NOT; Lutz, Rubel, et al., 2019).

As mentioned before, a therapist's ability to perceive and course-correct when patients veer off course may be inhibited in part by their self-assessment bias (Walfish et al., 2012). Systems like the TTN aim to improve the perception of these cases by differentiating between OT and NOT cases, and subsequently providing therapists with more detailed information about what areas for an individual patient have been flagged as being NOT (Lutz, Rubel, et al., 2019). The use of this kind of system for a specific case example is described in Schaffrath and colleagues' 2022 paper. Algorithms have also been developed in order to empirically identify interventions that particularly suit individual patients over the course of therapy, offering specific modules that fit the patients' needs (Fernandez et al., 2017; Lutz, Rubel, et al., 2019). Other systems also prompt therapists to discuss cases in supervision once patients become NOT (Delgadillo et al., 2018).

These kinds of feedback systems have become increasingly widespread, though their implementation is strenuous and time-consuming. Much of the existing literature comes from the United States and United Kingdom, though more German university-based outpatient centers are beginning to implement them. Beyond Trier, one such system exists in Greifswald, in form of the Greifswalder Psychotherapy Navigator System (GPNS; Demir et al., 2022).

There are already many promising results with regards to the effects these ROM systems can have on patient outcomes, with several naturalistic trials (Bovendeerd et al., 2021; Byrne et al., 2012; de Jong et al., 2014; Delgadillo et al., 2018; Kendrick et al., 2017; McAleavey et al., 2021; Simon et al., 2012) and meta-analyses supporting their effectiveness via small to moderate effect sizes (de Jong et al., 2021; Knaup et al., 2009; Lambert et al., 2003; Lambert et al., 2018; Lambert & Shimokawa, 2011; Rognstad et al., 2022; Shimokawa et al., 2010). However, more severe psychiatric diagnoses appear to have a negative effect on how effective ROM feedback can be (Davidson et al., 2015). Similarly, the majority of studies reviewed in the aforementioned meta-analyses primarily included moderately burdened patients and/or patients undergoing shorter therapies. Despite the fact that ROM-based feedback appears to be consistently helpful for the vast majority of psychotherapy patients, more research and innovation is required to be able to increase effect sizes and be more useful for more severely impaired patients.

1.2.2 Pre-treatment feedback

In addition to ROM, feedback can also be provided at intake or at the beginning of therapy. Pre-treatment feedback may represent one way to boost the effects of ROM and be more useful for a broader group of patients. One tool used to create some forms of pre-treatment feedback consists of the so-called Personalized Advantage Index (PAI; Cohen &

DeRubeis, 2018; DeRubeis et al, 2014). The PAI makes use of a "Big Data" approach in order to predict how the patient will progress in therapy or which type of intervention is most appropriate for them (van Bronswijk et al., 2021). Following these kinds of pre-treatment recommendations has also shown to benefit patient outcomes (Deisenhofer et al., 2018; DeRubeis et al, 2014; van Bronswijk et al., 2021).

However, providing these kinds of recommendations in clinical practice may only be semi-helpful for a treating therapist, who may not realistically be able to refer their patient to a specialist in the PAI-recommended therapeutic approach. In this way, making use of patients' own data may be another promising route for creating pre-treatment feedback. However, newer methods with fewer system-level barriers and drastic implications for treating therapists are in development and will be described in the section that follows.

1.3 New possibilities in pre-treatment feedback

Advances in technology and statistical analysis methods mean that several new horizons for pre-treatment feedback have been opened. Since an increasing proportion of the population have access to internet-enabled smartphones (Pew Research Center, 2021), making use of this availability for data collection and subsequently producing pre-treatment feedback is a logical next step. In this way, technological developments have supported the expansion of pre-treatment feedback: by facilitating time-intensive longitudinal data collection via ecological momentary assessment (EMA). Advanced statistical methods are required to wrangle and analyze these complex datasets, including methodologies like network analysis.

1.3.1 Ecological momentary assessment (EMA)

EMA methodologies involve participants filling out questionnaires over an extended period of time, sometimes several times per day. Some EMA protocols also include the collection of physiological measurements or geolocation information (for example, through wearable fitness trackers). EMA methodology also largely overlaps with other data collection methods like ambulatory assessment and experience/event sampling methodologies (Trull & Ebner-Priemer, 2009). For the sake of brevity and clarity, this dissertation will use EMA as an umbrella term for these methods.

The necessity for the use of EMA methods becomes clear when reviewing papers such as that of Hehlmann and colleagues (2021). They showed how unique individual patients' symptoms dynamics were, particularly in their reactions to stressors. These dynamics become clear due to the high frequency of the EMA methodology, allowing for the measurement of highly time-variable constructs, such as heart rate variability (Hehlmann et al., 2021).

In fact, many subjectively-rated constructs make sense to measure in these high frequency schedules, given that their variability has been well-documented, with affect and emotion regulation being key examples (O'Connell et al., 1998; Solhan et al., 2009). Past studies have found discrepancies between participants' responses to cross-sectional or retrospective questionnaires, in comparison to EMA questionnaires (Ebner-Priemer et al., 2006; Schuler et al., 2019; Southwick et al., 1997; Stone et al., 1998). This points to a need to measure constructs, like emotional variability, with appropriate methodologies like EMA. In many cases, more affective variability can be linked to higher levels of distress (Heller et al., 2019; Koval et al., 1997) and poorer sleep (Leger et al., 2022). Given how different patients can be over time, both in their subjective and physiological reactions in everyday life, using EMA within the psychotherapy context provides an opportunity for insight that cross-sectional questionnaires on their own do not.

Given how useful this level of information seems, it is unsurprising that EMA has also been expanded to include intervention modules in so-called ecological momentary interventions (EMI; McDevitt-Murphy et al., 2018). These kinds of programs hold promise for expanding on existing psychotherapy services and aiding in the transfer of knowledge into day-to-day life, as well as intervening "just in time" outside of the therapy room (Hardeman et al., 2019; McDevitt-Murphy et al., 2018). Specific programs and modules have been investigated for a variety of diagnostic groups, including those experiencing psychosis (Bell et al., 2017) and a variety of other health-related concerns (Myin-Germeys et al., 2016). However, there are other ways in which EMA can be made clinically useful.

1.3.2 Network models

EMA data can also be used to create network models of psychopathology. Network models visually portray relationships between variables in a two-dimensional space, making use of tenets from graph theory and data visualization (Bondy & Murty, 1976). Network models consist of nodes and edges: Visually speaking, nodes represent points/circles or vertices, while edges refer to the lines that connect them (Bondy & Murty, 1976). In network models of psychopathology, nodes typically consist of individual symptoms, while edges can represent the correlations or regression coefficients between them, among other options (Borsboom, 2017; Hofmann et al., 2016).

The exact metric used (i.e., a partial correlation or regression coefficient) to model the network's edges varies depending on the analytic method. Depending on the metric, edges may also include arrows to depict directed effects. Networks with directed effects in them are sometimes referred to as time-lagged networks. Though these directed models may imply that the relations between particular nodes are causal, these interpretations should be viewed with caution. Though directed effects may reflect underlying causal mechanisms and help build causal hypotheses, they should not be treated as confirmation thereof (Borsboom et al., 2021; Haslbeck et al., 2019).

If calculating directed effects is not the goal or not possible, as is the case in partial correlation networks, the edges do not contain arrows and are referred to as undirected (Bondy & Murty, 1979). These undirected networks can be referred to as contemporaneous networks, and can also be calculated for time series data by calculating partial correlations over all observed time points. The strength and valence of each edge is also visually represented through its color (green/blue representing a positive relation) and thickness and/or opaqueness (thicker/opaquer representing a stronger relation; Bondy & Murty, 1976).

1.3.2.1 Nomothetic vs. idiographic approaches

In addition to variations in what metrics can be visualized in a network, there are also two different approaches to network modeling more generally: nomothetic and idiographic approaches. The first of these two, the nomothetic approach, is the most common in the field of psychology and public health. Nomothetic research and network models aim to identify trends at the group level, finding average patterns across multiple people and groups (Lamiell, 1998). The second approach, idiographic, focuses on the individual level (Molenaar, 2004). In idiographic research and network models, data collection methodologies are often personalized to best suit an individual (Lamiell, 1998). Idiographic network models are also typically shared in a single case format (Fried & Cramer, 2017).

Of these two approaches, the idiographic alternative aligns more closely with the goals of personalized medicine and person-centered therapies (Hayes et al., 2016; Schiepek et al., 2015). However, being able to make inferences across multiple participants has more sweeping implications. Since both approaches present benefits for transferring knowledge to clinical practice, finding a middle ground between the two may represent the ideal compromise. This can be done by aggregating idiographic data in order to perform nomothetic analyses (Hofmann et al., 2016) or by mixing standardized and personalized methodologies (Beltz et al., 2016; Gates & Molenaar, 2012).

1.3.2.2 Clinical theories within the network methodology

Regardless of which approach is taken, there has been an increasing interest in building clinically relevant theories based on network methodology, such as critical thresholds and network destabilization (Hofmann et al., 2016; Robinaugh et al., 2016). In both of these theories, the assumption is that regardless of whether or not a person is mentally ill, different states and/or symptoms interact as a network. Networks of mental health and mental illness seek stability and do not change easily, especially in highly interconnected networks. Changing or "toppling" a network of mental illness would require a large amount of effort, similar to pushing a ball up a hill in hopes of reaching a peak that leads to the next valley (Robinaugh et al., 2016; Scheffer, 2010). In this analogy, the valleys represent different, stable states at which the network can rest without automatically rebounding to the state before (Scheffer, 2010).

Network destabilization theory posits that pushing the ball up that hill requires several considerable changes within the network, leading to a destabilization of the network structure and thereby forcing it into a new, alternative stable state (Scheffer, 2010; Wichers & Groot, 2016). Approaching this point of destabilization becomes noticeable through critical thresholds. Critical thresholds represent metaphorical tipping points, which are followed by major changes to the network structure. Critical thresholds are said to be preceeded by critical slowing down, wherein networks rebound to their original state more slowly than before (Scheffer, 2010; van de Leemput et al., 2014; Wichers & Groot, 2016). This can be reflected in increased autocorrelation across time (Hofmann et al., 2016; Scheffer, 2010).

More research on the extent to which the destabilization of networks is possible and how critical threshold can be identified is needed. However, it is assumed that destabilization can consist of psychotherapeutically treating various nodes within a network, removing external stressors, and activating positive nodes within patients' networks.

1.3.2.3 Network-based tools to guide clinical decisions

It is also common, in network models of psychopathology, to calculate metrics that summarize individual nodes' so-called "centrality" within the network overall (Borsboom, 2017). One typical example of a centrality metric within undirected networks is "strength", which summarizes how many nodes another node is connected to and how strong the corresponding edges are in absolute terms (Bringmann et al., 2019). Using centrality metrics allows viewers of these visualizations to more quickly understand which individual nodes, or individual symptoms in psychopathological networks, may be most important. In this way, centrality measures may hold promise for helping to identify which symptoms to target first or most intensely in a psychotherapy context (Rodebaugh et al., 2018; Rubel et al., 2018). However, these kinds of interpretations must be done cautiously and with much consideration for what analytic strategy was used and without jumping to causal conclusions (Bringmann & Eronen, 2018).

Difficulties in the interpretations of these complex models and their centrality metrics represents a considerable hurdle in integrating them into clinical practice. Additionally, just because a node is flagged as having high centrality does not automatically mean it can easily be intervened on (Haslbeck & Fried, 2017). For example, if financial strain plays a significant role in the development of someone's psychopathology, the amount of appropriate psychotherapeutic interventions are extremely limited and can only target the problem indirectly. Additionally, even if a highly central node is well-suited for intervention, like "poor sleep hygiene", it does not necessarily mean that treating it and thereby removing it from the network will sufficiently destabilize and eventually dissolve the remaining psychopathology (Haslbeck & Fried, 2017).

Few studies have investigated whether network models are intuitive enough for non-expert researchers to interpret. Even amongst researchers, the danger of overinterpretation is large and has been reiterated several times (Bringmann et al., 2019; Bringmann & Eronen, 2018; Fried & Cramer, 2017; Terluin et al., 2016). It is therefore essential, if shared with clinicians not well-versed in network modeling and associated statistical specificities, that support for network interpretation is provided.

Despite these challenges, several research groups have begun to explore how network models could be made useful in clinical practice. Von Klipstein and colleagues (2020) explored how personalized network models could support psychotherapists in building their case conceptualizations. Kroeze and colleagues (2017) describe a case example, wherein the patient's own network model was discussed in a therapy session as a form of mutually constructed and validated case concept and psychoeducation. A similar case example is also presented by von Klipstein and colleagues (2023), wherein therapist and patient co-construct a suitable interpretation of the patient's personalized network model, with the guidance of an expert researcher. In their 2019 literature review of network methodology, Contreras and colleagues summarize that centrality measures are conceptualized as a way to guide which symptoms to prioritize intervening on, as a way to provide direction for therapy planning.

This echoes the assertions of Rodebaugh and colleagues (2018), that influential nodes may represent promising treatment targets. Though many of these projects are still ongoing, they demonstrate that network models can have specific clinical uses, despite statistical and methodological challenges.

2 The TheraNet Project

2.1 Objectives

The aims of the TheraNet Project (Hall & Rubel, 2020) were manifold, but focused on the design and implementation of EMA-based, patient-level, pre-treatment network feedback and how therapists perceived and subsequently used the feedback. In the long term, and beyond the scope of this dissertation, the project also aims to quantitatively model potential differences between the intervention group, for whom EMA-based feedback was produced, and the control group (who received treatment as usual, TAU, with no feedback). The overarching objectives of the project were to explore the extent to which network models could potentially help therapists tailor therapy to individual patients, shorten their therapies, contribute to lowering drop-out rates, and be related to greater decreases in symptomatology compared to TAU.

Given that this was a large-scale project, the papers presented in this dissertation do not cover all of the aforementioned research objectives. However, the papers presented here aim to provide detailed information about the preparatory research done prior to TheraNet's launch, present the rationales behind key study design decisions, and give qualitative insights into therapists' perspectives on the EMA-based network feedback at the beginning and at the end of patient recruitment.

2.2 Stages of the TheraNet Project

Given the complexity of the TheraNet Project, a more specific chronologic description of the project's many stages will follow. This includes the preparatory stages prior to the beginning of data collection. The first two stages of the TheraNet Project were (1) *preparation*, in the form of researching and building rationales for the project's design and (2) *preregistration*, clearly stating and openly sharing the aforementioned rationales for the final design of the project.

What followed was (3) the *implementation* phase, which required the recruitment and onboarding of therapists and their patients. Therapists were recruited on a rolling basis, as they began working at the outpatient training center, and their patients were recruited within the first 5-6 weeks of therapy (a phase referred to in Germany as the "Probatorik" or probationary phase, used primarily for diagnostic procedures and paperwork). Patients were randomly assigned to either a control group, who were not required to fill out any additional questionnaires and received treatment as usual, or an intervention group, who underwent 2 weeks of EMA data collection that was then used to create feedback. Each day, intervention group patients were prompted 4 times per day to fill out the EMA. In order to produce the feedback, at least 44 of the 56 total data collection time points needed to be completed. The resulting feedback contained a contemporaneous network model, a line diagram of patient-reported sleep quality, and a list of patient-reported difficult experiences. When the participating therapists' first intervention group patient successfully completed their EMA, thereby producing feedback, they were provided with a 1-on-1 workshop whereby they were to learn how to interpret the feedback.

The following stage is still ongoing, and consists of (4) the *routine outcome monitoring* of both control and intervention group patients using a session-to-session symptom severity measure. The final stage consisted of (5) *retrospective focus groups* among a subgroup of the participating therapists. All participating therapists were invited to take part and share their experiences within the project, including but not limited to how they did/did not use the feedback, what hindered them from being able to use it more effectively, and how they would alter the feedback to make it more clinically useful.

2.3 Aims of the individual studies

This dissertation includes several important findings from the TheraNet Project, each connected to different stages of the study. Figure 1 depicts how each of the studies relates to the aforementioned stages.

Study 1 was based on the first stage of the TheraNet Project, which focused on preparation of the research design. In Study 1, we present an extensive systematic review of how the EMA methodology has been used to study symptoms of depression and anxiety. In search of standard practices to adhere to in the TheraNet Project, we instead found a large amount of heterogeneity in EMA design, which provided little guidance in the conception of the TheraNet EMA design specifically. One major finding from Study 1 was that a large portion of published EMA studies did little to describe the methodology used, reducing the reproducibility of this type of research.

In that way, Study 1 led to the aims of Study 2, a proof of principle paper that aimed to provide detailed descriptions and explanations for the design of our study, along with two illustrative examples. In the spirit of open science, Study 2 therefore aimed to boost the transparency and reproducibility of the TheraNet Project, describing in depth how the study was designed and the empirical basis for each decision. The examples were added to the paper, presenting the feedback of two intervention patients and their treating therapists' qualitatively assessed reactions thereto, in order to aid the readers in their comprehension.

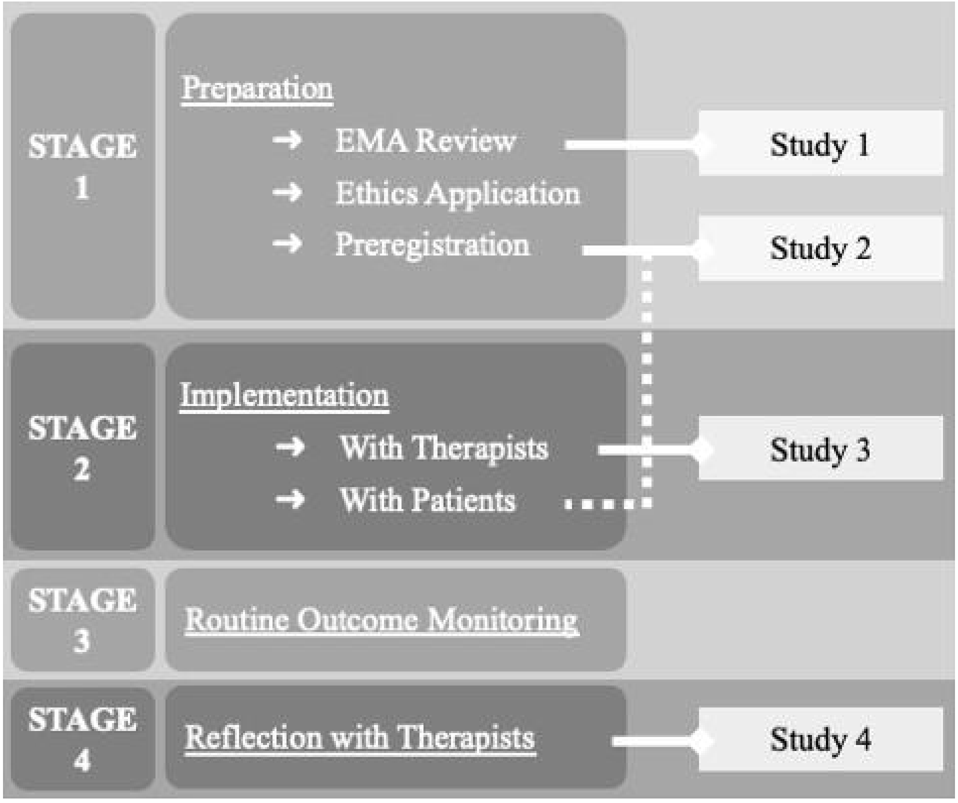

Figure 1. How each dissertation study relates to the stages of the TheraNet Project.

The two qualitatively assessed therapist responses briefly described in Study 2 are then described in their entirety in Study 3. As mentioned previously, therapists were given a 1-on-1 workshop based on their first intervention patient's feedback. In these workshops, therapists were trained in the interpretation of the network model, the sleep diagram, and list of difficult experiences. The workshops were divided into two parts. First, didactic questions were posed, followed by explanations of the visualizations, their interpretations, and their limitations. Second, concrete use suggestions were provided for how to make use of the visualizations. This division of the workshop is important because the aim of Study 3 was to explore the intuitive therapists' ideas for using the feedback prior to receiving concrete suggestions.

Lastly, Study 4 aimed to capture therapists' experiences later on in the study, after they had received the workshop. These therapists were invited to participate in retrospective focus groups with other therapists, to discuss how they used the feedback (and if not, why). The focus groups also aimed to explore any way their patients' participation in TheraNet influenced the therapeutic relationship.

3 Studies 1 – 4

3.1 Study 1

Hall, M., Scherner, P. V., Kreidel, Y., & Rubel, J. A. (2021). A systematic review of momentary assessment designs for mood and anxiety symptoms. *Frontiers in Psychology*, *12*, 642044. https://doi.org/10.3389/fpsyg.2021.642044

Background Altering components of ecological momentary assessment (EMA) measures to better suit the purposes of individual studies is a common and oftentimes necessary step. Though the inherent flexibility in EMA has its benefits, no resource exists to provide an overview of the variability in how convergent constructs and symptoms have been assessed in the past. The present study fills that gap by examining EMA measurement design for mood and anxiety symptomatology. **Methods** Various search engines were used to identify 234 relevant studies. Items administered, data collection schedules (i.e., beeps per day), response scales (i.e., Likert), data collection platforms (i.e., apps), and psychometric properties (i.e., reliability) were extracted. **Results** Study designs varied greatly in all aspects across the identified papers. Over 4,600 extracted items were qualitatively analyzed, resulting in the identification of 12 themes. The most EMA items focused on affect, with categories such as “happiness” and “tension” appearing most frequently. We provide all of our data extraction in the format of an open-source database. **Limitations** Despite our best attempts to include as much of the relevant literature as possible, this review and the accompanying database are not exhaustive, but can easily be built upon to include other, newer studies. **Conclusions** The fact that the affect theme featured both positive and negative emotional constructs highlights the dichotomous focus on valence and affect within the literature surrounding anxious and depressive symptomatology. We hope that our database will act as a helpful design decision-making resource for researchers studying this kind of symptomatology in the future. **Systematic Review Registration** PROSPERO (CRD42019139409).

3.2 Study 2

Hall, M., Wagner, A. A., Scherner, P. V., Michael, K. L., Lawyer, G., Lutz, W., & Rubel, J. (under review). Using personalized assessment and network model feedback in psychotherapy: Proof of principle for the TheraNet project. *Cognitive Therapy and Research.*

PsyArXiv Preprint available at https://psyarxiv.com/8deyj/

Background Providing therapists with feedback about their patients has been shown to be beneficial in several ways. Network models may provide a novel way to depict individual patients' symptomatology. Ecological momentary assessment (EMA) methods are often used, so that a patient-level database can be used for the necessary calculations. **Methods** TheraNet is an ongoing mixed methods randomized control trial (RCT) at an outpatient psychotherapy center. Within TheraNet, therapists receive pre-therapy, EMA-based feedback about individual patients (including a network model) and a training on its interpretation. These trainings were qualitatively analyzed. **Results** The present study summarizes therapists' reactions to their first TheraNet feedback, shows two case examples, along with the corresponding therapists' reactions to these cases. These findings serve a first insight into this ongoing pragmatic RCT. Overall, therapists viewed the feedback positively and as having a multitude of possible uses. Additionally, some therapists voiced critiques or points for further improvement. **Conclusions** Network model feedback appears to be a valuable additional source of information for therapists, though its impact on treatment requires further research. Therapists varied in how they reacted to and planned to use the feedback, though all agreed it was insightful. Data collection for this project is ongoing.

3.3 Study 3

Wagner, A. A., **Hall, M.**, Scherner, P. V., & Rubel, J. A. (under review). If you give a therapist a network: A qualitative analysis of therapists' reactions to their patients' EMA-based network models. *Clinical Psychological Science.*

PsyArXiv Preprint available at https://psyarxiv.com/hqyft

Background Network models hold much promise for use in the form of personalized feedback, which the TheraNet Project aims to investigate. In the present study, we share therapists' first reactions to patient network models. **Methods** Therapists ($N = 24$) were taught to interpret the network models based on their patient's data. They were provided with concrete use suggestions at the end of the workshop. The workshops were analyzed using descriptive qualitative content analysis. The resulting codes were then grouped thematically. **Results** Themes included "case conceptualization", "study design", "therapy planning", and "psychoeducation". Before the concrete suggestions, therapists most frequently mentioned codes belonging to "case conceptualization". After the suggestions, "psychoeducation" codes were mentioned most frequently. **Conclusions** Therapists intuitively connected network models to case conceptualizations. Once concrete suggestions were provided, therapists more frequently discussed networks as psychoeducative tools.

3.4 Study 4

Hall, M., Lappenbusch, L., Wiegmann, E., & Rubel, J. A. (under review). To use or not to use: Exploring therapists' experiences with pre-treatment EMA-based personalized feedback in the TheraNet Project. *Administration and Policy and Mental Health Services.*

PsyArXiv Preprint available at https://psyarxiv.com/xjb8m

Background Using idiographic network models in psychotherapy has been a growing area of interest. However, little is known about the perceived clinical utility of network models. The present study aims to explore therapists' experiences with network model-based feedback within the context of the TheraNet Project. **Methods** Therapists who had received network-based feedback were invited to retrospective focus groups. The focus group questions related to how participation in the study influenced the therapeutic relationship, how the networks were used, and what might improve their clinical utility. The transcribed focus groups were analyzed descriptively using qualitative content analysis. **Results** Most therapists mentioned using the feedback to solidify their case concept, while fewer therapists discussed the feedback directly with the patients. Several barriers to using the feedback were discussed, as well as various suggestions for how to make it more clinically useful. Many therapists reported skepticism with regards to research in the outpatient training center in general, though they were also all pleasantly surprised by being involved, having their opinions heard, and showing a readiness to adapt research to their needs/abilities. **Conclusions** This study highlights the gap between researchers' and therapists' perceptions about what useful feedback should look like. The TheraNet therapists' interest in adapting the feedback and building more informative feedback systems signals a general openness to the implementation of clinically relevant research. We provide suggestions for future implementations of network-based feedback systems in the outpatient clinical training center setting.

4 Discussion

4.1 Summary of study results

Overall, this dissertation summarizes several stages of TheraNet, providing several insights into this innovative project. Study 1 shows how diverse EMA design can be, and pointed out how important transparent reporting is. Study 2 responds to this appeal for transparency from Study 1 by presenting the full design, alongside illustrative examples, for the TheraNet Project.

In Study 3, therapists' first reactions to the TheraNet feedback were summarized, and showed that all therapists included could successfully interpret the network models. They also discussed several ideas for the network models' uses before being prompted to do so, and focused primarily on using them as case conceptualization tools. After receiving concrete suggestions for possible uses of the networks, therapists reported a particular interest in discussing the networks with their patients (as a form of psychoeducation).

Lastly, in Study 4, therapists retrospectively reported their experiences in the TheraNet Project. Despite all therapists voicing an interest in discussing the networks with their patients, Study 4 showed that only some of the therapists reported being able to use the network effectively in-session. Though many reported using the networks as a tool to corroborate their case conceptualization, they also discussed many barriers to discussing the networks with their patients, such as prioritizing the therapeutic relationship over using the feedback, and allowing patients to more actively influence the session agendas. Overall, the final study of this dissertation highlights the need to consider the context in which the TheraNet Project data was collected: Within trainee psychotherapists and within a flexible naturalistic study setting.

4.2 Discussion in light of current literature

Overall, the TheraNet Project and associated papers presented in this dissertation represent an important milestone in improving the transparency and reproducibility of EMA-based studies. The recent literature surrounding psychopathological networks has been booming, often highlighting their potential applications for clinical practice. However, the direct investigation of the clinical utility of network models in naturalistic settings has been limited. The TheraNet Project presents an example for how studies looking to investigate the clinical utility of network-focused pre-treatment feedback can be implemented.

4.2.1 A need for more transparency

Study 1 highlighted a need for increased transparency in EMA research, which is mirrored in projects such as the ESM Item Repository (Kirtley et al., 2021). Measurement plays an important role in designing solid research designs, and seemingly small details can have an impact on how participants respond to questions (Flake & Fried, 2019). Another challenge in measurement is that the use of Likert scales may obfuscate multimodal distributions which, when averaged, disappear entirely (Haslbeck et al., 2022). Therefore, it is important to carefully consider the design decisions involved in EMA studies, as well as the intentions driving these decisions. That is what Study 1 aimed to build for the TheraNet Project.

The final design decisions were then presented and explained in Study 2 in an effort to improve transparency and in hopes of encouraging future replication studies. Replication is important given the replication crisis wreaking havoc within the field of psychological research (Flake & Fried, 2020; Oberauer & Lewandowsky, 2019), with several seminal findings not replicating. These non-replications signal that original studies may have published significant results that are, in actuality, statistical exceptions. Overall, replication is extremely important for strengthening the evidence across disciplines, but especially in psychology (Flake & Fried, 2020; Oberauer & Lewandowsky, 2019).

4.2.2 Network models of psychopathology

Though TheraNet, as presented in Study 2, represents an important milestone in investigating the clinical utility of network models, other similar studies have begun to appear (Burger et al., 2019; Kroeze et al., 2017; Lutz, Rubel et al., 2019; Riese et al., 2021; von Klipstein et al., 2023). Several other studies have also studied psychopathology in general. Though several of these papers draw clinical inferences, they did not directly investigate the effect of using a network in a clinical context.

Robinaugh and colleagues (2016), for example, investigated the centrality of nodes within complicated grief networks and simulated interventions on specific nodes. Their findings suggest that this approach holds promise, and that emotional pain and feelings of emptiness play a particularly important role in complicated grief networks. However, these findings were based on data simulations, and are therefore limited in their generalizability to naturalistic, real-life therapy settings. Blanken and colleagues (2019), on the other hand, investigated whether direct connections could be found between treatment and specific symptoms in nomothetic networks of insomnia and depression. They measured symptoms before, during, and after treatment and included a binary treatment node in the network models in order to investigate how and to what extent specific symptoms were affected by treatment (Blanken et al., 2019). However, in this example, the networks were used as a tool to model the effects of a therapy program, and not as a pre-treatment feedback tool for therapists' use. Despite the fact that there are differences in the design and use of networks in these specific studies, they mirror important aspects of interest mentioned by therapists in Study 3: how does therapy influence specific nodes in a network or how can I make use of the network to identify where to intervene?

Network models can also be created using methods other than EMA. One example of this kind of method involves people drawing perceived causal graphs of their subjective experiences and how they relate to one another. This method is often referred to as the perceived causal relations (PCR) method (Frewen et al., 2012). Using PCR allows participants to visually represent their own conceptualization of their problems and how they relate to one another. Klintwall and colleagues (2021) adapted PCR to be more clinically relevant, dubbing it the models perceived causal networks (PECAN). PECAN models for depressed adults varied greatly, though some symptoms were mentioned frequently across participants (i.e., rumination). When presented to clinicians, these models were judged to be clinically useful by the vast majority (Klintwall et al., 2021). However, PECAN and other network models have only rarely been directly integrated into routine care, with TheraNet being one of the first to do so.

4.2.3 Clinically used network models

One example of a more long-standing project that integrates network models into clinical practice and mirrors many aspects of the PCR method has been pioneered by Schiepek and colleagues (2015), wherein a systemic approach is taken for mapping the connections between different symptoms, problem areas, and resources. One key difference in the approach taken by Schiepek and colleagues (2015), is that patients and therapists establish the variables (including but not limited to symptoms) and their relationships collaboratively. All the aspects identified in the resulting visualization are then added to a patient-specific questionnaire, which the patient then fills out as EMA. The resulting data are then used to identify systems within the patients' networks, which may be hindering them or benefiting them (i.e., learning processes, healthy behavior patterns). In this approach, the networks and systems identified within them, play a central role in the therapy that follows.

Many of these studies suggest that network models could be used to either help understand patients' experiences with mental illness and/or suggest that networks could be used to identify appropriate treatment targets. Wittenborn and colleagues (2015) collaboratively developed maps of patients' depressive symptoms, explored potentially causal feedback loops in an approach similar to Schiepek and colleagues' (2015). They found a large amount of variability between patients, particularly when it came to the focus of feedback loops. These idiosyncratic feedback loops existed across patients, but varied in their content, and could aid in understanding the etiology of individual patients' depression and could thereby guide treatment (i.e., by targeting more prominent feedback loops; Wittenborn et al., 2015). These two research groups show how networks can be created and used in clinical practice, with more involvement from the patients and therapists.

In comparison to the two approaches discussed above, TheraNet represents a more simplified approach to integrating network models in clinical practice. In Study 3, therapists discussed several potential uses for the network models, both before and after the concrete suggestions. The ideas discussed by therapists in Study 3 also overlap with the uses in other, more simplified integrations of network models in practice: Kroeze and colleagues (2017) used network models as a form of psychoeducation with a related intervention; von Klipstein and colleagues (2020) highlighted uses of networks for case conceptualization. Both of these uses from other studies were also mentioned by therapists prior to receiving concrete suggestions in Study 3.

Though network centrality measures have not yet been used to test the effectiveness of treatment planning, several papers mention this as a potential use (Fisher et al., 2017; Lutz, Rubel et al., 2019; Robinaugh et al., 2016; Rodebaugh et al., 2018; Rubel et al., 2017). This could be an indicator that non-researcher clinicians intuitively understand and have a curiosity in using network models for psychoeducation, case conceptualization, and therapy planning. Lutz and colleagues (2018) also identified that expected force, another type of centrality measure for network models, differed between patients who completed and dropped out of therapy. This prediction of drop out likelihood, if implemented in routine care, would also undoubtedly play a role in planning treatment, in hopes of preventing drop out.

However, these recommendations for use in clinical practice must always be viewed with caution. Different researchers may have very different perpsectives on how to use EMA or similar data to form treatment recommendations. Bastiaansen and colleagues (2020) found that, if presented with the same data, different researchers would analyze it differently and thereby make different treatment recommendations. Even amongst those who chose to represent the data as network models, treatment recommendations varied greatly (Bastiaansen et al., 2020). This represents a very large challenge for integrating networks into clinical practice, and calls to a need to directly investigate how different researchers use the models specifically (as Studies 3 and 4 did) and which uses are tied to better patient outcomes.

4.2.3 Barriers to network use in clinical practice

Implementing and replicating systems that intensively focus on network models, such as those mentioned above (Schiepek et al., 2015; Wittenborn et al., 2015), in routine outpatient care in Germany would be difficult. In these settings, such as the one TheraNet was conducted in, therapies must be approved by insurance companies and are limited to a specific number of sessions, making the implementation of intensively network-focused interventions (i.e., those pioneered by Schiepek at l., 2015) more challenging. Establishing this kind of infrastructure (i.e, training therapists to build these visualizations) would most likely have been time-intensive and beyond the scope of a doctoral dissertation. New therapist cohorts often begin working at such outpatient centers multiple times a year and only stay for two to three years at most, raising questions about the practicality of implementing such training-intensive processes in this context. In other words, network-based tools must strike a balance between how time-consuming their implementation is and how detailed and person-specific they are. This was the goal behind balancing personalization and standardization in the TheraNet EMA questionnaires, as well as having one-time interpretation workshops for each therapist.

Other studies have also tried to strike this compromise. For example, von Klipstein and colleagues (2020) aimed to outsource the interpretations of patient network models by having a researcher present during a therapy session. In this way, therapists did not have the responsibility of having to learn and remember the interpretations of the network models. This was one barrier to using the networks mentioned in Study 4 – that the interpretation was no longer clear. If therapists were unsure of the interpretations of the networks, this may have reduced their ability to use the networks as feedback, potentially reducing any positive effects the feedback may have had on patient outcomes. Therefore, comprehension of the networks (or providing interpretation supports) represents an important point to consider when designing studies focused on the clinical utility of new tools, including networks. In the aforementioned approach, that barrier is removed and the burden is lifted from the therapists' shoulders (von Klipstein et al., 2020).

Another clear barrier to use were the therapists' perceptions of how useful or relevant it was. A study by Ellison (2020) highlights the fact that practicing clinicians are less likely to view EMA as helpful when cases are more complex, favoring more traditional assessment methods, specialized workshops, and super-/intervision. However, therapists who viewed evidence-based cross-sectional assessment as helpful were also generally more likely to favor EMA methods (Ellison, 2020). Several other studies also support this skepticism among clinicians regarding the utility of EMA (Frumkin et al., 2021; Zimmermann et al., 2019). Studies 3 and 4 contained several criticisms of the study design of TheraNet, including the EMA design. However, the use of EMA itself was not questioned directly. In fact, several potential benefits were highlighted, such as patients gaining an openness to other therapeutic interventions involving regular documentation of emotions and/or events.

In past research, institutional conditions had a small but negative influence on the development of psychotherapists (Lorentzen et al., 2011). This stress seems particularly salient when conditions are perceived as a specific lack in support, particularly as it relates to an inability to relieve training-induced stressors (Kumary & Baker, 2008). Another study found that higher life stress among therapists was highly correlated with economic insecurity, among other things (Heinonen et al., 2022). However, working with patients, getting supervision, and personal therapy were rated amongst the most influential and positive influences on development. Being involved in research also played a minor positive role, but was not rated as highly as the aforementioned positive influences (Lorentzen et al., 2011). These institutional level barriers may have also played a role in TheraNet, though further research is required in this area. If high stress at the institution-level played a role in TheraNet, it is possible that this influenced whether or not therapists had the resources needed to be make use of the TheraNet feedback. This becomes particularly relevant when considering that Rubel and colleagues (2017) found that the positive effects of feedback only hold true if it is actively used.

4.3 Clinical implications and future directions

Given the information presented thus far, several clinical implications can be solidified for future research in this burgeoning field. An important factor is attitudes towards these questionnaires, from both the patient and therapist perspectives, which were largely positive but dependent on the perception of their usefulness (Piot et al., 2022; Solstad et al., 2021; Soyster et al., 2022). Therapists also appear to be more critical than patients with regards to EMA (Frumkin et al., 2021; Koementas-de Vos et al., 2022; Zimmermann et al., 2019). With this in mind, implementation of EMA methodologies in clinical settings should be explained succinctly to therapists involved, placing a particular emphasis on how these measures may be clinically useful. Providing interpretation aids, resources, or support staff to make use of the data would most likely encourage a positive attitude with regards to EMA data collection. Von Klipstein and colleagues (2020) provide an example for how researchers can make themselves available to help with interpretations in-session, thereby removing that responsibility from the therapist.

In addition to highlighting EMA's practical uses, future research should also carefully consider the degree to which questions can be personalized. Based on findings presented in this dissertation, therapists' preference appeared to be more personalization. However, this must be carefully planned and must be compatible with the research questions to be explored. Personalization offers clinical advantages, but makes comparison across patients more challenging. Fisher and colleagues (2017) highlight the importance of the idiographic method, and exemplify how research questions can be developed in this area. In line with the first two studies in this dissertation, design decisions, such as the degree of personalization and the procedures through which personalization is set, should be documented and made clear to readers.

Though ROM was not the focus of this dissertation, it was also implemented as part of the TheraNet Project. Similarly to EMA measures, therapists are more motivated to participate and utilize ROM measures when they understand them. Given that its uses can be so different depending on the case, presenting specific case examples may be a promising way forward (i.e., de Jong & Aafjes-van Doorn, 2022). In addition to the subjective perception of ROM's usefulness, its actual use plays an important role in its effectiveness: if therapists do not use ROM feedback, their patients do not reap the benefits thereof (Rubel et al., 2017). However, therapists-in-training are often preoccupied by multiple stressful tasks and therefore require resources that are easily accessible and understandable, such as ROM trajectories. These features can be found in several existing ROM systems (de Jong et al., 2014; Demir et al, 2022; Lutz, Rubel, et al., 2019) and support the design of this existing ROM system suits the wishes of therapists-in-training. A common concern regarding ROM also focuses on the length of the chosen questionnaire and not wanting to place too large of a burden on patients (Lutz et al., 2009). Therefore, it is important to consider the length of ROM questionnaires. Several short-forms of these ROM questionnaires have been developed in an effort to mitigate the perceived burden of these questionnaires (Lutz et al., 2006; Timman & Arrindell, 2022).

Once all the therapies have concluded, next steps for the TheraNet Project will include investigating group differences using 3-level hierarchically nested multilevel models. This analytic approach was selected and preregistered (Hall & Rubel, 2022), given that the data structure is nested (time points nested within patients, who were nested within therapists). Since that previous research has found that the usage of feedback plays an important role in attaining benefits for patient outcomes, it will be interesting to see whether there will be group differences between our control and intervention groups (Simon et al., 2012). Based on the results reported in Study 4, that use was inconsistent and often not concretely discussed with the patient, it would be unfortunately unsurprising if a null effect is found. On the other hand, if an effect is present, it could speak to a need to more closely study how feedback is used, not simply dichotomizing it "use" vs "no use".

4.4 Conclusion

Overall, the TheraNet Project is a milestone in showing to what extent network models can be useful in clinical practice. The first two studies presented within this dissertation share information necessary for its replication. The latter two qualitative studies provide more in-depth information about the therapists' initial reactions to the feedback, as well as reflections on how they used the feedback or, if they did not, why. Nonetheless, further research is required to investigate network models as pre-treatment feedback tools.

References

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders (5th ed.)*.

Barkham, M., Lutz, W., Castonguay, L. G., Bergin, A. E., & Garfield, S. L. (Eds.). (2021). *Bergin and Garfield's handbook of psychotherapy and behavior change* (7th edition, 50th anniversary edition). Wiley.

Bass, B. M., & Yammarino, F. J. (1991). Congruence of Self and Others' Leadership Ratings of Naval Officers for Understanding Successful Performance. *Applied Psychology*, *40*(4), 437–454. https://doi.org/10.1111/j.1464-0597.1991.tb01002.x

Bastiaansen, J. A., Kunkels, Y. K., Blaauw, F. J., Boker, S. M., Ceulemans, E., Chen, M., Chow, S.-M., de Jonge, P., Emerencia, A. C., Epskamp, S., Fisher, A. J., Hamaker, E. L., Kuppens, P., Lutz, W., Meyer, M. J., Moulder, R., Oravecz, Z., Riese, H., Rubel, J., … Bringmann, L. F. (2020). Time to get personal? The impact of researchers choices on the selection of treatment targets using the experience sampling methodology. *Journal of Psychosomatic Research*, *137*, 110211. https://doi.org/10.1016/j.jpsychores.2020.110211

Bell, I. H., Lim, M. H., Rossell, S. L., & Thomas, N. (2017). Ecological Momentary Assessment and Intervention in the Treatment of Psychotic Disorders: A Systematic Review. *Psychiatric Services*, *68*(11), 1172–1181. https://doi.org/10.1176/appi.ps.201600523

Bennemann, B., Schwartz, B., Giesemann, J., & Lutz, W. (2022). Predicting patients who will drop out of out-patient psychotherapy using machine learning algorithms. *The British Journal of Psychiatry*, *220*(4), 192–201. https://doi.org/10.1192/bjp.2022.17

Blanken, T. F., Van Der Zweerde, T., Van Straten, A., Van Someren, E. J. W., Borsboom, D., & Lancee, J. (2019). Introducing Network Intervention Analysis to Investigate Sequential, Symptom-Specific Treatment Effects: A Demonstration in Co-Occurring Insomnia and Depression. *Psychotherapy and Psychosomatics*, *88*(1), 52–54. https://doi.org/10.1159/000495045

Bondy, J. A., & Murty, U. S. R. (1976). *Graph theory with applications*. North Holland.

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

Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., Robinaugh, D. J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A.-M., Wysocki,

A. C., van Borkulo, C. D., van Bork, R., & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers*, *1*(1), 58. https://doi.org/10.1038/s43586-021-00055-w

Bovendeerd, B., De Jong, K., De Groot, E., Moerbeek, M., & De Keijser, J. (2022). Enhancing the effect of psychotherapy through systematic client feedback in outpatient mental healthcare: A cluster randomized trial. *Psychotherapy Research*, *32*(6), 710–722. https://doi.org/10.1080/10503307.2021.2015637

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T. W., & Snippe, E. (2019). *What do centrality measures measure in psychological networks?* https://doi.org/10.3929/ETHZ-B-000368126

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

Burger, J., van der Veen, D. C., Robinaugh, D., Quax, R., Riese, H., Schoevers, R. A., & Epskamp, S. (2019). *Bridging the Gap Between Complexity Science and Clinical Practice by Formalizing Idiographic Theories: A Computational Model of Functional Analysis* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/gw2uc

Buser, O. (1983). Avalanche forecast with the method of nearest neighbours: An interactive approach. *Cold Regions Science and Technology*, *8*(2), 155–163. https://doi.org/10.1016/0165-232X(83)90006-X

Byrne, S. L., Hooke, G. R., Newnham, E. A., & Page, A. C. (2012). The effects of progress monitoring on subsequent readmission to psychiatric care: A six-month follow-up. *Journal of Affective Disorders*, *137*(1–3), 113–116. https://doi.org/10.1016/j.jad.2011.12.005

Bystedt, S., Rozental, A., Andersson, G., Boettcher, J., & Carlbring, P. (2014). Clinicians' Perspectives on Negative Effects of Psychological Treatments. *Cognitive Behaviour Therapy*, *43*(4), 319–331. https://doi.org/10.1080/16506073.2014.939593

Chekroud, A. M., Bondar, J., Delgadillo, J., Doherty, G., Wasil, A., Fokkema, M., Cohen, Z., Belgrave, D., DeRubeis, R., Iniesta, R., Dwyer, D., & Choi, K. (2021). The promise of machine learning in predicting treatment outcomes in psychiatry. *World Psychiatry*, *20*(2), 154–170. https://doi.org/10.1002/wps.20882

Christodoulou, E., Ma, J., Collins, G. S., Steyerberg, E. W., Verbakel, J. Y., & Van Calster, B. (2019). A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models. *Journal of Clinical Epidemiology*, *110*, 12–22. https://doi.org/10.1016/j.jclinepi.2019.02.004

Cohen, Z. D., & DeRubeis, R. J. (2018). Treatment Selection in Depression. *Annual Review of Clinical Psychology*, *14*(1), 209–236. https://doi.org/10.1146/annurev-clinpsy-050817-084746

Contreras, A., Nieto, I., Valiente, C., Espinosa, R., & Vazquez, C. (2019). The Study of Psychopathology from the Network Analysis Perspective: A Systematic Review. *Psychotherapy and Psychosomatics*, *88*(2), 71–83. https://doi.org/10.1159/000497425

Cook, J. M., Biyanova, T., Elhai, J., Schnurr, P. P., & Coyne, J. C. (2010). What do psychotherapists really do in practice? An Internet study of over 2,000 practitioners. *Psychotherapy: Theory, Research, Practice, Training*, *47*(2), 260–267. https://doi.org/10.1037/a0019788

Davidson, K., Perry, A., & Bell, L. (2015). Would continuous feedback of patient's clinical outcomes to practitioners improve NHS psychological therapy services? Critical analysis and assessment of quality of existing studies. *Psychology and Psychotherapy: Theory, Research and Practice*, *88*(1), 21–37. https://doi.org/10.1111/papt.12032

de Jong, K., & Aafjes-van Doorn, K. (2022). Routine outcome monitoring: The need for case examples. *Journal of Clinical Psychology*, *78*(10), 1963–1972. https://doi.org/10.1002/jclp.23441

de Jong, K., Conijn, J. M., Gallagher, R. A. V., Reshetnikova, A. S., Heij, M., & Lutz, M. C. (2021). Using progress feedback to improve outcomes and reduce drop-out, treatment duration, and deterioration: A multilevel meta-analysis. *Clinical Psychology Review*, *85*, 102002. https://doi.org/10.1016/j.cpr.2021.102002

de Jong, K., Timman, R., Hakkaart-Van Roijen, L., Vermeulen, P., Kooiman, K., Passchier, J., & Busschbach, J. V. (2014). The effect of outcome monitoring feedback to clinicians and patients in short and long-term psychotherapy: A randomized controlled trial. *Psychotherapy Research*, *24*(6), 629–639. https://doi.org/10.1080/10503307.2013.871079

Deisenhofer, A., Delgadillo, J., Rubel, J. A., Böhnke, J. R., Zimmermann, D., Schwartz, B., & Lutz, W. (2018). Individual treatment selection for patients with posttraumatic stress disorder. *Depression and Anxiety*, *35*(6), 541–550. https://doi.org/10.1002/da.22755

Delgadillo, J., de Jong, K., Lucock, M., Lutz, W., Rubel, J., Gilbody, S., Ali, S., Aguirre, E., Appleton, M., Nevin, J., O'Hayon, H., Patel, U., Sainty, A., Spencer, P., & McMillan, D. (2018). Feedback-informed treatment versus usual psychological treatment for depression and anxiety: A multisite, open-label, cluster randomised controlled trial. *The Lancet Psychiatry*, *5*(7), 564–572. https://doi.org/10.1016/S2215-0366(18)30162-7

Demir, S., Schwarz, F., & Kaiser, T. (2022). Therapy from my point of view: A case illustration of routine outcome monitoring and feedback in psychotherapeutic interventions. *Journal of Clinical Psychology*, *78*(10), 2029–2040. https://doi.org/10.1002/jclp.23408

DeRubeis, R. J., Cohen, Z. D., Forand, N. R., Fournier, J. C., Gelfand, L. A., & Lorenzo-Luaces, L. (2014). The Personalized Advantage Index: Translating Research on Prediction into Individualized Treatment Recommendations. A Demonstration. *PLoS ONE*, *9*(1), e83875. https://doi.org/10.1371/journal.pone.0083875

Dunning, D., Heath, C., & Suls, J. M. (2004). Flawed Self-Assessment: Implications for Health, Education, and the Workplace. *Psychological Science in the Public Interest*, *5*(3), 69–106. https://doi.org/10.1111/j.1529-1006.2004.00018.x

Ebner-Priemer, U. W., Kuo, J., Welch, S. S., Thielgen, T., Witte, S., Bohus, M., & Linehan, M. M. (2006). A Valence-Dependent Group-Specific Recall Bias of Retrospective Self-Reports: A Study of Borderline Personality Disorder in Everyday Life. *Journal of Nervous & Mental Disease*, *194*(10), 774–779. https://doi.org/10.1097/01.nmd.0000239900.46595.72

Ellison, W. D. (2020). An Initial Study of Practicing Psychologists' Views of the Utility of Ecological Momentary Assessment for Difficult Psychotherapy Cases. *Administration and Policy in Mental Health and Mental Health Services Research*. https://doi.org/10.1007/s10488-020-01093-4

Fernandez, K. C., Fisher, A. J., & Chi, C. (2017). Development and initial implementation of the Dynamic Assessment Treatment Algorithm (DATA). *PLOS ONE*, *12*(6), e0178806. https://doi.org/10.1371/journal.pone.0178806

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

Flake, J. K., & Fried, E. I. (2020). Measurement Schmeasurement: Questionable Measurement Practices and How to Avoid Them. *Advances in Methods and Practices in Psychological Science*, *3*(4), 456–465. https://doi.org/10.1177/2515245920952393

Frewen, P. A., Allen, S. L., Lanius, R. A., & Neufeld, R. W. J. (2012). Perceived Causal Relations: Novel Methodology for Assessing Client Attributions About Causal

Associations Between Variables Including Symptoms and Functional Impairment. *Assessment*, *19*(4), 480–493. https://doi.org/10.1177/1073191111418297

Fried, E. I., & Cramer, A. O. J. (2017). Moving Forward: Challenges and Directions for Psychopathological Network Theory and Methodology. *Perspectives on Psychological Science*, *12*(6), 999–1020. https://doi.org/10.1177/1745691617705892

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

Galatzer-Levy, I. R., & Bryant, R. A. (2013). 636,120 Ways to Have Posttraumatic Stress Disorder. *Perspectives on Psychological Science*, *8*(6), 651–662. https://doi.org/10.1177/1745691613504115

Gates, K. M., & Molenaar, P. C. M. (2012). Group search algorithm recovers effective connectivity maps for individuals in homogeneous and heterogeneous samples. *NeuroImage*, *63*(1), 310–319. https://doi.org/10.1016/j.neuroimage.2012.06.026

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

Hall, M., & Rubel, J. (2022). *[TheraNet] Using Personalized Assessment and Network Model Feedback in Psychotherapy*. https://doi.org/10.17605/OSF.IO/QUPTY

Hall, M., Scherner, P. V., Kreidel, Y., & Rubel, J. A. (2021). A Systematic Review of Momentary Assessment Designs for Mood and Anxiety Symptoms. *Frontiers in Psychology, 12*, 642044. https://doi.org/10.3389/fpsyg.2021.642044

Hall, M., Wagner, A., Scherner, P. V., Michael, K. L., Lawyer, G., Lutz, W., & Rubel, J. (2022). Using personalized assessment and network model feedback in psychotherapy: Proof of principle for the TheraNet Project [Preprint]. *PsyArXiv*. https://doi.org/10.31234/osf.io/8deyj

Hannan, C., Lambert, M. J., Harmon, C., Nielsen, S. L., Smart, D. W., Shimokawa, K., & Sutton, S. W. (2005). A lab test and algorithms for identifying clients at risk for treatment failure. *Journal of Clinical Psychology*, *61*(2), 155–163. https://doi.org/10.1002/jclp.20108

Hansen, N. B., Lambert, M. J., & Forman, E. M. (2002). The psychotherapy dose-response effect and its implications for treatment delivery services. *Clinical Psychology: Science and Practice*, *9*(3), 329–343. https://doi.org/10.1093/clipsy.9.3.329

Haslbeck, J. M. B., & Fried, E. I. (2017). How predictable are symptoms in psychopathological networks? A reanalysis of 18 published datasets. *Psychological Medicine*, *47*(16), 2767–2776. https://doi.org/10.1017/S0033291717001258

Haslbeck, J. M. B., Ryan, O., & Dablander, F. (2022). *Multimodality and Skewness in Emotion Time Series* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/qudr6

Haslbeck, J. M. B., Ryan, O., Robinaugh, D., Waldorp, L., & Borsboom, D. (2019). *Modeling Psychopathology: From Data Models to Formal Theories* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/jgm7f

Hatfield, D. R., & Ogles, B. M. (2007). Why Some Clinicians Use Outcome Measures and Others Do Not. *Administration and Policy in Mental Health and Mental Health Services Research*, *34*(3), 283–291. https://doi.org/10.1007/s10488-006-0110-y

Hayes, A. M., Yasinski, C., Ben Barnes, J., & Bockting, C. L. H. (2015). Network destabilization and transition in depression: New methods for studying the dynamics of therapeutic change. *Clinical Psychology Review*, *41*, 27–39. https://doi.org/10.1016/j.cpr.2015.06.007

Hehlmann, M. I., Schwartz, B., Lutz, T., Gómez Penedo, J. M., Rubel, J. A., & Lutz, W. (2021). The Use of Digitally Assessed Stress Levels to Model Change Processes in CBT - A Feasibility Study on Seven Case Examples. *Frontiers in Psychiatry*, *12*, 613085. https://doi.org/10.3389/fpsyt.2021.613085

Heinonen, E., Orlinsky, D. E., Willutzki, U., Rønnestad, M. H., Schröder, T., Messina, I., Löffler-Stastka, H., & Hartmann, A. (2022). Psychotherapist Trainees' Quality of Life: Patterns and Correlates. *Frontiers in Psychology*, *13*, 864691. https://doi.org/10.3389/fpsyg.2022.864691

Heller, A. S., Fox, A. S., & Davidson, R. J. (2019). Parsing affective dynamics to identify risk for mood and anxiety disorders. *Emotion*, *19*(2), 283–291. https://doi.org/10.1037/emo0000440

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

Hofmann, S. G., Curtiss, J., & McNally, R. J. (2016). A Complex Network Perspective on Clinical Science. *Perspectives on Psychological Science*, *11*(5), 597–605. https://doi.org/10.1177/1745691616639283

Jensen-Doss, A., & Hawley, K. M. (2010). Understanding Barriers to Evidence-Based Assessment: Clinician Attitudes Toward Standardized Assessment Tools. *Journal of*

Clinical Child & Adolescent Psychology, *39*(6), 885–896. https://doi.org/10.1080/15374416.2010.517169

Jensen-Doss, A., & Hawley, K. M. (2011). Understanding Clinicians' Diagnostic Practices: Attitudes Toward the Utility of Diagnosis and Standardized Diagnostic Tools. *Administration and Policy in Mental Health and Mental Health Services Research*, *38*(6), 476–485. https://doi.org/10.1007/s10488-011-0334-3

Karpen, S. C. (2018). The Social Psychology of Biased Self-Assessment. *American Journal of Pharmaceutical Education*, *82*(5), 6299. https://doi.org/10.5688/ajpe6299

Kendrick, T., Stuart, B., Leydon, G. M., Geraghty, A. W. A., Yao, L., Ryves, R., Williams, S., Zhu, S., Dowrick, C., Lewis, G., & Moore, M. (2017). Patient-reported outcome measures for monitoring primary care patients with depression: PROMDEP feasibility randomised trial. *BMJ Open*, *7*(3), e015266. https://doi.org/10.1136/bmjopen-2016-015266

Keum, B. T., Morales Dixon, K., Kivlighan, D. M., Hill, C. E., & Gelso, C. J. (2020). Do therapists improve in their ability to assess clients' satisfaction? A truth and bias model. *Journal of Counseling Psychology*. https://doi.org/10.1037/cou0000525

Kirtley, O. J., Lafit, G., Achterhof, R., Hiekkaranta, A. P., & Myin-Germeys, I. (2021). Making the Black Box Transparent: A Template and Tutorial for Registration of Studies Using Experience-Sampling Methods. *Advances in Methods and Practices in Psychological Science*, *4*(1), 251524592092468. https://doi.org/10.1177/2515245920924686

Klintwall, L., Bellander, M., & Cervin, M. (2023). Perceived Causal Problem Networks: Reliability, Central Problems, and Clinical Utility for Depression. *Assessment*, *30*(1), 73–83. https://doi.org/10.1177/10731911211039281

Knaup, C., Koesters, M., Schoefer, D., Becker, T., & Puschner, B. (2009). Effect of feedback of treatment outcome in specialist mental healthcare: Meta-analysis. *British Journal of Psychiatry*, *195*(1), 15–22. https://doi.org/10.1192/bjp.bp.108.053967

Koementas-de Vos, M. M. W., van Dijk, M., Tiemens, B., de Jong, K., Witteman, C. L. M., & Nugter, M. A. (2022). Feedback-informed Group Treatment: A Qualitative Study of the Experiences and Needs of Patients and Therapists. *International Journal of Group Psychotherapy*, *72*(3), 193–227. https://doi.org/10.1080/00207284.2022.2086557

Koval, P., Sütterlin, S., & Kuppens, P. (2016). Emotional Inertia is Associated with Lower Well-Being when Controlling for Differences in Emotional Context. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.01997

Kroeze, R., van der Veen, D. C., Servaas, M. N., Bastiaansen, J. A., Voshaar, R. C. O. V., Borsboom, D., Ruhe, H. G., Schoevers, R. A., & Riese, H. (2017). Personalized feedback on symptom dynamics of psychopathology: A proof-of-principle study. *Journal for Person-Oriented Research*, *3*(1), 1–11. https://doi.org/10.17505/jpor.2017.01

Kumary, A., & Baker, M. (2008). Stresses reported by UK trainee counselling psychologists. *Counselling Psychology Quarterly*, *21*(1), 19–28. https://doi.org/10.1080/09515070801895626

Lambert, M. J., Gregersen, A. T., & Burlingame, G. M. (2004). The Outcome Questionnaire-45. In M. E. Maruish (Ed.), *The use of psychological testing for treatment planning and outcomes assessment: Instruments for adults* (pp. 191–234). Lawrence Erlbaum Associates Publishers.

Lambert, M. J., Hansen, N. B., & Harmon, S. C. (2010). Outcome Questionnaire System (The OQ System): Development and Practical Applications in Healthcare Settings. In M. Barkham, G. E. Hardy, & J. Mellor-Clark (Eds.), *Developing and Delivering Practice-Based Evidence* (pp. 139–154). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470687994.ch6

Lambert, M. J., Harmon, C., Slade, K., Whipple, J. L., & Hawkins, E. J. (2005). Providing feedback to psychotherapists on their patients' progress: Clinical results and practice suggestions. *Journal of Clinical Psychology*, *61*(2), 165–174. https://doi.org/10.1002/jclp.20113

Lambert, M. J., & Shimokawa, K. (2011). Collecting client feedback. *Psychotherapy*, *48*(1), 72–79. https://doi.org/10.1037/a0022238

Lambert, M. J., Whipple, J. L., Hawkins, E. J., Vermeersch, D. A., Nielsen, S. L., & Smart, D. W. (2003). Is It Time for Clinicians to Routinely Track Patient Outcome? A Meta-Analysis. *Clinical Psychology: Science and Practice*, *10*(3), 288–301. https://doi.org/10.1093/clipsy.bpg025

Lambert, M. J., Whipple, J. L., & Kleinstäuber, M. (2018). Collecting and delivering progress feedback: A meta-analysis of routine outcome monitoring. *Psychotherapy*, *55*(4), 520–537. https://doi.org/10.1037/pst0000167

Lamiell, J. T. (1998). \`Nomothetic' and \`Idiographic': Contrasting Windelband's Understanding with Contemporary Usage. *Theory & Psychology*, *8*(1), 23–38. https://doi.org/10.1177/0959354398081002

Leger, K. A., Charles, S. T., & Fingerman, K. L. (2019). Affect variability and sleep: Emotional ups and downs are related to a poorer night's rest. *Journal of Psychosomatic Research*, *124*, 109758. https://doi.org/10.1016/j.jpsychores.2019.109758

Lorentzen, S., Rønnestad, M. H., & Orlinsky, D. (2011). Sources of influence on the professional development of psychologists and psychiatrists in Norway and Germany. *European Journal of Psychotherapy & Counselling*, *13*(2), 141–152. https://doi.org/10.1080/13642537.2011.570016

Lutz, W., Leach, C., Barkham, M., Lucock, M., Stiles, W. B., Evans, C., Noble, R., & Iveson, S. (2005). Predicting change for individual psychotherapy clients on the basis of their nearest neighbors. *Journal of Consulting and Clinical Psychology*, *73*(5), 904–913. https://doi.org/10.1037/0022-006X.73.5.904

Lutz, W., Neu, R., & Rubel, J. (2019). *Evaluation und Effekterfassung in der Psychotherapie* (1. Auflage). Hogrefe. https://doi.org/10.1026/02912-000

Lutz, W., Rubel, J., Schiefele, A.-K., Zimmermann, D., Böhnke, J. R., & Wittmann, W. W. (2015). Feedback and therapist effects in the context of treatment outcome and treatment length. *Psychotherapy Research*, *25*(6), 647–660. https://doi.org/10.1080/10503307.2015.1053553

Lutz, W., Rubel, J. A., Schwartz, B., Schilling, V., & Deisenhofer, A.-K. (2019). Towards integrating personalized feedback research into clinical practice: Development of the Trier Treatment Navigator (TTN). *Behaviour Research and Therapy*, *120*, 103438. https://doi.org/10.1016/j.brat.2019.103438

Lutz, W., Schürch, E., Stulz, N., Böhnke, J. R., Schöttke, H., Rogner, J., & Wiedl, K. H. (2009). Entwicklung und psychometrische Kennwerte des Fragebogens zur Evaluation von Psychotherapieverläufen (FEP). *Diagnostica*, *55*(2), 106–116. https://doi.org/10.1026/0012-1924.55.2.106

Lutz, W., Schwartz, B., Hofmann, S. G., Fisher, A. J., Husen, K., & Rubel, J. A. (2018). Using network analysis for the prediction of treatment dropout in patients with mood and anxiety disorders: A methodological proof-of-concept study. *Scientific Reports*, *8*(1), 7819. https://doi.org/10.1038/s41598-018-25953-0

Lutz, W., Tholen, S., Schürch, E., & Berking, M. (2006). Reliabilität von Kurzformen gängiger psychometrischer Instrumente zur Evaluation des therapeutischen Fortschritts in Psychotherapie und Psychiatrie. *Diagnostica*, *52*(1), 11–25. https://doi.org/10.1026/0012-1924.52.1.11

McAleavey, A. A., Nordberg, S. S., & Moltu, C. (2021). Initial quantitative development of the Norse Feedback system: A novel clinical feedback system for routine mental healthcare. *Quality of Life Research*, *30*(11), 3097–3115. https://doi.org/10.1007/s11136-021-02825-1

McDevitt-Murphy, M. E., Luciano, M. T., & Zakarian, R. J. (2018). Use of Ecological Momentary Assessment and Intervention in Treatment With Adults. *FOCUS*, *16*(4), 370–375. https://doi.org/10.1176/appi.focus.20180017

Molenaar, P. C. M. (2004). A Manifesto on Psychology as Idiographic Science: Bringing the Person Back Into Scientific Psychology, This Time Forever. *Measurement: Interdisciplinary Research & Perspective*, *2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Myin-Germeys, I., Klippel, A., Steinhart, H., & Reininghaus, U. (2016). Ecological momentary interventions in psychiatry. *Current Opinion in Psychiatry*, *29*(4), 258–263. https://doi.org/10.1097/YCO.0000000000000255

O'Connell, K. A., Gerkovich, M. M., Cook, M. R., Shiffman, S., Hickcox, M., & Kakolewski, K. E. (1998). Coping in real time: Using ecological momentary assessment techniques to assess coping with the urge to smoke. *Research in Nursing & Health*, *21*(6), 487–497. https://doi.org/10.1002/(SICI)1098-240X(199812)21:6<487::AID-NUR3>3.0.CO;2-G

Oberauer, K., & Lewandowsky, S. (2019). Addressing the theory crisis in psychology. *Psychonomic Bulletin & Review*, *26*(5), 1596–1618. https://doi.org/10.3758/s13423-019-01645-2

Pew Research Center. (2021). *Mobile Technology and Home Broadband 2021*. Pew Research Center Report.

Piot, M., Mestdagh, M., Riese, H., Weermeijer, J., Brouwer, J. M. A., Kuppens, P., Dejonckheere, E., & Bos, F. M. (2022). Practitioner and researcher perspectives on the utility of ecological momentary assessment in mental health care: A survey study. *Internet Interventions*, *30*, 100575. https://doi.org/10.1016/j.invent.2022.100575

Riese, H., von Klipstein, L., Schoevers, R. A., van der Veen, D. C., & Servaas, M. N. (2021). Personalized ESM monitoring and feedback to support psychological treatment for depression: A pragmatic randomized controlled trial (Therap-i). *BMC Psychiatry*, *21*(1), 143. https://doi.org/10.1186/s12888-021-03123-3

Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology*, *125*(6), 747–757. https://doi.org/10.1037/abn0000181

Rodebaugh, T. L., Tonge, N. A., Piccirillo, M. L., Fried, E., Horenstein, A., Morrison, A. S., Goldin, P., Gross, J. J., Lim, M. H., Fernandez, K. C., Blanco, C., Schneier, F. R., Bogdan, R., Thompson, R. J., & Heimberg, R. G. (2018). Does centrality in a cross-sectional network suggest intervention targets for social anxiety disorder? *Journal of Consulting and Clinical Psychology*, *86*(10), 831–844. https://doi.org/10.1037/ccp0000336

Rognstad, K., Wentzel-Larsen, T., Neumer, S.-P., & Kjøbli, J. (2023). A Systematic Review and Meta-Analysis of Measurement Feedback Systems in Treatment for Common Mental Health Disorders. *Administration and Policy in Mental Health and Mental Health Services Research*, *50*(2), 269–282. https://doi.org/10.1007/s10488-022-01236-9

Rubel, J. A., Fisher, A. J., Husen, K., & Lutz, W. (2018). Translating Person-Specific Network Models into Personalized Treatments: Development and Demonstration of the Dynamic Assessment Treatment Algorithm for Individual Networks (DATA-IN). *Psychotherapy and Psychosomatics*, *87*(4), 249–251. https://doi.org/10.1159/000487769

Rubel, J. A., Zilcha-Mano, S., Giesemann, J., Prinz, J., & Lutz, W. (2020). Predicting personalized process-outcome associations in psychotherapy using machine learning approaches—A demonstration. *Psychotherapy Research*, *30*(3), 300–309. https://doi.org/10.1080/10503307.2019.1597994

Rubel, J. A., Zimmermann, D., Deisenhofer, A.-K., Müller, V., & Lutz, W. (2017). Nutzung von psychometrischem Feedback als empirische Unterstützung des Supervisionsprozesses bei Ausbildungstherapien. *Zeitschrift für Klinische Psychologie und Psychotherapie*, *46*(2), 83–95. https://doi.org/10.1026/1616-3443/a000413

Schaffrath, J., Weinmann-Lutz, B., & Lutz, W. (2022). The Trier Treatment Navigator (TTN) in action: Clinical case study on data-informed psychological therapy. *Journal of Clinical Psychology*, *78*(10), 2016–2028. https://doi.org/10.1002/jclp.23362

Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dakos, V., Held, H., van Nes, E. H., Rietkerk, M., & Sugihara, G. (2009). Early-warning signals for critical transitions. *Nature*, *461*(7260), 53–59. https://doi.org/10.1038/nature08227

Schiepek, G., Eckert, H., Aas, B., Wallot, S., Wallot, A., & Schiepek, G. (2015). *Integrative psychotherapy: A feedback-driven dynamic systems approach*. Hogrefe.

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

Schuler, K., Ruggero, C. J., Mahaffey, B., Gonzalez, A., L. Callahan, J., Boals, A., Waszczuk, M. A., Luft, B. J., & Kotov, R. (2019). When Hindsight Is Not 20/20: Ecological Momentary Assessment of PTSD Symptoms Versus Retrospective Report. *Assessment*, 107319111986982. https://doi.org/10.1177/1073191119869826

Shimokawa, K., Lambert, M. J., & Smart, D. W. (2010). Enhancing treatment outcome of patients at risk of treatment failure: Meta-analytic and mega-analytic review of a psychotherapy quality assurance system. *Journal of Consulting and Clinical Psychology*, *78*(3), 298–311. https://doi.org/10.1037/a0019247

Simon, W., Lambert, M. J., Harris, M. W., Busath, G., & Vazquez, A. (2012). Providing patient progress information and clinical support tools to therapists: Effects on patients at risk of treatment failure. *Psychotherapy Research*, *22*(6), 638–647. https://doi.org/10.1080/10503307.2012.698918

Solhan, M. B., Trull, T. J., Jahng, S., & Wood, P. K. (2009). Clinical assessment of affective instability: Comparing EMA indices, questionnaire reports, and retrospective recall. *Psychological Assessment*, *21*(3), 425–436. https://doi.org/10.1037/a0016869

Solstad, S. M., Kleiven, G. S., Castonguay, L. G., & Moltu, C. (2021). Clinical dilemmas of routine outcome monitoring and clinical feedback: A qualitative study of patient experiences. *Psychotherapy Research*, *31*(2), 200–210. https://doi.org/10.1080/10503307.2020.1788741

Southwick, S. M., Morgan 3rd, C. A., Nicolaou, A. L., & Charney, D. S. (1997). Consistency of memory for combat-related traumatic events in veterans of Operation Desert Storm. *American Journal of Psychiatry*, *154*(2), 173–177. https://doi.org/10.1176/ajp.154.2.173

Soyster, P. D., Song, F., & Fisher, A. J. (2023). Clinician Opinions: Perceived Utility of and Barriers to Incorporating Pretreatment Ecological Momentary Assessment Into Clinical Care. *Behavior Therapy*, *54*(2), 200–213. https://doi.org/10.1016/j.beth.2022.08.005

Stone, A. A., Schwartz, J. E., Neale, J. M., Shiffman, S., Marco, C. A., Hickcox, M., Paty, J., Porter, L. S., & Cruise, L. J. (1998). A comparison of coping assessed by ecological momentary assessment and retrospective recall. *Journal of Personality and Social Psychology*, *74*(6), 1670–1680. https://doi.org/10.1037/0022-3514.74.6.1670

Strauss, B., Gawlytta, R., Schleu, A., & Frenzl, D. (2021). Negative effects of psychotherapy: Estimating the prevalence in a random national sample. *BJPsych Open*, *7*(6), e186. https://doi.org/10.1192/bjo.2021.1025

Terluin, B., de Boer, M. R., & de Vet, H. C. W. (2016). Differences in Connection Strength between Mental Symptoms Might Be Explained by Differences in Variance: Reanalysis of Network Data Did Not Confirm Staging. *PLOS ONE*, *11*(11), e0155205. https://doi.org/10.1371/journal.pone.0155205

Trull, T. J., & Ebner-Priemer, U. W. (2009). Using experience sampling methods/ecological momentary assessment (ESM/EMA) in clinical assessment and clinical research: Introduction to the special section. *Psychological Assessment*, *21*(4), 457–462. https://doi.org/10.1037/a0017653

van Bronswijk, S. C., DeRubeis, R. J., Lemmens, L. H. J. M., Peeters, F. P. M. L., Keefe, J. R., Cohen, Z. D., & Huibers, M. J. H. (2021). Precision medicine for long-term depression outcomes using the Personalized Advantage Index approach: Cognitive therapy or interpersonal psychotherapy? *Psychological Medicine*, *51*(2), 279–289. https://doi.org/10.1017/S0033291719003192

van de Leemput, I. A., Wichers, M., Cramer, A. O. J., Borsboom, D., Tuerlinckx, F., Kuppens, P., van Nes, E. H., Viechtbauer, W., Giltay, E. J., Aggen, S. H., Derom, C., Jacobs, N., Kendler, K. S., van der Maas, H. L. J., Neale, M. C., Peeters, F., Thiery, E., Zachar, P., & Scheffer, M. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences*, *111*(1), 87–92. https://doi.org/10.1073/pnas.1312114110

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

von Klipstein, L., Servaas, M. N., Schoevers, R. A., van der Veen, D. C., & Riese, H. (2023). Integrating personalized experience sampling in psychotherapy: A case illustration of the Therap-i module. *Heliyon*, *9*(3), e14507. https://doi.org/10.1016/j.heliyon.2023.e14507

Wagner, A. A., Hall, M., Scherner, P. V., & Rubel, J. A. (2023). If you give a therapist a network: A qualitative analysis of therapists' reactions to their patients' EMA-based network models [Preprint]. *PsyArXiv*. https://doi.org/10.31234/osf.io/hqyft

Walfish, S., McAlister, B., O'Donnell, P., & Lambert, M. J. (2012). An Investigation of Self-Assessment Bias in Mental Health Providers. *Psychological Reports*, *110*(2), 639–644. https://doi.org/10.2466/02.07.17.PR0.110.2.639-644

Wichers, M., Groot, P. C., & Psychosystems, ESM Group, EWS Group. (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. *Psychotherapy and Psychosomatics*, *85*(2), 114–116. https://doi.org/10.1159/000441458

Wittenborn, A. K., Rahmandad, H., Rick, J., & Hosseinichimeh, N. (2016). Depression as a systemic syndrome: Mapping the feedback loops of major depressive disorder. *Psychological Medicine*, *46*(3), 551–562. https://doi.org/10.1017/S0033291715002044

Zimmermann, J., Woods, W. C., Ritter, S., Happel, M., Masuhr, O., Jaeger, U., Spitzer, C., & Wright, A. G. C. (2019). Integrating structure and dynamics in personality assessment: First steps toward the development and validation of a personality dynamics diary. *Psychological Assessment*, *31*(4), 516–531. https://doi.org/10.1037/pas0000625

Acknowledgments

Since I arrived in Germany in 2019, I have been the very fortunate recipient of an extraordinary amount of support. I fear I will not be able to name everyone, but I will do my best to remain concise.

First, I would like to thank Prof. Dr. Julian Rubel, for entrusting me with the role of his first doctoral student. I began admiring his and Prof. Dr. Wolfgang Lutz's, my second supervisor's, research about psychotherapy personalization and network modeling during my Master's degree. Back then, I never dreamed I would be able to work with two of my idols. In particular, I would like to thank Prof. Dr. Rubel for never losing faith in me, despite the multiple obstacles that popped up unexpectedly. I would also like to acknowledge the time and effort of the members of my defense commission. I would additionally like to thank my third reviewer.

Of course, I would also like to acknowledge all my colleagues: Robin Wester, Christopher Lalk, Flavio Iovoli, Paloma Scherner, Katharina Michael, Emily Wiegmann, Michael Krug, and so many other research assistants who made this project manageable. I would also like to thank all who helped me implement the TheraNet Project at the outpatient center at the University of Giessen. Of course I would not have been able to reach this point without all those who participated in my study, both patients and therapists. Thank you for trusting me throughout this process: I dedicate this work to you.

In particular, I would like to thank the following friends, who provided invaluable support in the last year of my doctorate: Miriam Hale, for (at literally any hour of the day) answering my calls; Miriam Hehlmann, Jana Schaffrath, Jana Bommer, and Dr. Anne-Katharina Deisenhofer, for your support from afar but especially during our writing retreat; Katharina Kühn, Marie Straßmann, Sophie Deissmann, Lukas Bille, and the rest of my therapist cohort, for empathically listening to my research woes and reliably providing well-timed distractions; Denis Koch and his family, for helping me focus in times of doubt; and Hannah Weisenberg, for always having an open ear (and a chilled bottle of wine) at the ready.

Last, but certainly not least, I would like to sincerely thank my parents, Robert and Diane, for answering all my phone calls in times of desperation, for comforting me, and for supporting me in my academic endeavors. I'm glad you're in my corner.

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Publications

This list includes Studies 1 through 4, as well as the associated preprints.

Bechtold, S., **Hall, M.**, Scherner, P. V., Kaven, L., & Rubel, J. A. (2023). Veränderung der therapeutischen Beziehung in Folge eines coronabedingten Wechsel von Präsenz- zu Videotherapiesitzungen: Eine qualitative Analyse von Therapeut*inneninterviews. *PPmP - Psychotherapie · Psychosomatik · Medizinische Psychologie.* https://doi.org/10.1055/a-2017-5338

Hall, M., Lappenbusch, L. M., Wiegmann, E., & Rubel, J. A. (under review). To use or not to use: Exploring therapists' experiences with pre-treatment EMA-based personalized feedback in the TheraNet Project. *Administration and Policy and Mental Health Services.*

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

Hall, M., Scherner, P. V., Kreidel, Y., & Rubel, J. A. (2021). A Systematic Review of Momentary Assessment Designs for Mood and Anxiety Symptoms. *Frontiers in Psychology, 12*, 642044. https://doi.org/10.3389/fpsyg.2021.642044

Hall, M., Servaas, M. N., & Riese, H. (in preparation). Advances in ESM-derived feedback integrated into psychological therapy. In CBT: Science into Practice. Springer Nature.

Hall, M., Wagner, A., Scherner, P. V., Michael, K. L., Lawyer, G., Lutz, W., & Rubel, J. (under review). Using personalized assessment and network model feedback in psychotherapy: Proof of principle for the TheraNet Project. *Cognitive Therapy and Research.*

Hall, M., Wagner, A., Scherner, P. V., Michael, K. L., Lawyer, G., Lutz, W., & Rubel, J. (2022). Using personalized assessment and network model feedback in psychotherapy: Proof of principle for the TheraNet Project [Preprint]. *PsyArXiv*. https://doi.org/10.31234/osf.io/8deyj

Hall, M., Wucherpfennig, F., & Rubel, J. A. (2020). Qualitative Inhaltsanalyse [Qualitative content analysis]. *PPmP - Psychotherapie · Psychosomatik · Medizinische Psychologie, 70*(09/10), 429–431. https://doi.org/10.1055/a-1193-1022

Hanewald, B., Knipper, M., Daub, J., Ebert, S., Bogdanski, C., Hinder, L., **Hall, M.**, Berthold, D., & Stingl, M. (2022). Addressing the Mental Health Challenges of Refugees—A Regional Network-Based Approach in Middle Hesse Germany. *International Journal of Environmental Research and Public Health*, *19*(20), 13436. https://doi.org/10.3390/ijerph192013436

Rubel, J. A., **Hall, M.**, & Lutz, W. (2022). Methods of Clinical Psychology. In Comprehensive Clinical Psychology (pp. 96–123). Elsevier. https://doi.org/10.1016/B978-0-12-818697-8.00076-5

Wagner, A. A., **Hall, M.**, Scherner, P. V., & Rubel, J. A. (under review). If you give a therapist a network: A qualitative analysis of therapists' reactions to their patients' EMA-based network models. *Clinical Psychological Science.*

Wagner, A. A., **Hall, M.**, Scherner, P. V., & Rubel, J. A. (2023). If you give a therapist a network: A qualitative analysis of therapists' reactions to their patients' EMA-based network models [Preprint]. *PsyArXiv*. https://doi.org/10.31234/osf.io/hqyft

Wester, R. A., Rubel, J., Zimmermann, J., **Hall, M.**, Kaven, L., & Watson, D. (2022). Development and validation of the Inventory of Depression and Anxiety Symptoms–II—German version. *Psychological Assessment*, *34*(12), e88–e99. https://doi.org/10.1037/pas0001185

Chronological Conference Contributions

Hall, M., Hehlmann, M., & Fernández Alvarez, J. (2023, June). Insights into patients' everyday life: Integrating EMA in psychotherapy contexts. Workshop organized & presented at the 54th Annual Society for Psychotherapy Research Conference. Dublin, Ireland.

Hall, M., Lappenbusch, L. M., Wiegmann, E., & Rubel, J. A. (2023, June). Does network model feedback make a difference? Findings from the TheraNet Project. Paper presented at the 54th Annual Society for Psychotherapy Research Conference. Dublin, Ireland.

Hall, M., Scholten, S., Burger, J., & Piccirillo, M. L. (2023, June). Data-informed personalization and feedback in clinical settings: Lessons learned and best practices. Structured discussion as moderator & discussant at the 54th Annual Society for Psychotherapy Research Conference. Dublin, Ireland.

Iovoli, F., **Hall, M.**, & Rubel, J. A. (2023, June). Exploring the complex interrelation between depressive symptoms, risk and protective factors: An integrative network analysis. Poster presented at the 54th Annual Society for Psychotherapy Research Conference. Dublin, Ireland.

Hall, M. & Rubel, J. A. (2023, June). The clinical utility of EMA-based network models: Methodology and therapist perceptions of the TheraNet Project. Paper presented at the 2023 Society for Ambulatory Assessment Conference. Amsterdam, Netherlands.

Hall, M. & Rubel, J. A. (2023, May). Bringt Netzwerkmodell-Feedback etwas? Erkenntnisse aus dem TheraNet-Projekt [Does network model feedback make a difference? Findings from the TheraNet Project]. Paper presented at the 2nd Annual German Psychotherapy Conference. Berlin, Germany.

Hall, M., Wagner, A. A., Scherner, P. V., Michael, K. M., & Rubel, J. A. (2022, September). Therapists' intuitive responses to patient network feedback: Pilot data from the TheraNet study. "Using network models in clinical practice" panel moderated & paper presented at the 9th Joint UK & European Society for Psychotherapy Research Chapters Conference. Rome, Italy.

Hall, M., Riese, H., Aas, B., Moller, N., & Rost, F. (2022, September). Integrating qualitative & quantitative methods in psychotherapy research: The way forward? Structured discussion as moderator & discussant at the 9th Joint UK & European Society for Psychotherapy Research Chapters Conference. Rome, Italy.

Hall, M., Wagner, A. A., Scherner, P. V., Michael, K. M., & Rubel, J. A. (2022, July). Therapists' intuitive responses to patient network feedback: Pilot data from the TheraNet study. Paper presented at the 53rd Annual Society for Psychotherapy Research Conference. Denver, CO, USA [Hybrid/online presentation].

Hall, M., Scherner, P. V., Kreidel, Y.., & Rubel, J. A. (2021, June). Systematic review of momentary assessment designs for adult mood and anxiety symptoms. Paper presented at the 52st Annual Society for Psychotherapy Research Conference. Heidelberg, Germany [Online conference].

Hall, M., Scherner, P. V., Kreidel, Y.., & Rubel, J. A. (2020, June). Systematic review of momentary assessment designs for adult mood and anxiety symptoms. Paper was to be presented at the 51st Annual Society for Psychotherapy Research Conference. Amherst, MA, USA [Conference cancelled].

Hall, M., Michael, K., Scherner, P. V., Demtschenko, E., & Rubel, J. A. (2019, September). Systematic review of momentary assessment designs for adult mood and anxiety symptoms. Poster presented at the 5th Joint UK & European Society for Psychotherapy Research Chapters Conference. Krakow, Poland.