A Scoping Review into Personalised Treatment Based On Person-Specific Networks in Mental Health Care

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Abstract

Introduction. Network theory is the study of how symptoms, experiences, thoughts, and behaviour of an individual interact with each other to form a network. Personalised treatment for mental health disorders can be achieved by taking a person-specific approach which tailors' therapy to the specific needs and circumstances of each individual patient, leading to better outcomes and improved quality of care. However, to date, this domain has not been explored sufficiently, and no reviews about the topic exist. Therefore, the goal of the current study is to perform a scoping review and provide an overview of studies that use person-specific approaches for the personalisation of treatment.

Methods. In order to discover relevant literature, three online databases were searched: Scopus, PsycInfo and Wiley Online Library. After a comprehensive examination, 10 studies were deemed eligible to be included into the scoping review. Those studies were investigated regarding study characteristics, population characteristics, method of variable selection for networks, feasibility and effectiveness of personalised treatments based on person-specific networks.

Results. Most of the studies investigating personalised treatments' effects were uncontrolled studies or open trials. Predominantly, the studies were carried out in the United States. A majority of the records applied a longitudinal research design with a 1-month period, utilising experience sampling methodology (ESM). Methods for variable selection varied a lot. Primarily adult women particpated in the studies. The disorders represented within the studies were major depressive disorder (n = 4), generalised anxiety disorder (n = 4), eating disorders (n = 3), borderline personality disorder (n = 1) or a combination of disorders (n = 3). Feasibility varied throughout the studies. Studies provided positive effect sizes for effectiveness.

Discussion. This scoping review suggests that personalised treatments based on person-specific networks are potentially effective. Nonetheless it may be difficult to establish correct effect sizes due to the complexity of measuring treatment results. The feasibility of personalised treatments is connected to the design of the ESM study and the characteristics of the target group. The findings contribute to a growing evidence base of personalised treatment options based on person-specific approaches. This review provides a valuable starting point for informing future researchers about the possibilities within this domain and identify knowledge gaps.

Keywords: Network Theory, Person-Specific Networks, Personalised Treatment, ESM, Mental Health Care

Introduction

The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), is a popular resource for mental health professionals. The manual comprises many common symptoms of mental health disorders and clusters these into diagnostic criteria (Bailey, 2022). Despite its success, the DSM-5 has some shortcomings. It has been criticised for focusing on categorical diagnoses rather than appropriate (personalised) treatment and for failing to account for heterogeneity in the symptom presentation of mental illness (Galatzer-Levy & Bryant, 2013; Raskin & Gayle, 2016). Current psychopathology research supports the concept that two people with the same condition have the same or similar symptoms. This view persists although it has been found that symptom expression varies greatly between individuals (Fried, 2017). Furthermore, the DSM-5 is used to find the most appropriate mental illness diagnosis, and other related diseases are frequently ruled out (Galatzer-Levy & Bryant, 2013). As a result, any potential comorbidity is disregarded.

Network Theory

To give a new perspective on mental illnesses, Borsboom and Cramer (2013) introduced network theory. Two main assumptions are underlying network theory. First, there are causal interactions between the symptoms. Second, the symptoms represent the disorder and do not result from an underlying cause (de Boer et al., 2021). In this domain, it is of particular interest to discover self-reinforcing feedback loops that might develop among symptoms. Such feedback loops are thought to be a sustaining factor in mental illness. A feedback loop can be activated by, for example, negative life events. The network eventually becomes self-sustaining, leading to a state of mental illness (Borsboom, 2017). If the feedback loop can be interrupted (i.e., the network cannot sustain itself), the individual can return to a healthy state. The variables included in a network are called "nodes." Almost anything can be declared as nodes, ranging from symptoms to social or environmental factors (Bringmann et al., 2022). The connections between the nodes are called edges (Borsboom & Cramer, 2013).

Furthermore, network theory includes environmental and social factors in the development of a mental disorder. These are usually considered to have a unidirectional effect or cause the symptoms (De Boers et al., 2021). To get an idea of the significance of nodes in transferring information to each other within the network, centrality measures are useful. These give an indication of the importance of a node or edge in transmitting the information. Strength centrality has been deemed the most usable and is used to show how the nodes interact with each other and if there are strong connections between them (Castro et al., 2019;

Wichers et al., 2021).

There is also another statistical method to show relationships within a network. This is called lagged regressions (i.e., VAR models). These are useful to visualize the timely associations and influence of changes within a network. For example, when the node "stress" increases first, it can affect the node "worry" as a result or vice versa. Therefore, the process becomes apparent in which symptoms, experiences, thoughts, and behaviour impact each other (Bringmann et al., 2022). This approach could potentially open a new direction in the future of personalised care (Bringmann, 2021).

Individual Networks and Personalised Treatment

Network theory enables research about individual heterogeneity in mental illness. There is an emphasis on idiographic within-person associations, which refers to researching the development of mental illness in one person across time. Most of the current psychopathological research is focused on between-person effects and how treatment is affected on a group level.

Between-person effects show differences across several individuals (Bringmann et al., 2022). However, generalizing findings from a group-level to the individual can be inaccurate (Curran and Bauer, 2011). It is argued that between-person studies do not allow for the substantial individual differences. Within-person effects show the change of specific variables in one participant. For example, it can be investigated that if a person scores higher in the variable stress, then they might also score higher or lower in the variable worry in comparison at the same time (Bringmann et al., 2022). Thus, person-specific networks make it easier to detect person-specific elements that influence the development of mental diseases (Bringmann, 2021). Overall, it is of special interest in what way personalised therapy based on person-specific approaches can be best tested and investigated in a scientific manner. This concerns which study designs are applied, how the mental illness is assessed, and where the study has been performed. These can be referred to as study characteristics. Likewise, it is questioned which individuals, if not everyone, might profit most from individualised therapy.

Process-based therapy (i.e., functional analysis and case conceptualization) is useful for building personalised networks. These give a good indication about the intentions of the client, how their symptoms influence each other and how thoughts, behaviours and emotions are connected (Jones & Robinaugh, 2021). This information is utilised to identify target symptoms for an intervention. These should be prominent symptoms which are related to the patient's goals, easily manipulated, and directly connected to other symptoms. This interacts well with the idea of feedback-loops. When these feedback loops are interrupted, symptomatic patterns can be treated. This can be done by performing adaptations or manipulations to the individual network. These manipulations can be sorted into three main categories. These are 1) “symptom interventions”, which means directly targeting to change one or more symptoms; 2)” interventions in the external field”, which means making adaptions to the environment or removing triggering causes; and lastly, 3) “network interventions”, these tackle the network structure itself and is concerned with changing symptom-symptom connections (Borsboom, 2017). One potential method to construct networks is the experience sampling method (ESM).

ESM is a structured self-report measure, in which participants are asked to fill out a set of questionnaires several times a day over a certain period. According to Myin-Germeys et al. (2018), ESM is well suited to measure fluctuating variables (e.g., moods and symptoms). The term ESM can be used interchangeably with the term ecological momentary assessment (EMA). This research method can also be useful in the selection of nodes for networks.

Challenges and Prospects of Personalised Treatment based on Individual Networks

Variable selection is an important consideration to address when constructing person-specific networks for personalised treatment. When applying network theory, it can be challenging to decide which nodes should be part of that network. It is important that the nodes align as strictly as possible with the hypotheses formulated by the clinician (in correspondence with the patient). According to Bringmann et al. (2022), nodes should possess two distinct characteristics: being independently recognizable and being changeable. This means that one node should be identifiable from the others, and it should be manipulable without affecting the others. A set of nodes should be minimally complete, which means that all important nodes are included, and unnecessary nodes are sorted out. It can be difficult to determine what “minimally complete” entails since this might vary by case (Bringmann et al., 2022). To make an appropriate decision, the nodes can be discussed with the patient through case conceptualization. Alternatively, DSM-5-symptom clusters can be utilised as nodes (Borsboom & Cramer, 2013). Overall, this process can be quite complex.

Likewise, capturing (within-person) network dynamics is often regarded as impractical. Therefore, the feasibility and effectiveness of person-specific networks in mental health care is often questioned. Especially the work with ESM might be a high burden to the participant and the therapist which could lead to high treatment drop-out (Myin-Germeys et al., 2018). However, researchers see potential in the personalisation of treatment. Fisher et al.

(2019) encourage the development of personalised treatment. They state that clients who do not recognize any improvements are more likely to drop-out of treatment. Therefore, adapting treatment to the wishes and needs of the client may improve treatment outcomes and motivation. It is suggested to systematically test different treatment lengths and treatment selection approaches to estimate factors which could lead to an increase in “efficacy-per-unit-time” (Fisher et al., 2019). Further, studies about personalised networks incorporate a lot of data within one person, thus making a big sample size redundant. One person is enough to derive conclusions about severity, idiosyncratic syndrome structures or treatment responses (Burger et al., 2022). Personalised treatment based on the person-specific network approach are generally seen as promising as it tailors therapy to the specific needs and circumstances of each individual patient, leading to better outcomes and improved quality of care.

Current Study

Personalised therapies are expected to bring promising results in the future and create a shift in the current understanding of psychopathology. Nonetheless, there can be no valid inferences drawn about the value of personalised treatment based on person-specific networks in mental health care. To date, there are no reviews available which summarise the usage of person-specific networks for personalised interventions. Similarly, an overview of person-specific networks and how they are used in treatment is currently missing. This concerns study characteristics (such as study design, country of origin and form of assessment) and population characteristics of studies using person-specific networks for treatment. For population characteristics, it is of special interest which mental illnesses have been diagnosed, and the age and gender of the patients. Next to that, a closer look is taken at the different methods of variable selection. Finally, it remains questionable how effective and feasible personalised treatment based on person-specific networks are. Therefore, the goal of the current study is to review studies which investigate personalised treatments based on person-specific networks. This information will be acquired in the form of a scoping review. Such reviews are useful to guide further research and identify knowledge gaps (Van Lotringen et al., 2021). Further, knowledge from this review can work as a starting point for researchers to investigate specific topics more in-depth. This scoping review will provide a clear thematic overview of the current state-of-the-art research on person-specific networks for treatment of mental disorders. The following research objectives will be addressed:

1. What are the characteristics of studies that investigate the effectiveness of personalised treatment based on person-specific networks?
2. What are the population characteristics that investigate the effectiveness of personalised treatment based on person-specific networks?
3. How are the variables for an individual network chosen?
4. How effective are the individually tailored treatments for mental disorders?
5. Is the application of personalised treatment based on person-specific networks feasible in mental health care?

Methods

This research was performed according to the PRISMA-guidelines by Moher et al (2009).

Search Strategy

The search was performed on three different platforms: Scopus, PsycINFO, and Wiley Online Library. These online databases were used to find research articles that matched the determined content and inclusion criteria. Since research in that domain is narrow, there was no publication date restriction set. Further, the search was performed in "All Fields" which included more than abstract, title and keywords. For example, it was also searched in the full-text, author section and many more.

First, Scopus was chosen because of its scientific importance and breadth of coverage. Second, PsycInfo was chosen due to its emphasis on psychological and mental health studies. Finally, the Wiley Online Library was searched because it has been established that many key research publications originated from this database (Van Lotringen et al., 2021).

All three databases offerd the opportunity to conduct thorough research. The search strings used for each platform are listed in Table 1 (see Appendix). A systemic search was constructed by grouping the terms into four blocks with different foci,.

Inclusion Criteria

1) The article must be written about original research.
2) The article must be published in a peer-reviewed journal.
3) The language of the article can be German or English.
4) The article must be about a population suffering from mental health problems.
5) The article must cover a person-specific approach.
6) The research must provide an explanation of which treatment they applied or would recommend based on the person-specific approach.

Study Selection

All the data collection was done by one researcher. In the first step, all the duplicates have been removed in EndNote. The remaining articles were downloaded in an RIS file and then uploaded on ASReview. This software is helpful for determining relevant articles for a systematic review process. Before starting the screening process in ASReview, the researcher needs to label one article as relevant (1) and one as irrelevant (0) to give the AI an indication about the topic (van de Schoot et al., 2021). In the next step, the reviewer can read the titles and abstracts of the articles and label these further. During this process, ASReview gains "knowledge" about the relevant attributes of the article and predicts which records might be relevant to the researcher and sorts these according to their predicted relevancy (van de Schoot et al., 2021). This prediction changes according to the new input given through continuous labelling.

After finding 59 articles that were relevant, the review process was stopped because the active learning cycle kept suggesting articles that were irrelevant, suggesting an adequate saturation of articles. The researcher obtained an excel file containing the final list of records from ASReview in order to determine whether any potentially important records had been overlooked. In the last step, the researcher read the relevant papers fully to determine their eligibility for this review. This was the case when the seven inclusion criteria were met. The flowchart (see Figure 1), which is based on the PRISMA guidelines (Moher et al., 2009), shows the steps of the process. However, three additional articles have been included into the final list. These were discovered during previous literature searches and included as "found in preliminary search" in the flowchart.

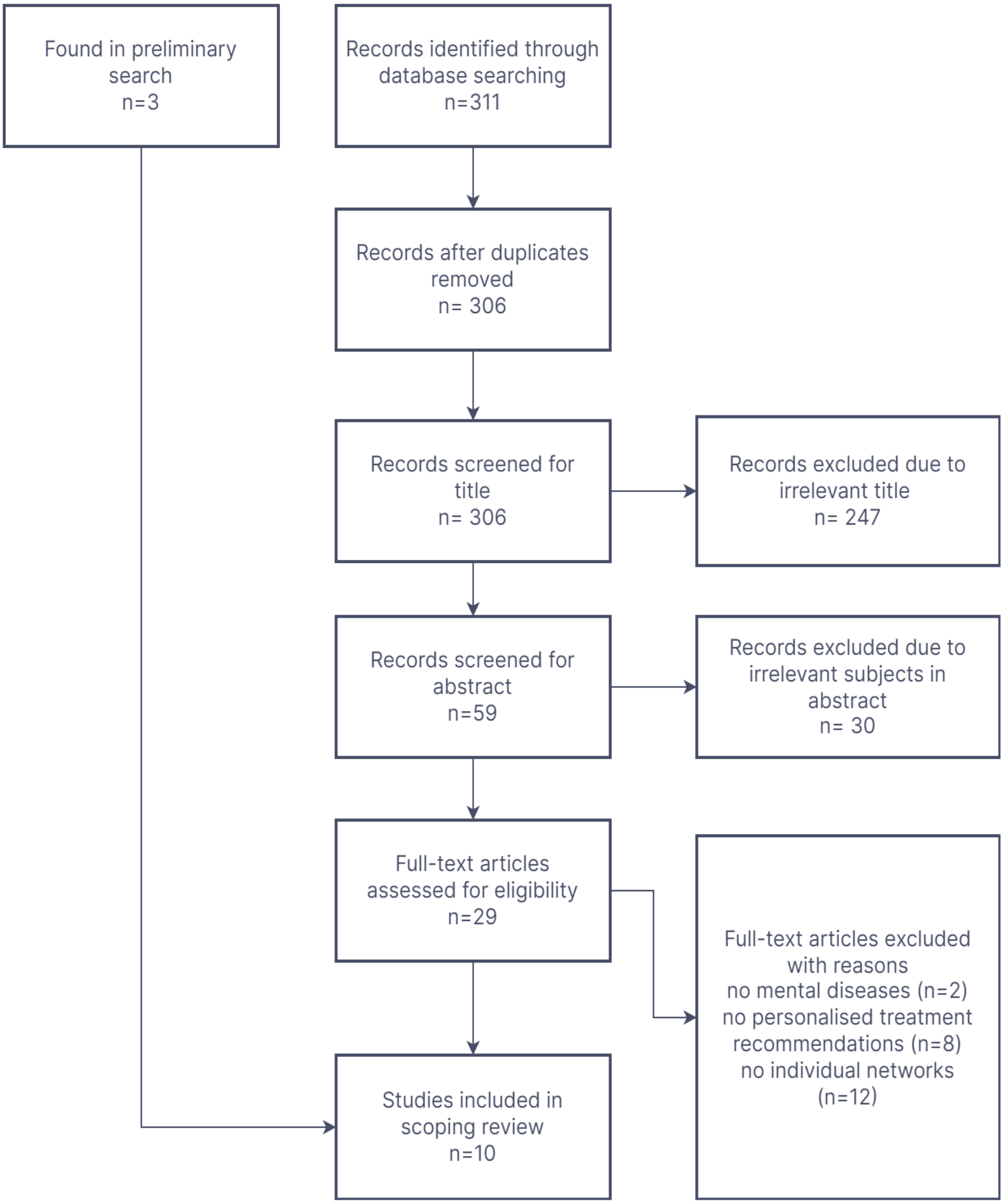

Figure 1

A flowchart showing the process of the study selection for the scoping review according to the Prisma guidelines (Moher et al., 2009)

Data Extraction

According to the review's research goal, all relevant publications were read and reviewed. Participant characteristics, study design characteristics, and findings are among the data items that were extracted. All data was extracted by the measures of one researcher.

The parameters of the study design were first taken out to provide some context for the methodology and history of the investigation. The country in which the study was done, the study's design, assessments, and variable selection strategy were all study design aspects. The assessments covered the overall number of measures, how frequently they were taken each day, and how long they kept records. Additionally, the items used in the assessments were summarised.

Next to that, the parameters about population characteristics were extracted. Henceforth, a summary of the population and its mental health issues was collected. The sample size was retrieved in order to gain a complete picture of the study's scope. Additionally, demographics of the population like age and gender were gathered.

Moreover, data about the feasibility and effectiveness of the studies was extracted. The different network types and the corresponding individualised therapy recommendations are derived even though they are not directly related to the study objectives. This was done since it provides useful background for the researcher's study methodology. Along with that, the study's findings were taken, and any information regarding the method's feasibility and efficacy in the treatment of mental illness were extracted. For feasibility, mostly information about drop-out rates of participants and average observation numbers were extracted. Effectiveness refers to the effect sizes and how the personalised treatment was evaluated for its effectiveness.

Results

Study Characteristics

In total, ten studies were included in this scoping review. The study features of the selected studies are shown in Table 2. The United States (*n* = 8) was the nation where most of the studies were carried out. Klintwall et al. (2021) conducted their study in Sweden and Burger et al. (2022) conducted research in the Netherlands. Most studies had an uncontrolled study design (*n* = 8). One study was an open trial design (Fisher et al., 2019). Burger et al. (2022) worked with a case study design.

Next to that, for the assessments, most studies used ESM for conducting longitudinal research (*n* = 8). One study used Intensive Repeated Measures Methodology (Fisher & Boswell, 2016). Another study used the online test Perceived Causal Networks (PECAN) instead and therefore had only two measurement points (Klintwall et al., 2021). The PECAN is a clinically adapted version of the Perceived Causal Relations (PCR) scale. This scale is supposed to gather sufficient information to build a network within a limited timeframe. For this, clients can rate their symptoms for severity and explain how the symptoms influence each other. It was common that the ESM studies had around 120-150 observations over a 1-month period (*n* = 5). Two studies used a shorter period with only 75 observations. Levinson et al. (2018) used only 28 measurements over a week. In comparison, Yang et al. (2018) used a longitudinal design over the course of a year and therefore used around 450 observations. The items utilised for the studies usually were composed of hallmark symptoms, cognitions, or behaviours (*n* = 3) and/or DSM-5 criteria of the corresponding mental illness (*n* = 3).

Lastly, the method of variable selection for the construction of a person-specific network is summarised. It was common to include the items which had the highest mean and centrality (*n* = 3). Other studies made use of R-scripts like uSEM, VAR-packages or GIMME to determine which variables should be included (*n* = 4). Two studies let the client and/or the professional decide which variables should be included.

Table 2

Study characteristics of included studies

	Authors (year)	Country	Study Design	Assessments	Method of variable selection
1	Burger et al. (2022)	Netherlands	Case Study	75 observations, 5 times a day for 15 days (ESM) 56 items spanning a broad range of eating disorder and related symptoms	- selected items that have been specified by either clinician or patient - if given that all items showed sufficient variability, the items with the highest mean were chosen
2	Fisher & Boswell (2016)	United States	Uncontrolled Study	120 observations, 4 times a day for at least 30 days (Intensive Repeated Measures Methodology) Items included DSM-5 symptom criteria for GAD and MDD and additional three behavioral symptoms: avoided activities, procrastinated, and sought reassurance	N/A
3	Fisher et al. (2017)	United States	Uncontrolled Study	120 observations, 4 times a day for at least 30 days (ESM) Items included the DSM-5 criteria for GAD and MDD and an additional 11	- the items with the highest strength in-strength and out-strength centrality are represented in the network

				items gauging positive affect, negative affect, rumination, behavioral avoidance, and reassurance seeking	
4	Fisher et al. (2019)	United States	Open Trial	120 observation, 4 times a day for at least 30 days (ESM) Items included symptom criteria of DSM-5 for GAD and MDD and additionally 11 items measuring positive affect, negative affect, rumination, behavioral avoidance and reassurance seeking	N/A
5	Kaurin et al. (2022)	United States	Uncontrolled Study	126 observations, 6 times a day for 21 days (ESM) Items included negative affect, hostility, positive affect, impulsivity and suicidal ideation	- used the gimmeSEM function built into the R package gimme - this algorithm searches to estimate unified structural equation models
6	Klintwall et al. (2021)	Sweden	Two-Step Design Evaluation Uncontrolled Study	2 observations through online test Perceived Causal Networks (PECAN) - list of 26 items (behavioral/emotional problems) - based on piloting of different versions of the questionnaire and settling on a list that	Study 1: - Respondents were asked to select 7-15 items - each item was rated for severity by the participants

				yielded both acceptable reliability and high therapist ratings of utility - only 26 to limit participant burden	
7	Levinson et al. (2021)	United States	Proof-of-Concept Uncontrolled Study	75 observations, 5 times a days for two weeks (ESM) - Items included 55 selected symptoms of Eating Disorders, as well as co-occurring symptoms	- Decided a priori to select 15 items with the highest individual means out of all items - large enough number for comprehensive model, but not too large to impact estimation procedures
8	Levinson et al (2018)	United States	Pilot Uncontrolled Study on an Applied Tutorial	28 observations, 4 times a day for one week (ESM) - 11 items which were classified as eating disorder cognitions or eating disorder behaviours	- used graphical VAR package - included the variables with the highest strength centrality, highest in-strength and out-strength
9	Piccirillo and Rodebaugh (2022)	United States	Uncontrolled Study	150 observations, 5 times a day for 30 days (ESM) - hallmark symptoms of SAD - theoretical factors related to comorbidity - treatment-related factors - DSM-5 diagnostic criteria for a MDD	- used multilevel (ML-VAR) and person-specific VAR models - calculated expected node influence and centrality

10	Yang et al. (2018)	United States	Uncontrolled Study	450 observations for 21 days, three 21 days measurement periods over a year (ESM) - used all available emotion and interpersonal variables in the experience sampling protocol	- uSEM was used to determine variables which underlie each person's 13-dimensional multivariate time-series data at each burst (422 networks)

Note. MDD = Major Depressive Disorder, SAD= Social Anxiety Disorder, GAD= Generalised Anxiety Disorder, ESM= Experience Sampling Methodology

Participant Characteristics

The research paper population characteristics are compiled in Table 3. Target populations varied throughout the experiments. Some studies chose to emphasize comorbidity (*n* = 3) while others did not stick to a DSM-5 diagnosis (*n* = 2). It is noteworthy that three research papers examined one or more types of eating disorders. Investigations into major depressive disorder (*n* = 4) and anxiety disorders (*n* = 4) were common as well. The populations in the selected research were primarily female (*n* = 7). Even studies that only included female volunteers (*n* = 2) were found. All studies targeted adults over the age of 18. The most common mean age group was above 30 and under 65 (*n* = 4). There were two samples with young adults, therefore the average age group for these studies was below 25 years old.

Table 3.

Participant characteristics of included studies

	Author (year)	Sample (N)	Gender (%)	Age (years), mean (SD)
1	Burger et al. (2022)	Anorexia Nervosa restricting subtype (2)	100% female	M= 36.5
2	Fisher & Boswell (2016)	Primary Diagnosis of Generalised Anxiety Disorder and/or Major Depressive Disorder (13)	N/A	18 to 65 years
3	Fisher et al. (2017)	Diagnosis of Major Depressive Disorder or Generalised Anxiety Disorder; no psychosis or mania (40)	65% female	18 to 65 years
4	Fisher et al. (2019)	Individuals with symptomatic experiences consistent with possible diagnoses of GAD and MDD; no psychosis or mania (32)	62,5% female	18 to 65 years
5	Kaurin et al. (2022)	Borderline Personality Disorder with Suicidal Ideation (95)	80% female	M= 33.71 (SD=9.43)
6	Klintwall et al. (2021)	Study 1: Symptoms of Depression, no specified diagnosis (231)	Study 1: 90% female 9% male	Study 1: M=39.4 years (SD= 12.9) Study 2: N/A

		Study 2: psychologists and psychotherapists (50)	1% other genders	
7	Levinson et al., 2021	Eating Disorder Patients (34)	91% female	M=34.52 (SD=11.11)
8	Levinson et al (2018)	Eating Disorder Patients (66) with comorbid disorders such as Anxiety disorder (41), Depressive Disorder (38), OCD (13) and PTSD (7)	97% female	M= 24.98 (SD= 7.31)
9	Piccirillo and Rodebaugh (2022)	Midwestern University Community, Social Anxiety Disorder and Major Depressive Disorder (35)	100% female	M =21.37 years (SD =5.20)
10	Yang et al. (2018)	Pennsylvania State University and surrounding community, no specified mental illness	50% female	M =47.10 (SD=18.76)

Effectiveness and Feasibility

Table 4 summarises key findings from selected studies, including feasibility and effectiveness of the findings. Most studies used contemporaneous and temporal networks (n = 6), while some incorporated group-level networks for comparison (*n* = 4). Two studies used the person-specific latent factor approach instead of networks. Many treatment recommendations were tailored to the symptoms with the highest centrality or mean level (*n* = 5). One study suggested utilizing impulsive response analysis to improve treatment options (Yang et al., 2018).

Overall, all 10 articles found a huge variety in symptom presentation for mental illness and concluded that nomothetic investigations would not be able to explain for all the variances. Levinson et al. (2018) noted variability in both symptom presentation and treatment response. Klintwall et al. (2021) found the PECAN to be a good substitute for longitudinal ESM data and case conceptualization. Treatment targets varied based on the data collection method (i.e., ESM or case conceptualization) and symptom severity differed across individuals (*n* = 2). For example, Kaurin et al. (2022) found negative affect is not a suicide risk factor for some. Levinson et al (2021) suggested many potential therapeutic targets (in the example, 13-22) without one being more influential than the others. Yang et al (2018) found a temporal relationship between daily emotional experiences and interpersonal behaviours.

Individualised treatments were generally effective and described to have high potential in the future (N=3). Some studies noted that the detail needed to establish personalised therapy would likely be overlooked in generalised therapy and nomothetic research (N=4). Fisher et al (2019) evaluated person-specific treatment with an average Hedge's g effect size of 1.62 and an effect of g=0.17 per session. These results were stable in a six-month follow-up. Fisher & Boswell (2016) had promising effect sizes, with example client Peter improving in post-treatment assessment and being less anxious and depressed. However, Mary was less depressed but more anxious in the post-treatment condition.

Feasibility varied, with a large portion of participants who did not meet inclusion criteria in most studies (N=4), reducing the quantity. Fisher et al. (2017) had an 81.6% completion rate, and Fisher et al. (2019) had a 56% completion rate. Klintwall et al. (2021) had a 36% completion rate, and Kaurin et al. (2022) could only include 62% of the participants. Levinson et al. (2018) had a 73% compliance rate and an average of 7.28 missed observations (out of 28).

Table 4

Effectiveness and Feasibility of included studies

	Author (year)	Types of Networks	Personalised Treatment recommendation base	Findings	Feasibility	Effectiveness
1	Burger et al. (2022)	- 3 networks per participant - One based on Case Conceptualization - One based on EMA data - One based on Integration of Case Conceptualization and EMA	-Recommendations are targeted on the top two central symptoms per network - Between the three types of networks, the most central symptoms varied	- showed that each approach generated different results and impacted the personalised treatment targets - showed how to integrate EMA data and case conceptualization	N/A	- this approach of combining case conceptualization and EMA data provided more effective algorithms than using either of these methods alone
2	Fisher & Boswell, 2016	N/A	- have developed the dynamic assessment treatment algorithm (DATA), for selecting and ordering treatment modules	- two case examples, Peter and Mary - Peter: there is a co-occurrence of MDD and GAD given - Mary: factor for depression driven by	- 13 (65%) out of 20 participants completed treatment	<u>Peter:</u> - HDRS: decrease of 5 points, from 13 to 8 points - HARS: decrease of 7 points, from 13 points to 6 points

			- selection of treatment modules were targeted toward symptoms with the highest mean level	anhedonia, showed a moderate, positive correlation with anxiety		Mary: - HDRS: decrease of 10 points, from 17 points to 7 points - HARS: increase of 2 points, from 9 to 11 points
3	Fisher et al. (2017)	Individual networks: 1. Contemporaneous concentration network at Time *t*, 2. directed network for lagged relationships between *t* and *t*+1, and 3. residual concentration network at Time *t*+1 Group networks: - contemporaneous concentration & temporal networks	- highlighting the possible utility of positive mood as an influential treatment target	- great heterogeneity between participants - Nomothetic approach not able to display heterogeneity - results emphasize importance of positive affect in distress syndrome - simultaneously underline “anger” as a potentially primary experience in mood and anxiety	- 148 participants were recruited - only 49 individuals (33%) met inclusion criteria - 40 participants (81% of 49) finished the study - mean number of observations was 130.43 (SD = 19.27)	- potential to revolutionize the classification and assessment of mood and anxiety psychopathology - individualised treatment as a promising strategy for enhancing the effects of psychotherapy

4	Fisher et al. (2019)	N/A	- based on symptom predominance - established through the explanatory power of identified factors, both within (P-technique) and across time (dynamic modeling)	- the primary outcome measure for the study – was 8.03 points, with an average Hedge's g effect size of 2.33, for the treatment completers - the expert panel performed 3.25 points better than the algorithm on the HRSD	- 57 out of 174 individuals met the inclusion criteria - 40 began treatment - 7 participants dropped out during treatment; 32 participants were included in the study - 21 returned for six-month follow-up assessments	- the HRSD effect was g=0.24/session for treatment completers - HARS average change: 9.22 points - average Hedge's g = 1.62 → effect of g=0.17/session - Treatment effects stable at six months follow-up
5	Kaurin et al. (2022)	- Used Gimme and uSEM frameworks to make individual, group and subgroup networks - Individual Networks show contemporaneous	- targeting the most predictive risk factors for a given individual - "each personalised network invites comprehensive analyses and interpretations, just	- reasons for suicidality are highly idiosyncratic - even negative affect is not a relevant risk factor for everyone	- originally 153 individuals with BPD were included - 58 participants did not meet criteria	- crucial pieces of information would be missed if only general risk factors at the population level would have been applied

		effects and lagged effects	as is commonly done in therapy”	- absence of shared paths related to suicidal ideation across individuals or even subgroups or similar patterns	- resulted in a sample size of *n* = 95 (62%)	
6	Klintwall et al. (2021)	- created Perceived Causal Problem Networks	“In free-text questions, psychotherapists could decide for potential treatment targets and propose an intervention or state which information was missing for them”	- the networks were rated to contain on average 47% of the information typically collected during an assessment phase in therapy	*Study 1:* - 992 individuals were recruited - 36% (n = 355) completed the full questionnaire - 124 were excluded - final sample consisted of 231 respondents *Study 2:* N/A	utility rating: M=4.2 (SD= 1.2) - 89% of psychotherapists saw it as a basis for discussion together with the client - no sufficient reliability yet - not evaluated for validity

7	Levinson et al. (2021)	- contemporaneous and temporal networks for both a 15 symptoms and eight-symptom networks using graphicalVAR package in R	<u>Temporal Targets:</u> - Focus on Two symptoms identified via out-strength - possibility to focus on in-strength symptoms <u>Contemporaneous Targets:</u> - Focus on the two strongest contemporaneous symptoms	- symptom profiles were highly heterogeneous - found between 13–22 different treatment targets	N/A	- Hypothesis: specific central symptoms as treatment targets → effective for shorter treatment - tailoring of treatment to focus on different aspects of weight and shape concerns in different individuals
8	Levinson et al. (2018)	- Three group-level networks (temporal, contemporaneous and between-subjects) - temporal and contemporaneous VAR networks for three individuals	- target specific maintaining symptoms - possibility that intra-individual network analysis is useful to identify severe symptoms as treatment targets	- “desire for thinness” might be a maintaining role for EDs within individuals and across time - EDs are heterogeneous in symptom presentation and treatment response	- average compliance was 73% - average number of observations missed is 7.28 (SD = 6.97) out of 28 observations	N/A

9	Piccirillo and Rodebaugh (2022)	- Temporal VAR models - contemperanous networks - also made group level networks for comparison	- targeting depressed mood → more effective than focusing on anxiety or related factors - combination of skills targeting depressed mood and skills targeting loneliness → higher impact	- high heterogeneity in symptoms relations for each woman with comorbidity - depressed mood, feeling lonely, and feeling calm had the highest expected influence	N/A	- personalised EMA feedback could improve outcomes from standard psychological interventions
10	Yang et al. (2018)	- Socio emotional Networks and Recovery Time - lagged and contemporaneous network - Temporal Networks	- clinicians can discover maladaptive feedback loops and design a targeted treatment plan - impulse response analysis could be used to compare potential efficiency of different treatment plans	- individuals with longer recovery times had higher overall level of depressive symptoms → even after controlling for recent life events	- on average, 427.4 observations (SD*T* = 145.7, Range = 88 to 869) during 422 measurement burst periods (of a possible 450, because of some sample attrition).	N/A

Note HARS = Hamilton Anxiety Rating Scale; HDRS = Hamilton Depression Rating Scale; ED = Eating Disorders

Discussion

This scoping review outlines the available research on personalised treatment options based on person-specific networks. Ten articles were included that studied different ways of individualised interventions. These articles examined several participant-, study-, and intervention-related factors, as well as the feasibility and effectiveness of the treatment.

Regarding the first research question about study characteristics, the following evidence can be presented: Two thirds of the articles were conducted in the United States. The other two studies are from Sweden and the Netherlands. Therefore, personalised treatments are mainly represented in western, individualistic countries. This implies an increased interest in personalised therapy for these cultures. Indeed, there is evidence of a growing demand for tailored mental health treatment in Western countries (Insel, 2009). This may be due to several factors. This includes an increased focus on the importance of addressing individual differences in treatment response and a growing awareness of the limitations of more traditional, one-size-fits-all approaches to therapy (Piccirillo & Rodebaugh, 2019; Bosley et al., 2016). Besides, this could lead to an increased interest in the future.

For the second question, information about the study populations was gathered. A variety of disorders were investigated with a focus on eating disorders, depressive disorders, and anxiety disorders. Often this was done with a focus on comorbidity. This suggests a demand for a shift in treatment for comorbid disorders. So far, treatment for comorbid disorders has been unsuccessful, and a shift in perspective could lead to more appropriate treatments (Köhne & Isvoranu, 2021). This demand created a research gap, which was explored by these researchers with a personalised approach. Furthermore, it stands out that most participants in the experiments are female. It is worth noting that studies on mental illness, interpersonal and emotional problems primarily include women. A reason for this could be that women are more likely to seek out health care facilities than men (Samulowitz et al., 2018). This might explain the overrepresentation of women, as they were likely more compliant, resonated more with the issue and hence agreed to participate.

The third research question addressed the method of variable selection for the networks. Some studies decided in cooperation with the clients and/or therapists. Often, the variables with highest centrality or means were included in the construction of the network. The heterogeneity of approaches suggests that there is no standard method for variable selection in networks. Instead, the network approach is used to establish a hypothesis which can be tested with the most fitting model (Bringmann, 2021). Further, this suggests that researchers were trying different approaches to gain insight into diverse methods and perspectives. It is possible that alternative statistical outcomes can be obtained from the same basic data set (Bastiaansen et al., 2020). Furthermore, the variability of variable selection influences the decision of treatment targets. For example, in one study 13-22 different treatment targets were found which were all equally significant (Levinson et al., 2021). In conclusion, there is a huge variety of methods for variable selection. So far, it is not known if certain methods of selection generate more significant results than the other. Likewise, this difference in variable selection has an influence on treatment target selection and could therefore influence treatment efficacy.

This relates to the fourth question about the effectiveness of personalised treatments. Within this study's sample, there was a widespread view that individualised treatment based on person-specific networks are potentially effective. Two studies (Fisher & Boswell, 2016; Fisher et al., 2019) addressed that through the individual approach, they could determine well what should be worked on during therapy and demonstrate positive results. This implies that there is a positive effect on treatment outcomes through personalization. Nonetheless, it might be difficult to establish correct effect sizes due to the complexity of measuring treatment results. This may explain why most research in this review, did not determine impact estimates for their proposed therapies. Additionally, it is advised to focus on an individual's treatment goals rather than the evaluation of symptoms to determine therapy progress (Lindhiem et al., 2016). Through case conceptualisation, the client and therapist may explore the issue and its corresponding goal. This information is then helpful for developing the most efficient therapy.

The last question is about the feasibility of personalised treatments based on person-specific networks. Some studies had good compliance rates and a high average number of observations. This suggests that these participants were motivated and filled out their daily surveys diligently. This is supported by Frumkin et al. (2021) who states that clients often reacted positively to ESM despite it being burdensome. Others had less than 50% of study completers. This suggests that the participant burden might have been too high in these studies. Vachon et al. (2019) found that on average the compliance rates for ESM studies are around 78.7% and retention at 93.1%. There are some factors which influence the compliance rates in ESM studies. For example, people who experience psychosis, struggle more to keep up with an ESM study. This relates to some studies which had excluded participants with mania or psychosis symptoms and had a completion rate of 80-81% (Fisher et al., 2017; Fisher et al., 2019). Further, it is advised to plan the study over a longer period with less observations per day (Vachon et al., 2019). This relates to Kaurin et al. (2022) who had six ESM queries per day and only 62% of completers. In conclusion, feasibility is connected to the design of the ESM study and the characteristics of the target group. Overall, personalised treatment based on person-specific approaches can be feasible but needs to adhere to a set of regulations.

Limitations

This research has certain drawbacks. The first one being that there is no inter-rater reliability of this scoping review. The selection and data extraction of articles is a subjective process, hence reviews are usually done by at least two people. When two or more researchers work on one review it is more likely that all relevant records for the study can be identified (Stoll et al., 2019). Therefore, there is a possibility that important articles might have been missed. In the same vein, this scoping review can only draw limited conclusions about the effectiveness of personalised treatments. There were only two articles who presented results with comparable effect sizes. There is a possibility that more articles which covered this were missed in the selection process in ASReview. Due to the categorisation algorithm of ASReview, some articles might have been unintentionally missed. However, according to van de Schoot et al. (2021), this is unlikely because researcher fatigue often leads to a higher rate of exclusion than working with ASRreview. In addition to this, an Excel file from ASReview was downloaded to check for unnoticed important articles. Since this was not the case, it is likely that all relevant articles from this search have been included.

Lastly, gray literature was excluded. Gray literature is defined as documents which are not published in academic journals or books (Godin et al., 2015). Often there is a considerable time gap between conduction of research and publishing it in a peer-reviewed journal. In some cases, the research never gets to be published formally. Therefore, excluding gray literature might result in a publication bias (Godin et al., 2015). However, the decision to include only peer-reviewed publications was made to ensure the validity of this review. Articles that have been peer-reviewed can ensure a scientific quality (Ali & Watson, 2016) that would have been difficult to establish and maintain with the usage of gray literature.

Recommendations for Future Research

Personalised treatment based on person-specific approaches is still a developing research domain, therefore, there is a lot which can be explored in the future. Often, the treatment targets were the symptoms with the highest centrality even though centrality as a metric has been questioned for its validity (Wichers, 2021; Bringmann et al., 2022;

Bringmann, 2021). Therefore, it might be worth looking into treatment targets which have more scientific evidence.

Another recommendation is looking into ways how to make person specific networks more usable in mental health care. One proposal is to standardise the process of creating person-specific networks. For example, that everyone uses the same method of variable selection or that there are only limited options available. There are some issues within the network theory domain for example the boundary specification problem. This describes the issue to form a decision which nodes should be included within a network (Neal & Neal, 2021). In theory, a network should include all nodes which relate to a population. This can lead to complications how to decide for “important” nodes. Since this approach is impractical, perhaps future study should focus on how this choice can be made more feasible and which factors merit the most attention within a network.

Furthermore, for more exact data about efficacy, larger-scale research is required. This might be accomplished, for instance, by Randomised Controlled Trials (RTCs). These are the initial steps towards individualised treatments, and while they appear promising, more research is advised.

The last recommendation is to develop more person specific networks for different target groups. For example, in countries with more collectivistic cultures or for children. There is already some interest taken for network theory in more collectivistic countries (Choi et al., 2015; Huang et al., 2023). Nonetheless, this can be deepened in future research.

In general, personalised therapy solutions are still in their early stages and should be explored more in the future.

Conclusion

In conclusion, this study provided evidence that personalised treatment recommendations based on network analysis methods have the potential to revolutionise the classification and assessment of mental health psychopathology and enhance the effects of psychotherapy. While there are challenges to developing personalised treatment recommendations, the potential benefits of tailoring psychological treatments to the specific characteristics of individual patients are promising. Lastly, the future and development of personalised treatments based on person-specific networks will rely upon its ability to add value to mental healthcare facilities. This scoping review provided a valuable starting point for informing future researchers about the possibilities within this research area. Likewise, it was intended to show challenges, opportunities, downsides, and advantages to encourage future research pathways in this domain.

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Appendix

Table 1

The different search strings for each database are displayed. They are constructed by a combination of keywords and Boolean operators

Search String Scopus à 146 results
(“person-specific network” OR “individual network”) AND (“treatment” OR “intervention” OR “therapy” OR “counselling”) AND (“variable” OR “node”) AND (psychopath* OR “mental illness” OR “mental health”)

Search String PsycINFO à 90 results
(“person-specific network” OR “individual network”) AND (“treatment” OR “intervention” OR “therapy” OR “counselling”) AND (“variable” OR “node”) AND (“psychopath*” OR “mental illness” OR “mental health”)
Search String Wiley Online Library à 100 results
(“person-specific network” OR “individual network”) AND (“treatment” OR “intervention” OR “therapy” OR “counselling”) AND (“variable” OR “node”) AND (“psychopath*” OR “mental illness” OR “mental health”)