Network analysis studies in patients with eating disorders: A systematic review and methodological quality assessment

Network analysis studies in patients with eating disorders: a systematic review and methodological quality assessment

Giuliano Tomei[1], Maria Francesca Pieroni[1], Elena Tomba[1]

[1] Department of Psychology, University of Bologna, Bologna, Italy

Authors contribution: All three authors equally contributed to the conceptualization and to define the methodology of the work. G.T. and M.F.P. curated the writing of the original draft, while E.T. curated the supervision, revising and editing of the original and revised version of the document.

Conflict of interest: No author has any conflict of interest to declare.

Funding: None

Data availability statement: Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Corresponding Author:

Elena Tomba, Ph.D.

Department of Psychology, University of Bologna, Bologna, Italy

Viale Berti Pichat 5, Bologna, 40122

E-mail: elena.tomba@unibo.it

Keywords: systematic review, network analysis, network models, eating disorders, study quality assessment, anorexia nervosa, bulimia nervosa, binge eating disorder, otherwise specified feeding and eating disorder

ABSTRACT

Introduction: Network psychometrics has been enthusiastically embraced by researchers studying eating disorders (ED), but a rigorous evaluation of the methodological quality of works is still missing. This systematic review aims to assess the methodological quality of cross-sectional network analysis (NA) studies conducted on ED clinical populations. **Methods:** PRISMA and PICOS criteria were used to retrieve NA studies on ED. Methodological quality was evaluated based on 5 criteria: variable-selection procedure, network estimation method, stability checks, topological overlap checks, handling of missing data. **Results**: 33 cross-sectional NA studies were included. Most studies focused on populations that were female, white and, with an anorexia nervosa (AN) diagnosis. Depending on how many criteria were satisfied, 27.3% of studies (n=9) were strictly adherent, 30.3% (n=10) moderately adherent, 33.3% (n=11) sufficiently adherent, 9.1% (n=3) poorly adherent. Missing topological overlap checks and not reporting missing data represented most unreported criteria, lacking respectively in 63,6% and 48.5% of studies. **Conclusions:** Almost all reviewed cross-sectional NA studies on ED report those methodological procedures (variable-selection procedure, network estimation method, stability checks) necessary for a network study to provide reliable results. Nonetheless these minimum reporting data require further improvement. Moreover, elements closely related to the validity of an NA study (controls for topological overlap and management of missing data) are lacking in most studies. Recommendations to overcome such methodological weaknesses in future NA studies on ED are discussed together with the need to conduct NA studies with longitudinal design, to address diversity issues in study samples and heterogeneity of assessment tools.

(250/250 words)

INTRODUCTION

Eating disorders (ED) represent a complex category of psychiatric conditions, characterized by heterogeneous presentations (Smith et al., 2018; Wildes et al., 2011), diagnostic migration and comorbidity (Castellini et al., 2011), and high rates of residual diagnoses and symptoms (Tomba et al., 2019). Additionally, there is scarce knowledge of prognostic indicators and predictors of clinical outcomes (Linardon et al., 2017). Recently a large number of studies turned to network analysis (NA) to explore EDs at symptom level, in an attempt to tackle their intricacies (Levinson et al., 2018; Smith et al., 2018).

The conceptual basis of NA, that is the representation of psychiatric conditions as a constellation of interacting symptoms (Borsboom 2017), seems particularly relevant to study EDs, allowing researchers to model eating disorders as they present in everyday clinical practice (Treasure et al., 2020). In general, NA is an ensemble of statistical tools which can be applied in a variety of disciplines (Barabási, 2011; Newman et al., 2010; Zweig, 2016) and studies dynamic interactions between phenomena through modelling of networks. These networks are composed of units called *nodes*, representing a variable of choice, which are connected by *edges* (or *links*), representing the pairwise interactions between the nodes. In psychopathology, NA has been proposed as a framework to conceptualize psychological constructs: personality, intelligence, and mental disorders are framed as complex systems of interacting variables (Costantini et al., 2015; Schmittmann et al., 2013). Through its granular level analysis, NA allows to differentiate symptoms in terms of clinical relevance, rather than considering them equivalent indicators of an underlying disorder, and also allows to describe how they influence and reinforce each other (as postulated by many psychopathological theories of specific disorders) beyond diagnostic categories (i.e., to explain psychiatric comorbidities).

Since its development in the second decade of the 2000's, NA in psychopathology has been rapidly evolving to overcome its limitations, assuage doubts about the methodology (McNally, 2021) and answer the specific needs of clinical research (i.e. studying treatment effects), as well as to integrate latent variable models (Blanken et al., 2019; Haslbeck, Borsboom, & Waldorp 2019; van Bork et al., 2021; van Borkulo et al., 2017; Waldorp & Marsman 2020). The sudden burst in popularity of NA in psychopathology resulted in a high number of studies published in a relatively short amount of time developing different models of networks (i.e. cross-sectional and temporal networks) from different kinds of data and methodological approaches.

Within this context groups of NA experts were encouraged to publish a list of reporting guidelines and standards for studies using cross-sectional (Burger et al., 2022) and temporal (Blanchard et al.,

2022) networks, to reduce inhomogeneity and clarify which study procedures and results should be reported when adopting the psychological network approach.

These guidelines mainly cover technical issues and list study elements which are pivotal in critically reviewing a network study from a methodological perspective. Due to the technical nature of these guidelines, though, some of the proposed aspects might not be of immediate relevance for clinicians, or might not be readily accessible to an untrained audience. On the other hand, Burger and colleagues (2022) rightly highlight how the identification of objective reporting standards for network analysis studies represents a fundamental contribute towards improving the quality of empirical network studies. Study quality itself may maximize the validity of study findings and it can be defined as the degree to which researchers conducting a study have taken all appropriate steps (Khan et al., 2011). The validity of a study in turn is closely related to the generalizability of its results: the precision with which a study identifies a psychological construct is linked to its applicability on the broader population sharing those specific psychological characteristics (Yarkoni, 2021). Therefore, making these shared reporting standards explicit and accessible as much as possible should facilitate the quality assessment of network studies, with a positive effect on translatability and reproducibility of their results.

In their recent systematic review on NA studies on ED populations, Monteleone and Cascino (2021) reported the most important symptoms, the nodes connecting groups of symptoms, and the prognostic value of network nodes. However, the authors did not include a methodological quality assessment of the works selected. Because of missing evaluation of study quality, it is difficult to assess the reliability of the NA study results on ED considered in their review limiting the possibility of confidently translating NA studies results into clinical practice.

Thus, the aim of the following systematic review is to evaluate the quality of NA studies on clinical populations with ED. This will be accomplished using a selection of the recently published best practices for reporting standards of cross-sectional NA studies by Burger et al. (2022). The rationale guiding the selection process was to identify and extrapolate in a structured way those aspects of NA methodological procedures which may represent the optimal balance between clinical relevance, methodological rigor and accessibility by non-experts. Through this work we aim to further support the appropriate interpretation of this novel approach in ED research as well as promote its potential, in addition to promoting NA results among clincians and researchers who might not have technical knowledge of NA methodology.

METHODS

Information sources and searches

The following review has been developed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-analysis guidelines (Moher et al., 2009). A publication date limit was set between March 2020 and July 2022; Medline and EBSCO PsycINFO databases were searched for published peer-reviewed scientific works, using the following combination of keywords and Boolean operators: "*network analysis" AND ("eating disorders" OR "disordered eating" OR "feeding disorder" OR "anorexia nervosa" OR "bulimia nervosa" OR "binge-eating disorder" OR "binge eating")*. Titles and abstracts were screened by two authors independently (M.F.P. and G.T.). Articles that appeared potentially relevant were retrieved and reviewed by M.F.P., and G.T. who independently assessed each of the full reports, arriving at a consensus regarding eligibility. When disagreements between the two authors arose, multiple rounds of full-text revision and discussions were done until consensus was reached, with the involvement of the third author (E.T.) when needed.

Eligibility criteria and data extraction

Eligibility criteria and data extraction were based on ED clinical population and study methods (i.e. application of psychological cross-sectional NA) (Centre for Reviews and Dissemination 2006). Studies presenting NA of ED symptoms and symptoms from comorbid disorders in ED clinical populations were deemed eligible. For a more detailed breakdown of Population, Intervention, Comparison and Outcomes (PICOS) (Centre for Reviews and Dissemination, 2006) criteria see Table 1. Eligible works were redacted in English and were selected for inclusion if the sample was composed of eating disorder patients evaluated with DSM IV-TR or DSM 5 (APA, 2000, 2013) in any study design and setting where NA was applied to estimate cross-sectional network models. During the electronic search, studies were excluded for the following reasons: the ED diagnosis was established uniquely through self-report instruments, participants received a diagnosis of clinically relevant obesity only, the sample was composed of medically ill patients with pathologies not related to ED, the study sample was composed of mixed clinical and non-clinical populations, Bayesian, temporal or non-psychometric network analysis was applied (i.e. social network analysis, neural networks, gene networks), the source was a review, opinion statement, meta-analysis, book, case study or progress report. Remaining studies received full-text review to determine the final selection. Data extraction was performed independently by two of the authors (G.T. and M.F.P). The authors followed the PICOS pre-set extraction criteria, see Table 1. Disagreements on inclusion were solved as in eligibility assessment. Data extracted regarding general studies' characteristics included: demographics (age, gender distribution, race, socioeconomic

status), sample size, diagnostic distribution of the samples, study design, ED clinical features included in the network and measurements. The studies included in the final selection were then grouped and discussed based on the outcome of the quality assessment.

Table 1. PICOS criteria.

Quality assessment

To assess the methodological quality of the studies included, the reporting guidelines and standards for cross-sectional psychological NA studies proposed by Burger and colleagues (2022) were considered. In their paper, Burger and colleagues (2022) organize the reporting guidelines and standards in two main categories: one pertaining the methodology and the other the results section of NA studies. Each section is further divided in three sub-sections covering: 1) ***General Analysis Routine*** reporting standards shared across all applications of cross-sectional NA models, regardless of the research question or study design; 2) ***Analysis-specific routine*** reporting standards pertaining to specific research questions and methods; 3) ***What to watch out for*** general considerations which Burger and colleagues (2022) include in multiple parts of their work. Such considerations are important when reporting network studies on psychological data and are more closely related to interpretation and validity of NA studies.

Among these reporting standards, five were selected to assess the methodological quality of the studies included in this review. Specifically, three were selected from the *General Analysis* section (both from Methods and Results subsections): (a) *Variable selection procedure*, (b) *Network estimation method*, (c) *Results of accuracy and stability checks*. The remaining fourth and fifth reporting standards were taken from the "*What to watch out for"* box A and box B respectively and include: (d) the need to control for *topological overlap* of variables included in the analyses, (e) *presence and handling of missing data*.

The rational that guided this selection was to include those NA reporting standards common to all studies adopting the network approach and which represent the optimal balance between methodological rigor, clinical relevance and accessibility to non-experts. Moreover, additional criteria other than the five above were excluded because they evaluate aspects of study design or NA methodology which are not necessarily shared across all NA studies. Therefore, they are more focused on the quality assessment of the nature of the NA research question rather than on NA study methodological robustness. More specifically, the reporting standards (a), (b), and (c) were selected

because of their importance in any NA study, irrespectively of the design or research question. Those three criteria represent the basic foundation of applying network psychometrics and are the key information around which the most prominent NA tutorial papers revolve (Epskamp et al., 2018a; Hevey et al., 2018), as well as being present in recent guidelines on other network methodologies (Blanchard et al., 2022). These three elements have to be provided for a network study to be interpretable and methodologically acceptable. In particular:

a) *Variable selection procedure* informs on what the theoretical background is and the construct being analyzed, as validity of network studies depends on the theoretical assumptions guiding the selection of variables from which the network will be built;

b) *Network estimation method* indicates what the methodology (the estimation function) used to recover the network structure was;

c) *Results of accuracy and stability checks* inform whether the results (*in particular in term of value of the* network stability coefficient) can be generalized, as interpretability and generalizability of a network is dependent upon its stability.

The reporting standards (d) and (e) were selected among the general considerations that Burger and colleagues (2022) indicated more as interpretation guidelines than methodological reporting standards. Similarly, to criteria (a), (b) and (c), these two aspects were selected because of their relevance no matter the research question or the network analysis methodology applied, and by virtue of the considerable influence they exert on the quality and validity of the results (Borsboom et al., 2021). Failing to report criteria (d) and (e) may indeed potentially become a source of misinterpretation of the obtained network structures and impact their clinical relevance of the results. In particular, (d) topological overlap is the presence of overlapping variables, which measures at least partially the same construct within a single network. Topological overlap constitutes an important risk of bias in network studies, as it alters the network structure independently from the real data observed. Information on whether steps were taken to remove or minimize the impact of topological overlap, or if present to what extent it influences the network structure should be immediately accessible to the reader. The declaration of (e) *presence and handling of missing data* is also important because the presence and trends (i.e random vs. systematic) of missing data is a critical piece of information, as systematic missingness can hint at study design issues and determine problematic inferences with significant impact on the conclusions drawn from the NA study results.

For each of the 5 reporting standards specific criteria were extracted. For details see Table 2. Depending on how many of the 5 reporting standards were included in each study, an overall quality methodology score was assigned. Specifically, each study was defined as either strictly adherent (satisfying 5 out 5 criteria), moderately adherent (satisfying 4 out 5 criteria), sufficiently adherent (satisfying 3 out of 5 criteria) or poorly adherent (satisfying 2 or less out of the 5 criteria). Data on methodological quality extraction was performed independently by two of the authors (G.T. and M.F.P.). When disagreements between the two authors occurred, multiple rounds of full-text revision and discussions would be done until consensus was reached, with the involvement of the third author (E.T.) if necessary. During the actual process of assigning methodological quality scores, no disagreement arose between the authors (G.T., M.F.P., E.T.), as each criterion was selected considering whether its presence can be objectively verified. The presence of each of the five criteria in a scientific work can be easily assessed by reading the work itself, leaving little to no room for ambiguity: either a procedure is reported, thus meeting the quality criteria, or it is not. Data on methodological quality extraction and total score assigned to individual studies are also reported in full in Table 3.

RESULTS

Selection of articles and study characteristics

The search yielded 107 records after removal of duplicates. The abstract screening led to the exclusion of 39 articles. The full text of the remaining 65 articles and 3 dissertations were assessed, leading to the exclusion of an additional 35 articles. The remaining 33 articles were thus included in the review (Brown et al., 2020; Calugi et al., 2020, 2021, 2022; Cascino et al., 2019; Chen et al., 2022; de Vos et al., 2021; DuBois et al., 2017; Elliott et al., 2020; Forrest et al., 2018, 2019; Goldschmidt et al., 2018; Hagan et al., 2021; Hilbert et al., 2020; Kerr-Gaffney et al 2020; Levinson et al., 2017; Mares et al., 2022; Meier et al., 2020; Monteleone et al., 2019, 2020, 2021, 2022; Olatunji et al., 2018; Ralph-Nearman et al., 2021; Schlegl et al., 2021; Smith et al., 2019; Smith et al., 2020; Solmi et al., 2018, 2019; Vanzhula et al., 2019; Vervaet et al., 2021; Wang et al., 2019; Wong et al., 2021). See figure 1 for the flowchart of the selection process, including reasons for exclusion at each step.

Figure 1. Selection of studies: PRISMA flowchart.

Socio-demographic information

Twenty-one (63.7%) studies included a mixed age sample (12-67 years). Seven (21.2%) studies examined exclusively adults and four (12.1%) studies examined exclusively children/adolescents. One (3.0%) study did not specify age range of the sample (Chen et al., 2022), thus it is not possible to isolate specific age groups (children, adolescents, adults) involved in the study. For more details, see Table 3.

No study explicitly reported considering differences between sex assigned at birth and gender. The majority of studies (n=19; 57.6%) did not use any specific terminology hinting at whether sex or gender was considered, whereas 4 (12.1%) studies used the term "sex" and 10 (30.3%) used the term "gender". Regarding the range of options available to respondents for gender/sexual identity, only 3 studies (Hagan et al., 2021; Meier et al., 2020; Wong et al., 2021) reported including a nonbinary option. Nine (27.3%) provided only two options, "female" and "male", while in 18 studies (54.5%) the range of alternatives provided was not presented, as "female" was an inclusion criterion for the study or only the percentage of female participants was reported. The remaining 3 studies did not include information regarding sex/gender. The majority of studies (N=22; 66.7%) reported including mixed samples, with a high majority of females (67% - 97.8%), while six (18.2%) studies included female participants only. Five (15.1%) studies did not report the male:female ratio of participants. For details and references, please see Table 3 and Table 4.

Fourteen (42.4%) of the 33 studies included reported race composition of the study sample, all examining predominantly white/Caucasian individuals (range: 69.4% - 96%). The remaining 19 (57.6%) studies did not include information on race composition of their study sample. More details on race reporting are available in Table 3 and Table 4.

The socio-economic status of participants was reported by 11 studies (33.3%). The most frequent indicator used was educational level, in terms of degree obtained (3%) or years of education (7%), followed by employment status, reported by one study (3%). Of the eleven studies reporting socio-economic status, three (9%) included both educational level and employment status. For details, see Table 4.

Sample size

Ten (30.3%) of the studies included a sample of more than 600 participants. Twelve (36.4%) studies included between 200 and 600 participants, while eleven studies (33.3%) built networks from less than 200 participants. For details and references, please see Table 3.

Diagnostic distribution of the samples

The selected studies have been divided by diagnostic group from which networks were built. Studies building different networks for different diagnostic categories are thus reported multiple times, depending on how many diagnosis-specific networks were included in the article. Eighteen (54.5%) of the 33 studies included built networks from participants with AN. Eight studies (24.2%) built networks from participants with BN. Five studies (16.1%) built networks from participants with BED. Two studies conducted networks from participants with Other Specified Feeding or Eating-Disorder (OSFED). Two (6.4%) studies ran networks from a mixed population with AN or BN. Finally, fourteen studies (42.4%) built networks from a mixed eating disorder clinical population sample, from here referred as transdiagnostic sample (TD). See Table 3 for details.

Study design

Among the 33 reviewed studies, six studies (18.2%) modelled cross-sectional networks from data obtained at different time points (i.e. pre- and post- treatment) and compared them, therefore adopting a longitudinal study design (Brown et al., 2020; Calugi et al., 2022; Elliott et al., 2020; Mares et al., 2022; Monteleone et al., 2022; Smith et al., 2019). The remaining 27 studies (81.8%) applied a cross-sectional study design (Calugi et al., 2020, 2021; Cascino et al., 2019; Chen et al., 2022; de Vos et al., 2021; DuBois et al., 2017; Forrest, et al., 2018, 2019; Goldschmidt et al., 2018; Hagan et al., 2021; Hilbert et al., 2020; Kerr-Gaffney et al., 2020; Levinson et al., 2017; Meier et al., 2020; Monteleone et al., 2019, 2020, 2021; Olatunji et al., 2018; Ralph-Nearman, et al., 2021; Schlegl et al., 2021; Smith et al., 2020; Solmi et al., 2018, 2019; Vanzhula et al., 2019; Vervaet et al., 2021; Wang et al., 2019; Wong et al., 2021). Twenty-five studies (75.7%) used network analysis as the primary data analysis procedure, involved treatment seeking patients and were uncontrolled (Brown et al., 2020; Calugi et al., 2020, 2021, 2022; Cascino et al., 2019; Chen et al., 2022; de Vos et al., 2021; DuBois et al., 2017; Forrest et al., 2018, 2019; Goldschmidt et al., 2018; Kerr-Gaffney et al., 2020; Mares et al., 2022; Meier et al., 2020; Monteleone et al., 2019; Monteleone et al., 2020, 2021; Olatunji et al., 2018; Schlegl et al., 2021; Solmi et al., 2018, 2019; Vanzhula et al., 2019; Vervaet et al., 2021; Wang et al., 2019; Wong et al., 2021). Results from the remaining eight (24.3%) of the 33 studies included in this review are based on secondary analyses of data (Elliott et al., 2020; Hagan et al., 2021; Hilbert et al., 2020; Levinson et al., 2017; Monteleone et al., 2022; Ralph-Nearman et al., 2021; Smith et al., 2019; Smith et al., 2020). For further details about the design of the studies, including the instruments used and whether network nodes were obtained by psychometric questionnaire subscales scores or single items, please see Table 3.

Assessment of methodological quality

Methodological quality total score

Nine studies (27.3%) were found to strictly adhere to all 5 criteria, 9 studies (27.3%) were moderately adherent (satisfying 4 out 5 of the criteria), 12 studies (36.3%) were sufficiently adherent (satisfying 3 out of the 5 criteria), and 3 studies (9.1%) poorly adherent (satisfying 2 out of the 5 criteria). See Table 3 for references.

In the 9 studies which were moderately adherent, the main unsatisfied criteria were not reporting for topological overlap control procedures (N=7; 21.2%), and not mentioning presence or exclusion from analyses of missing data (N=2; 6.1%). In those 12 studies found to satisfy the sufficient methodological quality criteria (score: 3/5), in all but one case the studies did not report presence and handling of missing data, and controlling for topological overlap. In only one case, a score of sufficient methodological quality was assigned on the basis of missing specific CS value and not evaluating topological overlap using standardized methods.

The three studies (9.1%) considered poorly adherent reported information on variable-selection procedure and a general evaluation of the stability, but either did not mention the exact CS values or did not include the specific network estimation method used. See Table 3 for references.

(a) Variable selection procedure

All 33 articles included in this work provided an explanation based on data from scientific literature or theoretical models in support for the rationale guiding selection of the nodes included in the networks prior to performing data analysis.

(b) Network estimation function

Thirty-one out of 33 (94%) studies reported applying network estimation functions which included glasso regularization (Friedman et al., 2008). Of these, 15 studies (45.4%) manually tuned the regularization/penalty applied to correlations (λ value) (Elliott et al., 2020; Forrest et al., 2018, 2019; Hagan et al., 2021; Hilbert et al., 2020; Kerr-Gaffney et al., 2020; Levinson et al., 2017; Olatunji et al., 2018; Ralph-Nearman et al., 2021; Schlegl et al., 2021; Smith et al., 2019, 2020; Vanzhula et al., 2019; Vervaet et al., 2021; Wang et al., 2019; Wong et al., 2021), while the remaining 16 (48.5%) derived the λ value using the Extended Bayesian Information Criterion glasso (EBICglasso; Chen & Chen 2005) (Brown et al., 2020; Calugi et al., 2020, 2021, 2022; Chen et al., 2022; de Vos et al., 2021; DuBois et al., 2017; Cascino et al., 2019; Goldschmidt et al., 2018, Meier

et al., 2020; Monteleone et al., 2019, 2020, 2021; Solmi et al., 2018, 2019). None of the studies included provided the rationale for deciding whether to apply glasso or EBICglasso or why it was considered necessary to apply a regularization technique. One (3%) article (Mares et al., 2022) derived the network structure from the data without regularization, by estimating a set of regularized networks and subsequently fitting un-regularized networks for each of these models, and finally performing a model selection procedure. Finally, one article (3%) did not report the specific network estimation function applied to retrieve the network model (Monteleone et al., 2022).

(c) Network stability coefficient (CS)

In this section we considered the individual CS of networks built for each ED clinical population in each study. As such, a study may appear multiple times if they developed multiple networks within the same study (i.e. baseline and one or more follow-ups, or groups comparison). To avoid confusion, please note that the following percentages of studies are referred to their respective diagnostic categories (AN, BN, BED, OSFED, TD). Concerning CS, we used as reference values those proposed by Epskamp and colleagues (2018) (acceptable CS ≥ .25; good CS ≥.5; excellent CS ≥.7).

In the AN networks included (N= 23), all the networks considered the stability coefficient following the guidelines proposed by Epskamp and colleagues (2018), however one (Goldschmidt et al., 2018) did not provide the specific value of the CS. Nine networks (39.1%) showed excellent CS coefficient (≥0.7; range: 0.7 - 0.81), nine networks (39.1 %) showed good CS coefficients (≥ 0.5; range: 0.52 – 0.67), and four networks (17.4%) showed acceptable CS coefficient values (>0.25; range: 0.28 – 0.44). In one study (4.4%), authors reported excellent CS coefficient but did not include the specific values.

Concerning CS of the eight BN networks considered, only one study (12.5%) reported a CS coefficient value reaching the excellence (≥ 0.7), threshold 0.81). Three studies (37.5%) reported good CS coefficient (≥ 0.5; range = 0.59 – 0.67), two studies (25.0%) reported adequate (≥ 0.25) stability coefficient values (0.28; 0.29). Two studies (25.0%) did report good CS coefficient values but did not include the specific values.

Concerning CS of 6 BED networks considered, two studies (33.3%) reported excellent (≥ 0.7) CS values (range: 0.74-0.75). Three networks (50.0%) showed good (≥ 0.5; range: 0.59- 0.67) CS coefficient values. One network (16.7%) showed acceptable CS coefficient (0.28).

Concerning CS of OSFED networks, one study (50%) reported good stability (CS=.52), while another study (50%) did not present the specific CS coefficient of the network, though it is reported by the authors as good.

Concerning CS of the 15 TD networks considered, six studies (40%) reported excellent (≥ 0.7) CS coefficient values (range: 0.75 – 0.75), five studies (33.4%) reported good (≥ 0.5) CS coefficient values (range: 0.52 – 0.67) and two (13.3%) reported acceptable (≥ 0.25) CS coefficient value (0.43-0.44). The two remaining studies (14.3%) did not report specific CS values. Individual CS coefficient for each study is available in Table 3.

(d) Topological overlap

Of the 33 studies included in this work, 12 (36.4%) explicitly mentioned checking for potential topological overlap of nodes and addressing it prior to modelling the network. The remaining 21 studies (63.6%) out the 33 included did not report checking for potential topological overlap of nodes or addressing it prior to modelling the network. For references, please see Table 3. Among the 12 studies which conducted checks for topological overlap, eleven (91.7%) did so using the goldbricker algorithm. The remaining study (8.3%) (Goldschmidt et al., 2018) did not explicitly mention applying the goldbricker algorithm, but did report collapsing items assessing importance of weight and importance of shape in individual nodes.

(e) Missing data management

Among the 33 reviewed articles, 17 (51.5%) reported missing data. Fifteen of these (88.2%) also discussed how missing data was managed (imputation or exclusion) (Brown et al., 2020; Calugi et al., 2020; Elliott et al., 2020; Forrest et al., 2018, 2019; Hagan et al., 2021; Hilbert et al., 2020; Meier et al., 2020; Schlegl et al., 2021; Ralph-Nearman et al., 2021; Smith et al., 2020; Smith et al., 2019; Vanzhula et al., 2019; Vervaet et al., 2021; Wong et al., 2021). The remaining 16 articles (48.5%) did not mention either presence nor absence of missing data in their studies. See Table 3.

Discussions

The aim of the present systematic review was to assess, for the first time, the methodological quality of existing literature on NA studies in clinical populations with ED. To achieve this goal, we proposed a customized quality assessment checklist based on the best practices for reporting standards in cross-sectional NA studies developed by Burger and colleagues (2022). In a relatively novel and emerging field such as NA, clinical professionals outside academia might not be familiar with the methods and interpretation of psychopathological networks. It is therefore important to provide an accessible yet relevant framework with which an untrained audience (clinicians and researchers alike) might interpret the data on psychological network studies in ED, and evaluate their methodological quality and potential validity for their clinical and research practice.

Considering the five selected methodological quality criteria, more than half of the studies included were strictly or moderately adherent to them while the remaining studies were found to report them sufficiently or, in a minor part, poorly. Therefore, in the wake of the rapid multiplication of studies applying NA, it is encouraging that almost all of the studies using NA in ED and reviewed here reported those basic criteria which are considered the minimum amount of data that must necessarily be provided for a network study to be both interpretable and be able to obtain reliable results. The minimum data include: reporting the theoretical rationale that guided the nodes selection, the network estimation method used and consider the magnitude of network stability coefficients. Nonetheless, when looking in more detail at how these criteria were reported, there are some aspects of implementation that require further consideration. Moreover, an even greater careful examination should be conducted of the other selected aspects of methodological quality (control for topological overlap and handling for missing data) that were found to not be considered by as much as half of the included NA studies on ED, at the detriment of interpretability and clinical applicability of their results. This represents a significant obstacle that must be overcome to translate NA studies on ED in meaningful data for clinical practice as other authors previously reported in NA studies in general (McNally, 2021).

Starting with the criterion of (a) variable selection procedure, all studies reported the rationale for selecting which variables to include in the network and provided a theoretical background of reference to interpret the results. However, the wide breadth of psychometric instruments applied in the NA studies reviewed makes it difficult to pool and interpret their results and gather uniform evidence to inform clinical practice. Specifically, eight different tools were employed across 33 studies to assess ED symptomatology alone. Moreover, 10 studies assessed depressive symptomatology using five different instruments, and five studies assessed anxiety using five different instruments. As discussed by Newson and colleagues (2020), heterogeneity of assessment tools significantly and negatively affects the translatability of study results to clinical practice, as the observed results may be affected by bias implicit in the assessment tool of choice. Additionally, roughly half of the studies included selected single instrument scale items as a variable of choice, while the other half opted for instrument sub-scale scores. Unless supported by robust theoretical and methodological choices, the use of single items as nodes might not be optimal when considering that instrument sub-scales and scales are usually controlled for their discriminant and construct validity, while individual items not always undergo this kind of examination. Ultimately, the choice of single items rather than sub-scales represents a further source of risk to the validity and generalizability of NA studies considered. Therefore, future NA studies in the field should provide clear methodological statements able to offer an explanation of their choice of single items or of sub-scales use as nodes.

Looking at (b) the reporting of network estimation methods (or functions), all but one study reported the applied specific network estimation function. Most studies, reported employing regularized network estimation functions by adopting glasso applications to stabilize the networks. Regularization or thresholding techniques such as glasso are used to improve network stability in specific situations, such as when the sample size is too small for the number of nodes included (Epskamp et al., 2018a). In the studies included in this review, however, the application of regularization functions (i.e.glasso) to retrieve the network model appeared independent of the sample size, and was applied even when the study samples might have allowed to not use it. It is important to note that the indiscriminate use of regularization techniques even when unnecessary may be problematic for a number of reasons (Williams et al.,2019; Wysocki & Rhemtulla, 2021). Among these, the glasso regularization techniques employ a regularizing penalty by which only a relatively small number of strong edges are included in the network, with effects in terms of high sensitivity but lower specificity (Burger et al., 2022). This means that the weaker edges included in the estimated network may be more prone to be false positives (i.e., Type I errors). Consequently, regularization techniques might remove weaker but true positive edges from the network model with a potential loss of information regarding the network structure. A careful interpretation of the remaining edges and the study results in general is therefore necessary.

As discussed above, the decision to employ a specific network estimation function is closely related to the topic of the sample size. However, no specific reporting standards regarding sample size were included in the present quality assessment because there are no definitive guidelines in the first place on how to estimate the appropriate number of participants to return a stable network in relation to the variables included (Epskamp et al., 2018b; Blanken et al., 2022). A potential optimal solution as observed by Epskamp and colleagues (2018) and Blanken and colleagues (2022), is increasing sample size to improve stability of a given network to a point where regularization techniques might not be necessary. Preferably, nodes should be limited to a maximum of 30, while sample size should be as large as possible (Blanken et al., 2022). Otherwise, another more technical potential solution is to estimate the stability of a network at different sample sizes prior to data collection by conducting pre-hoc simulations (Epskamp et al., 2018a). However, no study reviewed here reported simulating their data for measuring the stability before starting data collection or data analysis. Considering the scope and limitations of regularization techniques (Williams et al.,2019; Wysocki & Rhemtulla, 2021), it would be advisable that future network studies discuss the rationale supporting the selection of specific network estimation methods. This is especially relevant in light

of the widespread application of regularized network estimation methods even when the ratio between network nodes and study participants would allow the application of non-regularized methods.

Looking at (c) the stability of the networks considered in this work, most NA networks of ED clinical populations reported good to excellent network stability, while a few reached acceptable stability only. Nonetheless, this high rate of stable networks observed among the studies reviewed might be influenced by the almost ubiquitous application of regularization techniques as discussed above. Additionally, it is also likely that publication bias effect is present in NA studies on ED, as well as the tendency to only publish empirical studies that reject the null hypothesis (Ferguson & Heene, 2012).

The methodological points that however emerged as the most neglected in this review on NA studies on ED are pertaining the (d) lack of control of topological overlap and (e) handling of missing data. Topological overlap was the most overlooked criterion, at the expense of study quality and validity. Only 36.4% of the studies included reported checking for topological overlap and using the goldbricker algorithm, currently considered the recommended procedure to test it (Monteleone and Cascino, 2021). Not accounting for topological overlap may limit generalizability of the results, particularly in relation to the data collection instrument used and the node selection criteria applied (Christensen et al., 2020). This issue is further compounded by the wide range of assessment instruments applied, already discussed above, which pose a challenge when one tries to compare results across studies investigating the same construct utilizing different questionnaires.

The goldbricker algorithm is certainly not the only way to check for topological overlap. As alternatives, the identification of one or more overlapping items or sub-scales can be informed by the psychometric properties of the scale (i.e. whether multiple items or scales deliberately measure the same phenomenon) or by the decision process conducted by experienced clinicians or researchers. While the former of these two alternative methods is somewhat more reliable, there is still a margin of error with both approaches. Therefore, we considered the application of goldbricker algorithm as the only reliable procedure to check for topological overlap, as it represents a standardized and consistent method. While it might be argued that goldbricker algorithm was introduced only in 2017 (Jones, 2017) and might have not been immediately known to the scientific community, 91% of the NA studies on ED here reviewed that did not applied *goldbricker* were published when the R function and its package (Jones, 2017) were already freely available online. Thus, it would be advisable that all future NA studies on ED apply goldbricker algorithm as a way to assess for topological overlap, and that readers consider whether it is present when interpreting NA study results.

The other critical issue in many of the reviewed NA studies on samples of patients with ED is the absence of missing data reporting. Reporting missing data management in network studies is extremely important. As explained by Burger and colleagues (2022), accurate inferences are dependent upon a thorough understanding of the dataset composition and causes of missingness; missingness mechanisms need to be elucidated to draw appropriate conclusions from the results. For example, some data might be systematically missing because of specific characteristics of the assessment instrument (i.e. skip question structure of an instrument, such as SCID-5). Therefore, as specific information might be included for some participants but missing for others (i.e. skip question not relevant for a specific case), cases might be erroneously classified as missing. As such, information might not be included in the network structure or would be erroneously classified. This consideration makes reporting missing data a key piece of information not only in network studies, but in psychology research in general. On other hand, to the best of our knowledge there are no specific indications on how much missing data should be considered unacceptable in network studies and, moreover, network estimation function methodology automatically produces a network despite the presence of even large portions of missing data (Burger et al., 2022). This determines a grey area for missingness handling in network models, leaving researchers with a number of options and no gold-standard of how to proceed. Considering the lack of general consensus on how to handle missing data in NA studies, it is even more important to report as much information as possible about missing data to allow correct interpretation of the results.

From this systematic review one can observe how the methodological quality of NA studies on ED patients tended to improve over time, with more recent studies usually meeting more of the criteria considered here compared to early NA studies. This is likely due to the novelty of this approach, the rapid methodological advancements and the dissemination of guidelines and primers (Epskamp et al., 2018; Hevey, 2018); older works, which represent roughly one fifth (21.2%) of the articles included in this review, might not have had some of the tools or guidelines available to report information we now consider pivotal in evaluating a network study. However, there is still a number of studies which have been published as recently as 2022 that do not show the same degree of adherence to our selection of best practices of reporting data in NA studies on ED when compared with contemporaneous publications on the topic. All of the 24 studies (72.7%%) that received a methodological quality score of 4 or lower either failed to include controls for topological overlap or did not report missing data, or both. Of these, only the works of Levinson and colleagues (2017) and DuBois and colleagues (2017) were published before guidelines and tutorials on these two aspects

became available in the literature. The remaining 22 studies (66.6%) did not include either discussion regarding missing data and/or performed checks for topological overlap of variables despite documentation about both topics being available in the literature (Fried & Cramer, 2017; Jones, 2017). This would seem to suggest that lack of availability of materials and guidelines might not entirely explain some critical aspects of the studies' methodology, considering the most commonly neglected aspects were already being discussed, and solutions were being proposed (Epskamp et al., 2018; Fried & Cramer, 2017; Jones et al., 2018)

Further and conclusive comments are related to the general characteristics of the NA studies considered. Study populations were composed mostly, when not exclusively, of females, either adults or adolescents or both. ED have been historically perceived as "female" disorders, and the majority of research on ED diagnosis and treatment has relied predominantly on female samples (Murray et al., 2016). Therefore, it is possible that male-specific ED manifestations might have been overlooked, not recognized (Murray et al., 2017) and not included in NA networks yet. Additionally, more than half the studies did not report information regarding differences between sex assigned at birth and gender. Lack of this differentiation further compounds issues regarding identification of ED in individuals who identify with minoritized groups and limits the applicability of studies' results, as gender minorities present with unique clinical profiles and concerns (Nagata et al., 2020). Less than half the studies included data regarding years of education, a strong indicator of income and wealth (Psacharopoulos & Patrinos, 2018), family income or employment status. Lack of data on these characteristics is a missed chance to further understand how ED might present differently in different socioeconomic groups. Issues regarding diversity are also present in terms of racial diversity. Less than half of the NA studies reviewed here reported the actual racial/ethnic composition of the study sample, and even when present, all studies recruited at least 60% of white/Caucasian participants. Recognition of ED in different socioeconomic and racial/ethnic composition populations is a key aspect to improve treatment of these disorders, given the disparities in ED treatment caused by stereotypes surrounding the typical ED patient – *skinny, white, affluent girls* (Sonneville & Lipson, 2018; Franko et al., 2007).

In terms of diagnoses, AN emerged as the most studied ED diagnostic group, immediately followed by the broader TD population. Studies in BN, BED and OSFED patients were less frequently investigated. This is similar to what was observed by Monteleone & Cascino in their recent review (2021), where they report most studies including a TD sample, with AN being the second most studied clinical population. The disparity in the number of studies investigating the various ED diagnostic

groups does not seem justified by epidemiological data, which indicate BED and OSFED as the most common ED conditions (Santomauro et al., 2021).

In terms of study design, among the utilized network estimation functions to build cross-sectional networks, a minority of the studies (18.2%) proceeded to model multiple cross-sectional networks from different data collection time points, thus adopting cross-sectional networks within a longitudinal study design. However, this is different from building longitudinal networks using specific estimation methods such as the multilevel vector autoregression (mlVAR), with which cross-sectional networks share only some characteristics (Blanchard et al., 2022). Cross-sectional networks are by default undirected, meaning they can show the relations between two variables, but not the direction of that relation (which variable activates or causes the other). As such, limited inferences can be drawn from cross-sectional networks. Even considering these limitations, it is still advisable that future studies choosing to employ cross-sectional networks try to implement them within a longitudinal study design. As also discussed by Monteleone and Cascino (2021), studies adopting a longitudinal design are needed to improve identification of clinically similar subgroups and study changes in response to treatment to advance our understanding and our ability to treat ED.

Some important limitations concerning the methodology applied for this review however might affect the results of this work. The selection process adopted for the quality assessment criteria constitutes a major limit to the present work. Despite being based on the most cited and adopted NA tutorials (Epskamp et al., 2018; Hevey et al., 2018), the process of selecting the criteria has been conducted internally by a group of researchers, clinical psychologists and psychotherapists involved in this work and thus may be biased. However, the inclusion of only five among the various criteria proposed by Burger and colleagues (2022) reflects a deliberate decision to include criteria evaluating those specific NA methodological aspects shared by all network studies. The inclusion of additional criteria would have probably created different scores assigned to specific studies by virtue of different research questions rather than methodological robustness. Therefore, examining any of the remaining criteria would not have unduly influenced the conclusions of our assessment on methodological quality. An example is the inclusion of *predictability* of a node as a criterion of methodological quality assessment*:* NA studies might miss data on predictability because that is not part of their research goals, rather than it being due to poor methodological adherence. In this scenario, the inclusion of a *predictability* report would have contributed to the assignment of a score pertaining to aspects that are not strictly related to methodology quality as much as research interests.

Furthermore, the search of the present review was limited to networks built using cross-sectional modelling functions, and in clinical populations with an established diagnosis of ED only.

As a result, other relevant studies investigating ED symptomatology in non-clinical populations and/or using other network modelling techniques have been certainly left out, which represents an obvious loss of important information. However, restricting the focus of this work to a specific NA methodology and clinical population provided a coherent framework for comparison of methodological quality and considerations regarding validity and replicability across studies.

Conclusions

This systematic review on the methodological quality of NA cross-sectional studies in ED confirms that the literature on this topic advanced considerably in a relatively short amount of time with most studies reporting methodological procedures necessary for a network study to provide valid and reliable results. Still, some critical issues in methodological quality emerged which support some recommendations for future NA studies on ED. This is especially relevant considering that the present work already applied a restricted and more accessible version of the checklist of best guidelines for reporting data in NA studies proposed by Burger and colleagues (2022).

First of all, it would be advisable that future studies carry out simulations before sample recruitment to estimate accurately the adequate sample size in relation to the number of variables selected, so that ideally one might avoid the use of regularization techniques and thus reduce potential false negative results. Moreover, it is important to minimize the heterogeneity of assessment scales to improve translatability of study results into clinical practice.

More importantly, procedures closely related to study validity such as controls for topological overlap and management of missing data, that still were absent in the majority of studies reviewed, need to be included systematically in future NA studies on ED. The exclusion of such information limits the generalizability and validity of the current available results, or needs to be accounted for in their data interpretation to be really accessible for clinicians that must inform their practice with ED patients.

Finally, our results support and complement the conclusions of previous work from Monteleone and Cascino (2021) who suggest the need to increase the number of longitudinal studies to capture the dynamics of ED symptomatology. Future studies should ideally adopt a longitudinal design more frequently, either confronting multiple cross-sectional networks from different time points or building temporal networks depending on their specific research question (Borsboom et al., 2021; Blanchard et al., 2022). Network psychometrics hold remarkable potential in studying the dynamics that underpin clinical manifestations, comorbidities and diagnostic migrations in ED, and we look forward to more studies designed to adopt such an approach on longitudinal data on ED. Additionally, future

NA studies should be more focused on BED and OSFED populations as well as include more racially, ethnically, socioeconomically diverse participants with particular attention to gender-balanced study samples and representation of sexual minorities.

It should be noted that our attempt to provide a selection of accessible and clinically-relevant criteria to evaluate NA ED studies is not exhaustive nor definitive, and represents but a step of an ongoing process to increase popularity and accessibility of methodology of NA studies on ED. We strongly advocate in favour of future studies reviewing and amending the criteria we proposed, to expand or restrict the range of criteria considered depending on the specific type of study and research methodology, to include other network modelling techniques and test their applicability on ED clinical and non-clinical populations.

Acknowledgments

The authors would like to thank Dr Lucia Tecuta, PhD, for her contribution in proofreading and editing this manuscript in her capacity as native English speaker.

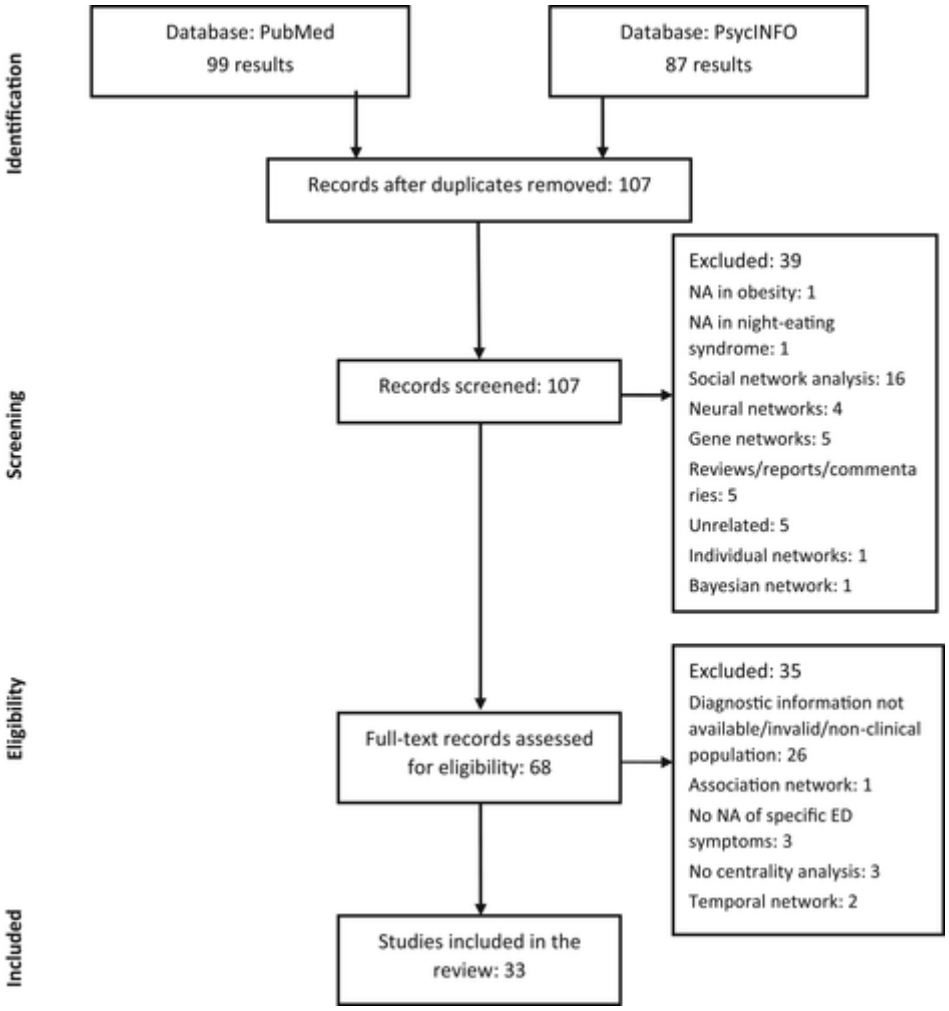
Public Significance statement

The present work aims to evaluate the quality of ED NA studies to support applications of this approach in ED research. Results show that most studies adopted basic procedures to produce reliable results; however, other important procedures linked to NA study validity were mostly neglected. Network methodology in ED is extremely promising, but future studies should consistently include topological overlap control procedures and provide information on missing data.

Table 1. PICOS criteria.

PICOS	Inclusion criteria	Exclusion criteria	Data extracted
Patient	-individuals with ED diagnosis according to DSM-IV-TR or DSM 5 -adults, adolescents, children or mixed -male, female or mixed	- absence of ED diagnosis according to DSM-IV-TR or DSM 5 or mixed clinical/non-clinical samples - ED diagnosis based on self-report tools - obesity diagnosis - sample composed of medically ill patients with pathologies not related to EDs	- age range, average age and standard deviation - female % - race - sample size - ED diagnosis and comorbidity
Intervention	- studies with or without therapeutic intervention		
Comparison group	- studies with or without control groups		
Outcome	- network analysis of specific ED symptoms (with or without other DSM symptoms and clinical variables related to EDs)	-Association networks, Bayesian networks, idiographic networks, temporal networks - social network analysis - neural networks - gene networks - studies on blogs/forum	- centrality indices - network stability assessment - bridge symptoms - network connectivity - prognostic value of network indices
Study design	- Prospective or Retrospective cohort, cross-sectional, case–control, or RCT - Any length of follow-up - cross-sectional network estimation method - English language	- Reviews - Case studies - Opinion statements -Book - Meta-analysis - Progress report	- study design -nodes selection criteria -type of network estimation -missing data management -topological overlap management

Figure 1. Selection of studies: PRISMA flowchart.



APPENDIX

Table 2: Quality assessment criteria and evaluation tool

For each of the 5 selected reporting standards, check whether the following data were extracted from each study included in this review. Sum the number of YES boxes ticked to obtain the total score, then confront against the quality score interpretation guideline

(a) Was the theoretical background used as rationale for node selection process was provided?

☐ Yes ☐ No

(b) Did the authors report the network estimation function was applied (i.e. Graphical least absolute shrinkage and selection operator [graphical lasso, or glasso] or Exteneded Bayesian Information Criteria glasso [EBICglasso] or mixed graphical models [mgm] or Isingfit)?

☐ Yes ☐ No

(c) Was stability coefficient (CS) and its magnitude reported? (Acceptable CS $\geq$ 0.25; good CS $\geq$ 0.5; excellent CS $\geq$ 0.7);

☐ Yes ☐ No

(d) Was risk of topological overlap assessed through the application of the *goldbricker* algorithm?

☐ Yes ☐ No

(e) Was presence and handling of missing data discussed (i.e. whether missing data was present, in which percentage, were missing data imputed and how)

☐ Yes ☐ No

Total criteria satisfied ☐ **/5**

Score interpretation guidelines

5/5: strictly adherent; 4/5: moderately adherent;3/5: minimally adherent; 2/5: weakly adherent

Table 3: Description of included studies

Authors	Sample numerosity and characteristics (% females; mean age ± sd; race)	Diagnosis	Scales	Outcomes	Findings	Quality assessment criteria satisfied
Studies meeting 5/5 criteria (strictly adherent)						
1. Brown et al. 2020	428 adults and adolescents (94.8%; 21.7 ± 8.8; white/Caucasian: 74.5%)	Transdiagnostic	EDE-Q, MAIA (items)	Centrality	Having a strong desire to lose weight, feeling guilty, and listening for information from the body about emotional state as most central nodes	All criteria met.
				Outcome centrality	Greater desire to lose weight predicted lower likelihood of remission at treatment discharge	
				Bridge symptoms	(Not) feeling that one's body is a safe place, (mis)trust in body sensations and ignoring physical tension/discomfort until it becomes severe highest bridge expected influence	
2. Calugi et al. 2020	522 adolescents (96.3%; 16.3 ±1.9; N.R.) 724 adults (95.9%; 29.7 ±8.9; N.R.)	AN	EDE-Q (subscales)	Centrality	Shape overvaluation and desiring weight loss as the most central nodes in both samples	All criteria met.
3. Elliot et al. 2020	142 adults (97.8%; N.R.; N.R.)	AN	EDE, DASS-21 (items)	Centrality	Feeling fat, fear of weight gain, strong desire to lose weight, discomfort seeing one's own body, dissatisfaction with weight as most central nodes	All criteria met.

761 **Table 4. Information on the demographic diversity of samples reported in the**
762 **studies**
763
764

ARTICLE	SEX vs GENDER TERMINOLOGY AND *OPTIONS CONSIDERED*	SES		RACE AND ETHNICITY	OTHER
		EDUCATION LEVEL	ECONOMIC PARAMETERS		
1. Brown et al., 2020	Sex *Options:* *unclear; only % of female respondents reported.*	N.R.	N.R.	Race Caucasian 74,5% Asian 6,1% African American 0,4% Native Hawaiian/Pacific Islander 0,2% American Indian/Alaska Native 0,7% Other 17,8% Ethnicity Hispanic 16,8% Non-Hispanic 83,1%" Reported also for adult and adolescent subgroups	
2. Calugi et al., 2020	Gender *Options:* *unclear; only % of female respondents reported.*	N.R.	N.R.	N/R	
3. Calugi et al., 2021	Gender *Options:* *unclear; only % of female respondents reported.*	N.R.	N.R.	N.R.	
4. Calugi et al., 2022	Gender *Options:* *unclear; only % of female respondents reported.*	N.R.	N.R.	N.R.	
5. Cascino et al., 2019	Gender *Options:* *Unspecified; female gender is an inclusion criterion*	N.R.	N.R.	N.R.	
6. Chen et al., 2022	N.R.	Years of education (patients group: 20.8±2.7; control group: 20.9±2.6)	N.R.	N.R.	
7. de Vos et al., 2021	N.R.	N.R.	N.R.	N.R.	
8. DuBois et al., 2017	Sex *Options:* *Male* *female*	High school graduate (or less) 24,7% College student (currently) 24,7%	N.R.	Race White 89,4% Asian 5,6%	Sexual orientation Heterosexual 82,5%

		College graduate 50,6%		African American/Black 4,6% Native Hawaiian/Pacific Islander 0,5% American Indian/Alaska Native 0%	Homosexual 8,8% Bisexual 5,6% Other 3,1%
9. Elliot et al., 2020	Gender *Options* *Female* *Male*	*Years of education *15,8±2,3* *(data available for 125/142 participants)*	N.R.	In the limitation section, it's acknowledged that the majority of the sample is composed by participants who are White, but no data are provided.	*In relationship 35,2% *(data available for 138/142 participants)*
	* Information not reported in the article; the authors refer to the study by Schmidt et al., (2015) for the original data				
10. Forrest et al., 2018	Unspecified *Options:* *Unspecified; "girls" and "women" are inclusion criteria*	AN High school graduate or less 36,5% Technical training 1,0% Some college or Associate's degree 35,1% Bachelor's degree 16,4% Graduate school 10,8% BN High school graduate or less 27,7% Technical training 1,5% Some college or Associate's degree 41,7% Bachelor's degree 19,9% Graduate school 8,8%	N.R.	Race/ethnicity **AN** European American 86,6% African American 0,7% Asian/Pacific Islander 2,6% Hispanic 3,8% Native American 0,2% Multiracial 2,5% Other 1,7% Race/ethnicity BN European American 78,4% African American 2,7% Asian/Pacific Islander 2,3% Hispanic 6,3% Native American 0,6% Multiracial 4% Other 2,9%"	
11. Forrest et al., 2019	Gender *Options:* *Boy/man* *Girl/woman*	N.R.	N.R.	Race Caucasian 74,7% Asian 5,7% Black 2% Native Hawaiian/Pacific Islander 0,3% American Indian/Alaska Native 0,3% Other 16,6% Ethnicity Hispanic 19,9% Non-Hispanic 76%"	
12. Goldschmidt et al., 2018	Unspecified *Options:* *Unspecified;*	N.R.	N.R.	Race White 88,1% Black 6,8% Asian 2,7%	

	only % of female respondents reported.			American Indian/Alaskan Native 0,8% Mixed race/other 1,6%"	
13. Hagan et al., 2021	Child sex *Options:* *Female* *Male* *other*	N.R.	Family income: *<US $ 50000: 12%* *US $ 50000-80000: 11,2%* *US $ 81000-100000: 13,9%* *US $ 101000-150000: 19,6%* *> US $ 150000: 41,1%*	Child race Caucasian 69,4% African American/Black 0,7% Asian 12,5% American Indian/Alaska Native 0,2% Native Hawaiian/Pacific Islander 4,6% Multi-racial 7,6% Child ethnicity Hispanic/Latinx 12,0% Non-Hispanic/non-Latinx 69,4%"	Intact family Yes 60,6% No18,1% Missing data 21,3%
14. Hilbert et al., 2020	*Unspecified *Options:* *Female* *Male*	*Years of education ≥ 12 Self-help group: 53% CBT group: 50%	*Employed Self-help group: 68,7% CBT group: 76,7%	N.R.	*Married Self-help group: 36,1% CBT group: 51,2%
	*Information not reported in the article; the authors refer to the study by de Zwaan et al., (2017) for the original data				
15. Kerr-Gaffney et al., 2020	Unspecified *Options:* *Unspecified,* *only % of female respondents reported.*	Years of education *16,33±2,89* *(range 10-27)*	N.R.	N.R.	
16. Levinson et al., 2017	Unspecified *Options:* *Unspecified,* *only % of female respondents reported.*	N.R.	N.R.	Ancestries European 84,2% African American 5,6% Asian 2,6% Native Hawaiian/Pacific Islander 0,5% Other 5,1%"	
17. Mares et al., 2022	Gender *Options:* *unclear; only % of female respondents reported.*	N.R.	N.R.	N.R.	
18. Meier et al., 2020	Unspecified *Options:* *Women 84,82* *Men 14,85* *Nonbinary 0,33*	College degree *68%* *Other titles not reported*	N.R.	"Caucasian (95%)" Other races not reported	
19. Monteleone, et al., 2019	Unspecified *Options:* *Female* *Male*	N.R.	N.R.	N.R.	Family type (united, separated, single parent)

20. Monteleone et al., 2020	Unspecified *Options:* *Unspecified;* *"Women" is an inclusion criterion*	Years of education *AN-R 16,05±2,89* *AN-P 16,06±2,53* *BN 15,56±3,38*	Months unemployed *AN-R 5,85±22,34* *AN-P 9,06±29,21* *BN 6,56±13,66*	N.R.	
21. Monteleone, et al., 2021	Unspecified *Options:* *Female* *Male*	N.R.	N.R.	"Italian population"	
22. Monteleone et al., 2022	Gender *Options:* *unclear; only % of female respondents reported.*	Years of education *Patients: 11.7±1.9* *Carers: 15.4±3.6*	Employment status *Employed (full time/part time)* *Patients: 8%* *Carers: 69%* *Unemployed/retired/ sick leave/student* *Patients: 91%* *Carers: 21%* Other/missing *Patients: 0.7%* *Carers: 9%*	N.R.	
23. Olatunji et al., 2018	Unspecified *Options:* *Unspecified,* *"female" is an inclusion criterion*	N.R.	N.R.	Ethnic breakdown Caucasian 93,6% Mixed/Unknown 2,7% Hispanic 2,1% Asian 0,9% African American 0,7% Native American 0,2%"	
24. Ralph-Nearman et al., 2021	Sex *Options:* *Male* *Female*	N.R.	N.R.	Race/ethnicity White 86.5% Hispanic 4.1% Asian 1.2% Black 0.7% Multi-racial 2.2% Not reported 5.2%	
25. Schlegl et al., 2021	Unspecified *Options:* *Unspecified;* *"female" is an inclusion criterion*	N.R.	N.R.	N.R.	
26. Smith et al., 2019	Unspecified *Options:* *Unspecified,* *only % of female respondents reported.*	N.R.	N.R.	"Caucasian (96%)" Other races not reported	
27. Smith et al., 2020	Gender *Options:* *Male* *Female*	N.R.	N.R.	Race/ethnicity (ED group) White 90,7% Asian/Pacific Islander 1,7% Black 1,26% Native American/Alaskan Native 0,8% Hispanic 0,8% Other 0,8% Non reported 0,4%"	

				Data reported also for the two comparison groups.	
28. Solmi et al., 2018	Unspecified *Options:* *Unspecified,* *only % of female respondents reported.*	N.R.	N.R.	N.R.	
29. Solmi et al., 2019	N.R.	Years of education AN-B-P 13,04±2,90 AN-R 12,73±3,12	N.R.	N/R	
30. Vanzhula et al., 2019	Unspecified *Options:* *Unspecified,* *only % of female respondents reported.*	N.R.	N.R.	Ethnicity European American 93,7% African American 0,6% Hispanic 1,9% Asian 0,6% Multiracial 1,9%	
31. Vervaet et al., 2021	Unspecified *Options:* *Female* *male*	N.R.	N.R.	N/R	
32. Wang et al., 2019	Unspecified *Options:* *Unspecified,* *only % of female respondents reported.*	N.R.	N.R.	Race White 73,8%" Other races not reported	
33.Wong et al., 2021	Gender *Options:* *Male* *Female* *Other*	N.R.	N.R.	Ethnicity/ race European American 75.1% Hispanic 4.8% Black 1.3% Chinese or Chinese American 0.9% Indian or Indian-American 0.4% Japanese or Japanese American 0.4% Other Asian origin 0.4% Multiracial or biracial 2.2% Unlisted 0.9% Did not report 13.5%	

N.R.: not reported

References

Barabási AL. 2011. The network takeover. *Nature Physics, 8*(1), 14-16. doi:10.1038/nphys2188

Blanchard MA, Contreras A, Kalkan RB, Heeren A. 2022. Auditing the research practices and statistical analyses of the group-level temporal network approach to psychological constructs: A systematic scoping review. Behav. Res. Methods, 1-21. 10.3758/s13428-022-01839-y. Advance online publication. doi: 10.3758/s13428-022-01839-y

Blanken T, Isvoranu AM, Epskamp S. Estimating Network Structures using Model Selection. In: Isvoranu AM, Espkamp S, Waldrop LG, Borsboom D, editors. Network psychometrics with R. A guide for behavioral and social scientists. 1st ed. Oxford (GB): Taylor and Francis; 2022. p. 128.

Blanken TF, Van Der Zweerde T, Van Straten A, Van Someren EJW, Borsboom D, Lancee J. 2019. Introducing Network Intervention Analysis to Investigate Sequential, Symptom-Specific Treatment Effects: A Demonstration in Co-Occurring Insomnia and Depression. *Psychother Psychosom, 88*(1), 52-54. doi:10.1159/000495045

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

Borsboom D, Deserno MK, Rhemtulla M, Epskamp S, Fried EI, McNally RJ. Et al., 2021. Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers, 1*(1): 58. doi:10.1038/s43586-021-00055-w

Brown TA, Vanzhula IA, Reilly EE, Levinson CA, Berner LA, Krueger A. et al., 2020. Body mistrust bridges interoceptive awareness and eating disorder symptoms. *J Abnorm Psychol, 129*(5): 445-456. doi:10.1037/abn0000516

Burger J, Isvoranu A-M, Lunansky G, Haslbeck JMB, Epskamp S, Hoekstra RHA, Fried EI, Borsboom D, Blanken TF. 2022. Reporting Standards for Psychological Network Analyses in Cross-sectional Data. *Psychological Methods.* DOI: 10.1037/met0000471

Calugi S, Dametti L, Chimini M, Dalle Grave A, Dalle Grave R. 2021. Change in eating-disorder psychopathology network structure in patients with anorexia nervosa treated with intensive cognitive behavior therapy. *Int J Eat Disord, 54*(10), 1800-1809. doi:10.1002/eat.23590

Calugi S, Dametti L, Dalle Grave A, Dalle Grave R. 2022. Changes in specific and nonspecific psychopathology network structure after intensive cognitive behavior therapy in patients with anorexia nervosa. *Int J Eat Disord*, 1–10. https://doi.org/ 10.1002/eat.23755

Calugi S, Sartirana M, Misconel A, Boglioli C, Dalle Grave R. 2020. Eating disorder psychopathology in adults and adolescents with anorexia nervosa: A network approach. *Int J Eat Disord, 53*(5), 420-431. doi:10.1002/eat.23270

Cascino G, Castellini G, Stanghellini G, Ricca V, Cassioli E, Ruzzi V. 2019. The Role of the Embodiment Disturbance in the Anorexia Nervosa Psychopathology: A Network Analysis Study. *Brain Sci, 9*(10). doi:10.3390/brainsci9100276

Castellini G, Lo Sauro C, Mannucci E, Ravaldi C, Rotella CM, Faravelli C, Ricca V. 2011. Diagnostic crossover and outcome predictors in eating disorders according to DSM-IV and DSM-V proposed criteria: a 6-year follow-up study. *Psychosom Med, 73*(3), 270-279. doi:10.1097/PSY.0b013e31820a1838

Centre for Reviews and Dissemination. (2006). *Systematic Reviews: CRD's guidance for undertaking reviews in health care* (U. o. York Ed.).

Chen Y, Guo L, Wu M, Zhang L, He Q, Zheng Y, Wu L, Zheng H and Chen J. 2022. Network Analysis

of Eating Disorders Symptoms Co-occurring With Impulsive Personality Traits and Negative Mood States in Patients With Bulimia Nervosa. *Front. Psychiatry,* 13. doi: 10.3389/fpsyt.2022.899757

Christensen AP, Golino H, Silvia PJ. 2020. A psychometric network perspective on the validity and validation of personality trait questionnaires. *Eur. J. Pers.* 34, 1095–1108.

Costantini G, Epskamp S, Borsboom D, Perugini M, Mõttus R, Waldorp LJ, Cramer AOJ. 2015. State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality, 54*, 13-29. doi:10.1016/j.jrp.2014.07.003

Centre for Reviews and Dissemination. (2006). Systematic reviews: CRD's guidance for undertaking reviews in health care. York, UK: University of York.

de Vos JA, Radstaak M, Bohlmeijer ET, Westerhof GJ. 2021. The psychometric network structure of mental health in eating disorder patients. *Eur Eat Disord Rev, 29*(4), 559-574. doi:10.1002/erv.2832

de Zwaan M, Herpertz S, Zipfel S, Svaldi J, Friederich HC, Schmidt F, Mayr A, Lam T, Schade-Brittinger C, Hilbert A. Effect of Internet-Based Guided Self-help vs Individual Face-to-Face Treatment on Full or Subsyndromal Binge Eating Disorder in Overweight or Obese Patients: The INTERBED Randomized Clinical Trial. JAMA Psychiatry. 2017 Oct 1;74(10):987-995. doi: 10.1001/jamapsychiatry.2017.2150. PMID: 28768334; PMCID: PMC5710472.

DuBois RH, Rodgers RF, Franko DL, Eddy KT, Thomas JJ. 2017. A network analysis investigation of the cognitive-behavioral theory of eating disorders. *Behav Res Ther, 97*, 213-221. doi:10.1016/j.brat.2017.08.004

Elliott H, Jones PJ, Schmidt U. 2020. Central Symptoms Predict Posttreatment Outcomes and Clinical Impairment in Anorexia Nervosa: A Network Analysis. *Clinical Psychological Science, 8*(1), 139-154. doi:10.1177/2167702619865958

Epskamp S, Borsboom D, Fried EI. 2018a. Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods.* 50(1): 195–212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp S, van Borkulo CD, van der Veen DC, Servaas MN, Isvoranu AM, Riese H, Cramer AOJ. 2018b. Personalized Network Modeling in Psychopathology: The Importance of Contemporaneous and Temporal Connections. Clin Psychol Sci. 6(3):416-427. doi: 10.1177/2167702617744325.

Ferguson CJ, Heene M. 2012. A Vast Graveyard of Undead Theories:Publication Bias and Psychological Science's Aversion to the Null. *Perspectives on Psychological Science, 7*(6): 555-561. doi:10.1177/1745691612459059

Forrest LN, Jones PJ, Ortiz, SN, Smith AR. 2018. Core psychopathology in anorexia nervosa and bulimia nervosa: A network analysis. *Int J Eat Disord, 51*(7): 668-679. doi:10.1002/eat.22871

Forrest LN, Sarfan LD, Ortiz SN, Brown TA, Smith AR. 2019. Bridging eating disorder symptoms and trait anxiety in patients with eating disorders: A network approach. *Int J Eat Disord, 52*(6): 701-711. doi:10.1002/eat.23070

Franko DL. Race, ethnicity, and eating disorders: considerations for DSM-V. Int J Eat Disorder. 2007;40:S3.

Fried EI, Cramer AOJ. 2017. Moving Forward: Challenges and Directions for Psychopathological Network Theory and Methodology. Perspect Psychol Sci. 12(6): 999-1020. doi:10.1177/1745691617705892

Friedman J, Hastie T, Tibshirani R. 2008. Sparse inverse covariance estimation with the graphical lasso. *Biostatistics (Oxford, England)*, *9*(3): 432–441. https://doi.org/10.1093/biostatistics/kxm045

867 Goldschmidt AB, Crosby RD, Cao L, Moessner M, Forbush KT, Accurso EC, Le Grange D. 2018.
868 Network analysis of pediatric eating disorder symptoms in a treatment-seeking,
869 transdiagnostic sample. *J Abnorm Psychol, 127*(2): 251-264. doi:10.1037/abn0000327
870 Hagan KE, Matheson BE, Datta N, L'Insalata AM, Onipede ZA, Gorrell S. et al., 2021. Understanding
871 outcomes in family-based treatment for adolescent anorexia nervosa: a network approach.
872 *Psychol Med*, 1-12. doi:10.1017/s0033291721001604
873 Haslbeck J, Borsboom D, Waldorp L. 2019. Moderated Network Models. *Multivariate Behavioral*
874 *Research, 56*: 1-32. doi:10.1080/00273171.2019.1677207
875 Hevey D. 2018. Network analysis: A brief overview and tutorial. *Health Psychology and Behavioral*
876 *Medicine*, 6(1): 301–328. https://doi.org/10.1080/21642850.2018.1521283
877 Hilbert A, Herpertz S, Zipfel S, Tuschen-Caffier B, Friederich HC, Mayr A, de Zwaan M. (2020).
878 Psychopathological Networks in Cognitive-Behavioral Treatments for Binge-Eating Disorder.
879 *Psychother Psychosom, 89*(6): 379-385. doi:10.1159/000509458
880 Jones PJ. 2017. networktools: Assorted Tools for Identifying Important Nodes in Networks. R
881 package version 1.0.0. https://CRAN.R-project.org/package=networktools.
882 Jones PJ, Mair P, McNally RJ. 2018. Visualizing psychological networks: A tutorial in R. *Frontiers in*
883 *Psychology*, 9. https://doi.org/10.3389/fpsyg.2018.01742
884 Khan K, Kunz R, Kleijnen J, Antes G. 2011. Systematic Reviews to Support Evidence-Based Medicine.
885 London: Hodder Arnold.
886 Kerr-Gaffney J, Halls D, Harrison A, Tchanturia K. 2020. Exploring Relationships Between Autism
887 Spectrum Disorder Symptoms and Eating Disorder Symptoms in Adults With Anorexia
888 Nervosa: A Network Approach. *Front Psychiatry, 11*, 401. doi:10.3389/fpsyt.2020.00401
889 Levinson CA, Vanzhula IA, Brosof LC, Forbush K. 2018. Network Analysis as an Alternative Approach
890 to Conceptualizing Eating Disorders: Implications for Research and Treatment. *Curr*
891 *Psychiatry Rep, 20*(9). doi:10.1007/s11920-018-0930-y
892 Levinson CA, Zerwas S, Calebs B, Forbush K, Kordy H, Watson H, et al., 2017. The core symptoms of
893 bulimia nervosa, anxiety, and depression: A network analysis. *J Abnorm Psychol, 126*(3): 340-
894 354. doi:10.1037/abn0000254
895 Linardon J, de la Piedad Garcia X, Brennan L. 2017. Predictors, Moderators, and Mediators of
896 Treatment Outcome Following Manualised Cognitive-Behavioural Therapy for Eating
897 Disorders: A Systematic Review. *Eur Eat Disord Rev, 25*(1): 3-12. doi:10.1002/erv.2492
898 Mares SHW, Burger J, Lotte HJM, van Elburg AA, Vroling MS. 2022. Evaluation of the cognitive
899 behavioural theory of eating disorders: A network analysis investigation. *Eat Behav*, 44. doi:
900 10.1016/j.eatbeh.2021.101590
901 McNally RJ. 2021. Network Analysis of Psychopathology: Controversies and Challenges. *Annu Rev*
902 *Clin Psychol*, 17: 31-53. https://doi.org/10.1146/annurev-clinpsy-081219-092850
903 Meier M, Kossakowski JJ, Jones PJ, Kay B, Riemann BC, McNally RJ. 2020. Obsessive-compulsive
904 symptoms in eating disorders: A network investigation. *Int J Eat Disord, 53*(3): 362-371.
905 doi:10.1002/eat.23196
906 Moher D, Liberati A, Tetzlaff J, Altman DG. 2009. Preferred reporting items for systematic reviews
907 and meta-analyses: the PRISMA statement. *PLoS Med, 6*(7), e1000097.
908 doi:10.1371/journal.pmed.1000097
909 Monteleone AM, Cardi V, Ambwani S, Cascino G, Albano G, Pellegrino F, Treasure J. 2020. Network
910 intervention analysis to assess the trajectory of change and treatment effects associated
911 with the use of online guided self-help for anorexia nervosa. Early Intervention in Psychiatry,
912 https://doi.org/10.1111/eip.13064

Monteleone AM, Cascino G. 2021. A systematic review of network analysis studies in eating disorders: Is time to broaden the core psychopathology to non specific symptoms. *Eur Eat Disord Rev, 29*(4): 531-547. doi:10.1002/erv.2834

Monteleone AM, Mereu A, Cascino G, Criscuolo M, Castiglioni MC, Pellegrino F, et al., 2019. Re-conceptualization of anorexia nervosa psychopathology: A network analysis study in adolescents with short duration of the illness. *Int J Eat Disord, 52*(11): 1263-1273. doi:10.1002/eat.23137

Monteleone MA, Mereu A, Cascino G, Ruzzi V, Castiglioni MC, Patriciello G, et al., 2021. The validity of the fifth and the 10th Body Mass Index percentile as weight cut-offs for anorexia nervosa in adolescence: No evidence from quantitative and network investigation of psychopathology. *Eur Eat Disord Rev, 29*(2): 232-244. doi:10.1002/erv.2814

Monteleone AM, Cascino G, Salerno L, Schmidt U, Micali N, Cardi V, Treasure J. 2022. A network analysis in adolescent anorexia nervosa exploring the connection between both patient and carer reactions and outcome. *Eur Eat Disord Rev*, 1– 11. https://doi.org/10.1002/erv.2933

Murray SB, Griffiths S, Mond JM. 2016. Evolving eating disorder psychopathology: conceptualising muscularity-oriented disordered eating. Br J Psychiatr 208(5):414–415. https://doi.org/10.1192/bjp.bp.115.168427

Murray SB, Nagata JM, Griffiths S, Calzo JP, Brown TA, Mitchison D, Blashill AJ, Mond JM. 2017 The enigma of male eating disorders: a critical review and synthesis. Clin Psychol Rev 57:1–11. https://doi.org/10.1016/j.cpr.2017.08.001

Nagata JM, Ganson KT, Austin SB. 2020. Emerging trends in eating disorders among sexual and gender minorities. *Curr Opin Psychiatry*. 33(6): 562-567. doi: 0.1097/YCO.0000000000000645

Newman SD, Ikuta T, Burns T Jr. 2010. The effect of semantic relatedness on syntactic analysis: An fMRI study. *Brain Lang, 113*(2), doi:10.1016/j.bandl.2010.02.001

Newson JJ, Hunter D, Thiagarajan TC. 2020 The Heterogeneity of Mental Health Assessment. *Front Psychiatry*, 11. doi: 10.3389/fpsyt.2020.00076

Olatunji BO, Levinson C, Calebs B. 2018. A network analysis of eating disorder symptoms and characteristics in an inpatient sample. *Psychiatry Res, 262*: 270-281. doi:10.1016/j.psychres.2018.02.027

Psacharopoulos G, Patrinos HA. 2018. Returns to investment in education: a decennial review of the global literature. Education Economics, 26:5, 445-458, DOI: 10.1080/09645292.2018.1484426

Ralph-Nearman C, Williams BM, Ortiz AML, Smith AR, Levinson CA. 2021. Pinpointing core and pathway symptoms among sleep disturbance, anxiety, worry, and eating disorder symptoms in anorexia nervosa and atypical anorexia nervosa. *J Affect Disord, 294*: 24-32. doi:10.1016/j.jad.2021.06.061

Santomauro DF, Melen S, Mitchison D, Vos T, Whiteford H, Ferrari AJ. 2021. The hidden burden of eating disorders: an extension of estimates from the Global Burden of Disease Study 2019. The Lancet Psychiatry, 8(4): 320-328. doi:https://doi.org/10.1016/S2215-0366(21)00040-7

Schlegl S, Smith KE, Vierl L, Crosby RD, Moessner M, Neumayr C, Voderholzer U. 2021. Using network analysis to compare diagnosis-specific and age-specific symptom networks in eating disorders. *Int J Eat Disord*. doi:10.1002/eat.23523

Schmidt U, Magill N, Renwick B, Keyes A, Kenyon M, Dejong H, Lose A, Broadbent H, Loomes R, Yasin H, Watson C, Ghelani S, Bonin EM, Serpell L, Richards L, Johnson-Sabine E, Boughton N, Whitehead L, Beecham J, Treasure J, Landau S. The Maudsley Outpatient Study of Treatments for Anorexia Nervosa and Related Conditions (MOSAIC): Comparison of the Maudsley Model of Anorexia Nervosa Treatment for Adults (MANTRA) with specialist

supportive clinical management (SSCM) in outpatients with broadly defined anorexia nervosa: A randomized controlled trial. J Consult Clin Psychol. 2015 Aug;83(4):796-807. doi: 10.1037/ccp0000019. Epub 2015 May 18. PMID: 25984803.

Schmittmann VD, Cramer AOJ, Waldorp LJ, Epskamp S, Kievit RA, Borsboom D. 2013. Deconstructing the construct: A network perspective on psychological phenomena. *New Ideas in Psychology, 31*(1): 43-53. doi:10.1016/j.newideapsych.2011.02.007

Smith AR, Forrest LN, Duffy ME, Jones PJ, Joiner TE, Pisetsky EM. 2020. Identifying bridge pathways between eating disorder symptoms and suicidal ideation across three samples. J Abnorm Psychol, 129(7): 724-736. DOI: 10.1037/abn0000553

Smith KE, Mason TB, Crosby RD, Cao L, Leonard RC, Wetterneck CT, et al., 2019. A comparative network analysis of eating disorder psychopathology and co-occurring depression and anxiety symptoms before and after treatment. *Psychol Med, 49*(2): 314-324. doi:10.1017/S0033291718000867

Solmi M, Collantoni E, Meneguzzo P, Degortes D, Tenconi E, Favaro A. 2018. Network analysis of specific psychopathology and psychiatric symptoms in patients with eating disorders. *International Journal of Eating Disorders, 51*(7): 680-692. doi:10.1002/eat.22884

Solmi M, Collantoni E, Meneguzzo P, Tenconi E, Favaro A. 2019. Network analysis of specific psychopathology and psychiatric symptoms in patients with anorexia nervosa. *Eur Eat Disord Rev, 27*(1): 24-33. doi:10.1002/erv.2633

Sonneville KR, Lipson SK. 2018. Disparities in eating disorder diagnosis and treatment according to weight status, race/ethnicity, socioeconomic background, and sex among college students. *Int J Eat Disord*, 51: 518– 526. https://doi.org/10.1002/eat.22846

Steinglass JE, Eisen JL, Attia E, Mayer L, Walsh BT. 2007. Is anorexia nervosa a delusional disorder? An assessment of eating beliefs in anorexia nervosa. *J Psychiatr Pract, 13*(2): 65-71. doi:10.1097/01.pra.0000265762.79753.88

Tomba E, Tecuta L, Crocetti E, Squarcio F, Tomei G. 2019. Residual eating disorder symptoms and clinical features in remitted and recovered eating disorder patients: A systematic review with meta-analysis. *Int J Eat Disord, 52*(7): 759-776. doi:10.1002/eat.23095

Treasure J, Duarte TA, Schmidt U. 2020. Eating disorders. *Lancet, 395*(10227): 899-911. doi:10.1016/S0140-6736(20)30059-3

van Bork R, Rhemtulla M, Waldorp LJ, Kruis J, Rezvanifar S, Borsboom D. 2021. Latent Variable Models and Networks: Statistical Equivalence and Testability. *Multivariate Behav Res, 56*(2): 175-198. doi:10.1080/00273171.2019.1672515

van Borkulo C, van Bork R, Boschloo L, Kossakowski J, Tio P, Schoevers R, et al., 2017. Comparing network structures on three aspects: A permutation test. *Psychological Methods.* doi: 10.1037/met0000476

Vanzhula IA, Calebs B, Fewell L, Levinson CA. Illness pathways between eating disorder and post-traumatic stress disorder symptoms: Understanding comorbidity with network analysis. Eur Eat Disord Rev. 2019 Mar;27(2):147-160. doi: 10.1002/erv.2634.

Vervaet M, Puttevils L, Hoekstra RHA, Fried E, Vanderhasselt MA. 2021. Transdiagnostic vulnerability factors in eating disorders: A network analysis. *Eur Eat Disord Rev, 29*(1): 86-100. doi:10.1002/erv.2805

Waldorp L, Marsman M. 2020. Relations between networks, regression, partial correlation, and latent variable model. *Multivariate Behavioral Research*. DOI: 10.1080/00273171.2021.1938959

Wang SB, Jones PJ, Dreier M, Elliott H, Grilo CM. 2019. Core psychopathology of treatment-seeking patients with binge-eating disorder: a network analysis investigation. *Psychol Med, 49*(11): 1923-1928. doi:10.1017/s0033291718002702

Williams DR, Rhemtulla M, Wysocki AC, Rast P. 2019. On Nonregularized Estimation of Psychological Networks. *Multivar Behavl Res, 54*(5): 719-750. doi:10.1080/00273171.2019.1575716

Wong VZ, Christian C, Hunt RA, Levinson CA. 2021. Network investigation of eating disorder symptoms and positive and negative affect in a clinical eating disorder sample. *Int J Eat Disord, 54*(7): 1202-1212. doi:10.1002/eat.23511

Wysocki AC, Rhemtulla M. 2021. On Penalty Parameter Selection for Estimating Network Models, *Multivariate Behavioral Research*, 56(2): 288-302, doi:10.1080/00273171.2019.1672516

Yarkoni, T. (2021). The generalizability crisis. Beha. Brain Sci. doi: 10.1017/S0140525X20001685

Zweig KA. 2016. Network Analysis Literacy: A Practical Approach to the Analysis of Networks. Springer: Vienna. https://doi.org/10.1007/978-3-7091-0741-6