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Using Theory to Guide Exploratory Network Analyses

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Abstract

The use of exploratory network analysis has increased in psychopathology research over the past decade. A benefit of exploratory network analysis is the wealth of information it can provide; however, a single analysis may generate more inferences than what can be discussed in one manuscript (e.g., centrality indices of each node). This necessitates that authors choose which results to discuss in further detail and which to omit. Without a guide for this process, the likelihood of a biased interpretation is high. We propose that the integration of theory throughout the research process makes the interpretation of exploratory networks more manageable for the researcher and more likely to result in an interpretation that advances science. The goals of this paper are to differentiate between exploratory and confirmatory network analyses, discuss the utility of exploratory work, and provide a practical framework that uses theory as a guide to interpret exploratory network analyses.

Keywords: theory, network analysis, exploratory analysis, guide

Using Theory to Guide Exploratory Network Analyses

The past decade has shown a notable increase in the use of network theory as a framework to conceptualize and describe psychological disorders and clinical symptoms (for review, see Robinaugh et al., 2020). Additionally, advances in the ease and accessibility of statistical methods to test these theories (i.e., network analysis) have resulted in a preponderance of studies integrating these new techniques. As with any major advancement in science, even meritorious advancements can become meretricious if guidelines do not keep up with the practical use of new methodologies.

A standard cross-sectional network analysis consists of several variables that are represented in the network as circles called "nodes." The relationships between the nodes are typically calculated using partial correlations, which provide estimates of the relationship between two nodes, controlling for all other nodes in the network. The most commonly-used statistical model used to examine these associations is the Gaussian graphical model (GGM), although there are several other estimation procedures available to conduct statistical networks (such as the Ising model for binary data; Finneman et al., 2021). The partial correlations are depicted in the network as lines called "edges," and the thickness of an edge signifies the magnitude of the relationship between two nodes (for more detail, see Epskamp, Waldorp et al., 2018). Network analysis is incredibly versatile and can be beneficial in analyzing many types of data (Blanken et al., 2021; Epskamp, Waldorp et al. 2018; Haslbeck & Waldorp, 2020; Jordan et al. 2020) and may be particularly helpful in exploratory research. Network analyses provide a path for exploring many variables at once, in a way that is much more feasible than attempting to do so with more traditional methods, as popular packages in R (e.g., *bootnet*, *mgm*; Epskamp, 2020; Haslbeck & Waldorp, 2020) provide options designed to reduce Type-I errors (Espkamp &

Fried, 2018). For example, it would be relatively easy to estimate a network that includes 50 variables, all as separate nodes, using regularization techniques[1] to reduce the likelihood of possibly spurious edges. Conducting a similar set of analyses using traditional methods, like regression,[2] would require 50 multiple regressions (each with 49 predictor variables and one outcome variable) to provide an approximation of the number of edges that can be estimated.

The relative ease of running large network analyses can pose ethical and methodological issues, however, just as with other promising statistical advances (see Winer et al., 2016). Because network analyses can include such a large number of variables, it would be nearly impossible to provide specific theory-based hypotheses for every possible relationship in a large network.[3] A lack of *a priori*, theory-based hypotheses means that many large network analyses should be considered exploratory analyses. A pressing issue presented by the increasingly common use of exploratory analyses is a lack of guidance on how to interpret exploratory analyses, especially when interpreting networks with a large number of nodes. Even the most careful and well-intentioned researcher may have difficulty interpreting the results of a large, exploratory network without bias. To build on the hypothetical 50-node network introduced above, a 50-node network would have 1,225 possible edges. Even a network where only 10% of possible edges were present would result in over 122 edges. One may also decide to examine centrality indices (a relatively common practice in network analysis) which often quantifies the most influential node in the network by determining its number of connections and their magnitudes with other nodes. Even if one decided to examine only one of several possible

[1] In the context of network analysis, regularization is a process that runs multiple iterations of a model, with penalties imposed for added complexity. This process can be used to identify and remove potentially spurious edges, although this process can paradoxically include false positives as well (see Isvoranu & Epskamp 2021).
[2] To be clear, regression analyses do underlie the covariance matrix used to generate a network structure; however, network analyses include more sophisticated techniques to do this efficiently while limiting spurious results.
[3] This is particularly true in early stages of theory development. During later stages of theory development (e.g., when building a computational model), creating specific theory-based hypotheses for each variable is required.

centrality indices (e.g., strength), that adds an additional 50 nodes to interpret, along with the aforementioned 122 edges.

There may be some cases in which the interpretation of a large network is relatively straightforward. For example, it is possible that centrality estimates could result in a very clearly defined constellation of results in which a small number of nodes evidence notably high strength, and all the others are relatively weak. However, in reality, many exploratory network analyses do not evidence clearly defined cut points when attempting to interpret strong edges and central nodes, and attempting to compare results across studies is also difficult, as these indices are known to vary, based on the number of nodes in the network and the type of centrality index used. The sheer number of possible interpretations, and the absence of a guide for interpretation, can be overwhelming, and may lead researchers to unintentionally cherry pick the results that are interpreted and discussed in greater detail within the discussion session. Practically speaking, it is unlikely that any journal would publish a manuscript with a thorough outline of the respective strength of 122 edges and 50 nodes (nor should they). This necessitates that researchers choose which results to discuss and which to omit. On its own, this is not a problem; however, without a guide for interpretation and a clearly defined plan regarding which variables to include in a discussion and which to omit, the likelihood of a biased interpretation of results is high.[4]

Importantly, the goal of this paper is not to belittle the importance and relevance of exploratory research; in fact, we affirm that exploratory analyses can be incredibly useful *when they are recognized and clearly defined as being exploratory*. There are currently tutorials and guidelines regarding how to estimate and report network analyses (e.g., Burger et al., 2022; Epskamp et al., 2018; Epskamp & Fried, 2018; Isvoranu & Epskamp, 2021), but the literature

[4] Burger et al. (2022) includes a set of reporting guidelines that can help minimize the likelihood of selective reporting.

lacks a guide on how to interpret exploratory network analyses. Therefore, the goals of this paper are to (1) differentiate between exploratory and confirmatory network analyses, (2) discuss the utility of exploratory work, as well as areas where exploratory work may be problematic, and (3) provide a practical framework for how to use theory as a guide to interpret exploratory network analyses.

Exploratory Versus Confirmatory Network Analyses

The majority of empirical network analysis studies have presented networks as exploratory (Robinaugh et al., 2020). The assumption that network analyses are exploratory makes sense; researchers often include several variables as nodes and examine the strong edges between specific nodes and quantify the strength of specific nodes by examining centrality indices (e.g., strength, expected influence, and so forth). As such, it is difficult to expect, *a priori*, that a given node will be "highly central" or share strong connections with specific nodes in the network, namely due to a) the absolute number of possible connections between nodes; and b) that there is less precedence to rely on for hypothesizing what node will be central in a network analysis, given the amount of information that can go into a specific network.

As an example of the latter point, consider the number of studies assessing cross-sectional networks for major depressive and posttraumatic stress symptomology. Indeed, a majority of psychopathological networks have focused on depression and posttraumatic stress disorder (PTSD), given the heterogeneity of these syndromes (Contreras et al., 2019; Fried & Nesse, 2015; Galatzer-Levy & Bryant, 2013), with almost 70 empirical network studies examining depressive symptoms and 30 examining PTSD symptoms published between 2016 and 2018 alone (Robinaugh et al., 2020). Some of the these studies have used "gold standard" checklist measures, such as the PTSD Checklist for DSM-5 (PCL-5; Blevins et al., 2015) and the

Beck Depression Inventory (BDI-II; Beck et al., 1996); however, given one criticism of item-level network analyses includes an increased chance of measurement error (e.g., Fried & Cramer, 2017), would one expect that the centrality of a symptom or item would replicate in another study, especially in a study that possibly includes other nodes in the network? We have already seen commentaries discussing issues with centrality in general (cf. Bringmann et al., 2019), which makes these comparisons to previous studies even more difficult. Thus, researchers should be more cognizant of how they interpret their findings from network analyses, given these caveats.

In sum, it appears that the majority of empirical network studies are exploratory in nature – researchers determine what (and how many) nodes are appropriate for network estimation, configure the specific estimation procedures to be used (e.g., using *EBICglasso* regularization to mitigate Type I error), visualize the network, determine what centrality indices are most appropriate to report, and determine what specific (or strongest) edges need to be discussed – making broad conclusions about the "structure" of the network and phenomena of interest as a whole. Exploratory network analyses are often considered to be "hypothesis-generating structures," giving insight into what the true network structure *may* look like (Epskamp, Maris et al., 2018).

Recent methodological work has introduced the possibility of *confirmatory* network analyses alongside exploratory network analyses (Epskamp, 2020a, 2020b). To understand these differences, it is useful to compare these methods to exploratory and confirmatory factor models. Exploratory factor analysis (EFA), for example, aims to examine the underlying factor structure of a set of observed variable without imposing a predetermined structure on the outcome (Kline, 2015). Simply put, EFA is similar to exploratory network analysis techniques in that it aims to see what the structure could be. Confirmatory factor analysis (CFA), on the other hand, is used to verify or "confirm" the factor structure of a set of observed variables, allowing for hypothesis-testing as to the relationship between observed variables and their underlying latent construct(s). CFA allows one to draw from knowledge of a theory and/or empirical research to determine an *a priori* relationship pattern that can be tested statistically (Kline, 2015). Crucial to CFA is the ability to assess model *fit* to determine how well the model describes the data (and does not require re-specification). Though relatively new, studies using confirmatory network models are currently underway (see Kan et al., 2019), and it is yet to be determined if fitting a pre-defined network structure allows the model to be consistent with network theory.

As the use of confirmatory network analysis increases, there may be confusion regarding the theoretical or empirical literature from which one should draw. Cross-sectional partial correlation networks have been used to serve as analogues to the theoretical network structure of certain mental disorders or psychological phenomena (Bringmann & Eronen, 2018), but are likely not the best estimates of network theory. Statistical models themselves are *not* theoretical models, even though researchers often interpret them as such (Fried, 2020). Recent advances to computational modeling in psychology have allowed researchers to specify models that simulate data, given a theory (Robinaugh et al., 2021), which is an important step to clarifying theories (e.g., if the theory is true, then what would the relationships between items look like?).

Formulating the axioms of a theory, then, should be done with a level of precision and specificity similar to such a model. Fried (2020) lays this process out more explicitly in his paper, differentiating between *weak* and *strong* psychological theories. For instance, weak theories are analogous to narrative or imprecise hypotheses, often stating that two variables will significantly relate to one another, or there are significant group differences between patients with mental disorders versus those without. Further, weak theories are subjected to the "third variable problem," reducing the ability to make these theories *precise* and making it necessary for these theories to be continuously re-iterated (Fried, 2020; Morton, 2009). Strong theories, on the other hand, are precise sets of assumptions and axioms that explain or predict phenomenon in explicit terms (Fried, 2020). Strong theories are not mere descriptions of the data, they provide an explanation that enables one to examine what would happen under specific scenarios (hence the utility of computational models in strengthening theories; Fried, 2020; Robinaugh, et al., 2021). Extending to contemporary network analysis, then, researchers should be clearer and explicit in what they include in exploratory networks, leading into the next goal of this paper.

Utility of Exploratory (Network) Analyses

The ultimate goal of a scientific field of study is to advance knowledge and understanding in a particular domain, and theory building is a fundamental component of the scientific process. Indeed, the importance of building strong theories to advance knowledge has been emphasized throughout psychological science (Dubin, 1969), and the practice of developing weak theories has often been cited as an important contributor to many of the field's woes (e.g., failing to progress and the recent replication crisis; Fried, 2020; Meehl, 1978; Muthukriskna & Henrich, 2019; Oberauer & Lewandowsky, 2019).

The practice of exploratory data analysis was pioneered by Tukey throughout his career, beginning in the 1960s (for brief history, see Behrens et al., 2012; for more extensive collection of work, see Jones, 1986a; Jones 1986b). Unsurprisingly, because exploratory analyses are incredibly versatile and can be implemented in pursuit of diverse research goals, and are far less common in psychological science than analyses using the hypothetico-deductive method, there are few practical and specific guidelines for conducting such analyses and interpreting the results. Thus, it is important to consider broad scientific principles to guide exploratory analyses.

Like any type of analysis, exploratory analyses are only helpful if used in the appropriate context, at the appropriate stage of theory development,[5] a point described eloquently by Black and Champion (1976):

> Our inquisitiveness must be characterized by more than technical precision; it must be focused toward the realization of specific objectives. … Decisions about which research techniques to employ and about the sorts of usefulness the results of our studies can be expected to have must be made against a special background. That background must stress the goals of scientific inquiry. (p. 6)

The best way to assess this is through a clear and thorough identification of one's research goals, with specific attention to how one's research project will enhance knowledge and add to or refine theory.

Using Theory to Guide Exploratory Network Analyses

We propose the following steps be used as a guide for exploratory network analyses.[6]

Step 1: Be Familiar with the Extant Literature and Set a Research Goal

No amount of statistical knowledge can be substituted for theoretical knowledge in one's content area. Even research areas that have been heavily influenced by statistical modeling (e.g., trait-based theories of personality, theories of intelligence) require theoretical knowledge to interpret the findings. Prior to engaging in empirical research, the first step must be a thorough

[5] Borsboom et al. (2021) and Haslbeck et al. (2021) present frameworks that may help one to identify appropriate research goals that increase the likelihood that one's exploratory research will be useful in the development of formal theories.

[6] The proposed guide is to be used as a broad overview of the research process. For a guide related to the specific details of reporting of network analyses, see Burger et al. (2022).

review of the literature, including relevant theory and specific hypotheses. Without completing this step, it would be incredibly difficult to identify gaps in the literature that could benefit from additional empirical investigation.

After gaining expertise in one's content area and identifying gaps in the literature, one can create a research goal. Importantly, all research — including exploratory research — should have a specific goal that is used to guide one's investigation. For an example of this step, Lass and colleagues (2020) described the state of the literature related to distress tolerance, coping behaviors, and symptoms of depression, including the lack of formal theory, then stated their research goal as the identification of important variables and relationships to aid theory building efforts before embarking on exploratory analyses.

Step 2: Determine If/How an Exploratory Network Analysis Would Extend Knowledge

Next, one must determine if/how an exploratory network analysis would extend knowledge in that content area to meet one's research goal. This, of course, requires a thorough understanding of psychometrics. The statistics underlying network analyses are not fundamentally different from more traditional statistical techniques (Epskamp, Maris, et al., 2018). Therefore, the rationale that an analysis is worthwhile simply because the variable(s) of interest has not been examined via network analysis is not, on its own, a sufficient reason for investigation. For example, without a thorough knowledge of psychometrics, one might be curious about the network structure and connectivity of items in a popular symptom scale; however, if that scale has already undergone a substantial validation process to remove redundant and/or irrelevant items, it can be assumed that the network structure will be well-connected and will likely resemble the factors that they were derived to measure. This type of endeavor would only be of merit if one had a research goal that extended *beyond* a general interest in the network structure (e.g., an interest in the connectivity or centrality of *certain symptoms* of the scale). This is not because the network would not have additional information of interest; rather, it is because without sufficient background knowledge and a research goal, one may not be able to adequately interpret the results.

Wampold and colleagues (1990) outline the concept of hypothesis validity, along with its common threats. Though this paper was written with confirmatory research in mind, some of the general principles also apply to exploratory research. Notably, there should still be a clear connection between one's research goals and the statistical analyses used to examine them, as this connection is essential to being able to interpret results and use the findings to inform theory. For example, if one's research goal is to identify specific symptoms via network analysis that may be influential in the maintenance of a specific disorder, it is important to determine in advance what constitutes an "influential node." This would require knowledge of the various centrality indices, their relative strengths and weaknesses (Dablander & Hinne, 2019; Epskamp, Borsboom, et al., 2018), and their applicability to specific types of data (Bringmann et al. 2019).

A particularly good example of this step can be found in a paper by van den Berg and colleagues (2020). Van den Berg and colleagues use network analysis as a framework to examine dynamic risk factors in sex offenders. In addition to describing why exploratory network analysis could be helpful in working toward their research goals, they describe why it is more appropriate than alternative statistical approaches in relation to their research goals. They also discuss their interest in centrality, and more specifically, the shortest paths from risk factors to recidivism, as motivations for their exploratory analyses.

Step 3: Use Theoretical Knowledge to Determine Which Variables to Include in the Network, and How to Represent Them

After one has reached the stage of determining that an exploratory network analysis is a useful endeavor and has identified how to use it to meet one's research goals, the next step is to identify which variables should be included in the network, and how they should be represented. Certain variables may be represented in multiple ways. As an example, consider the construct of rumination. Rumination is a cognitive process that is characterized by repetitive negative thinking about oneself or one's situation and is often considered to be a multifaceted construct, consisting of brooding (i.e., self-criticism) and reflection (i.e., a more even-handed type of self-focus; for review, see Nolen-Hoeksema et al., 2008). If one is interested in examining the construct of rumination, one must determine whether rumination would be best represented as a single node, multiple nodes (e.g., brooding and reflection), or as individual items. This decision should be guided by the literature, as well as the level of analysis necessary to achieve one's research goal.

As an example of this, consider the following studies which both examine rumination using the Ruminative Responses Scale (RRS; Treynor et al., 2003). Bernstein and colleagues (2019) examined the interrelation of items in the scale to see if they formed different communities and, if so, to explore possible bridges between those communities. As such, rumination was represented as a single network, and nodes consisted of individual items from the RRS. Collins and colleagues (2021) examined how ruminative processes (e.g., brooding, reflection, depressive symptom preoccupation) relate to aspects of reward devaluation and depressive symptoms. As such, rumination was represented as 3 nodes, comprised of the RRS subscales. Both of these studies used the RRS as a measure of rumination, but represented the construct differently to fit their respective goals.

Importantly, for certain estimates (e.g., centrality) to be accurate, a prospective assumption is that a network must contain all causal variables; if causal variables are left out of a network, it may lead to incorrect estimations and interpretations (McNally, 2016). Including all potential sources of causality is of course a very high bar. Moreover, as noted by the two examples above, even the same construct may be operationalized in different ways depending on the goals of the researcher. So, there are often reasons to suspect that this assumption has not been met, and it is recommended that highlighting this potential limitation in discussion sections and where relevant in method and analyses sections becomes more normative in papers featuring network analysis.

Step 4: Use Knowledge of Network Psychometrics to Guide One's Analysis

It is beyond the scope of this article to describe network psychometrics in depth, as these topics have been covered extensively elsewhere (e.g., Epskamp, 2020a; Epskamp, Borsboom, et al., 2018; Epskamp & Fried, 2018; Jordan et al., 2020). Readers are encouraged to consult the relevant literature in this area and carefully select the appropriate models and model specifications for their research.

Step 5: Run Analyses, then Revisit Research Goals and Integrate Theoretical Knowledge to Interpret and Write-up the Results

It is likely that many exploratory network analyses will provide more findings than what can reasonably be discussed in a single manuscript. Though all analyses and results should be reported, it is obviously not feasible, nor is it recommended to remark on each individual edge, feedback loop, centrality estimate, reliability estimate, ad infinitum. One must decide what to include in the discussion of the results, which makes this step particularly vulnerable to researcher bias.

A helpful way to decide what to include in the discussion is to revisit one's research goals. After reorienting to the research question, discuss the results of the network analysis as they relate to the original purpose of the study. Assuming one has already developed explicit goals, including a thorough understanding of how a network analysis would aid the research question, this task may be relatively straightforward.

A more difficult decision may be determining what information to *exclude* from discussion. As with any analysis, one should check the literature to see if there is any precedent for specific procedures, like cut-off scores, etc. If no precedent exists, one may decide to create their own rule (e.g., discuss all nodes with a strength > 1*SD*)[7] and describe the rule that was used. If certain results are not explicitly discussed due to space constraints, it would be helpful to note how readers may access the results (e.g., tables with all edge weights, reliability analyses, etc.) via supplemental documents or links to data repositories.

Summary

As it stands, a great deal of time and effort within psychological science has been spent testing weak and nonspecific hypotheses (i.e., variable A will be positively associated with variable B) that do little to build or refine theory (Fried, 2020). Rather than engage in the menial process of testing weak (and arguably unfalsifiable) theories via null hypothesis significance testing, exploratory network analysis could be a very helpful tool to aid in theory development if used in the appropriate context.

We have provided a series of steps that use theory as a guide to exploratory network analysis. Using these steps alongside theory and prior research precedence to initiate and guide

[7] To be clear, we are not endorsing this as a rule; this is simply meant to be an example of what one might choose to do if it made sense in their specific situation.

the research process will allow exploratory network analysis to continue to help advance psychological science.

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