Original Article

Perspectives on using psychological network analysis in health psychology

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Research in psychology is about addressing complexity by exploring complex processes in individuals that evolve in complex systems (Fried & Robinaugh, 2020). Health psychology makes no exception as it covers a wide scope from preventing sickness to helping deal with illnesses (Baum et al., 2012). It considers the interactions between people's thoughts, feelings, behaviours, and biological processes in given social environments. Our understanding of the mesh they form is increasing and new methods are used to appraise them. One tool that can be used to account for that complexity is the network analysis (Hevey, 2018; Mkhitaryan et al., 2019).

Network analysis has been applied to psychological constructs to examine the relationships between different variables (e.g., behaviors, cognitions, items) (Hevey, 2018). This method is often referred to as the psychological network analysis (Burger et al., 2022) or psychometric network (Jones et al., 2021). It takes its source in a growing field of psychopathological research that questions how mental health conditions are conceived through the network theory of mental disorders (see Borsboom, 2017).

Psychological network analysis is an exploratory method to investigate patterns of statistical associations in multivariate psychological data (Borsboom et al., 2021). *Nodes* are variables (e.g., an item score) and *edges* are statistical associations between nodes. Most of the time, these statistical associations are partial correlation coefficients for continuous data and logistical regression coefficients for binary data. Both methods aim at identifying the presence and magnitude of *edges* between *nodes* while considering the role of all the other nodes in the network.

Several centrality indicators can be computed. Among these, *node strength* is one of the most important, as it shows the sum of its edges to other *nodes* (Bringmann et al., 2019). It shows how variables are importantly associated with the others included in the network, reflecting their important role within the network. By doing so, it suggests which variables could be key processes or even targets of interventions (for a nuanced discussion on the topic, see Bringmann et al., 2019). Beyond a focus on nodes, network analysis also allows the exploration of communities (i.e., a grouping of variables that share common features). Communities can be theory-based (independent from the network structure, e.g., a set of specific symptoms, Jones et al., 2021) or defined through statistical methods (dependent on the network structure, e.g., a set of variables that are densely inter-correlated and interact in a comparable way with other communities, Traag & Bruggeman, 2009). The investigation of communities allows for an exploration of how different groups of variables interact (e.g., a group of behaviours). One of the ways to do so is to explore which variables are *bridges* between, namely, variables that are essential to capture how two communities are associated (Jones et al., 2021).

An important element to consider is that network analysis can be used to understand the relationship between variables in two ways: single measurement (cross-sectional) and multiple, intensive measurements (intensive longitudinal methods such as ecological momentary assessment) (Borsboom & Cramer, 2013). They can therefore be used in the context of stable constructs to explore how they interact and their relative importance, but also to explore temporal dynamics between variables in short timeframes.

The benefit of such method in comparison to their multivariate counterparts (e.g., structural equation modeling) is to introduce more dynamic in the models through exploratory means by having little to no *a priori* conceptual assumption (Gérain et al., 2022). Therefore, it allows to explore how the investigated variables are associated together while not constraining them in a predefined model. This is particularly useful to provide first and unexpected insights into potential mediation paths, potentially leading to new considerations. Finally, network analysis provides an opportunity to explore potential causality paths between variables through Bayesian Networks representing conditional independence relationships (for more details, see Briganti et al., 2022).

Network analysis is a powerful tool for understanding and exploring this complexity as it provides an analytical method to represent the relationships among different elements (e.g., individuals, behaviours, thoughts). It allows researchers to gain insight into how these components are interconnected and can influence each other. As such, it is a valuable approach in helping us gain better insight into the complexities of human behavior within the context of health psychology research. In this context, psychological network analysis can be applied to different domains. The present work does not aim to be exhaustive but rather provides insights into how the health psychology field could benefit from using them. We propose three main approaches that would be useful: the interplay between constructs, comparing groups or at different moments, and ecological momentary assessment.

1) The interplay between psychological constructs

In the same way as what is performed in psychopathological research, network analysis can be used to explore how psychological constructs are associated. It can be done in two complementary ways. The first is to consider how traits or behaviours vary together to understand how two or more entities are related, in a comparable fashion as exploring the comorbidity or co-occurrence between mental health issues (Kaiser et al., 2021). This can be done for behaviours, as done in a study exploring the attitudes toward using different modes of transport (Kroesen & Chorus, 2020). The results highlighted how certain attitudes were more influential than expected (e.g., *cycling as fun* is more influential than *cycling as healthy*), which can help drive interventions on behaviour change.
This has also been done to explore beliefs associated with being an organ donor (Mkhitaryan et al., 2019). The results showed that the strongest node was "*believing that being a donor helps other people*", which reflects its important association with other beliefs and how they are interdependent.

The second approach to the interplay between constructs is to try to better understand risk and protective factors as well as processes involved in leading to a certain outcome, e.g., behaviours or well-being (Contreras et al., 2019). It can highlight what are the variables associated with an outcome while considering their respective interconnectivity. By doing so, it gives insights into the complex role of what is seen as e.g., a "risk factor", notably through its tentacular influence, the presence of circular causality, and what maintains certain processes (as suggested in Gérain et al., 2022). It proposes to nuance the approach of listing risk and protective factors by considering that one factor can have a more complex role (e.g., increasing a risk directly but decreasing it through another path) while being themselves influenced by other factors. This approach allows the identification of influential nodes that are involved (Bringmann et al., 2019) and paves the way to a process-based approach, by targeting specific influential processes (Hayes et al., 2020). This has for example been explored to investigate determinants of COVID-related behaviors during the pandemic (Chambon et al., 2022). The results highlighted that when taking all elements into account, only a fraction of determinants was directly related to performing the behaviours (e.g., believing in their efficacy) and that performing certain behaviours was only associated with doing other behaviours (e.g., repressive behaviours such as stay at home if ill were only associated with preventive behaviours such as washing hands). A study on informal caregivers' well-being has also highlighted the importance of dyadic interactions in the couple, which is the strongest node in the network (Gérain et al., 2022). This importance shows that what is merely seen as a predictor of well-being is rather the center of the associations in the network.

2) Compare networks between populations or in a pre-post design

Network analysis can be used to compare the network structure in different settings. These settings can be the comparison between populations or in pre-post designs. By comparing populations, they can help us understand how they differ, and therefore how we should address them differently. A study has for example compared the influence of different beliefs about smoking in samples of smokers with and without a recent attempt to quit smoking, showing how some beliefs are more influential than others in the two groups (Volz & Rothman, 2022). Such insights nuance the support that can be provided to them by showing that targeting certain beliefs would have a different impact on the two populations. Such comparison was also done by comparing psychological well-being of adolescents being either overweight or underweight, notably in showing the distinct role of social challenges in the two groups (Zeiler et al., 2021).

This comparison between groups can also be longitudinal, to explore if the network structure evolves over time (Bringmann & Eronen, 2018). This has been done by exploring how substance use and personality are associated during several stages of adolescence (Afzali et al., 2020). The results showed that one facet of personality that was important at one point may be less relevant later, and that our targets may have to evolve. This has also been done during the COVID crisis by exploring how networks' structures evolved during different phases of the crisis (Di Blasi et al., 2021). The natural evolution of that is to compare psychological networks as pre/post-test in interventions, by exploring if networks differ pre-post intervention.

3) In Ecological Momentary Assessment (EMA) research

A third application of network analyses is to analyze ecological momentary assessment (EMA) data (Borsboom & Cramer, 2013). EMA consists of repeatedly collecting data in an individual's normal environment (outside of the lab), typically in a short timeframe (e.g., several measurements per day for two weeks). We can distinguish two complementary kinds of analyses (Epskamp et al., 2018): a) the temporal network: the exploration of how variables influence each other at the next measurement (temporal relationship); b) the contemporaneous network: the relationship occurring within the same measurement (co-occurrence).

Contemporaneous networks inform on the co-occurrence and typology of the network, as presented for the interplay between variables. Because EMA focuses on states rather than traits, contemporaneous networks provide information about the co-occurrence and close proximity of states, feelings, and behaviours (e.g., how disease related-symptoms co-occur with worries and anxiety, Oreel et al., 2019). Temporal networks give the opportunity to explore the dynamic associations between variables across time points (Bringmann et al., 2013). In these analyses, the "lag-1" association is explored, which is particularly important regarding the dynamic nature of behaviours and psychological processes. This has been done in an EMA study examining how (un)healthy behaviours can predict behaviors in the following measurement (Dohle & Hofmann, 2019). The results indicated that certain behaviours reinforce themselves (e.g., physical activity predicts physical activity) but also highlighted the spillover of one behaviour onto others (e.g., unhealthy drinking is followed by sleep, relaxation, healthy eating, and physical activity).

Conclusion

This paper described only a fraction of what network analysis can offer to the field of health psychology. Network analysis can better inform us about the interplay between variables, compare groups or moments, and generate a deeper understanding of the relationships and interactions from EMA studies. Other approaches could not be addressed here and include providing insights into causality, use in psychometric scale validation, relevance in N = 1 research, or even the use of network analysis in meta-analyses. Several challenges are also posed by network analysis, such as how they complement regular multivariate analysis, sample size and statistical requirements, and the development and reliability of indices used (Contreras et al., 2019; McNally, 2021). Although far from being the panacea, network analysis is a useful tool that can produce fruitful, novel insights from our research. Its booming development is promising and holds potential for new uses and findings that will contribute to a better understanding of human functioning related to health.

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