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A New Method in Psychopathology Research: Network Analysis

Psikopatoloji Araştırmalarında Yeni Bir Yöntem: Ağ Analizi

Ülkü Güreşen[1]

[1]Aydın State Hospital, Aydın

ABSTRACT

Though network analysis has a long history in both natural and social sciences it has emerged as a new method in psychology in recent years. Unlike medical disorders, mental disorders are not observable in laboratory. However, we can identify them by the way of observable symptoms. According to the network perspective, a disorder occurs when an external event triggers a psychological symptom. Activated symptom also interacts with other symptoms and forms a pattern of symptoms. Network approach criticizes traditional categorical diagnostic approach and focuses on symptom organization. Probably, treating the most effective symptom will accelerate recovery process and provide more effective treatment. Network analysis can be used in both cross-sectional and longitudinal studies. Psychological networks provide opportunities to investigate direction of the relationship among symptoms, comorbidity, external triggers of psychological symptoms, effectiveness of treatment, comparison of symptom pattern according to sample characteristics. Despite the utility of psychological networks, accuracy of them has been questioned and certain methods to prove accuracy of networks proposed as response. Technological progress in recent years enabled network analysis to be more eligible in psychology. R Statistics software is very useful in network analysis which is totally free and open sourced and supported by many additional packages. This review article aims is to provide information about usage of network analysis in psychology, especially in clinical research. In the first part historical and theoretical background of network analysis was introduced and in the following parts structure, validity of psychological networks and R Statistics Software which is used for conducting network analysis were explained briefly.

Keywords: Network analysis, psychological networks, partial correlation networks, Bayesian networks, R statistics

ÖZ

Ağ analizi doğa bilimlerinde ve sosyal bilimlerde uzun zamandır kullanılan bir veri analizi yöntemi olmasına karşın psikoloji alanında kullanımı henüz yenidir. Psikolojik bozukluklarda diğer tıbbi hastalıklardan farklı olarak bozukluğun belirti vermeden önce laboratuvar ortamında ya da çeşitli görüntüleme yöntemleriyle gözlenebilmesi mümkün değildir. Ancak bütün psikolojik bozukluklar gözlenebilen belirtiler sayesinde tespit edilebilir. Buna göre tetikleyici bir dışsal bir etken tarafından etkinleştirilen belirti diğer belirtileri de etkinleştirerek bir döngü oluşturur. Klinik psikolojide ağ yaklaşımı geleneksel kategorik tanı yaklaşımlarına eleştiri getirerek öncelikle psikolojik bozuklukları oluşturan belirtilerin organizasyonunun ve aralarındaki etkileşimin incelenmesi gerektiğini savunur. Böylece sağaltım aşamasında önemli rol oynayan belirtilere müdahale edilmesi hem tedaviyi çabuklaştıracak hem de daha etkili bir sağaltım sağlayacaktır. Ağ analizi hem kesitsel hem de boylamsal çalışmalardan elde edilen verileri analiz etmek için kullanılabilmektedir. Psikometrik ağlar psikolojik bozukluğu oluşturan önemli belirtilerin yanı sıra bu belirtiler arası yönlü ilişkileri tespit edebilme, komorbidite, belirti örüntüsünü tetikleyici etkenlerin incelenmesi, müdahale etkililiğinin incelenmesi, farklı örneklem özelliklerine göre belirti örüntülerin karşılaştırılması gibi geniş olanaklar sağlamaktadır. Buna karşın psikometrik ağların geçerliği tartışma konusu olmuş ve psikometrik ağların güvenilirliğini arttırmak için çeşitli yöntemler geliştirilmiştir. Son yıllardaki teknolojik gelişmeler diğer bilimlerde olduğu gibi psikolojide de ağ analizinin uygulanmasını kolaylaştırmıştır. Özellikle ek paket programlarla da desteklenen ve tamamen ücretsiz olarak erişime açık olan R istatistiği yazılımı psikolojide ağ analizi gerçekleştirmek için geniş olanaklar sağlamaktadır. Bu derleme yazısında ağ analizinin tarihsel ve kuramsal alt yapısı, psikometrik ağların özellikle de klinik araştırmalarda kullanım alanları, yapısı ve geçerliliği, ağ analizi gerçekleştirmek için kullanılan R istatistiği yazılımı hakkında kısa bir bilgilendirme yapılması amaçlanmaktadır.

Anahtar sözcükler: Ağ analizi, psikometrik ağlar, kısmi korelasyon ağları, Bayes ağları, R istatistiği

Address for Correspondence: Ülkü Güreşen, Aydın State Hospital, Aydın, Türkiye
E-mail: ulkuguresen@gmail.com
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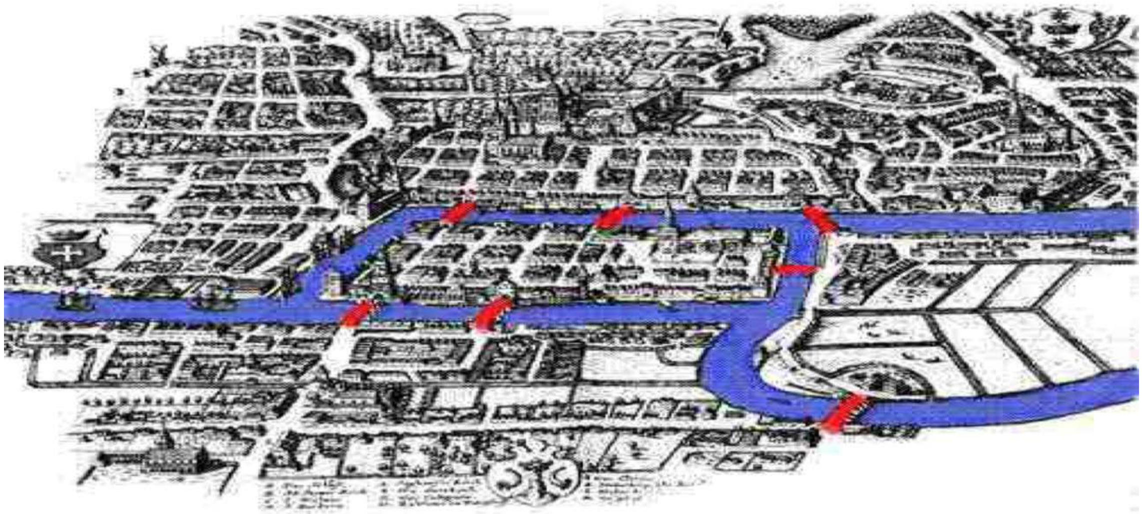
Introduction

In 1735, Swiss mathematician and physicist Leonard Euler asked a question about the seven bridges of Königsberg (today's Kaliningrad) on the Pregel River (Picture 1): whether or not it is possible to cross each bridge exactly once and turn back to the beginning point of this journey. Eventually, he concluded that it was impossible to travel the bridge network in the city of Königsberg, which consists of four nodes and seven connections, once and only once. By the way, he laid the foundation stone of graph theory (Gürsakal 2016).

Networks are all around us. Humans naturally organize themselves in networked systems. Moreover, non-human networks exist almost anywhere they look. Our genes and proteins interact with one another through complex biological networks. One of the ways the universe is organized is with networks (Luke 2015). Social network analysis investigates social structures made up of individuals, a group of individuals, and foundations that consist of group interactions and interrelated structures. Psychiatrist Jacob L. Moreno and psychologist Helen Jennings founded Modern Social Network Analysis (Güzeller et al. 2016). In the first social network analysis study, they investigated interactions among prisoners in a jail and students in a school.

The theoretical basis of psychometric network analysis was proposed in 2008, and the first applied studies were conducted in 2010 (van Borkulo et al. 2014). Today, network analysis is widely used in psychology, with innovations. In psychometric networks, we estimate a statistical model based on data, from which some parameters can be represented as a weighted network between observed variables. Thus, psychometric networks are strikingly different from network structures typically used in graph theory, such as social or ecological networks (Epskamp et al. 2018).

Despite network analysis having been used in both the natural and social sciences for many years, it is a new method in psychology. Mainly, references in Turkish about network analysis in psychology are rarely found. Hence, this review article briefly introduces network analysis and its usage in psychology.



Picture 1. Seven bridges of Köningsberg (Paoletti 2006)

Psychometric Networks

Psychometrician and theorist Denny Borsboom (2008) investigated interactions among symptoms of various psychiatric disorders and proposed a network theory. According to the network approach, negative life experiences activate psychological symptoms and lead to psychopathology (Boschloo et al. 2015). To illustrate this concept, one may consider the symptoms of a disorder network to be domino tiles and view the connections between the symptoms, as the toppling of one domino tile will result in the toppling of others. For instance, chronic stress may trigger insomnia, fatigue, and attention deficits, which create major depressive episodes (Borsboom and Cramer 2013). This symptom activation may continue for a long time, even if the triggering external factor disappears (Jones et al. 2018). For instance, a symptom pattern activated by an adverse life event experienced in childhood may be effective even in adulthood (Örsel et al. 2011). Accordingly, symptoms do not reflect underlying mental disorders; they are constitutive. (McNally 2016).

Psychological disorders should be evaluated differently than medical diseases because imaging techniques can identify a medical disorder in the laboratory.

For instance, lung cancer can be identified by observing symptoms such as a bloody cough and labored breathing. However, imaging techniques can diagnose cancer in its early stages, even if a cancer patient does not report any observable symptoms. For mental disorders, however, such scenarios are implausible. For example, depression cannot be identified by genetic tests, such as Down syndrome or panic disorder, which radioactive techniques cannot image. If major depression were a condition that existed independently of its symptoms, then it should be possible to be depressed without feeling blue or disinterested. If panic disorder were a separately identifiable disease, it should be possible to have it without experiencing panic attacks. If substance use disorder were a separately identifiable disease, then it should be possible to have this disorder without abusing a substance. (Borsboom and Cramer 2013).

According to the network perspective, an episode of disorder occurs whenever the requisite number of symptoms become activated for a sufficient duration. Recovery from a disorder occurs when symptoms deactivate, the links between them dissolve, or both. Hence, a mental disorder constitutes a causal system of dynamically interacting, possibly self-reinforcing, symptoms. (McNally 2016). Network analysis provides an opportunity to understand interactions among symptoms that other statistical methods cannot provide (Hevey 2018).

The usual categorical diagnostic approach considers symptoms that form a mental disorder as equally effective. However, the diagnostic importance of symptoms may be different. A symptom of a diagnosis can be more effective than other symptoms (Sorias 2015). Traditional categorical approaches to psychiatric diagnosis emphasize hallmark symptoms strongly associated with a single disorder but seldom associated with other disorders. Network analysis turns this entire enterprise on its head. Such symptoms may link two syndromes, and activation issuing from a bridge symptom can spread to both syndromes, producing diagnostic comorbidity (McNally 2016). For example, a sad mood, which is known as a depression symptom, may also play a crucial role in alcohol addiction.

A dimensional approach was proposed to fill the gaps in the traditional categorical approach. Despite its contribution of more than ns, a dimensional approach is needed. Because a treatment decision would be applied to a patient or the responsibility of a criminal suspect in terms of mental ability requires binary answers such as yes or no (Sorias 2015). Though network analysis criticizes the traditional categorical diagnostic approach, it does not completely reject it but also attempts to mediate categorical and dimensional diagnostic approaches (Sorias 2015, Gülöksüz et al. 2017).

Network analysis provides researchers with opportunities to identify symptom patterns of a psychological disorder, determine whether symptom patterns differed according to sample characteristics (e.g., gender), observe changes before and after manipulation, define the shortest paths between external factors and symptoms and among symptoms, understand sequences in a time series of longitudinal studies, and discover comorbidity.

Until now, so many studies have utilized network analysis in psychology since the publication of the first network analysis in 2010. Those studies investigated various issues such as depression (Fried et al. 2016, Mullarkey et al. 2019, Wasil et al. 2020, Gizjen et al. 2021), anxiety disorders (Heeren and McNally 2016 Ren et al. 2021), post-traumatic stress disorder (PTSD) (McNally et al. 2017, Green et al. 2019, Cero and Kilpatrick 2020, Gay et al. 2020) obsessive-compulsive disorder (McNally et al. 2017), eating disorders (Forrest et al. 2018, Olantunji et al. 2018, Cascino et al. 2022, Sala, Vanzhula et al. 2022), schizophrenia and psychosis (van Rooijen et al. 2017, Strauss et al. 2018), childhood trauma (Isvoranu et al. 2017, Betz et al. 2020, Breuer et al. 2020), alcohol and substance use disorders (Anker et al. 2017, Sanchez-Garcia et al. 2021, Kroon et al. 2023), emotions (Glück et al. 2017), risk factors of mental health (Pereira-Morales et al. 2017), efficacy of psyhotherapy methods (Johnson and Hoffart 2018), comorbidity (Boschloo et al. 2015, Heeren et al. 2018), personality patterns (Epskamp et al. 2012). Despite widely used network analysis in psychology, it is still a new method in Türkiye. Using a psychometric network, Güreşen and Dereboy (2023) investigated the relationship between childhood trauma and adult psychopathology. They also evaluated patterns of psychological symptom sets by using network analysis.

Structure of the Psychometric Networks

Psychometric networks consist of nodes representing observed variables, connected by edges representing statistical relationships (Epskamp et al. 2018). Nodes in a depression network may involve symptoms, whereas edges (connections) indicate how much symptoms influence each other (van Borkulo et al. 2014). The association between two nodes can be either positive or negative (McNally 2016). In visualizations, green (or blue) edges represent positive associations, and red edges represent negative associations (Jones et al. 2018).

Psychometric networks require statistical estimation, often with partial correlations reflecting the strength of the association between nodes. An edge's thickness corresponds to the association's strength (Jones et al. 2018). Hence, edges in psychometric networks are generally weighted. As the relationship between two nodes gets stronger—in other words, as the partial correlation coefficient increases—the edge becomes thicker.

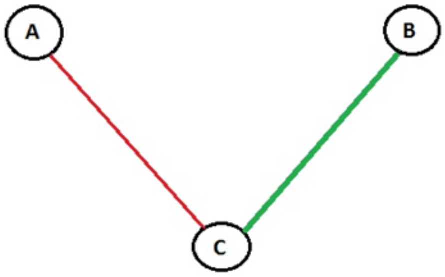


Figure 1. Nodes A, B, C and edges indicate relationship between them

Figure 1 shows the edges of undirected relationships among nodes A, B, and C. The Edge between A and C indicates a negative relationship. In contrast, the edge between B and C indicates a positive relationship. The green edge, which indicates a positive relationship between A and C nodes, is thicker than the red edge, which indicates a negative relationship between B and C. So, the relationship between A and C is more powerful.

The edges of networks can be undirected or directed. Directed networks consist of edges with arrow tips at one end of the edge, pointing in the direction of prediction and perhaps causation (McNally 2016). The location of a node in the network depends on its importance. The importance of a node can be identified by its centrality degree. There are various methods to identify the centrality degree of a node. These are explained briefly below.

1. Degree Centrality: A node's degree is the number of edges connected to it, and the higher the degree, the more central the node is to the network. This metric is common in unweighted networks. For example, consider a social network comprising individuals (nodes) and friendship connections (edges) between pairs of individuals. The person with many friends in the network would appear as a node with many edges, each connected to another node. (McNally 2016).
2. Strength Centrality: Strength centrality is important in weighted networks. Hence, the total weight of edges connected to a node is emphasized rather than the number of edges. In other words, the correlation coefficient is emphasized in strength centrality. A node's strength is the sum of the absolute value of its connections with other nodes in the network (Robinaugh et al. 2016).
3. Closeness Centrality: Closeness centrality indicates how close a node is to all other nodes in the network. It is calculated as the average of the shortest path length from the node to every other node in the network (Goldbeck 2013).
4. Betweenness Centrality: Betweenness centrality measures how important a node is to the shortest paths through the network. To compute the betweenness for node N, we select a pair of nodes and find all the shortest paths between those nodes. (Goldbeck 2013).
5. Expected Influence Centrality: As mentioned previously, strength centrality is important in psychometric networks. However, the existence of negative edges in a network may lead to biases in terms of strength centrality. Thus, van Borkoulo (2014) proposed expected influence centrality to solve this problem. Because interaction among nodes only occurs if edges are positive, For instance, increased appetite may influence weight gain since they are positively correlated. However, increased appetite does not influence weight gain despite the fact that there is a negative relationship between them. Thus, negative and positive edge weights are summed up without an absolute value to calculate expected influence centrality (Epskamp et al. 2018). Closeness and betweenness centralities are not emphasized in psychometric networks as much as strength and expected influence centralities (Epskamp et al. 2018, Jones et al. 2019;).

6. Bridge Centrality: Bridge centrality is utilized in cases where a network consists of two or more sets of variables. It is generally used in comorbidity studies. Bridge centrality also involves subtypes such as bridge strength, closeness, betweenness, and expected influence centralities (Jones et al. 2021). Generally, bridge expected influence centrality is emphasized among those centrality measurements. Bridge expected influence, much like bridge strength, indicates a node's sum connectivity with other disorders. Robinaugh and colleagues (2016) have devised the one-step (EI1) and two-step (EI2) expected influence metrics, two novel measures of node importance that can accommodate signed edges. EI1 aims to assess a node's influence with its immediate neighbors (e.g., the nodes with which it shares an edge). To take into account the secondary influence of a node via the influences of its immediate neighbors (i.e., the nodes with which it shares an edge), Robinaugh and his colleagues (2016) also devised the EI2 index (Heeren et al. 2018). Accordingly, the deactivation of bridge nodes might prohibit other disorder activation and prevent comorbidity spread (Jones et al. 2021).
7. In Strength and Out Strength Degrees, the outward degree is the sum of all outgoing connections from a node, while the inward degree is the sum of all incoming connections to a node (Johnson and Hoffart 2018).
8. Node Predictability: In addition to node centrality, node predictability can also be estimated to identify a node's role and importance in a network. Node predictability indicates how well all other nodes can predict node A. The predictability level is between 0 and 1. A higher predictability level indicates that node A was predicted mainly through other nodes in the network. In contrast, a lower predictability level indicates that node A predicted external factors not presented in the network. Node predictability is shown by adding pie charts. Pie charts are drawn directly into a node or shown in rings drawn around a node. R2 symbolizes the predictability level for continuous data. (Haslback and Waldrop 2018).

Types of Psychometric Networks

Psychometric networks may show variations according to the research question and the type of relationship that was investigated. Thus, a researcher should construct the appropriate type of network. The network types ever classified yet are given below:

1. Association Networks: These networks are derived from a zero-order correlation matrix R out of a standard n × m person-variable data matrix. (Mair 2018). Edges are undirected but weighted (McNally 2016). One issue that arises from using correlation matrices within a network context is that they typically lead to a fully connected graph, which makes it challenging to determine important connections in the network (Mair 2018). Thus, partial correlation networks are preferable to association networks. Figure 2 shows a densely connected symptom pattern of PTSD from an association network by McNally et al. (2014).
2. Concentration (Partial Correlation) Networks: Those networks use shrinkage methods to obtain a simpler and sparser network instead of a dense and complicated network. A partial correlation involving two nodes controls for the influence of all the remaining nodes in the network. Thus, the inferred edges are more reflective of direct influence among nodes (Mair, 2018). Concentration networks depict partial correlations that exceed some specified threshold (e.g., $r \geq 0.3$) to eliminate weak connections in the network. This way, we can make more appropriate inferences by focusing on apparent and stronger relationships (McNally et al. 2014). Graphical lasso is the most common shrinkage operator utilized in concentration networks. The idea of the graphical lasso is to shrink low correlations (i.e., edge weights) to 0 such that they disappear from the graph by using λ, the penalization parameter (Mair 2018). In concentration networks, the Gaussian Graphical Model (GGM) is used for continuous data (Likert type), whereas the Ising Model is used for binary data (Isvoranu 2021). In these networks, two connected nodes predict each other, and any node that connects the two nodes (e.g., node B in the pathway A-B - C) can be seen to mediate the predictive quality between the two nodes. As such, a partial correlation network can be viewed as a skeleton encompassing the existence of putative causal relations (Isvoranu 2021). Fruchterman-Reingold (1991) is a force-directed algorithm frequently used in partial correlation networks. In the FR algorithm, nodes with higher strength centrality are placed in the center of the network, whereas weaker nodes are placed in the periphery. Figure 3 shows a partial correlation network of PTSD symptoms. This network was drawn by McNally et al. (2014) to simplify the dense and complicated association network given in Figure 2. Figure 3 shows McNally et al. (2014) obtained a more sparse and precise network visual.

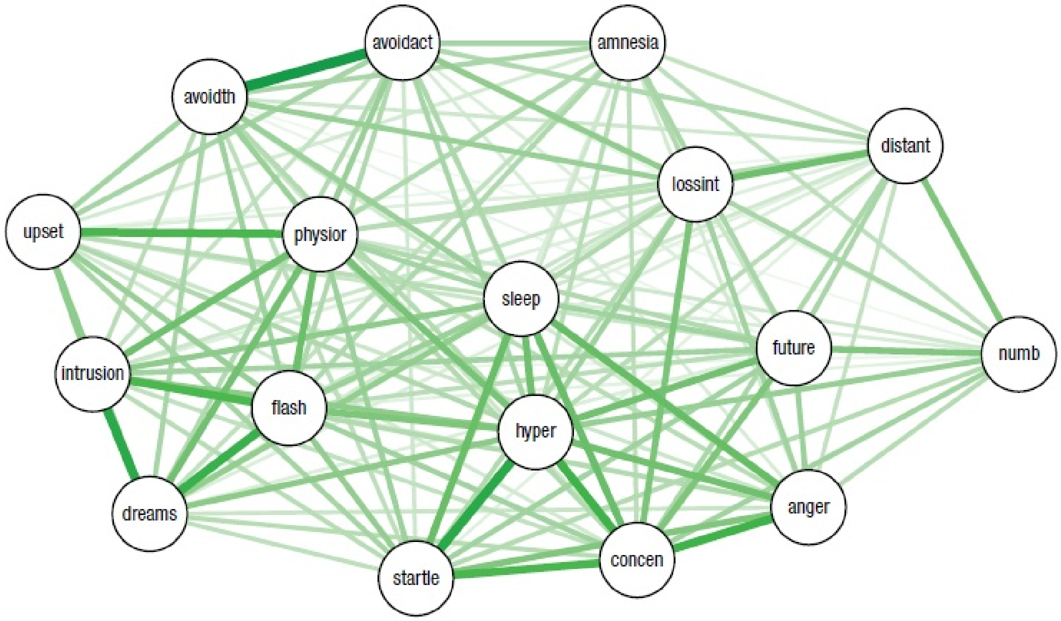


Figure 2. Association network of PTSD (McNally et al. 2014)

Note: intrusion = intrusive memories, thoughts, or images of the trauma, dreams = traumatic dreams, flash = flashbacks, upset = feeling upset in response to reminders of trauma, physior = physiological reactivity to reminders of the trauma, avoidth = avoidance of thoughts or feelings about the trauma, avoidact = avoidance of activities or situations reminiscent of the trauma, amnesia = having trouble remembering parts of the traumatic experience, lossint = loss of interest in previously enjoyed activities, distant = feeling distant or cut off from people, numb = feeling emotionally numb, future = feeling that your future will be cut short, sleep = difficulty falling or staying asleep, anger = feeling irritable or having angry outbursts, concen = difficulty concentrating, hyper = hypervigilant or watchful or super alert, startle = feeling easily startled or jumpy.

3. Relative Importance Networks: These networks are both weighted and directed. Hence, the graph depicts both the magnitude of the association and the direction of prediction, with arrows originating from the predictor node and terminating at the predicted node. Relative importance networks resemble partial correlation networks in that they control for the effects of other nodes when attempting to ascertain the magnitude of the prediction between node X and node Y. However, these networks describe the strength and direction of prediction, not causation (McNally 2016). Figure 5 shows a relative importance network of social anxiety disorder symptoms (Heeren and McNally 2016). Centrality indices of the nodes in this network are also presented in Figure 6.

4. Bayesian Networks: According to Bayesian statistics, as we acquire newer data, we update the relationship pattern that we had constructed using older data. In this way, relationship patterns are listed in a hierarchical order, from the lowest probability to the highest probability. Then, we eliminate lower probabilities and select higher probabilities (Bakırcı 2020). Such networks are called learning networks (Mair 2018). Bayesian network analysis is a parametric method that produces directed acyclic graphs (DAGs). A DAG is a directed network whereby each edge has an arrow tip on one end, signifying the direction of prediction and possibly causation (McNally 2016). A node that is a predecessor of another node is known as a parent node, and a node that is a successor of another node is known as a child node. Probability values show the degree of relationship among nodes in the conditional probability table (Sorias 2015). Bayesian network analysis aspires to discern causality, even from cross-sectional, observational data (McNally 2016). However, since causal inferences require an additional process that is hard to validate, the term "direction" is suggested instead of causality. From a statistical point of view, the probabilities of the edge directions from the bootstrap networks allow us to visualize directions among variables (Mair 2018). Bayesian networks are a group of complicated methods involving many algorithms (Sorias 2015). The Hill Climbing algorithm is widely used in Bayesian networks in psychology. In this algorithm, an activation from a node flows through the network without return. This algorithm adds edges, removes them, and reverses their direction until a goodness-of-fit target score is reached. (McNally 2016). Hence, a node at the top of the network functions as a driving force that activates other symptoms (McNally et al. 2017). Figure 7 shows a Bayesian network of PTSD symptoms with a hill-climbing algorithm (McNally et al. 2017). This network consists of the same nodes

shown in the partial correlation network in Figure 2. As seen in Figure 7, every edge has an arrow tip that indicates the direction of the relationship.

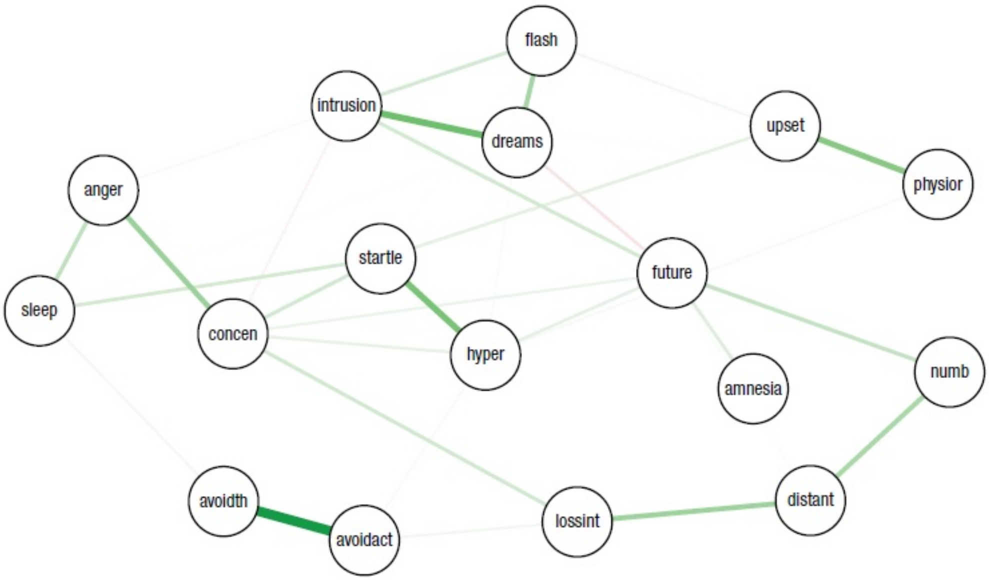


Figure 3. Partial correlation (concentration) network of PTSD symptoms (McNally et al. 2014)
Note: intrusion = intrusive memories, thoughts, or images of the trauma, dreams = traumatic dreams, flash = flashbacks, upset = feeling upset in response to reminders of trauma, physior = physiological reactivity to reminders of the trauma, avoidth = avoidance of thoughts or feelings about the trauma, avoidact = avoidance of activities or situations reminiscent of the trauma, amnesia = having trouble remembering parts of the traumatic experience, lossint = loss of interest in previously enjoyed activities, distant = feeling distant or cut off from people, numb = feeling emotionally numb, future = feeling that your future will be cut short, sleep = difficulty falling or staying asleep, anger = feeling irritable or having angry outbursts, concen = difficulty concentrating, hyper = hypervigilant or watchful or super alert, startle = feeling easily startled or jumpy

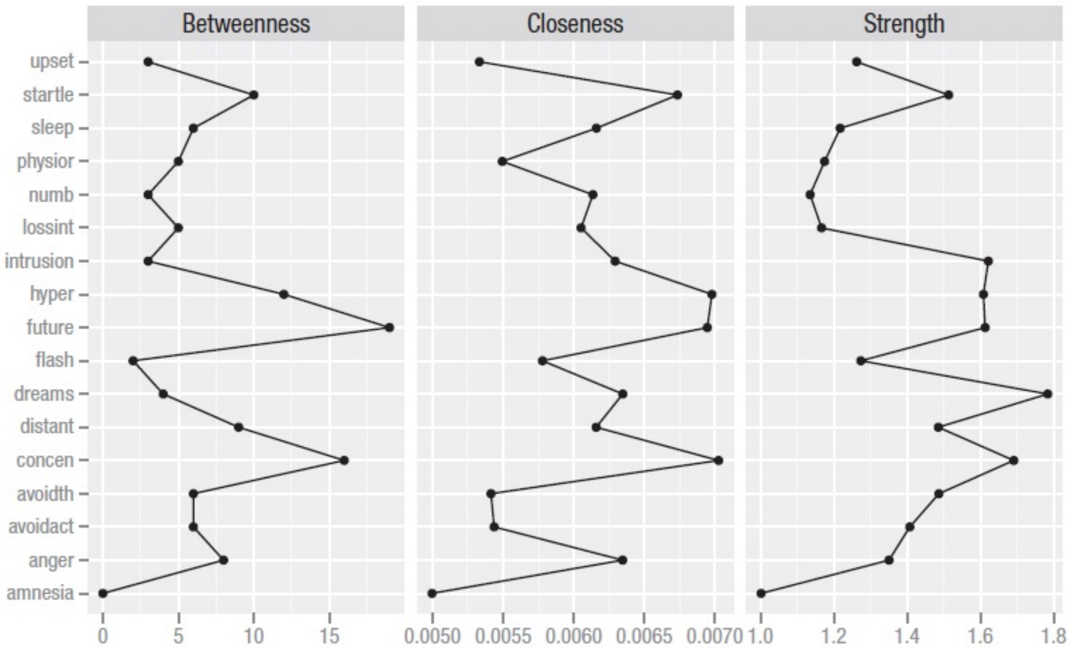


Figure 4. Centrality indices of the partial correlation network of PTSD symptoms (concentration) (McNally et al. 2014)
Note: intrusion = intrusive memories, thoughts, or images of the trauma, dreams = traumatic dreams, flash = flashbacks, upset = feeling upset in response to reminders of trauma, physior = physiological reactivity to reminders of the trauma, avoidth = avoidance of thoughts or feelings about the trauma, avoidact = avoidance of activities or situations reminiscent of the trauma, amnesia = having trouble remembering parts of the traumatic experience, lossint = loss of interest in previously enjoyed activities, distant = feeling distant or cut off from people, numb = feeling emotionally numb, future = feeling that your future will be cut short, sleep = difficulty falling or staying asleep, anger = feeling irritable or having angry outbursts, concen = difficulty concentrating, hyper = hypervigilant or watchful or super alert, startle = feeling easily startled or jumpy

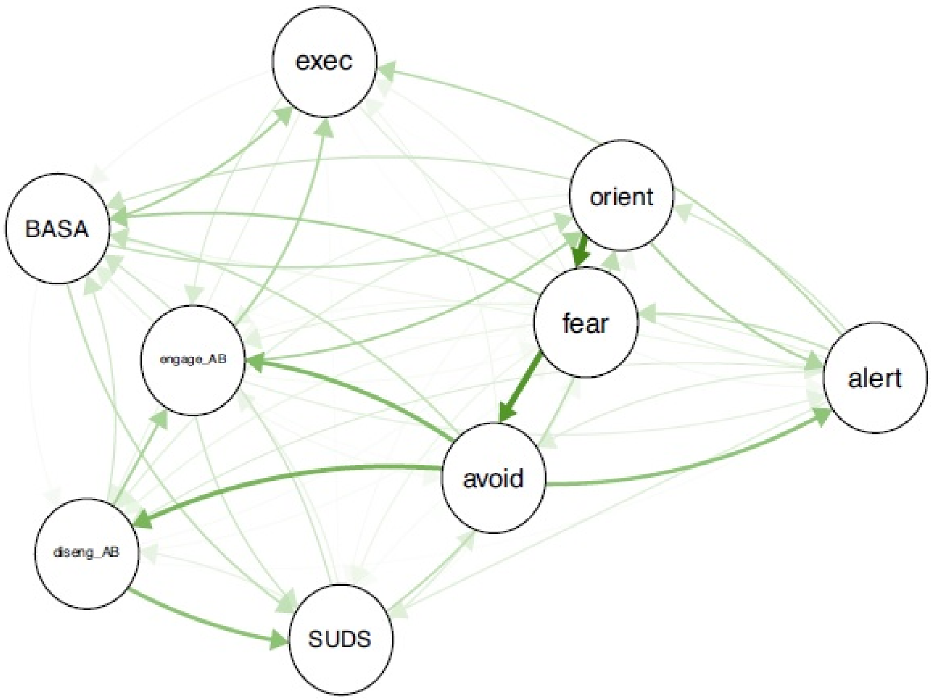


Figure 5. Relative importance network of social anxiety disorder (Heeren and McNally 2016)
Note: alert=Alert score of the Attention Network Task, avoid=Avoidance ratings of the Liebowitz Social Anxiety Scale, BASA= Behavioural Assessment of Speech Anxiety, diseng AB= difficulty disengaging attention from social threat, engage AB= preferential attentional engagement with social threat, exec = Executive score of the Attention Network Task, fear = Fear ratings of the Liebowitz Social Anxiety Scale, Orient = Orienting score of the Attention Network Task, SUDS= Subjective Units of Discomfort Scale

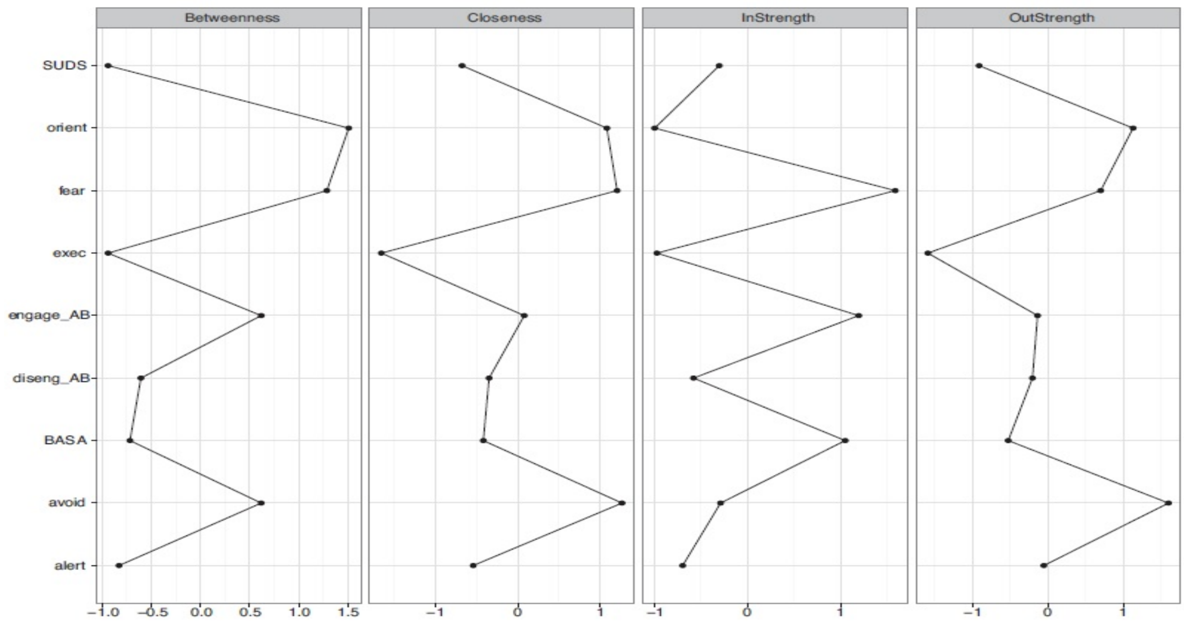


Figure 6. Centrality Indices of Relative importance network (Heeren and McNally 2016)
Note: alert=Alert score of the Attention Network Task, avoid=Avoidance ratings of the Liebowitz Social Anxiety Scale, BASA= Behavioural Assessment of Speech Anxiety, diseng AB= difficulty disengaging attention from social threat, engage AB= preferential attentional engagement with social threat, exec = Executive score of the Attention Network Task, fear = Fear ratings of the Liebowitz Social Anxiety Scale, Orient = Orienting score of the Attention Network Task, SUDS= Subjective Units of Discomfort Scale.

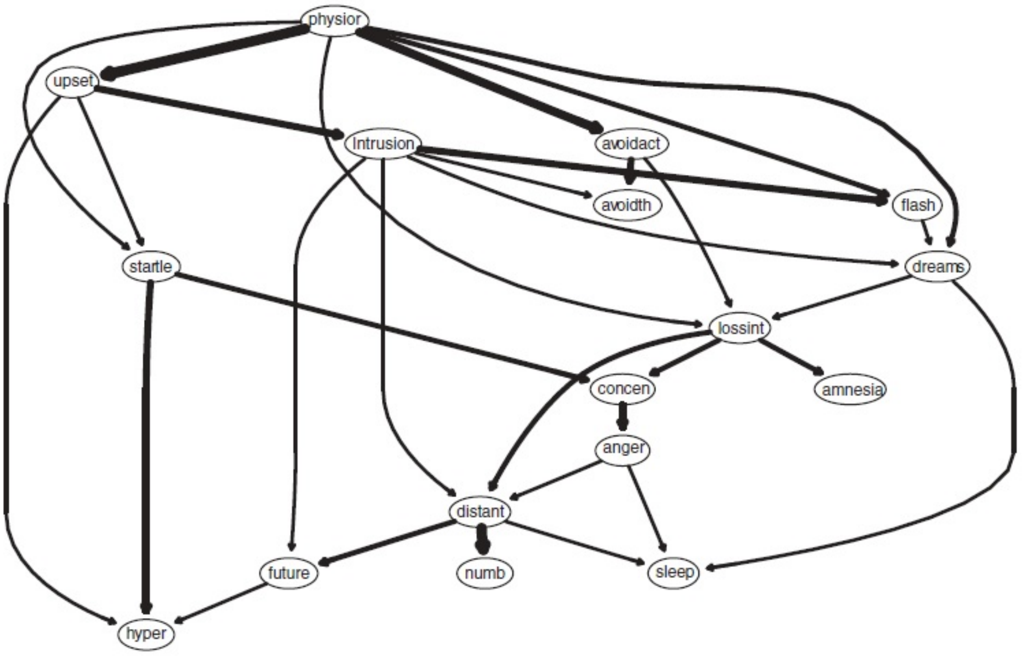


Figure 7. Bayesian network of PTSD symptoms based on directed irreversible graphs (McNally et al. 2017)

Note: intrusion=intrusive memories, thoughts, or images of the trauma, dreams=traumatic dreams, flash=flashbacks, upset=at reminders of the trauma, physior=physiological reactivity in response to reminders of the trauma, avoidth=avoid thoughts and feelings about the trauma, avoidact=avoid activities reminiscent of the trauma, amnesia=difficulty remembering important aspects of the trauma, lossint=loss of interest in previously enjoyed activities, distant=feeling distant or cut off from others, numb=emotionally numb, future=future foreshortening, sleep=difficulty falling or staying asleep, anger=feeling irritable or having angry outbursts, concen=difficulty concentrating, hyper=hypervigilant, startle =exaggerated startle

5. Temporal Networks: Partial correlation networks can function well in cross-sectional studies. However, continuous and serial measurements in longitudinal studies may require different methods. Those networks provide a cause-and-effect relationship by utilizing the vector autoregressive model instead of GGM in partial correlation networks. By being indicative of causality, we expect a temporal link if a causal relationship is genuine, although a link may also arise for other reasons (Epskamp et al. 2018). Those networks are helpful for large samples and single-case studies that consist of many repeated measures of only one individual (Bringman et al. 2022). Edges are directed and weighted. Unlike Bayesian networks, directed-cyclic graphs can be used in temporary networks. A node can be a predictor of another node and predicted by another node simultaneously. Figure 8 shows both temporary networks of depression symptoms in a longitudinal study and centrality indices of nodes (Johnson and Hoffart 2018).
6. Bridge Networks: These networks provide information about networks that consist of two or more variable communities and reveal a node's relationship with other community nodes (Robinaugh et al. 2016). Those networks are generally used to assess comorbidity levels between two different diagnostic communities. According to the bridge expected influence centrality degree, Bai et al. (2021) provide and display a bridge network of depression and anxiety in Figure 9.

Accuracy of Psychometric Networks

Researchers have questioned the validity and reliability of psychometric networks ever since they became popular as a research method. Forbes et al. (2017) proposed that psychometric networks, except association networks, had limited replicability and that network analysis should not be considered a reliable method. Borsboom et al. (2017) argued this view and concluded that the limited replicability of networks resulted from biased estimations used by Forbes et al. (2017). On the other hand, Borsboom et al. (2017) reported that networks had high levels of replicability as a reliable method, so earlier findings by Forbes et al. (2017) should be considered false alarms.

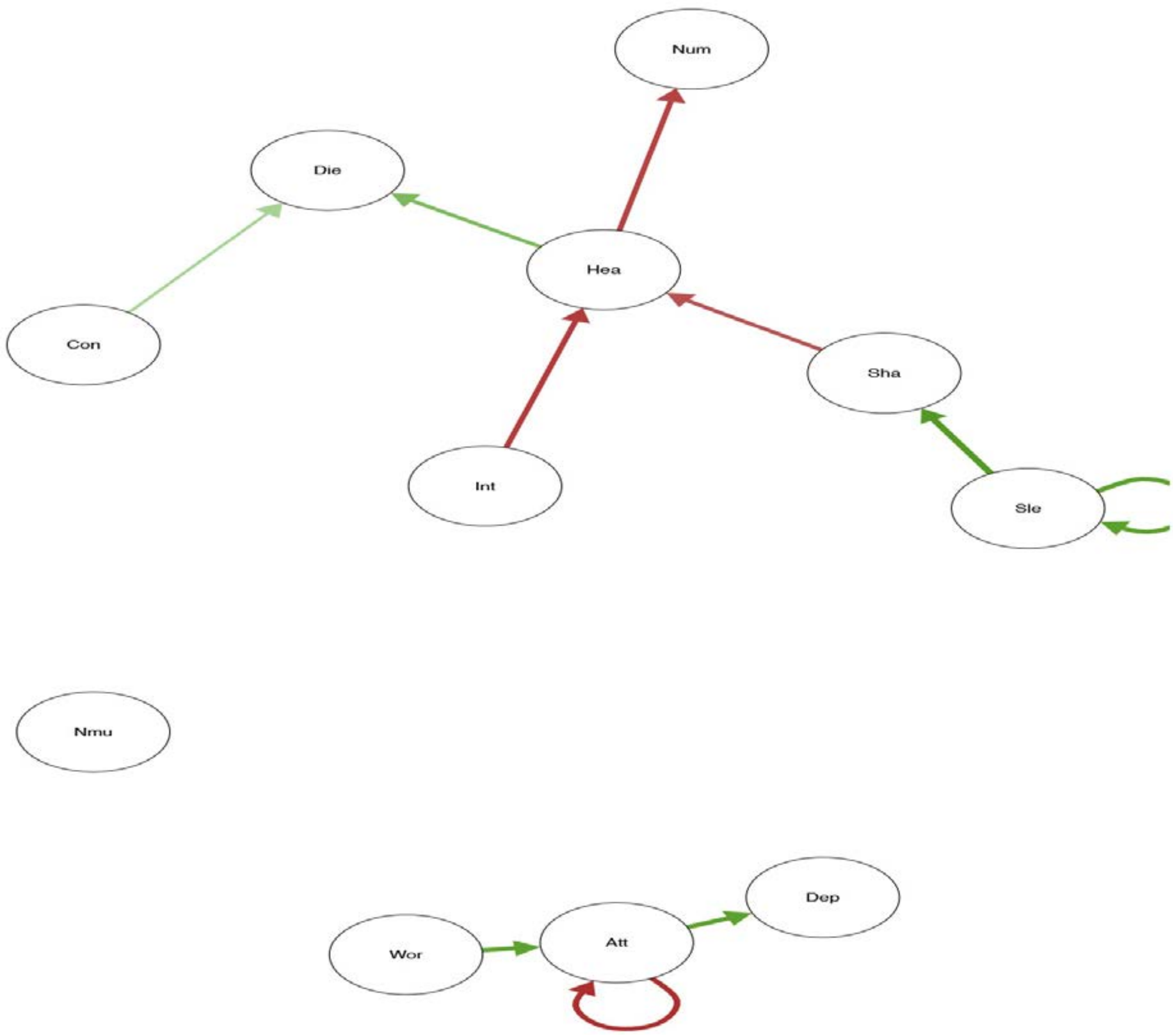


Figure 8. Temporal network from a study which assess influence cognitive-behavioral therapy on depression symptoms (Johnson and Hoffart 2018)

Note: wor=Worry or dwelling on your problems (CAS-1), att=Focusing attention on threatening things (CAS-1) Nmu=I cannot control my thoughts (CAS-1), con=Fear of loosing control (BAI), die=Fear of dying (BAI), num=Numbness or tingling (BAI), hea=Heart pounding/racing (BAI), sha=Shaky/unsteady (BAI), int=Little interest or pleasure in doing things (PHQ-9), dep=Feeling down, depressed or hopeless (PHQ-9),sle=Trouble falling or staying asleep,or sleeping too much (PHQ-9)

Those arguments motivated theorists to develop new methods to construct more stable and accurate network systems despite the information that networks had limited replicability, which was declared a false alarm. Epskamp et al. (2018) developed a priori and post-hoc bootstrapping methods, which are the most critical and well-known methods to assess the stability of networks. The stability of psychometric networks depends on various factors, such as sample size, structure, and size of networks (Borsboom et al. 2017). Sample size may complicate the stability of a network based on the Ising model used for networks of binary data. However, sample size is not a big issue for GGM, which uses continuous data. Shrinkage methods in GGM enable us to obtain a stable network despite a smaller sample size (Epskamp et al. 2018).

Before constructing a network, the number of parameters (every single node and all possible edges) should be calculated, and a sample must be used in which participants must respond to parameters (Epskamp et al. 2017, Epskamp et al. 2018). In a ten-node network, 55 parameters (ten threshold parameters and 10 × 9/2 = 45 pairwise association parameters) must be estimated already. This number grows to 210 in a network with 20 nodes and 1275 in a 50-node network (Epskamp et al. 2018). Three participants for each parameter would be sufficient for a stable network, and the minimum sample size required for this network would be found to be 165. This formula may be useful, but we need a more detailed estimation method to create an acceptable sample size. Simulating a network or testing obtained data in the case of different sample sizes by using a priori bootstrap may be more helpful.

Analyzing a sample by a priori bootstrapping is similar to power analysis in classical test methods. In this way, networks formed by simulated data and actual data can be compared, and intervals of network stability levels according to different sample sizes can be estimated (Epskamp and Fried 2018).

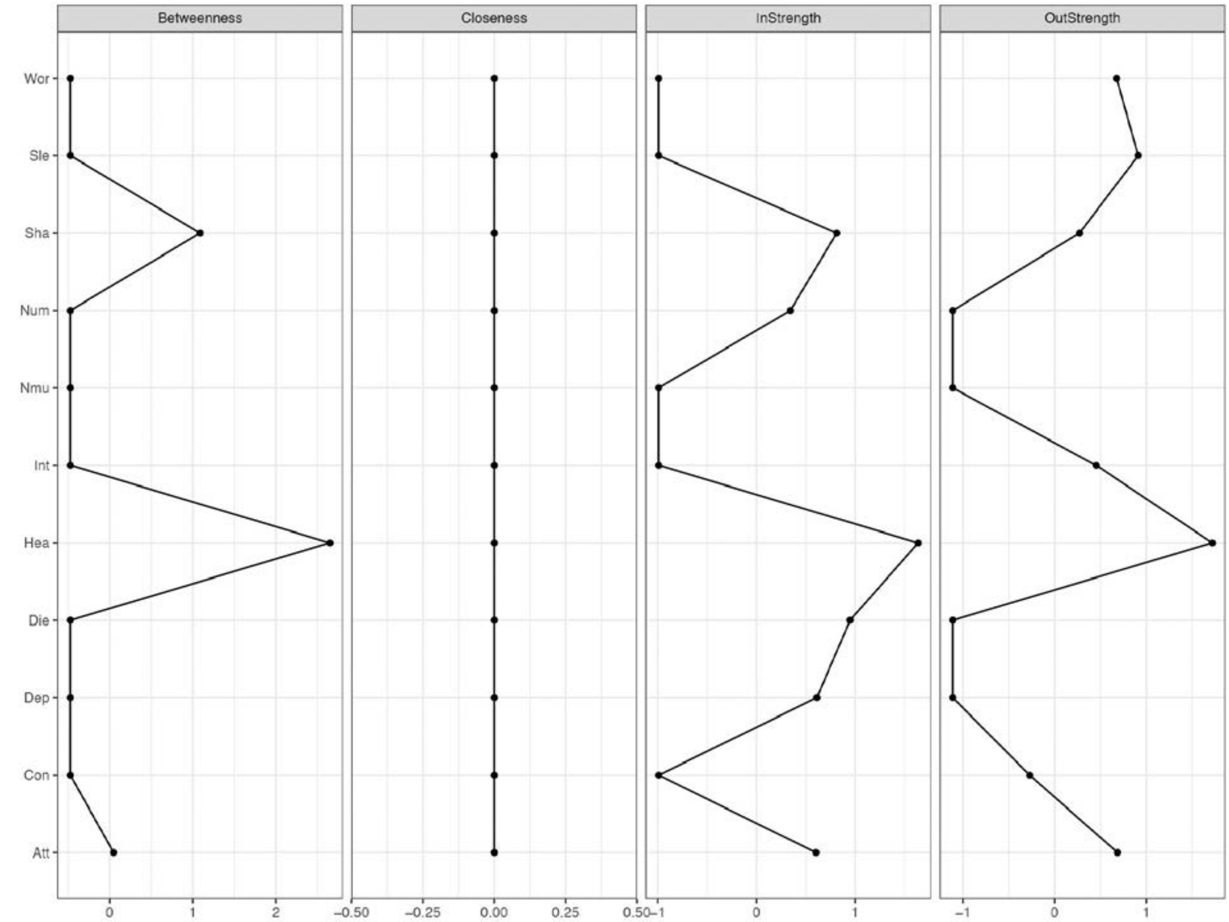


Figure 9. Centrality plots of temporal network from a study which assess influence Cognitive-Behavioral Therapy on depression symptoms (Johnson and Hoffart 2018)

Note: wor=Worry or dwelling on your problems (CAS-1), att=Focusing attention on threatening things (CAS-1) Nmu=I cannot control my thoughts (CAS-1), con=Fear of loosing control (BAI), die=Fear of dying (BAI), num=Numbness or tingling (BAI), hea=Heart pounding/racing (BAI), sha=Shaky/unsteady (BAI), int=Little interest or pleasure in doing things (PHQ-9), dep=Feeling down, depressed or hopeless (PHQ-9),sle=Trouble falling or staying asleep,or sleeping too much (PHQ-9)

Post-hoc bootstrapping is used for assessing the stability of networks in actual data. Parametric bootstrapping is suggested as the default. First, to assess the variability of edge weights, we can estimate a confidence interval (CI): In 95 % of the cases, such a CI will contain the true value of the parameter. Following the bootstrap, a1 – α CI can be approximated by taking the interval between quantiles ½ α ve a1 – 2α of the bootstrapped values. We term such an interval a bootstrapped CI (Epskamp et al. 2018). Assessment of the node centrality stability of the network is the second step of the post-hoc bootstrap. With stability, we indicate if the order of centrality indices remains the same after re-estimating the network with fewer cases or nodes. To quantify the stability of centrality indices using subset bootstraps, we propose a measure we term the correlation stability coefficient, or, in short, the CS-coefficient. To interpret centrality differences, the CS-coefficient should not be below 0.25, preferably above 0.5 and between 0.5 and 1. (Epskamp and Fried 2018, Epskamp et al. 2018).

The Network Comparison Test (NCT) is another method to check the validity of networks. This method compares the same variables' network pattern with another network of different sample characteristics and checks the similarity between networks. NCT also enables the assessment of the accuracy of a network by splitting the data set into two parts. NCT involves two processes named global structure (M) and global strength (S). M compares the similarity level of two networks regarding connections, regardless of edge strength. S is the comparison of the total edge weights of two networks (van Borkulo 2019).

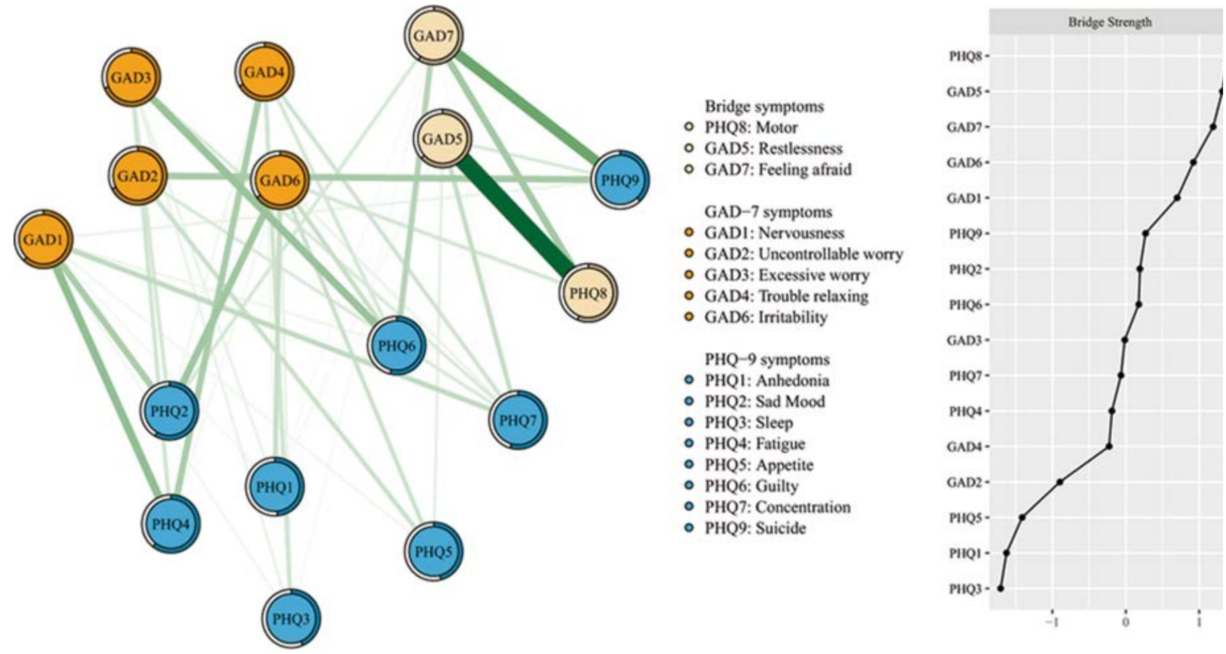


Figure 10. A bridge network that shows common symptoms of Depression and Anxiety and bridge strength indices (Bai et al. 2021)

Software

Today, R Statistics is used as software for constructing psychometric networks. R is free and open-sourced software. It can be used in various operating systems, such as Windows, Linux, and Mac OS. Moreover, R enables obtaining data from various statistical programs such as Excel, SAS, and SPSS and provides table or visual outputs in PDF, JPEG, LATEX, and HTML (Demir et al. 2017). After installing R Statistics, R Studio software, which provides an interface for R, should also be installed. R Studio is also free and open-source software (Hevey 2018).

Most other network analysis programs (e.g., Pajek, UCINet, and Gephi) are stand-alone packages and thus do not have the advantages of working within an integrated statistical programming environment. (Luke 2015). The R system includes several packages designed to accomplish specific network analytic tasks. Several R packages were also developed for psychometric networks. For example, "qgraph" is the most used package for constructing concentration networks (Epskamp et al. 2012). R statistics can be downloaded from www.cran.r-project.org and used freely in operating systems such as Windows, Linux, and Mac OS. Interface R Studio can also be downloaded from www.rstudio.com.

Conclusion

In recent years, network approaches to psychopathology have sparked much debate and have had a significant impact on how mental disorders are perceived in the field of clinical psychology. However, there are many vital challenges in moving from theory to empirical research and clinical practice. (Bringman et al. 2022). Despite ongoing debates about the accuracy of network methods, network analysis is still regarded as a functional method and widely used in various fields of psychology, especially clinical psychology.

In this article, we aimed to inform researchers about the usage of network analysis slightly without going deep. In the future, more detailed articles about network analysis methods may be published to provide more detailed information. Network analysis is a detailed and extensive method that cannot be summarized sufficiently in a single article. However, this article would raise awareness and contribute to the spread of this method. In the future, empirical research employing different network models and systematically reviewing those network studies should occur. Despite the functionality and widespread usage of networks in psychology, researchers should also strive to ensure the accuracy and reliability of their findings.

The increasing popularity of network modeling fits a more significant movement in psychology. It is a movement that emphasizes connections between components that were traditionally studied in isolation, recognizes qualitative as well as quantitative differences between people, engages with the time evolution of systems, actively integrates different modes of observation and levels of analysis, and has a relationship between the structure and dynamics of psychological systems as a central research topic. (Borsboom 2022).

As stated by Borsboom (2022), network analysis considers a human being as a complex system and provides ample opportunities to researchers, such as the evaluation of psychological symptom patterns, interactions between psychological symptoms and external factors of life events that activate them, causality among symptoms or discovering directional relationships, comparison of symptom patterns according to different sample characteristics, and assessment of comorbidity between diagnoses. Although network analysis criticizes the traditional categorical approach, it does not entirely reject categories and, on the contrary, accommodates the newer dimensional approach with a categorical approach (Sorias 2015). Free and open-sourced software R statistics enables the conduct of network analysis in psychology thanks to packages that can be added to R. Utilizing this software, both statistically and visually rich outputs can be obtained, which contribute to psychological research.

In Türkiye, we still have limited references about network analysis in psychology. So, this article, enriched with sample studies from the literature, is expected to contribute to the recognition of network analysis in psychology, especially in the clinical field.

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