Network Analysis Models for Inter-variable Relationships and Their Applications and Characteristics (Postprint)

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Abstract

Network analysis models for inter-variable relationships have been increasingly applied in psychological research in recent years. The objective of this article is to introduce the fundamental principles and commonly used metrics of network analysis, and to further showcase empirical studies employing this method across multiple domains, thereby promoting researchers' comprehension and utilization of network analysis models. Diverging from latent variable models that posit latent variables as common underlying causes of observed variables, network analysis models conceptualize observed variables as primary indicators and utilize graph-theoretic approaches to construct relational networks among observed variables, thus liberating the interconnections among observed variables from the limitations imposed by latent variable models. By leveraging metrics based on nodal characteristics (e.g., centrality) and those based on global structural properties (e.g., small-world characteristics) within variable networks, network analysis offers innovative visual descriptive approaches and interpretive perspectives for investigating diverse psychological phenomena. This article elaborates on the current applications of this methodology in personality psychology, social psychology, clinical psychology, and related fields, and further discusses future directions for developing and refining network analysis models to accommodate broader data types and expand into additional research areas.

Full Text

Network Analysis Models of Variable Relationships: Applications and Characteristics

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Abstract

Network analysis models have been widely applied in psychological research in recent years. This paper aims to introduce the fundamental principles and commonly used indicators of network analysis, and further illustrate its application in empirical research across multiple domains to promote researchers' understanding and application of network analysis models. Unlike latent variable models that treat latent variables as common antecedent factors of observed variables, network analysis models treat observed variables as primary indicators and employ graph theory methods to establish relational networks among observed variables, thereby freeing the associations among observed variables from the constraints of latent variable models. Through node-level indicators (e.g., centrality) and whole-network structural indicators (e.g., small-world properties), network analysis provides new visual descriptive approaches and theoretical perspectives for studying various psychological phenomena. This paper details the current applications of this method in personality psychology, social psychology, and clinical psychology, and further discusses future directions for developing and refining network analysis models to enable their application to more data types and research contexts.

Keywords: network analysis, latent variable model, psychometrics, clinical psychology, personality traits

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Accurately describing and explaining human psychology and behavior is one of the primary goals of scientific psychology. Over the past several decades, researchers have employed latent variable models to describe and measure human psychology and behavior, achieving fruitful results. For example, the Big Five personality model in personality psychology uses individual behavioral tendencies as observed variables and employs five latent traits (e.g., extraversion) to describe individual differences in these behavioral tendencies, thereby characterizing distinct personality profiles (McCrae & Costa, 2008). Similarly, the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-

V; American Psychiatric Association [APA], 2013) in clinical psychology treats different symptoms as observed variables and diagnosed mental disorders as latent variables that cause symptom manifestation. However, in recent years, a new method for describing individual psychological traits—the network analysis model—has rapidly emerged. As a complement to latent variable models, this approach provides researchers with new perspectives for understanding human psychological phenomena and has gradually been applied in fields such as personality and social psychology, clinical psychology, and psychiatry.

The network analysis approach represents the features and information of a system in network form, consisting of “nodes” and “edges.” In traditional network analysis research, nodes typically represent entities (neurons, stations, people), while edges represent connections among entities (synapses, routes, interpersonal relationships). Under data-driven approaches, the changing characteristics of nodes and edges reveal network features. In contrast to these traditional network analysis models, variable-based network analysis models (hereinafter referred to as network analysis) use attitudes, feelings, and behaviors as observed variable nodes, with edges representing connections among these observed variables (Borsboom, 2008). This method is also known as psychometric networks, symptom networks, or trait networks. [Figure 1: see original paper] presents a visualization of a network formed by applying a Gaussian graphical model (also called a partial correlation network model) to three dimensions of personality measurement items. Among network analysis methods, the Gaussian graphical model has the longest history and widest application. Therefore, this paper will primarily focus on the Gaussian graphical model to introduce the basic principles, main analytical indicators, characteristics, and applications across multiple psychological domains, and will specifically discuss other types of network models and future development directions for network analysis.

1. Basic Principles of Network Analysis

Network analysis can be traced back to 1735 when Leonard Euler solved the Seven Bridges of Königsberg problem (Newman, 2001). With the emergence of graph theory in mathematics, network analysis and its data fitting methods developed substantially during the 20th century and found widespread application in natural and social sciences. Examples include web networks and citation-based networks in information science, gene regulatory networks in biological science (Levine & Davidson, 2005; Teichmann & Babu, 2004), brain functional connectivity networks (Park & Friston, 2013; Sporns & Honey, 2006; Xia & He, 2017), and social networks in social science (Borgatti, Mehra, Brass, & Labianca, 2009). Among these, Stanley Milgram’ s “six degrees of separation” effect in social networks (Milgram, 1967; Travers & Milgram, 1969) is well known to psychology researchers.

Networks that consider only whether connections exist between nodes are called unweighted association networks. For example, in social network analysis, networks established based on nomination methods measuring friendship status are unweighted networks, where each edge only represents the presence or absence of a connection between nodes (here representing individuals). Unweighted networks describe connections between nodes through binary classification, which often fails to fully capture system characteristics. In psychological research employing continuous measures, it is necessary not only to describe the presence or absence of connections among observed variables but also to consider the strength of these connections. In such cases, weighted association networks are more appropriate for describing connections among observed variables, where edges represent the strength of connections between nodes (Borsboom, 2008). Due to differences in model fitting methods, researchers incorporate considerations of edge weight effects based on indicators from unweighted networks to obtain metrics describing individual nodes and overall network structure in weighted networks.

Cramer and colleagues (2010) first applied weighted association networks to psychological empirical research by constructing a network of human mental disorders to examine the comorbidity between major depressive disorder and generalized anxiety disorder, revealing extensive symptom overlap between the two conditions (Cramer, Waldorp, van der Maas, & Borsboom, 2010).

Cramer et al. (2010) employed the Gaussian graphical model to analyze symptom networks, which subsequently became the foundational method for applying network analysis to cross-sectional data. Specifically, when applying network analysis to psychometric data, numerous "spurious" correlations may exist in the network due to the large number of nodes. If two nodes are both correlated with a third node, they may appear statistically significant even without a direct connection. To avoid misleading results from such situations, Lauritzen (1996) and Pourahmadi (2011) proposed a solution using partial correlations to more accurately represent true connections between nodes. The partial correlation network model is based on weighted association networks (McNally et al., 2015) and considers the possibility that correlations between two nodes may be influenced by another node, providing a foundation for further accurate investigation of causal relationships between nodes (Borsboom & Cramer, 2013). Partial correlation coefficients range from 0 to 1, representing the correlation between two points while holding constant all other information in the network, and are therefore also called "conditional independence associations."

In actual modeling processes, when all connections between nodes are displayed, network visualizations can become overly complex and difficult to interpret effectively. Therefore, researchers introduce penalization factors, such as the Graphical Least Absolute Shrinkage and Selection Operator (GLASSO; Friedman, Hastie, & Tibshirani, 2008), to delete relatively weak connections in the network. By reducing the number of edges, the model can fit network structures that are more interpretable and have better predictive accuracy. [Figure 2: see original paper] presents the network analysis results after applying the GLASSO penalization factor to the network in [Figure 1: see original paper]. Compared with [Figure 1: see original paper], [Figure 2: see original paper] is more concise and clearly displays important connections, making the model easier to interpret.

The Gaussian graphical model based on partial correlation analysis is only applicable to cross-sectional data where all variables are continuous. For other data types, researchers have proposed corresponding network analysis methods. For example, for binary variable data, van Borkulo et al. (2015) proposed a network analysis method based on the Ising model, using logistic regression to calculate connection strength between nodes, with similar penalization factors available to simplify the network. For data containing both categorical and continuous variables, Haslbeck and Waldorp (2015) proposed using mixed graphical models to construct corresponding networks. For longitudinal data, researchers have proposed analytical methods using regression coefficients between variables to represent edge values (Epskamp, Waldorp, Mõttus, & Borsboom, 2018). In longitudinal network models, mutual prediction between variables becomes possible due to the temporal ordering of measurements. For different types of longitudinal data, researchers have gradually developed other network models, such as vector autoregressive models for single observed variable time series data (Bringmann et al., 2013) and principal component vector autoregressive models (Bulteel, Tuerlinckx, Brose, & Ceulemans, 2018), multilevel vector autoregressive models for multiple observed variables (Epskamp et al., 2018), and cross-lagged network models for data with few measurement time points (Rhemtulla, van Bork, & Cramer, 2019). These models can all calculate the network indicators introduced in the next chapter, differing only in model assumptions, construction, and fitting processes. Due to space limitations, this paper does not provide detailed introductions to these models.

2. Main Indicators of Network Analysis

Network analysis employs Gaussian graphical models to construct variable networks, yielding indicators that describe associations and structures among observed variables that are difficult to capture with traditional latent variable models. In practical research, these indicators often provide important insights about variable relationships, helping to address research questions that latent variable models cannot handle (especially exploratory research questions). Specifically, network analysis indicators include those describing node characteristics and those describing whole-network characteristics.

2.2.1 Centrality

Centrality represents the quantity, strength, and closeness of a node’ s connections with other nodes; changing a high-centrality node affects more other nodes. Centrality is an important indicator showing node characteristics: a node’ s centrality measures its direct relatedness with other nodes (Costantini, Epskamp, et al., 2015). Centrality includes three specific metrics: degree centrality, closeness centrality, and betweenness centrality. For unweighted networks, a node’ s degree centrality is the number of nodes directly connected to it, but this indicator does not consider other parts of the network not directly connected to the node and therefore cannot estimate the node’ s importance and position in the entire network. Closeness centrality and betweenness centrality introduce the concept of shortest path length (SPL), incorporating all nodes in the network into the criteria for measuring a particular node’ s centrality (Bringmann et al., 2013), thus enabling measurement of a node’ s position in the entire network.

[Figure 3: see original paper] illustrates a weighted network with four nodes, with edge weights shown as numerical values on the connections. In unweighted association networks, the SPL between two nodes is the number of edges required to connect them (for example, SPL equals 1 if two nodes are directly connected, and infinite if they cannot be connected through any edges). Closeness centrality is the reciprocal of the sum of SPLs from all other nodes in the network to that node (thus, when the network contains separate components where some nodes cannot be connected through edges, all nodes in the network have closeness centrality equal to 0). Betweenness centrality is also closely related to shortest paths, representing the frequency with which a node lies on the shortest path between any other two nodes. From the perspective of variable interactivity, nodes with relatively high closeness centrality are more easily influenced by variations in other nodes through direct (SPL=1) or indirect (SPL 1) pathways (Costantini, Epskamp, et al., 2015). Nodes with relatively high betweenness centrality often play very important roles in variable interactions, directly or indirectly participating in network change processes.

For weighted association networks, calculating SPL requires considering both edge weights and the number of edges based on SPL in unweighted networks. Early research only incorporated edge weights into shortest path and centrality calculations while ignoring the number of edges (Freeman, 1978). The sum of all edge weights for a node serves as its degree centrality indicator, called strength. In this definition, the shortest path between two nodes is defined as the path with the smallest sum of reciprocals of edge weights among all possible paths connecting the two points. Under this definition, a node’ s shortest path may not be the path with the fewest edges between two nodes. As shown in [Figure 3: see original paper], the shortest path between A and B is A-C-B (i.e., 1/0.5 + 1/0.2 = 7) rather than A-B (1/0.1 = 10).

However, recent scholarly consensus holds that both edge weights and the number of edges are factors measuring node importance and should both be incorporated into shortest path, closeness centrality, and betweenness centrality calculations. Nevertheless, their relative importance should vary across different networks. Therefore, Opsahl, Agneessens, and Skvoretz (2010) introduced a tuning parameter ( ) to adjust the weighting of edge weights and number of edges when calculating centrality across different networks: when is 0, edge weights are not considered; when is 1, the number of edges is not considered (see Supplementary Material Table S3 and Figure S1 for centrality calculation results for the network in [Figure 1: see original paper]).

2.1.2 Predictability

Although centrality reflects a specific node’ s connections with linked nodes, it cannot indicate the extent to which that node is influenced by other connected nodes—that is, how much of the node’ s variance is explained by variations in those connected nodes. To quantify this indicator in weighted association networks, Haslbeck and Waldorp (2015) proposed the predictability indicator to represent the degree to which a node’ s variance can be predicted by variations in its connected nodes (similar in logic to explanatory power in regression analysis). The average predictability of all nodes in a network reflects the degree of influence from extra-network factors (such as environmental and biological factors). Higher average predictability indicates that the network structure can better predict itself internally, with less variance explained by external factors.

2.1.3 Clustering

Clustering focuses on connections among other nodes linked to a particular node. This requires introducing the definition of a “triangle” : for a given node and any two other nodes connected to it, if these three nodes form a “triangle” (such as nodes A, B, and C in [Figure 3: see original paper]), information in the network can flow freely among the three points. A node’ s clustering is measured by the clustering coefficient, specifically the ratio of the number of triangles actually formed by the node and its connected nodes to the number of triangles that could possibly be formed. For example, for node A in [Figure 3: see original paper], the actually formed triangle is “ABC” (one triangle), while possible triangles are “ABC,” “ACD,” and “ABD” (three triangles). Therefore, node A’ s clustering coefficient is 1/3.

In empirical research, centrality, predictability, and clustering provide insights into a node’s (i.e., observed variable’s) status, characteristics, and utility value in the network. For example, in mental disorder networks, symptoms with higher degree centrality may have greater impact on patients because patients exhibiting this symptom are more likely to also exhibit other symptoms (McNally et al., 2015). Closeness centrality and betweenness centrality measure a node’ s importance for overall information transmission in the network (Costantini, Epskamp, et al., 2015; Freeman, 1978). According to network analysis assumptions, information between two nodes is often transmitted through the shortest path between them (Costantini, Epskamp, et al., 2015). Symptoms with higher closeness centrality, due to their shorter overall distance from other symptoms in the mental disorder network, can spread their effects to other symptoms more quickly (Borgatti et al., 2009). Nodes with higher betweenness centrality, due to their greater influence on shortest paths between other nodes in the network, substantially increase information transmission costs (total path length) when removed from the network. In comorbidity research, bridge symptoms in comorbidity networks often have high betweenness centrality, influencing the occurrence and development of other symptoms across two or more different mental disorders (McNally, 2016). Additionally, predictability has important clinical implications: for individual symptoms, when a symptom' s predictability is very low, attempting to improve this symptom by changing its connected nodes is unlikely to be effective; for disorder networks, when a mental disorder' s average predictability is high, intervening with external factors to treat the disorder is more difficult (Haslbeck & Fried, 2017).

2.2.1 Connectivity

Connectivity is related to the average shortest path length (L) between all pairs of nodes in the network. The smaller the L, the greater the network' s connectivity. As previously described, weighted and unweighted networks have different methods for calculating shortest path length, and accordingly, different methods for calculating connectivity. Higher network connectivity indicates tighter overall network connections and greater internal stability, meaning more nodes must be removed to disconnect the remaining nodes (Tio et al., 2016). Network connectivity is an important indicator for comparing whether two networks are identical (van Borkulo et al., 2017). Suppose [Figure 3: see original paper] represents Network 1 based on a female sample, where nodes ABC are all connected to each other, and only A is connected to D, while B and C are not connected to D. In another Network 2 based on a male sample, nodes BCD are connected, and only B is connected to A, while C and D are not connected to A. Comparison reveals that Network 1 and Network 2 have different structures but identical connectivity.

2.2.2 Transitivity

Transitivity is the global clustering coefficient and is highly correlated with node clustering coefficients. Corresponding to the "triangle" used in clustering coefficient calculation, when a node connects to two other nodes forming a series system, this series system (consisting of three points and two lines) is called a "connected triple." As shown in [Figure 3: see original paper], nodes B, C, and D form a "connected triple," while a triangle (such as "ABC") contains three connected triples. Newman (2003) defined transitivity in unweighted association networks as three times the number of triangles divided by the number of connected triples, and Opsahl and Panzarasa (2009) extended the transitivity indicator to weighted association networks. Higher transitivity indicates more detectable three-node clusters in the network, where variables are more likely to cluster in pairs rather than connect dispersedly (Costantini, Epskamp, et al., 2015). Although both network transitivity and connectivity are related to overall network edge density, they have important differences—when the network contains several separate components, the network' s overall connectivity is 0 while transitivity may still be strong.

2.2.3 Small-Worldness Index (SWI)

The small-worldness index is calculated by simultaneously considering average shortest path length and global clustering coefficient: SWI = (C/C') / (L/L'

), where L and C are the network' s shortest path length and global clustering coefficient, and L' and C' are the same indicators for an ER random network (Erdős-Rényi model; Erdős & Rényi, 1959) with the same number of nodes and edges. The small-worldness index reflects, compared with random networks, how easily any two nodes can connect through other nodes (Marcus, Preszler, & Zeigler-Hill, 2018). When SWI is greater than 1 (or greater than 3 under strict conditions), the network exhibits small-world properties, characterized by high connectivity, short paths between nodes, and tight overall connections (Borsboom & Cramer, 2013).

The three whole-network descriptive indicators (connectivity, transitivity, and small-worldness) have heuristic significance for understanding psychological phenomena. For example, Cao et al. (2018) found in their network analysis of posttraumatic stress response symptoms in adolescents of different genders that female network structures had higher connectivity, making positive treatment effects more difficult to achieve, and therefore recommended prioritizing interventions for females when medical resources are scarce. In the example personality network analysis model ([Figure 2: see original paper]), the small-worldness index is 1.38, indicating that under non-strict conditions the network exhibits small-world characteristics. This suggests that a behavior item under a personality "trait" in the Big Five inventory is not only related to other behavior items within that trait but rather has extensive connections with items measuring behaviors across traits.

It should be noted that the above whole-network descriptive indicators apply not only to entire networks but also to individual components that exist independently without connections to nodes outside the component. In some networks, components containing numerous nodes exist (without clear standards, generally around 50%), and such components are called giant components (Newman, 2001). For networks with giant components, analyzing the characteristics of the giant component is often more important than analyzing whole-network characteristics. For example, Tio et al. (2016) analyzed the giant components in the diagnostic criteria networks of the International Classification of Diseases and Related Health Problems, 10th Revision (ICD-10; World Health Organization [WTO]) and the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision (DSM-IV-TR; APA, 2000), finding that DSM-IV-TR (2000) had higher transitivity than ICD-10, indicating tighter internal connections among symptoms in the interconnected network component.

3. Characteristics of Network Analysis

Network analysis focuses on interconnections among variables, highlighting important components through statistical modeling, and can thus reveal data patterns difficult to see in latent variable models. In practical psychological research, network analysis has the following main characteristics:

3.1 Focus on Connections Among Observed Variables

Network analysis does not rely on latent variable definitions and can construct models based on observed variables, assuming correlations among observed variables and directly analyzing relationships among them. In many latent variable models, because latent variables are assumed to be common causes of observed variables within the same dimension, correlations among observed variables are completely explained by latent variables—that is, observed variables only have "local independence" (Lazarsfeld & Henry, 1968). Observed variables serve only as indicators for measuring latent variables, and their relationships with other observed variables are not the focus of the model. However, whether psychological constructs necessarily involve latent variables (i.e., common causes) is a controversial topic. For example, in medicine, various symptoms of cancer may share a common cause (the tumor), but unlike cancer, depression may not have a common cause—a "depression factor" causing various symptoms. Psychological disorders are more likely to result from mutual promotion and influence among different manifest symptoms of the same condition, ultimately leading to onset and development. In such cases, network analysis methods, as a complement to latent variable models, can construct and fit systems of interactions among observed variables (e.g., estimating mutual promotion and interaction among depression symptoms), thereby providing different perspectives on the same research questions. However, it should be noted that network analysis and latent variable models have similar limitations in understanding and defining psychological constructs: they cannot directly define psychological constructs through observed variables. The network itself is not equivalent to the psychological construct but is merely a method for describing its characteristics.

Furthermore, the correspondence between observed and latent variables involves theoretical and practical conflicts, and the assumption that observed variables can only be influenced by one latent variable is considered too restrictive. Many symptoms appear in diagnostic criteria for multiple mental disorders (e.g., insomnia, irritability). Network analysis allows observed variables to influence each other, better aligning with patterns of symptom emergence and development in practice. In contrast, a single mental disorder latent variable is not the cause explaining interactions among these symptoms. On the other hand, researchers can quantify the importance of different nodes in the network through centrality and related indicators, consistent with findings that symptoms connect across multiple psychological/mental disorder systems. For example, McNally (2016) proposed that bridge symptoms in comorbidity have high centrality and therefore play important roles in the entire network structure; Fried et al. (2015) found in their network study of bereavement and depressive symptoms that loneliness is the most important factor linking the two.

3.2 Interactivity Among Observed Variables

Network analysis can be used to study mutual influences among different nodes (observed variables) and their changes over time (by constructing longitudinal models of observed variables). For example, symptoms in mental disorders may be mutually causal and influential, leading to progressively increasing severity (Schmittmann et al., 2013). In initial stages, this process appears to occur at the symptom level (observed variables) rather than at the disorder level (latent variables). Studying these interactive relationships is important for understanding causal relationships among different symptoms and their temporal development processes, thereby helping researchers develop more targeted intervention and treatment plans.

Research has found that individuals suffering from the same mental disorder may exhibit completely different symptom profiles, with different interconnections among symptoms. For example, for individuals with major depression who have insomnia symptoms, the causal pathway of depression may be: stress → insomnia → concentration problems. For individuals whose depression results from somatic symptoms, the pathway may be: stress → increased blood pressure → myocardial infarction → low mood, easy fatigue, insomnia (Borsboom & Cramer, 2013). Interventions for these two cases should have different emphases. Additionally, Isvoranu et al. (2017) analyzed relationships between childhood trauma and later mental illness, finding that among three dimensions of psychosis measured later (positive symptoms, negative symptoms, general psychopathology symptoms), only the general psychopathology dimension had direct connections with childhood trauma, while positive and negative symptoms connected with childhood trauma through general psychopathology symptoms. From these examples, it is clear that under a network perspective, different observed variables play different roles in the system and are therefore important factors in system development and change.

3.3 Holism

Network analysis incorporates all observed variables into the network, examining the development of a psychological/behavioral system from the perspective of whole-network change. For example, Cramer et al. (2012) suggested from a network analysis perspective that personality may be a complete psychological system whose formation is influenced by genetic and biological factors, and which continuously interacts with environmental factors during development, actively seeking suitable behavior patterns, ultimately reaching an equilibrium state. For instance, people who easily feel threatened may actively avoid new environments and interactions with strangers, consequently feeling tense and lonely. Here, "feeling tense," "feeling lonely," and "easily feeling threatened" mutually influence each other to form a stable state of behavior, rather than being influenced by a latent "neuroticism" trait. If this individual experiences successful social interactions, they may increase interactions with strangers, and feelings of tension, loneliness, and being threatened may decrease—the so-called "pulling one hair moves the whole body."Even if a single external feedback cannot completely change an individual' s behavior pattern, it may change relevant components in the system. This change does not require altering a hypothesized latent variable (e.g., changing neuroticism or extraversion traits) to affect the entire system; it only requires changing specific observed variables and their connections with other observed variables. Mental disorder systems may work similarly, with symptoms mutually influencing each other to form stable systems that meet diagnostic criteria for certain disorders. A treatment approach first acts on one or several specific symptoms; by improving these symptoms, other related symptoms change indirectly. When treatment reaches a certain point, connections between specific symptoms change, and subsequently the overall system state changes.

In addition to these three points, network analysis has other characteristics. For example, it can construct models of relationships among dozens or even hundreds of variables in a short time, providing possibilities for exploring and mining complex psychological systems (e.g., personality systems, mental disorder systems, or political belief systems). Network analysis can globally display complex connections among variables, depicting a "big picture" of psychological phenomena. Furthermore, network analysis has excellent visualization characteristics—the variable network constructed by network analysis is essentially already a visual map (as in [Figure 1: see original paper]). In practical applications, benefiting from the development of R packages (e.g., qgraph, Costantini, Epskamp, et al., 2015), researchers can intuitively and clearly display complex structural features among nodes and the entire network with just a few lines of code (Marcus et al., 2018; McNally, 2016).

4. Applications of Network Analysis

As a new method, network analysis has been widely applied in psychology in recent years, particularly in personality psychology (e.g., Cramer et al., 2012), social psychology (e.g., Dalege, Borsboom, van Harreveld, & van der Maas, 2018), and clinical psychology (e.g., Borsboom & Cramer, 2013). The following sections illustrate practical applications of network analysis in these fields.

4.1 Applications in Personality and Social Psychology

In personality psychology, network analysis is often applied to data from traditional personality inventories, using questionnaire items as network nodes and partial correlations between items as edges to construct networks. Based on a review of existing research, network analysis can enhance our understanding of personality in three ways.

First, network analysis reveals new data patterns that supplement and revise conclusions from latent variable models. Beyond the cases shown in [Figure 1: see original paper] and [Figure 2: see original paper], researchers conducting network analysis of the Big Five personality found that agreeableness and extraversion items interpenetrate, indicating that correlations among items measuring agreeableness are not stronger than correlations between these items and extraversion items, making the two dimensions difficult to distinguish. Examining the items themselves, some extraversion items (e.g., "likes to talk with others") and some agreeableness items (e.g., "willing to spend time with others") indeed have high similarity and intrinsic behavioral connections (Cramer et al., 2012). Additionally, genetic analysis of personality traits at the item level revealed heterogeneity in genes associated with different items, which does not meet the homogeneity assumption required by latent variable models (Nagel, Watanabe, Stringer, Posthuma, & van der Sluis, 2018). Network analysis of personality disorders supplements existing theoretical systems: network analysis of pathological narcissistic personality disorder found that narcissistic traits in individuals with pathological narcissistic structures are less predictable by other traits (Di Pierro, Costantini, Benzi, Madeddu, & Preti, 2018). Hyatt et al. (2018) revealed connections (assertive friendship orientation) and distinctions (narcissism relates to callousness, unrealistic attitudes, and disparagement, while self-esteem does not) between narcissism and self-esteem through network analysis.

Second, network analysis breaks through previously proposed theories by integrating originally independent research topics or fields in psychology, drawing all relevant information into easily interpretable variable networks. Network analysis serves as an excellent "bridge" promoting interaction across research topics and theoretical breakthroughs across fields. For example, when exploring networks connecting adult temperament and personality traits, researchers found that personality can be viewed as a complex structure composed of temperament and other traits, identifying four clusters rather than the common five dimensions of the "Big Five" : (1) extraversion, (2) thought, conscientiousness, and agreeableness, (3) flexibility, openness, and imaginative thinking, and (4) neuroticism (Wechsler, Benson, Machado, Bachert, & Gums, 2018).

Third, network analysis cross-validates results obtained through latent variable models. For example, network analysis of the "Dark Triad"personality traits validated that interpersonal manipulation and callousness are central to this personality trait network (Marcus et al., 2018), cross-validating previous latent variable model results (Jones & Figueredo, 2013). Similar validation exists for conscientiousness research, where both exploratory factor analysis and network analysis clustering characteristics revealed four dimensions of conscientiousness: responsibility, impulse control, orderliness, and industriousness (Costantini, Richetin, et al., 2015).

Network analysis has also begun to be applied in social psychology. For example, research on causal network structures of attitudes provides exploratory evidence for understanding attitude formation (interactions among beliefs, feelings, and behaviors), maintenance, change, and strength (Dalege et al., 2016). Empirical research indicates that individuals' political interest can predict the overall connectivity of their attitude networks regarding presidential candidates, and this overall connectivity is significantly correlated with two determinants of attitudes (attitude stability and attitude' s influence on behavior) (Dalege et al., 2018). Building on previous research and network analysis perspectives, Brandt, Sibley, and Osborne (2019) proposed the concept of "political belief system" —they argued that individuals' various political beliefs form a network, with symbolic beliefs (i.e., party affiliation) at the core and attitudes toward specific policies at the periphery. However, the application of network analysis methods in social psychology is still in the exploratory stage, and this technique's enormous potential remains to be realized.

4.2 Applications in Clinical Psychology

In clinical psychology, network analysis applications mainly include exploring network structures of symptoms in traditional mental disorder diagnostic criteria, investigating comorbidity among different mental disorders, and examining intervention effects on specific symptoms and the entire symptom network.

First, network analysis provides new perspectives for understanding relationships among different symptoms in traditional mental disorder diagnoses. Researchers have used unweighted network analysis to explore network structures among symptoms of different mental disorders, including: (1) Borsboom, Cramer, Schmittmann, Epskamp, and Waldorp (2011) on networks connecting DSM-IV (1994) disorders and corresponding symptoms; (2) Boschloo et al. (2015) on networks of 120 symptoms related to 12 mental disorder categories in the Diagnostic and Statistical Manual; (3) Tio et al. (2016) on comparative analysis of network structures between ICD-10 and DSM-IV-TR (2000); and (4) Borsboom (2017) summarizing characteristics of mental disorder diagnostic criteria based on the above research. Overall, current mental disorder diagnostic criteria have the following characteristics: (1) complexity, meaning complex interactions among different components in psychopathological networks; (2) synergistic responsiveness of symptoms and components, meaning components in psychopathological networks respond synergistically to changes in symptoms (nodes); (3) direct causality, meaning network structures result from direct causal connections among symptoms; (4) mental disorders conforming to network structures, meaning some symptom connections are tighter in psychopathological networks, and these symptom clusters interact to trigger other symptoms; and (5) hysteresis, meaning mental disorders result from hysteresis effects in tightly connected symptom networks because activated symptoms can continue to activate each other even after triggering events disappear.

Second, network analysis effectively describes comorbidity among different mental disorders. By describing node characteristics to infer node roles in networks, network analysis can effectively identify "bridge" nodes between different mental disorder networks—that is, comorbid symptoms. Beyond Cramer et al. (2010) examining comorbidity mechanisms between major depressive disorder and generalized anxiety disorder, Ruzzano, Borsboom, and Geurts (2015) explored comorbidity mechanisms between autism and obsessive-compulsive disorder, finding that although repetitive stereotyped behaviors are shared diagnostic criteria, network analysis results showed that autism and obsessive-compulsive disorder are two completely different symptom clusters—aside from shared repetitive behaviors, symptoms have few direct correlations. This demonstrates from another angle that network analysis can deeply sort out comorbidity of mental disorders to identify disorders that are prone or resistant to comorbidity. Afzali et al. (2017) conducted network analysis on comorbidity mechanisms between posttraumatic stress disorder and major depressive disorder, finding that comorbidity bridge nodes were not limited to four shared symptoms (sleep problems, irritability, attention difficulties, and loss of interest) but also included non-shared symptoms such as self-blame, sadness, and flashbacks. The study further suggested that individual vulnerability to injury and negative emotionality may be causes of these comorbid symptoms.

Third, network analysis has begun to be applied to exploring intervention effects in mental disorders and identifying intervention pathways. Some studies introduce interventions as observed variables into networks, observing connections between the intervention variable and different symptoms and the variable’ s impact on overall network structure changes (e.g., Bekhuis et al., 2018; Santos, Kossakowski, Schwartz, Beeber, & Fried, 2018). External factor intervention can improve symptom indicators, change network structure, and ultimately achieve intervention effects. However, connection strength and patterns differ across symptoms (or different parts of the network): some symptoms have strong correlations with treatment, while others may only have indirect connections, which has important implications for clinical treatment research. For example, Blanken et al. (2019) applied network analysis to investigate the therapeutic effects of cognitive behavioral therapy for insomnia (CBT-I) on comorbid insomnia and depression, finding that CBT-I had obvious effects on insomnia symptoms, while its effects on depression were more indirect through improving insomnia symptoms.

5. Summary and Outlook

As a powerful complement to traditional latent variable models, network analysis has unique advantages in describing psychological constructs and has therefore been widely used in many psychological fields in recent years. Based on current research trends, network analysis may develop further in the following areas in the coming years.

First, integrating network analysis theory with empirical evidence, such as verifying whether important nodes revealed by network analysis also play key roles in changing network structures. As previously discussed, network analysis perspectives on mental disorders have identified some relatively important symptoms, with the most important symptoms often considered the network core. Therefore, it is inferred that changing these symptoms may be an important entry point for changing the entire network (i.e., treating the disorder). However, no research has yet verified whether focusing treatment on symptoms with stronger connections to more other nodes in the network can more effectively improve connected symptoms. Future research on mental disorder treatments should focus on this point (Fried et al., 2017).

Second, the replicability issue in network analysis. Since network analysis is essentially a “data-driven” exploratory analysis method, results may be limited to specific sample data and difficult to generalize to other samples. Although more data yields results closer to reality, perfect sample sizes are difficult to achieve. Therefore, whether network analysis truly reflects universal characteristics of psychological systems remains to be further verified (Epskamp, Borsboom, & Fried, 2018; Forbes, Wright, Markon, & Krueger, 2017; Borsboom et al., 2017). Although one study confirmed high replicability of network analysis within and between samples (Borsboom et al., 2017), demonstrating that network structures are at least replicable and generalizable under certain conditions, in the context of concerns about replicability in psychological research (Aarts et al., 2015; Hu et al., 2016), researchers' examination of replicability needs to be further deepened. Therefore, an important future research direction is developing confirmatory network modeling methods to determine the extent to which variable networks fitted based on a specific sample can be generalized to their population and even other populations, and to identify reasons why a network model may not be replicable. Potential reasons include problems with the network structure itself, such as study samples not representing their populations, resulting in network structure models limited to those samples and unable to generalize to their populations; or samples only representing a particular population that differs from other populations, which may also prevent generalization of results based on that sample, as the same network structure may not apply simultaneously to samples from general populations and patient populations (Borsboom et al., 2018).

Third, further integration with latent variable models. Although this paper has introduced many innovative aspects and advantages of network analysis models compared to traditional latent variable models, it must be acknowledged that latent variable models still have irreplaceable advantages over network analysis models. On the one hand, latent variable models (especially generalized structural equation models) incorporate examination and control of measurement errors (Borsboom, Mellenbergh, & Heerden, 2003), effectively addressing the problem that psychological measurement cannot be completely precise. On the other hand, latent variable models provide an effective confirmatory analysis framework. Future research should develop a more comprehensive method that can both demonstrate the interactive and holistic characteristics of network models and incorporate considerations of measurement error. Currently, Epskamp et al. (2017) provide preliminary attempts to integrate latent variable models and network models by constructing network models with latent variables as nodes. Future research can further refine this model to combine the advantages of latent variable models and network analysis models.

Fourth, network analysis applied to individuals (Borsboom & Cramer, 2013). Due to the unique psychological/behavioral characteristics of different individuals, establishing network analysis for each individual facilitates more accurate understanding of the emergence, maintenance, and development processes of individual psychological phenomena and mental disorders. Researchers should develop statistical methods to establish individual-based network analysis to help understand the causes of each individual' s attitudes, personality, and behavioral characteristics, as well as the triggers, pathways, and potential risks of each individual' s mental disorders. Ultimately, findings from network analysis should be applied to develop personalized intervention plans, provide personalized development recommendations, and promote each individual' s mental health and positive development.

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Supplementary Materials: Network Analysis Example Using Three Dimensions of the Big Five Inventory (BFI-44)

Purpose: This example uses network analysis methods to explore the traits of agreeableness, extraversion, and neuroticism in the Big Five Inventory (BFI-44).

Data: The data for this example analysis comes from Liu et al. (2019). The Big Five Inventory (BFI-44) is one of the most widely used personality questionnaires (Chinese version translated by Niu (2011)), including five traits: extraversion, agreeableness, openness, conscientiousness, and neuroticism. Specifically, extraversion contains 8 items, agreeableness 9 items, openness 10 items, conscientiousness 9 items, and neuroticism 8 items. All items use 5-point scales. In this dataset, the BFI-44 sample size is N = 555 (age = 21.69 ± 2.52, 237 males, 318 females). The specific items for agreeableness, extraversion, and neuroticism used in this analysis, along with age and descriptive statistics for each item, are shown in Table S1.

Analysis Process:

Step 1: Establish a partial correlation network model using data from the three dimensions (27 items). As described in the main text, because "spurious" correlations may exist in the network, we use partial correlation coefficients to more accurately describe the network' s true characteristics. Based on the partial correlation network, we further introduce a penalization factor, namely the Graphical Least Absolute Shrinkage and Selection Operator (GLASSO; Friedman, Hastie, & Tibshirani, 2008), to delete weaker connections, reduce the number of edges, more clearly display important connections in the network, and better reflect direct connections between nodes.

Step 2: Calculate three centrality indicators (strength, closeness centrality, and betweenness centrality) and clustering coefficient indicators for the GLASSO network to compare the importance of each node in the network. Additionally, for whole-network structure, calculate the small-worldness index to understand the network' s connectivity characteristics (calculation methods and interpretations of each indicator are described in the main text).

Network construction and indicator calculations were completed using the R package qgraph. Specific code and raw data are available at: osf.io/g74dz/

Results: Partial correlation network and GLASSO network diagrams are shown in [Figure 1: see original paper] and [Figure 2: see original paper] in the main text. Edge weights for the GLASSO network are shown in Table S2.

Whole-Network Structure: Both the partial correlation network and GLASSO network show that items belonging to different traits are correlated. Specifically, items within each trait show strong positive correlations, indicating that overall, the Big Five trait item divisions can reflect their belonging traits to some extent. Neuroticism items show negative correlations with items from the other two traits, but agreeableness and extraversion items show strong positive correlations and interpenetrate, indicating that correlations among items measuring agreeableness are not stronger than correlations between these items and extraversion items, making the two traits difficult to distinguish. Examining the items themselves, some extraversion items (e.g., "likes to talk with others") and some agreeableness items (e.g., "willing to spend time with others") indeed have high similarity and intrinsic behavioral connections (Cramer et al., 2012). Notably, agreeableness item A8 ("I can be cold and hard to approach") shows no connection with the other eight agreeableness items after penalization, but has relatively strong connections with neuroticism and extraversion (especially extraversion), suggesting this item more likely reflects extraversion characteristics than agreeableness. The GLASSO network' s small-worldness index is 1.38, indicating that under non-strict conditions the network exhibits small-world characteristics—high connectivity, short paths between nodes, and tight overall connections (Borsboom & Cramer, 2013). Items under each trait not only have close connections with other items within that trait but also have extensive connections with items under other traits.

Node Centrality and Clustering Coefficients: Since the GLASSO network can more concisely and accurately represent characteristics of psychological constructs, we first analyze and interpret its relevant indicators. The three centrality indicators and clustering coefficients for the GLASSO network are shown in Table S3 (see also line graph Figure S1). Among them, extraversion item E37 ("I am cheerful, outgoing, and sociable") has the highest betweenness centrality and strength, and the second-highest closeness centrality, indicating its high importance in the entire network. Its variation has strong influence on other nodes in the network, and removing it from the network would substantially impact overall network connections. The network diagram also shows this node occupies a central position within the extraversion trait, with strong connections to other nodes in that trait. Extraversion item E41 ("I am full of energy") has the highest closeness centrality and relatively high betweenness centrality and strength, also indicating high importance in the overall network. Extraversion items E44 ("I tend to be quiet") and E40 ("I am full of enthusiasm") have the highest and second-highest clustering coefficients, respectively, indicating that nodes connected to E44 and E40 are more likely to be connected to each other, suggesting these two nodes are relatively "redundant" in the network —that is, network characteristics reflected through them can also be reflected through other nodes (Costantini, Epskamp, et al., 2015).

Examining node indicators for the three traits separately, extraversion trait indicators for all three centrality metrics and clustering coefficients are above average, while agreeableness trait indicators are below average (with betweenness centrality and strength far below average), indicating that extraversion occupies an important position among the three traits in the network, while agreeableness indicators generally have fewer connections with other indicators and rarely lie on shortest paths between other node pairs, having less influence on information transmission in the network.

Interpretation of Results: The network structure reveals more information about items in the Big Five inventory and connections among items. Although the Big Five are often divided into five independent traits, traits are not completely independent. Instead, some items measuring one trait may have closer connections with items measuring other traits. Additionally, different traits occupy different positions in the overall personality network, with extraversion appearing more central than agreeableness. Therefore, when understanding personality as a psychological construct, evaluating personality characteristics solely through scores on individual traits may not be completely accurate.

Table S1: Items and Descriptive Statistics for Three Traits (Agreeableness, Neuroticism, and Extraversion) in the BFI-44 Big Five Personality Questionnaire

Table S2: Edge Weights in GLASSO Network ("-" indicates no connection between two nodes)

Table S3: Centrality and Clustering Coefficient Indicators for GLASSO Network

Figure S1: Line Graph of Node Centrality in GLASSO Network

Author Contribution Statement:

Cai Yuqing: Proposed and designed the research; collected and organized relevant literature; conducted data analysis for supplementary materials; drafted, revised, and finalized the manuscript.

Dong Shuyang: Proposed and designed the research; collected and organized relevant literature; proposed and designed the supplementary materials research plan; revised and finalized the manuscript.

Yuan Shuai: Proposed and designed the research; collected and organized relevant literature; proposed and designed the supplementary materials research plan; revised and finalized the manuscript.

Hu Chuanpeng: Proposed and designed the research; collected and organized relevant literature; obtained and provided supplementary materials data; revised and finalized the manuscript.

Note: Figure translations are in progress. See original paper for figures.

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