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PRIMER

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Network analysis of multivariate data in psychological science

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Abstract | In recent years, network analysis has been applied to identify and analyse patterns of statistical association in multivariate psychological data. In these approaches, network nodes represent variables in a data set, and edges represent pairwise conditional associations between variables in the data, while conditioning on the remaining variables. This Primer provides an anatomy of these techniques, describes the current state of the art and discusses open problems. We identify relevant data structures in which network analysis may be applied: cross-sectional data, repeated measures and intensive longitudinal data. We then discuss the estimation of network structures in each of these cases, as well as assessment techniques to evaluate network robustness and replicability. Successful applications of the technique in different research areas are highlighted. Finally, we discuss limitations and challenges for future research.

Node centrality
A generic term that subsumes a family of measures that aim to assess how central a node is in a network topology, such as node strength, betweenness and closeness.

Network structure estimation
The application of statistical models to assess the structure of pairwise (conditional) associations in multivariate data.

Network description
Characterization of the global network topology and the position of individual nodes in that topology.

Psychometric network analysis
The analysis of multivariate psychometric data using network structure estimation and network description.

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In many scientific fields, researchers study phenomena best characterized at the systems level[1]. To understand such phenomena, it is often insufficient to focus on the way individual components of a system operate. Instead, one must also study the organization of the system's components, which can be represented in a network[2]. The value of analysing the structure of a system in this way has been underscored by the advent of network science, which has delivered important insights into diverse sets of phenomena studied across the sciences[3,4]. This Primer discusses methodology to apply this line of reasoning to the statistical analysis of multivariate data.

Network approaches involve the identification of system components (network nodes) and the relations among them (links between nodes). Well-known examples include semantic networks (in which concepts are connected through shared meanings[5]), social networks (in which people are connected through acquaintance[6]) and neural networks (in which neurons are connected through axons[7]). After nodes and links are identified, and a network has been constructed, one can study its topology using descriptive tools of network science[8]. For instance, one can describe the global topology of a network (such as a small-world network or random graph[9]) or the position of individual nodes within the network (for example, by assessing node centrality[10]). These analyses are often carried out with the goal of relating structural features of the network to system dynamics[4,11].

Network representations have a long history as research tools in statistics, where they encode important information concerning the joint probability distribution of a set of variables[12]. For instance, in graphical models, unconnected nodes are conditionally independent given all or a subset of other nodes in the network[12]; in causal models, graphical criteria are used to determine whether parameters in an estimated causal model are identified[13]; and in structural equation models, path-tracing rules on network representations are used to determine the value of empirical correlations implied by the model[14].

In this Primer, we present network analysis of multivariate data as a method that combines both multivariate statistics and network science to investigate the structure of relationships in multivariate data. This approach identifies network nodes with variables and links between nodes and describes them with statistical parameters that connect these variables (for example, partial correlations). Statistical models are used to assess the parameters that define the links in the network, in a process known as network structure estimation. Then, using a process of network description, the resulting network is characterized using the tools of network science[15–17]. Here, we refer to this combined procedure of network structure estimation and network description as psychometric network analysis (FIG. 1).

Network approaches to multivariate data can be used to advance several different goals. First, they can be used to explore the structure of high-dimensional data in the absence of strong prior theory on how variables are related. In these analyses, psychometric network analysis complements existing techniques for the exploratory

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Node selection
The choice of which variables will function as nodes in the network model.

Network stability analysis
The assessment of estimation precision and robustness to sampling error of psychometric networks.

Conditional association
A statistical association between two variables that does not vanish when taking into account other variables that may explain the association.

Edge weight
In psychometric network analysis, edge weights typically are parameter estimates that represent the strength of the conditional association between nodes.

Pairwise Markov random field
(PMRF). An undirected network that represents variables as nodes and conditional associations as edges, in which unconnected nodes are conditionally independent.

analysis of psychological data, such as exploratory factor analysis (which aims to represent shared variance due to a small number of latent variables) and multidimensional scaling (which aims to represent similarity relations between objects in a low-dimensional metric space). The unique focus of psychometric network analysis is on the patterns of pairwise conditional dependencies that are present in the data. Second, network representations can be used to communicate multivariate patterns of dependency effectively, because they offer powerful visualizations of patterns of statistical association. Third, network models can be used to generate causal hypotheses, as they represent statistical structures that may offer clues to causal dynamics; for instance, networks that represent conditional independence relations form a gateway that connects correlations to causal relations[13,18,19].

Here, we review these functions of network analysis in the context of three types of application in psychological science, illustrating them with examples taken from personality, attitude research and mental health.

Experimentation

The schematic workflow of psychometric network analysis as discussed in this paper is represented in FIG. 2. Typically, one starts with a research question that dictates a data collection scheme, which includes cross-sectional designs, time-series designs and panel designs. Psychometric network analysis begins with node selection, a choice primarily driven by substantive rather than methodological considerations. The core of the psychometric network analysis methodology then lies in the steps of network structure estimation, network description and network stability analysis. Importantly, inferences drawn from the output of network analytic methods require both substantive domain knowledge and general methodological considerations regarding the stability and robustness of the estimated network in order to optimally inform scientific inference.

Network approaches to multivariate data are based on generic statistical procedures and thus invite applications to many types of data. The approaches discussed in this paper, however, have been developed and typically used in the context of psychometric variables such as responses to questionnaire items, symptom ratings and cognitive test scores[20], possibly extended with background variables such as age and gender[21], genetic information[22], physiological markers[23], medical conditions[24], experimental interventions[25] and anticipated downstream effects[26]. Accordingly, the nodes we discuss will ordinarily represent items and tests.

The majority of network modelling approaches use conditional associations to define the network structure prevalent in a set of variables[20,27]. A conditional association between two variables holds when these variables are probabilistically dependent, conditional on all other variables in the data. Which measure of conditional association to use depends on the structure of the data; for instance, for multivariate normal data, partial correlations would be indicated, whereas for binary data, logistic regression coefficients may be used. The strength of this conditional association is typically represented in the network as an edge weight that describes the connection between two nodes. If the association between two variables can be explained by other variables in the network, so that their conditional association vanishes when these other variables are controlled for, then the corresponding nodes are disconnected in the network representation.

The description of the joint probability distribution of a set of variables in terms of pairwise statistical interactions is a graphical model[12] known as the pairwise Markov random field (PMRF)[27]. Versions of the PMRF are known under several other names as well in the statistical literature; see REFS[28,29] for an overview of the relations between relevant statistical models. Many network modelling approaches attempt to estimate the PMRF, typically using existing statistical methodologies such as significance testing[30], cross-validation[31], information filtering[32] and regularized estimation[16,33–36]. Because of its prominence in the literature, this Primer is limited to network approaches that use the PMRF, although it should be noted that other approaches to the analysis of multivariate data exist, including models based on zero-order associations[37], self-reported causal relations between variables[38,39] and relative importance of variables[40].

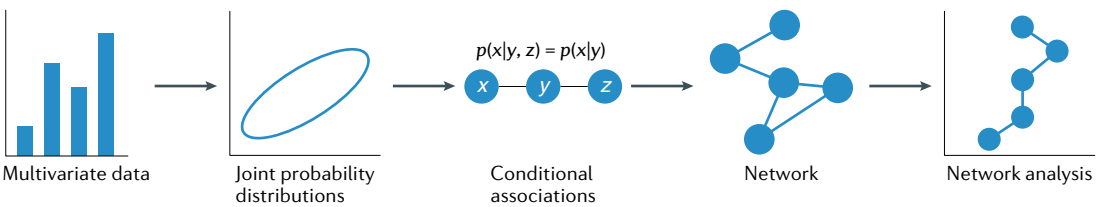


Fig. 1 | **Structure of psychometric network analysis.** Joint probability distribution of multivariate data characterized in terms of conditional associations and independencies. Conditional independencies translate into disconnected nodes; conditional associations translate into links between nodes, typically weighted by the strength of the association. The resulting structure is subsequently described and analysed as a network.

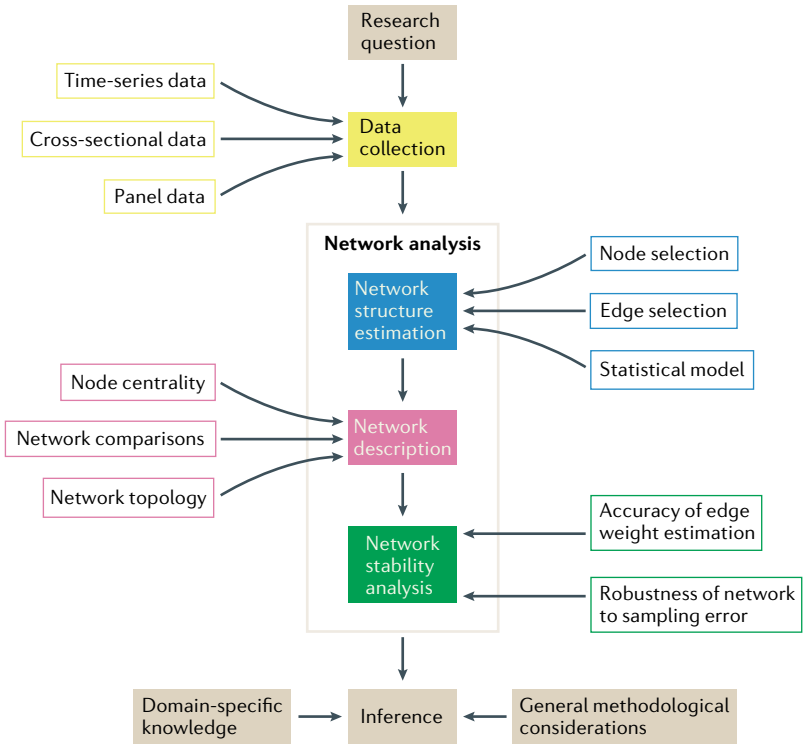


Fig. 2 | **Schematic representation of the workflow used in network approaches to multivariate data.** The heart of the psychometric network analysis methodology described lies in the steps of network structure estimation (to construct the network), network description (to characterize the network) and network stability analysis (to assess the robustness of results). These steps are informed by substantive research questions and data collection procedures. Output of the network approaches combines with general methodological considerations and domain-specific knowledge to support scientific inference.

Because, in typical multivariate data, a substantive subset of associations between variables vanishes upon conditioning, applications of network modelling generally return non-trivial topological structures and the description of such structures is an important goal of psychometric network analysis. For instance, the extent to which network nodes are connected and the network's general topology are of interest, as well as the position of individual nodes in that structure. Thus, psychometric network analysis typically involves interpreting the output of statistical estimation procedures, for example an estimated PMRF, as the input for network description techniques taken from network science (FIG. 1).

Types of data

Network models always operate on associations among sets of variables, but such associations can be extracted from many different experimental and quasi-experimental designs. We focus on three designs that represent typical data environments in social science where psychometric network analysis can be relevant: cross-sectional networks, longitudinal networks of panel data and time-series networks (FIG. 3).

Cross-sectional data. In applications to cross-sectional data, networks are representations of the conditional associations between variables measured at a single time point in a large sample ($T = 1$, $N =$ large). In this case, the associations between variables are driven by individual differences, which renders such networks useful for studying the psychometric structure of psychological tests[29]. In the cross-sectional data example used here, we are interested in the empirical relations among personality and personal goals. We analyse a data set in which three levels of personality structure are assessed via questionnaires, using network models to investigate empirical relations among these elements and personal goals. Our illustrative personality data set features 432 observations and 39 variables of interest[41].

We represent network structures as they arise at different levels of aggregation[42] at which personality can be described. These can be higher-order traits, such as conscientiousness; facets, such as orderliness, industriousness and impulse control[43]; or even specific single items, such as prudent, reflective and disciplined (items of impulse control[44]) that allow for a finer distinction of personality characteristics below facets (see REF.[45] for an example). The objective of psychometric network analysis, in this case, would be to offer insight into the multivariate pattern of conditional dependencies that characterize the joint distribution of these variables at these different levels of aggregation (BOX 1).

When cross-sectional data are analysed through network estimation and interpreted via network description, is it important to keep in mind that resulting topologies represent structures that describe differences between individuals, and that these are not necessarily isomorphic to processes or mechanisms that characterize the individuals who make up the data. That is, inter-individual differences do not necessarily translate to intra-individual processes[46,47]. If one is interested solely in the structure of individual differences, cross-sectional data are adequate, but research into intra-individual dynamics ideally complements such data sources with panel data or time series.

Panel data. In network applications to longitudinal data (also referred to as panel data), a limited set of repeated measurements characterize both the association structure of variables at a given time point and the way these conditional dependencies' change over time ($N > T$). Such measures can illuminate the structure of individual differences and intra-individual change in parallel.

In our example for network approaches to panel data, we use repeated assessments of emotions and beliefs towards Bill Clinton as represented in longitudinal panel data of the American National Election Studies (ANES) between 1992 and 1996. We aim to model consistency, stability and extremity of attitudes towards Bill Clinton during the time that he transitioned from governor of Arkansas to president of the United States. The network theory of attitudes (BOX 2) formalizes changes in attitude importance as network temperature, for example, increasing or decreasing interdependence between attitude elements. In the panel data example, network analyses can assist in modelling temperature changes in the interdependence of attitude elements towards BillClinton.

Topological structures
A generic term to characterize networks in terms of their global topology, for instance in terms of density or architecture.

Conscientiousness
A term used in personality research to designate the propensity to be self-controlled, responsible, hardworking and orderly and to follow rules. In most models of human personality, conscientiousness is considered a high-order factor.

Facets
Specific traits subsumed by a factor in hierarchically organized models of personality. For instance, orderliness and industriousness are facets of conscientiousness.

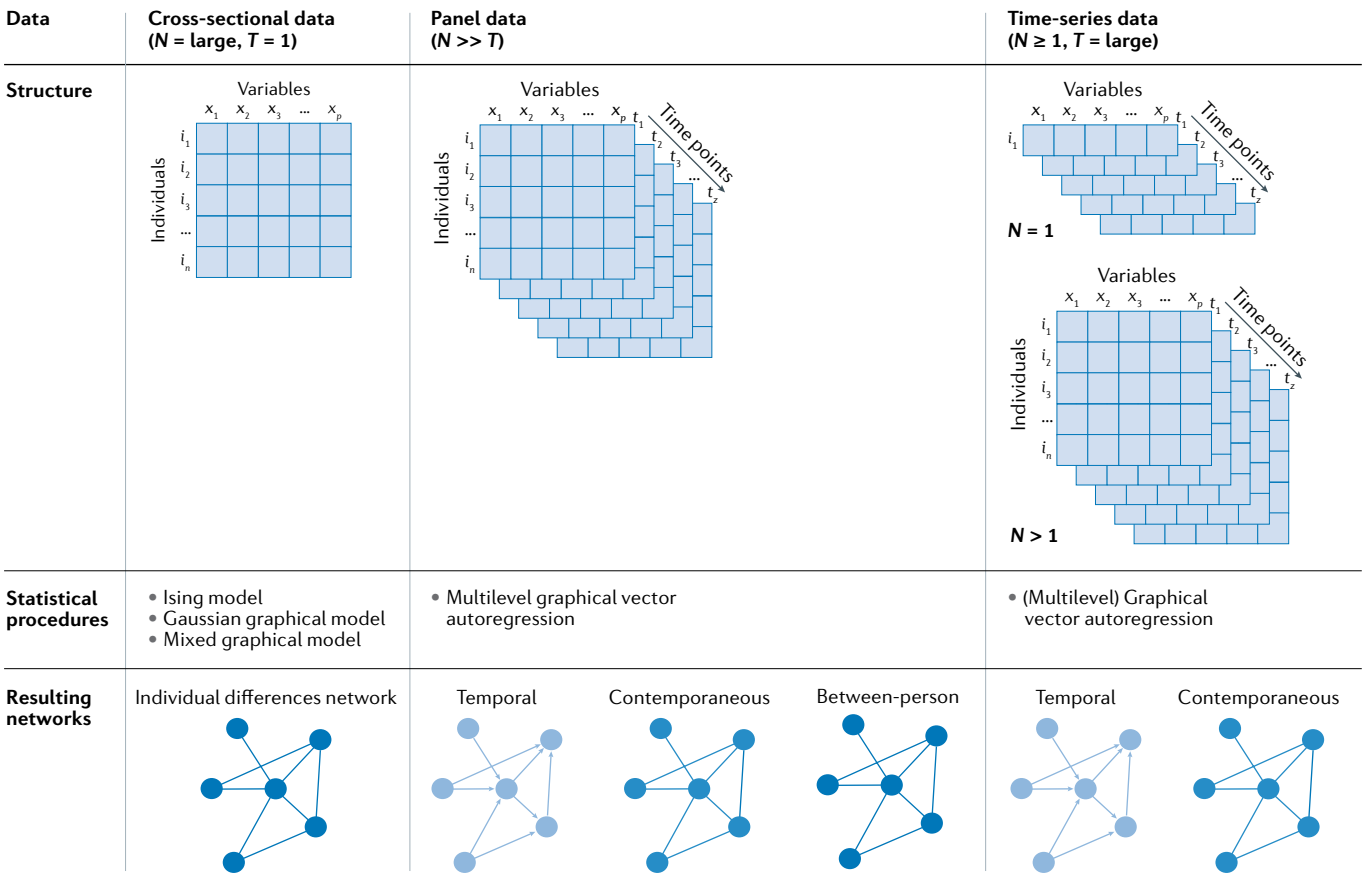


Fig. 3 | **Data structure, methods and resulting networks per typical data environment.** Typical data types include cross-sectional, panel and time-series data.

Time-series data. Networks as applied to time-series data of one or multiple persons characterize multivariate dependencies between time series of variables that are assessed intra-individually (T = large, $N \geq 1$). Such networks are most often applied in situations where one seeks insight into the dynamic structure of systems. For instance, in the social and clinical sciences, recent years have witnessed a surge of daily diary studies and ecological momentary assessment, conducted via smartphones and designed to study such dynamic structures. Studies typically measure experiences — such as mood states, symptoms, cognitions and behaviours — at the moment they occur[48,49]. In such cases, network analyses can assist in interpreting intensive longitudinal data by offering insightful characterizations of the multivariate pattern of dynamics.

In the time-series data example used here, we leverage data gathered during the onset of the COVID-19 pandemic to investigate the impact of reduced social contact due to lockdown measures on the mental health of students enrolled at Leiden University in the Netherlands. In this ecological momentary assessment study, students were followed daily for 2 weeks, assessing momentary social contact as well as current stress, anxiety and depression 4 times per day via a smartphone application[50]. In this situation, a network model can be fitted to these data to investigate to what degree social contact variables influence mental health variables over the course of hours and days. Because, in this case, multiple individuals were assessed multiple times, the design is mixed; in such situations, it is often profitable to use a statistical multilevel approach[27,51], in which the repeated observations are treated as nested in the individuals. This explicitly separates individual differences from time dynamics[52].

Results

In a PMRF, the joint likelihood of multivariate data is modelled through the use of pairwise conditional associations, leading to a network representation that is undirected. There are several benefits to the PMRF that make this particular network representation important. First, the PMRF encodes conditional independence relations (in terms of absent links between nodes), which form an important gateway to identify candidate data-generating mechanisms[29,53,54]. However, the PMRF does not require an a priori commitment to any particular data-generating mechanism (unlike directed acyclic graph estimation or latent variable modelling, for example). Because PMRFs do not place strong assumptions on the structure of the generating model but do hold clues to causal structure through conditional independencies, they are well suited to exploratory analyses (see also Limitations and optimizations). In addition, estimated PMRFs often describe the data successfully with only a subset of the possible parameters (for example, using sparse network structures), which leads to more insightful network visualizations. Finally, a priori commitments invariably lead to problems of underdetermination,

Network temperature
A parameter of network models that controls the entropy of node state patterns. A network with low temperature will allow only node states that align, such that positively connected nodes must be in the same state and negatively connected nodes must be in the opposite state, whereas a network with high temperature will allow more random patterns of activation.

Ecological momentary assessment
Daily diary methodology to measure psychological states and behaviours in the moment, for instance by using ambulatory assessment devices such as mobile phones to administer questionnaires that probe how the person feels or what the person does at that specific point in time.

Underdetermination
The problem that explanatory models often are not identifiable from the data.

Mixed graphical models
Models for relations between variables of continuous and discrete type based on conditional associations.

because many structurally different models will produce indistinguishable data, which is known as statistical equivalence. By contrast, the PMRF is uniquely identified, so there are no two equivalent PMRFs with different parameters that fit the data equally well.

If data are continuous, a popular type of PMRF is the Gaussian graphical model (also known as a partial correlation network) in which edges are parameterized as partial correlation coefficients[55,56]. If data are binary, a popular PMRF developed to estimate the Ising model can be used, in which edges are parameterized as log-linear relationships[16,29,36]. The Ising model and the Gaussian graphical model can be combined in mixed graphical models, in which edges are parameterized as regression coefficients from generalized linear regression models[57]. Mixed graphical models represent the most general approach to PMRF estimation and also allow for the inclusion of categorical and count variables.

Cross-sectional data

The PMRF can readily be estimated from cross-sectional data, in which case it can be reasonably assumed that all cases or rows in the data set — which usually represent people — are independent. This assumption is violated, however, in panel data and time-series designs, in which an individual case is not a person but, rather, a single measurement moment of one of the persons in the sample. In this case, violations of independence occur in two ways: temporal dependencies are introduced owing to the temporal aspect of data gathering (for example, a person who feels sad at 12:00 might still feel sad at 15:00), and responses from the same person may correlate more strongly with one another than responses between different persons (for example, a person might feel, on average, very sad in all responses). Thus, whereas cross-sectional data can use independence assumptions that allow for the application of population-sample logic, time-series data require a model to deal with the dependence between data points.

Time-series data

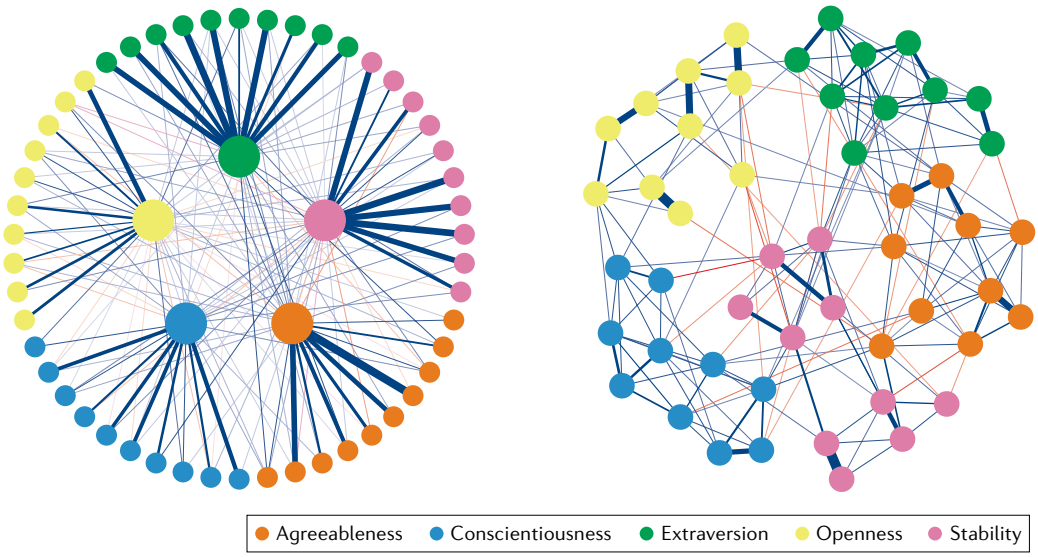
To address time dependencies, PMRFs may be extended with temporal effects that represent regressions on the previous time point in a single-person case. These temporal effects may, for instance, be estimated through the application of a vector autoregressive model.

Box 1 | **Psychometric structure of personality test scores**

A substantial part of the literature on human personality is concerned with the psychometric structure of personality tests. Research has shown that people's self-ratings on adjectives (such as outgoing, punctual and nervous) or responses to items that characterize them (I make friends easily, I get stressed out easily; see the International Personality Item Pool for an overview of psychometric items) show systematic patterns of correlations. These patterns of correlations are often described by a low-dimensional factor model; most often, solutions with five factors known as the Five Factor Model[142] or with six factors known as HEXACO[143] are proposed. The factors in the Five Factor Model are often interpreted as latent variables that cause the correlations between the item scores. However, attempts to ground these latent variables in psychological or biological theories of human functioning have met with limited success, and correlations between personality items may have other causes that include content overlap and the presence of direct relations between properties measured by these items[69]. Such hypotheses are consistent with the finding that items in personality scales typically either load on several factors simultaneously or feature correlated residuals, suggesting that the latent variable model does not fully account for the correlations between item scores. Recently, network models have been proposed as an alternative representation of the psychometric structure of personality tests that does not require a priori commitment to a particular generating model (such as a latent variable model) and may serve to identify alternative mechanisms that lead to correlations between items[44,144]. An exploratory factor model and a network model are visualized in the figure using IPIP-Big Five Factor Markers open data[145].

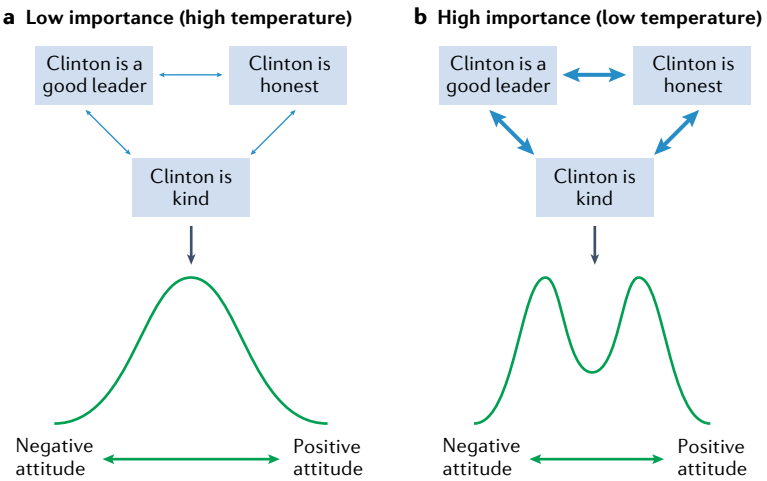
a Factor model: items measure latent variables

b Network model: items form communities



Box 2 | **Causal attitude network model and attitudinal entropy**

The network theory of attitudes holds that attitudes are higher-level properties emerging from lower-level beliefs, feelings and behaviours[111]. A negative attitude towards a politician might emerge from negative beliefs (that the politician is incompetent and bad for the future of the country), feelings (anger and frustration towards the politician) and behaviours (voting behaviour and making jokes about the politician). These different attitude elements can be modelled as nodes in a network, in which edges between attitude elements represent potentially bidirectional interactions between the elements. The network theory of attitudes relies on the central principle that interdependence between attitude elements increases when the attitude is important to the person and when an individual directs attention to the attitude object[111]. This theory uses analogical modelling of statistical mechanics and the effect of attitude importance, and attention is formalized as a decrease in temperature. The effect of decreasing network temperature is that the entropy of a multivariate system decreases by making (attitude) elements in the system more interdependent. In the case of attitudes, this effect translates to heightened consistency and stability of the attitude when it is important, because the different attitude elements rein each other in under low temperature compared with high temperature (see the figure, parts **a** and **b**). Low temperature leads to low variance of the overall attitude within an individual, and hence higher stability. By contrast, a group of individuals with low-temperature attitude networks have higher variance than a high-temperature group, because the pressure of attitude elements to align leads to higher extremity of the overall attitude, creating a bimodal distribution. As this bimodal distribution only occurs in a low-temperature/high-importance scenario, the network model offers a potential explanation for polarization: higher importance leads to more strongly connected networks, which in turn produces polarized attitudes.



The structure of the associations that remain after taking temporal effects into account can also be represented in a PMRF. This network is typically designated as the contemporaneous network. Thus, in contrast to the case of cross-sectional networks, the application of network modelling to multivariate time series returns separate network structures to characterize the dependence relation describing associations that link variables through time, and associations that link variables after these temporal effects have been taken into account. These networks have a distinct function in the interpretation of results. The temporal network can be read in terms of carry-over effects at the timescale defined by the spacing between repeated measures, where the temporal ordering can also assist causal interpretation. The contemporaneous network will include associations that are due to effects that occur at different timescales rather than those defined by the spacing between repeated measurements. Note that, just as cross-sectional networks, time-series networks almost always represent correlational data; interpretation of such networks in causal terms is never straightforward.

Contemporaneous network
A network that represents within-person conditional associations between variables within the same time point. Contemporaneous networks are often estimated after conditioning on effects of the previous time point, as expressed in a time-series model.

Edge selection
A method to determine which edges of a mixed graphical model are to be included and excluded.

Panel data

In panel data or $N>1$ time-series settings, multilevel modelling can differentiate between within-person and between-person variance In addition to the temporal and contemporaneous networks (both of which represent within-person information), one then obtains a third structure of associations that can be characterized as a PMRF. This third structure represents the conditional associations between the long-term averages of the time series between people. This structure, similar to that of cross-sectional networks, represents associations driven by individual differences and is known as the between-persons network. Thus, in the cross-sectional case one obtains one network (the PMRF of the association between individual differences), in the time-series case one obtains two networks (the directed temporal network of vector autoregressive coefficients and the undirected contemporaneous network of the regression residuals) and for multiple time series and panel data one obtains three networks (temporal and contemporaneous networks driven by intra-individual processes and the between-persons network driven by individual differences). In addition, one may use multiple time series to identify network structures that are (in)variant over individuals[58] or that define subgroups[59].

Edge selection

Methods of edge selection are based on general statistical theory as applied to the estimation of conditional associations. Three methods are featured in the literature. First, approaches based on model selection through fit indices can be used. For example, regularized estimation procedures[16,33] lead to models that balance parsimony and fit, in the sense that they aim to only include edges that improve the fit of the network model to data (for instance, by minimizing the extended Bayesian information criterion[35]). Second, null hypothesis testing procedures are used to evaluate each individual edge for statistical significance[30]; if desired, this process can be specialized to deal with multiple testing, through Bonferroni correction or false discovery rate approaches, for example. Last, cross-validation approaches can be used. In these approaches, the network model is chosen based on its performance in out of sample prediction, such as in *k*-fold cross-validation[31].

Network description

Once a network structure is estimated, network description tools from network science can be applied to investigate the topology of PMRF networks[3,60].

Global topologies that are particularly important revolve around the distinction between sparse versus dense networks. In sparse networks, few (if any) edges are present relative to the total number of possible edges. In dense networks, the converse holds, and relatively many edges are present. This distinction is important for two reasons. First, optimal estimation procedures may depend on sparsity, for example regularization-based

approaches can be expected to perform well if data are generated from a sparse network, but may not work well in dense networks. Second, in sparse networks the importance of individual nodes is typically more pronounced, because in dense networks all nodes tend to feature a similar large number of edges. Further analyses can be used to investigate the global topology of the network structure in greater detail; for example, Dalege et al.[61] investigate small-world features[9] of attitude networks and Blanken et al.[62] use clique percolation methodology to assess the structure of psychopathology networks. Although network visualizations are typically based on aesthetic principles — for example, by using force-based algorithms[63] — recently, techniques have been proposed to visualize networks based on multidimensional scaling[64]. These techniques allow node placement to mirror the strength of conditional associations in the PRMF, so that more strongly connected nodes are placed in closer vicinity to each other.

Local topological properties of networks feature attributes of particular nodes or sets of nodes. For example, measures of centrality can be used to investigate the position of nodes in the network. The most commonly used centrality metrics are node strength, which sums the absolute edge weights of edges per node; closeness, which quantifies the distance between the node and all other nodes by averaging the shortest path lengths to all other nodes; and betweenness, which quantifies how often a node lies on the shortest path connecting any two other nodes[65]. These metrics are directly adapted from social network analysis, and can be used to assess the position of variables in the network representation constructed by the researchers. Strength conveys how strongly the relevant variable is conditionally associated with other variables in the network, on average. However, note that closeness and betweenness treat association as distances, which can be problematic. More recently, new measures have been introduced, specifically designed for the analysis of PMRF structures. Expected influence is a measure of centrality that takes the sign of edge weights into account[66]; this can be appropriate when variables have a non-arbitrary coding, such as when the high values of all variables indicate more psychopathology. Predictability quantifies how much variance in a node is explained by its neighbours[54], which can be used to assess the extent to which the network structure predicts node states. Further extensions to the characterization of networks and nodes in terms of network science involve participation coefficients, minimal spanning trees and clique percolation as proposed by Letina et al.[67] and Blanken et al.[62]. Finally, the shortest paths between nodes may yield insight into the strongest predictive pathways, and clustering in the network may yield insight into potential underlying unobserved causes and the dimensionality of the system[68].

Applications

Although network approaches as discussed here draw on insights from statistics and network theory, the specific combination of techniques discussed in this paper has its roots in psychometric modelling in psychological contexts. This section discusses three areas in which this approach has been particularly successful. First, the domain of personality research, where network models have been applied to describe the interaction between stable behavioural patterns that characterize an individual. Second, the domain of attitude research, in which networks have been designed to model the interaction between attitude elements (feelings, thoughts and behaviours) to explain phenomena such as polarization. Last, the domain of mental health research, where networks have been used to represent disorders as systems of interacting symptoms and to represent key concepts such as vulnerability and resilience.

Personality research

Personality researchers are interested in examining the processes characterizing personality traits[69]. One type of these processes is motivational: research shows that traits such as conscientiousness or extraversion can be considered as means to achieve specific goals, for example getting tasks done and having fun, which have been identified as goals relevant for conscientiousness and extraversion, respectively[70]. Psychometric network analysis of personality traits and motivational goals combined offers a novel way to explore relations among relatively stable dispositions. Personality networks can represent personality at different levels of abstraction, from higher-order traits to facets to specific items. One could wonder which abstraction level should be preferred. The answer requires balancing simplicity and accuracy of predictions and of explanations. Focusing on a level that is too abstract might result in losing important details, whereas adding elements beyond necessary could result in noisy estimates and, thus, faulty conclusions. An approach that can help is out of sample predictability[71]. We illustrate this by reanalysing data from Costantini et al.[41] (Study 3) that include 9 goals identified as relevant for conscientiousness and 30 items from an adjective-based measure of conscientiousness that assess three main facets: industriousness, impulse control and orderliness[44].

Data and analysis. In this sample ($N = 432$) we explored how well we could predict goals using a tenfold cross-validation approach[72]. The networks depicted in FIG. 4 represent Gaussian graphical models estimated with the qgraph R package[15], using graphical lasso regularization. The lambda parameter for graphical lasso was selected through the extended Bayesian information criterion ($\gamma = 0.5$ (REF.[33])). We varied the level of representation of the personality dimensions from general (single trait) to specific (3 facets) to molecular (30 items) and explored the relationships between personality and 9 goal scores.

The results depicted in FIG. 4a suggest that some goals are positively associated and some negatively associated with an overall conscientiousness score. Two goals, personal realization (node 3) and be safe (node 7), do not show direct connections to the trait. However, this network does not consider several ways in which one can be conscientious. Some people can be more organized, others can be more controlled and yet others can be more industrious[43]. The facet-level network (FIG. 4b) shows that most goals are related to a specific subset of one or two of the three facets, thus characterizing more clearly specific

Polarization
A social process that leads to higher prevalence of more extreme attitudes in a population, leading to a bimodal population distribution, with only strong supporters and opponents, rather than a normal distribution in which most people obtain a middle position.

Lambda parameter
A regularization parameter to determine edge inclusion/exclusion that obtains a nominal false positive rate.

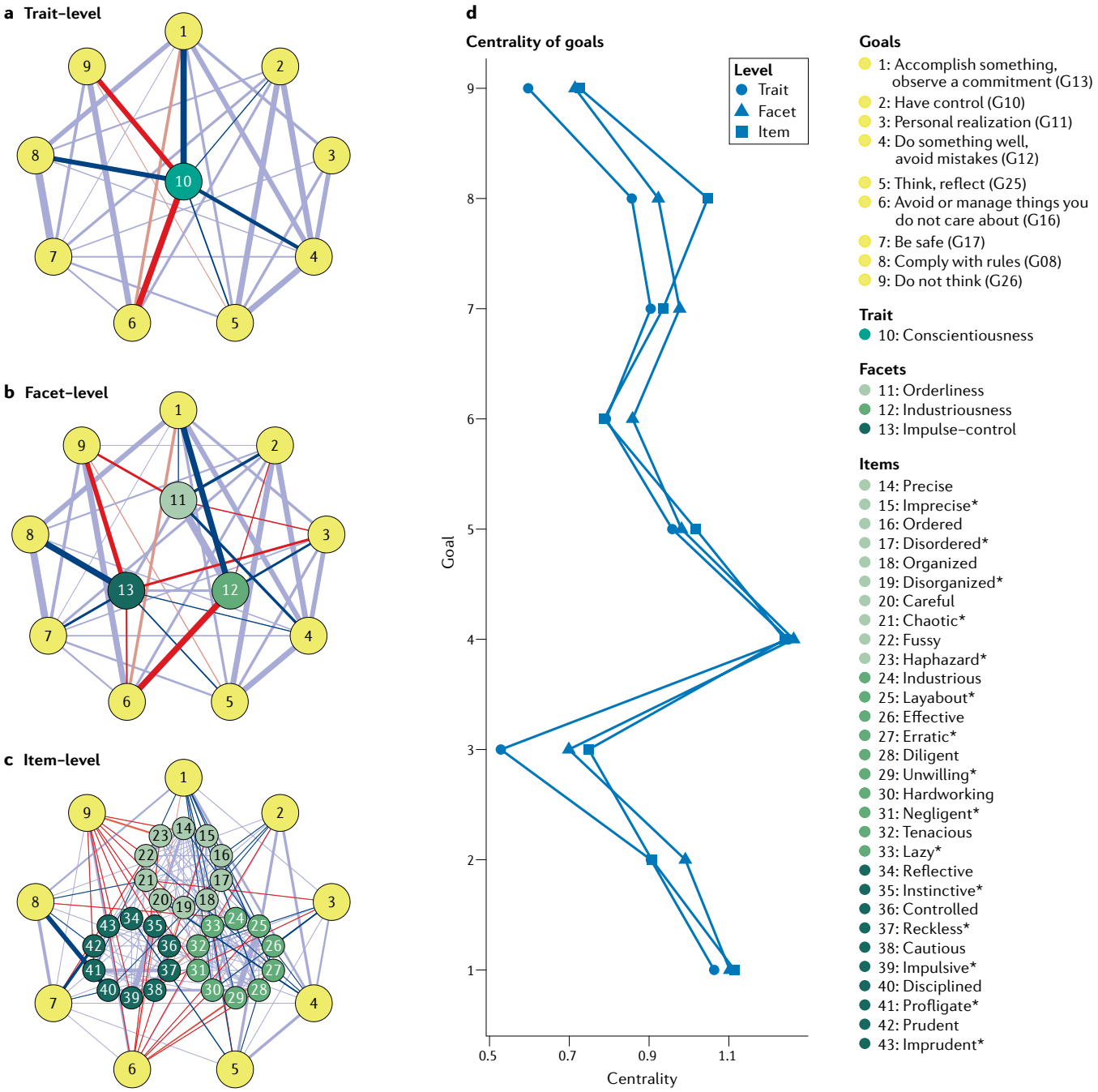


Fig. 4 | **Strength centrality estimates for all nodes in three networks of personality research data.** Network of relationships between motivational goals (yellow) and conscientiousness at the level of the trait (panel **a**), its facets (panel **b**) and items (panel **c**). Blue edges represent positive connections and red edges represent negative connections; thicker edges represent stronger relationships. Relationships between personality and goals are emphasized with saturated colours. *Items reverse-scored before entering network estimation. **d** | Strength centrality for each goal in each network.

portions of the trait. At this level, personal realization (node 3) is positively related to industriousness but negatively connected to the remaining facets, something that would not have been apparent had we considered the trait level exclusively. At the item level (FIG. 4c), connections appear generally consistent with those emerging at the facet level, albeit with some exceptions. For example, avoid or manage things you do not care about (node 6) shows relations with items of orderliness, whereas no such connection emerged at the facet level.

Results. FIGURE 4d shows strength centrality estimates for all nodes in the three networks. Irrespective of the abstraction level considered, the most central goal was do something well, avoid mistakes (node 4). The centrality of node 4 is due to connections to other goals, rather than to its connections to conscientiousness. Such connections suggest that node 4 might serve as a means for several other goals. For example, one could speculate that doing things well might be important in the pursuit of more abstract goals, such as personal

realization (node 3) or having control (node 2) (see REF.[72] for a discussion of the abstractness of these goals).

Results show that the trait level is never the best level for prediction and that some goals are best predicted at the item level and others at the facet level (TABLE 1), albeit in one case (goal 16) the trait level performed better than the item level. In general, specific levels might be useful if one is mainly interested in examining which elements of the personality system drive the association with a criterion[73] or if one is purely interested in prediction. In our example, the item level performed, on average, slightly better than the facet level in terms of prediction, although this was not the case for all goals (see also REF.[74]). A preference for more abstract levels sometimes amounts to sacrificing a small portion of prediction in exchange for a noticeable gain in theoretical simplicity. Furthermore, using abstract predictors can sometimes assuage multicollinearity. At the same time, abstracting too much can lump together concepts that are better understood separately. There is no ultimate answer to the selection of the best abstraction level in personality as it heavily depends on the questions being asked and the data available. In general, the facet level might often provide a good balance between specificity and simplicity[75,76].

Attitude research

Social psychologists are interested in how beliefs and attitudes can change over time. We illustrate the use of networks to improve our understanding of these processes with a study of attitudes towards Bill Clinton in the United States in the early 1990s. Based on the network theory of attitudes (BOX 2) one expects that temperature should decrease throughout the years, because Bill Clinton was probably more on individuals' minds when he was president than before he was president. We investigate changes in the network structure of these attitudes in the years before and during his presidency and whether the temperature of the attitude network changes. In this example, we estimate temperature using variations in how strongly correlated the attitude elements are at the different time points. Temperature of attitude networks can, however, also be measured by several proxies, such as how much attention individuals direct towards a given issue and how important they judge the issue.

Data and analysis. We use data from the open access repository of the ANES between 1992 and 1996 including beliefs and emotions towards Bill Clinton. For this example, the presented data have been previously reported[77,78]. Beliefs were assessed using a four-point scale ranging from describes Bill Clinton extremely well to not at all. Emotions were assessed using a dichotomous scale with answer options of yes, have felt and no, never felt. Dichotomizing the belief questions, we fit an Ising model with increasing constraints representing their hypotheses to this longitudinal assessment of beliefs and emotions in the American electorate. We investigate the impact on the fit of the model of constraining edges between nodes to be equal across time points, constraining the external fields to be equal across time points and constraining the temperature (the entropy of the system) to be equal across time points. Additionally, we tested whether a dense network (all nodes are connected) or a sparse network (at least some edges are absent) fits the data best. After estimating the network, we applied the walktrap algorithm to the network to detect different communities, such as, for example, sets of highly interconnected nodes[68,79]. The walktrap algorithm makes use of random walks to detect communities. If random walks between two nodes are sufficiently short, these two nodes are assigned to the same community.

Results. The results show a sparse network with a stable network structure, where edges do not differ between time points (FIG. 5). The model with varying external information and temperature fitted the data best. FIGURE 5a shows the estimated network at the four time points. The attitude network is connected: every attitude element is at least indirectly connected to every other attitude element. As can be seen, negative emotions of feeling afraid and angry are strongly connected to each other, as are positive emotions of feeling hope and pride. Within the beliefs, believing that Bill Clinton gets things done and provides strong leadership are closely connected. The belief that he cares about people is closely connected to the positive emotions. The walktrap algorithm detected two communities: one large community that contains all beliefs and the positive emotions; and one smaller community that contains the negative emotions. This indicates that positive emotions are more closely related to (positive) beliefs than positive and negative emotions are related to each other.

FIGURE 5b shows changes in temperature throughout the years. As can be expected from the network theory of attitudes (BOX 2), the temperature of the attitude network generally decreased throughout the years, with the sharpest drop before the election in 1996 revealing an increase in the specificity of respondents' attitudes towards Clinton. This implies that attitude elements became more consistent over time, resulting in more polarized attitudes. The increase in temperature between 1993 and 1994, however, is somewhat surprising.

FIGURE 5c shows the distribution of the overall attitude, separately measured on a scale ranging from 0 to 100, with higher numbers indicating more favourable attitudes. Based on the decreasing temperature of

Table 1 | **Out of sample predictive accuracy (R^2) of goals in networks at different abstraction levels**

Level	Goal								
	G08	G10	G11	G12	G13	G16	G17	G25	G26
Trait	0.458	0.527	0.342	0.665	0.547	0.309	0.440	0.580	0.234
Facet	0.477	0.538	0.357	0.668	0.566	0.311	0.445	0.582	0.245
Item	0.516	0.538	0.370	0.679	0.567	0.296	0.459	0.590	0.244

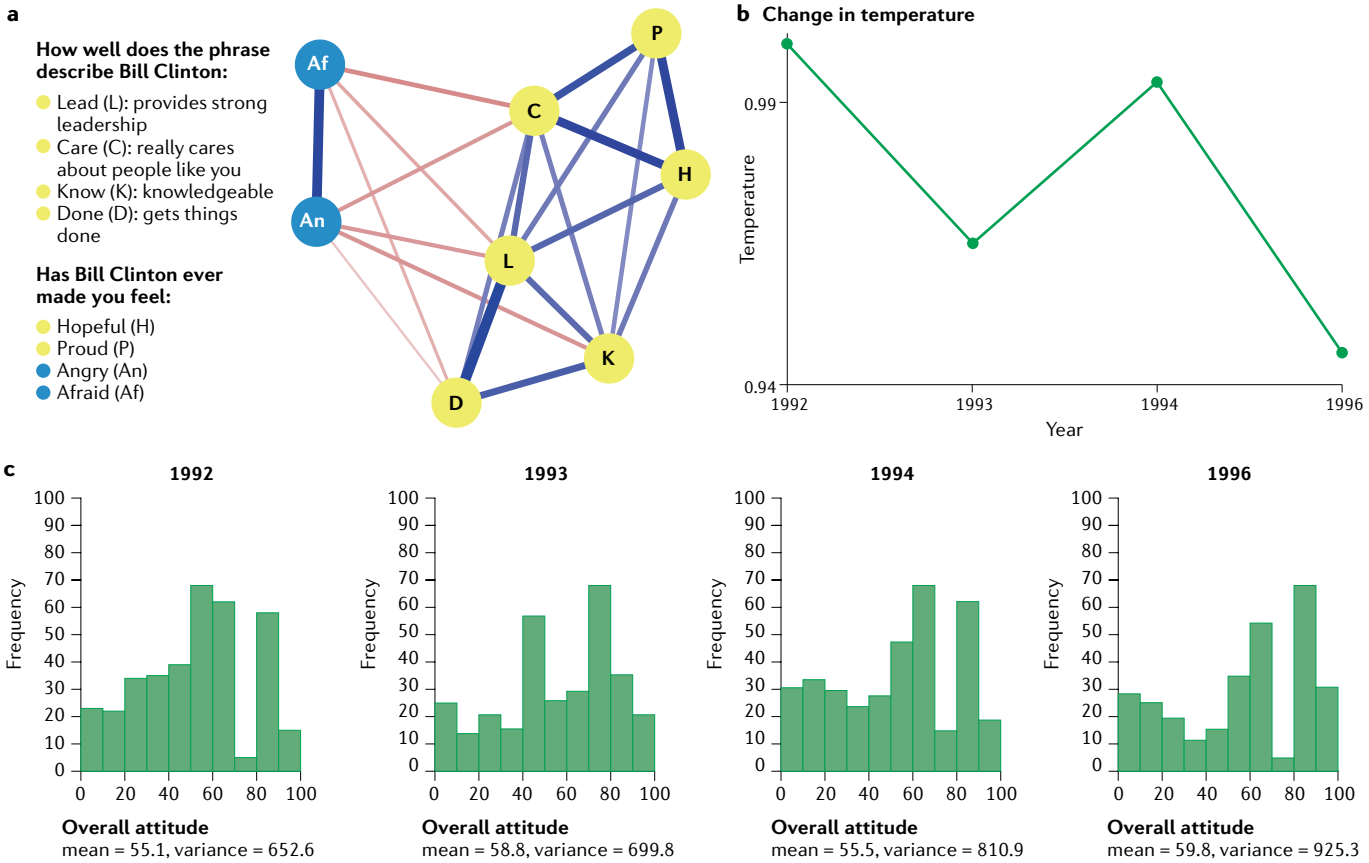


Fig. 5 | **Illustration of an estimated attitude network from panel data. a** | Estimated attitude network towards Bill Clinton. Colour of nodes corresponds to communities detected by the walktrap algorithm. Blue edges indicate positive connections between attitude elements and red edges indicate negative connections; width of the edges corresponds to strength of connection. **b** | Change in temperature throughout time. **c** | Histograms for overall attitude towards Bill Clinton in each year.

the attitude networks, a corresponding increase in the extremity of these distributions is to be expected. This is exactly what was found; the variance of the distributions increased in a somewhat similar fashion as the temperature of the attitude network decreased. The increase in the variance between 1993 and 1994 was the only exception.

Mental health research

Mental health research and practice rest on reportable symptoms and observable signs. Therapists interviewing patients will ask questions about subjective symptoms as well as assess signs of behavioural distress (such as agitated hand-wringing and crying). The challenge for both mental health researchers and therapists is to determine the cause of the person's constellation of signs and symptoms. Therapists, moreover, have the additional charge of using this information to devise an appropriate course of treatment. The network theory of psychopathology[80,81] suggests that mental disorders are best understood as clusters of symptoms sufficiently unified by causal relations among those symptoms that support induction, explanation, prediction and control[82,83] (BOX 3). Signs and symptoms are constitutive of disorder, not the result of an unobservable common cause. We illustrate this with an example study of social interaction and its relations to mental health variables in a student sample during the COVID-19 pandemic.

Data and analysis. Researchers have devised an ecological momentary assessment study following 80 students (mean age = 20.38 years, standard deviation = 3.68, range = 18–48 years; $n = 60$ female, $n = 19$ male, $n = 1$ other) from Leiden University for 2 weeks in their daily lives[50]. With 19 different nationalities represented, this sample is highly international. Most students are single ($n = 50$), one–third of the students are currently employed and about 1 in 5 students report prior mental health problems. In this study, participants are asked about the extent of their worry, sadness, irritability and other subjective phenomenological experiences four times per day via a smartphone application. We use multilevel vector autoregressive modelling to assess the contemporaneous and temporal associations among problems related to generalized anxiety and depression. As a reminder, the contemporaneous network covers relations within the same 3-h assessment window, and the temporal network lag – 1 relations between one 3-h window and the next.

Results. The resulting networks can be used to inform our understanding of how the modelled variables evolve over time (FIG. 6). In this application, the model suggests that the cognitive symptom worry and the affective symptom nervous exhibit a strong contemporaneous association but do not exhibit a conditional dependence relation in temporal analyses, indicating that the relation

Estimation error
The amount by which an estimate differs from the target value.

between these items may be limited to a 3-h time interval. Similarly, we can clarify the paths by which external factors, such as social interaction, predict and are predicted by mental health. For example, the contemporaneous association between offline social interaction (nodes 8) and worry (node 3) occurs via feelings of loneliness (node 7), information which could be used in the generation of hypotheses about the causal relationships among these symptoms. It is also notable that different types of social interaction are differentially associated with loneliness. Offline social interaction is conditionally associated with lower levels of loneliness, whereas online social interaction is associated with higher levels of loneliness. The temporal associations further inform our understanding of these relationships. Difficulty envisioning the future and difficulty relaxing predict online social interaction, and online social interaction predicts subsequent difficulty relaxing. This illustrates how psychometric network analysis of time series naturally leads to more detailed hypotheses about the system under study; do note that this use of network analysis is exploratory and that generated hypotheses require independent testing, ideally through research that utilizes experimental interventions.

Network analyses not only equip researchers to investigate the associations among symptoms but also provide a novel framework for conceptualizing treatment. There are at least two potential ways one can intervene on a system, such as that depicted in FIG. 6. First, we can lower the mean level of a node by diminishing its frequency or severity. For example, we could intervene on the online social interaction node, hoping, based on the contemporaneous relations, that it might promote offline social interaction, alleviate loneliness and, in turn, foster less worry, more optimism and greater interest and pleasure. However, even if initially successful, merely intervening on a node may be insufficient, leaving the person vulnerable to relapse, as the structure of the network remains intact. If pessimism and an inability to relax are, indeed, encouraging online social interaction, then when our intervention on this node ceases, the problem may return, erasing our treatment gains. Accordingly, instead of targeting a specific node (or symptom), we may target the link between symptoms, thereby changing the structure of the network. For example, rather than aiming to reduce online social interaction in general, we could specifically target the tendency to engage in online social interaction when the person experiences pessimism or difficulty relaxing, thereby eliminating the temporal association between these symptoms and online social interaction and disrupting the network.

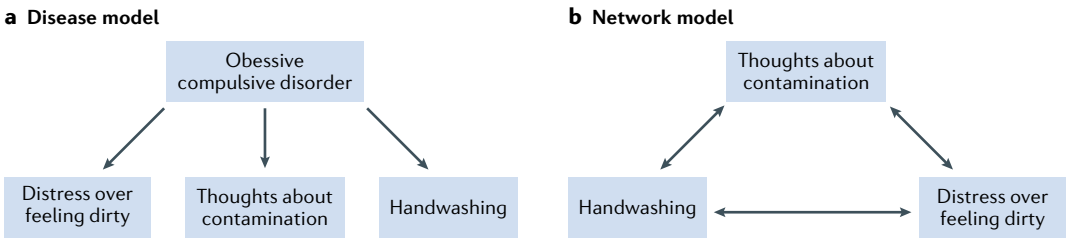
Reproducibility and data deposition

A challenge posed by the estimation of PMRFs from multivariate data is that estimation error and sampling variation need to be taken into account when interpreting the network model. For example, networks estimated from two different groups of people may look different visually but this difference may be due to sampling variation. Several statistical methods have been proposed for assessing the stability and accuracy of estimated parameters as well as to compare network models of different groups. For many statistical estimators, data resampling techniques such as bootstrapping and permutation tests have been developed for this purpose[17,84].

Standard approaches to robustness analyses involve three targets: individual edge weight estimates, differences between edges in the network and topological metrics

Box 3 | **Disease models versus network structures in mental health**

Symptoms and signs associated with mental illness do not co-occur randomly. For example, recurrent obsessive thoughts about potential contamination co-occur more often with compulsive handwashing than with paranoid delusions. The tendency for some symptoms to co-occur may be owing to a common underlying cause. For example, consider a patient complaining of fatigue, pain upon swallowing, a fever and white patches in the throat. A physician may posit the *Streptococcus* bacterium as the common cause of the co-occurrence of the patient's signs and symptoms[86,87], and can eliminate the patient's illness by therapeutically targeting the bacteria rather than the resulting symptoms. This bacterial model of disease became firmly entrenched early in psychiatry's history, shaping the field's methods and motivating researchers to identify the common underlying cause of regularly co-occurring signs and symptoms[81] (see the figure, part **a**). Despite the widespread and often implicit influence of the bacterial model of disease, failures to discover biomarkers of putative underlying entities have continued to mount during the past century[146]. The network theory of psychopathology provides an alternative account of why some symptoms tend to co-occur[37,80]. Rather than being the independent, functionally unrelated consequences of an underlying common cause, the network theory of psychopathology posits that symptoms co-occur owing to causal interactions among the signs and symptoms themselves[81,147] (see the figure, part **b**). Indeed, the Diagnostic and Statistical Manual of Mental Disorders criteria often specify functional relations among symptoms. For example, compulsive rituals diminish the distress provoked by obsessions and avoidance behaviour in panic disorder arises as a consequence of recurrent panic attacks. This simple idea forms the foundation of the network approach to psychopathology and motivates the effort to investigate the structure of relationships among symptoms using psychometric network analysis.



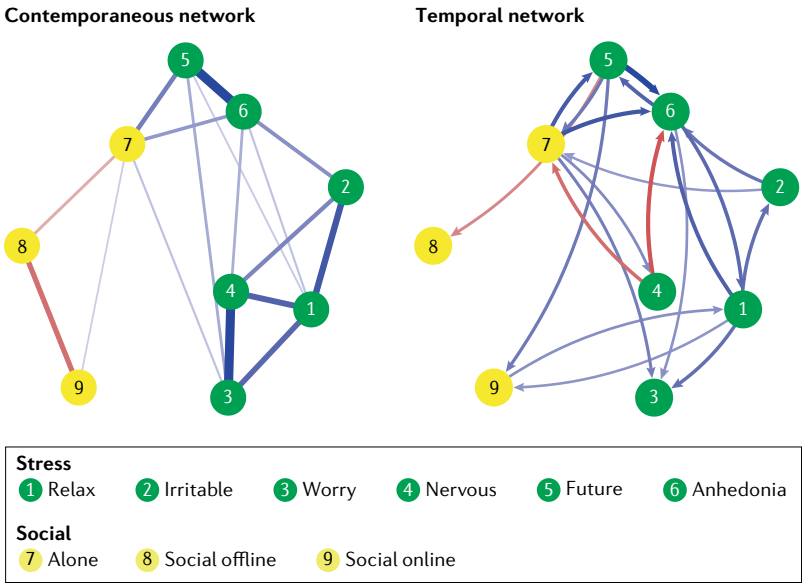


Fig. 6 | **Time-series networks.** Contemporaneous network (left) of conditional associations between variables obtained after controlling for temporal effects in the temporal network (right); latter represents carry-over effects from one time point to the next. Blue edges indicate positive connections and red edges indicate negative connections; width of edges corresponds to strength of connection.

defined on the network structure, such as node centrality. The robustness of edge weight estimates can be assessed by constructing intervals that reflect the sensitivity of edge weight estimates to sampling error, such as confidence intervals, credibility intervals and bootstrapped intervals (FIG. 7a). The robustness of differences between edge weights can be assessed by investigating to what degree the bootstrapped intervals for the relevant coefficients overlap (FIG. 7b). The robustness of network properties such as node centrality can be investigated through a case-dropping bootstrap, in which progressively fewer cases are sampled from the original data set to obtain subsamples; the correlation between centrality measures in these subsamples and the total sample is plotted as a function of the size of the subsamples (FIG. 7c). Various approaches are available to assess these forms of robustness, including approaches based on bootstrapping[17] and Bayesian statistics[85].

The generalizability of network structures can be assessed by comparing results in different samples. This is typically assessed by examining the similarity of network structures across samples. A formal test for the invariance of networks has been developed to assess the null hypothesis that the networks are identical at the level of the population from which individuals have been sampled[84] and Bayesian analyses[86] can also be used to assess invariance of networks. Finally, moderated network analysis[87] and multi-group analysis have been introduced as methods for statistically comparing groups[88]. To gain more insight into the degree to which pairwise associations correspond across networks, the correlation between edge weights in different groups can be inspected.

It should be emphasized that, owing to sampling variability, one should not ordinarily expect to reproduce the network completely, and that the degree to which the network structure replicates depends on several factors, including the network architecture itself[80,89]. For this reason, network analysts have developed tools to compute the expected reproducibility of network structure estimation results[27]. FIGURE 8 displays the expected replicability of one of the personality networks reported above that one should expect, if the estimated networks were the true networks, using different sample sizes. For instance, from this analysis it is apparent that the item-level network should be expected to replicate less strongly than the facet-level and trait-level networks.

In addition to sampling variability, network structures can be affected by random measurement error. The effects of measurement error differ depending on the type of network estimated. In cross-sectional networks, ignoring measurement error typically leads to an underestimation of network density. If the strength of edges is associated with the network structure itself, this may lead to an artificial magnification of network structure. In longitudinal and time-series networks, however, measurement error can also lead to spurious edges[90]. One way to deal with measurement error is to utilize latent variable modelling; in this case, the network model is augmented with a measurement model that relates multiple observables to a single latent node, and the PMRF is estimated at the level of these latent nodes[27].

To improve standardization and reproducibility, recent research explicates minimal shared norms in reporting psychological network analyses[91]. For methods sections of scientific papers, such norms include information on subsample and variable selection, the presence of deterministic relations between variables and skip structures that may distort the network, the estimation methods used as well as any additional specifications (such as thresholding, regularization, parameter settings), how the accuracy and stability of edge estimates were assessed and, finally, the statistical software and packages used, including their versions (TABLE 2).

In terms of results, current norms recommend reporting the final sample size after handling missing data, plotting and visualization choices and the accuracy and stability checks of any network model, in light of the research question of the researcher. If the research questions concern centrality estimates, case-drop bootstrap results would be reported, for example. Many reporting routines are dependent on the specific research goals of the researcher and different analysis routines result in different reporting choices. Burger et al.[91] elaborate on these routines and further discuss important considerations for network analysis and potential sources of misinterpretation of network structures.

Limitations and optimizations

Network structure estimation

Although many network structures are now estimable through standard software, some limitations still remain. First, although treatments of dichotomous, unordered categorical and continuous data and their combinations are well developed[57], treatments of ordinal data are still suboptimal. Ongoing research is developing approaches for such data, which are common in the social sciences[92,93]. Second, estimation routines have traditionally used nodewise regularized regression[16]

Nodewise regularized regression
An algorithm to obtain a network in which each node, in turn, is used as the dependent variable in a penalized regression function to identify which other nodes are connected to the relevant node.

Non-regularized estimation approaches
Approaches that do not use a penalized likelihood function in network structure estimation but rely on different methodologies for edge selection, such as null hypothesis testing or Bayesian approaches.

or the graphical lasso[33]. Although these techniques return visually attractive networks, statistically they are most appropriate when networks can be expected to be sparse[35,36]. Non-regularized estimation approaches based on model selection provide an important alternative, as research suggests that they can outperform regularized approaches in several situations[94,95]. Third, many network modelling techniques handle missing data suboptimally, for example through list-wise deletion. Emerging estimation frameworks use alternative approaches, which allow for better missing data handling, for instance through full-information maximum likelihood[88,96].

Interpretation

The fact that, in psychometric network models, edges are not observed but estimated necessitates the evaluation of sampling variance, which requires extensions. First, current techniques for edge selection do not guarantee that unselected edges are statistically indistinguishable from zero or that evidence for their absence is strong. Relatedly, many current estimation

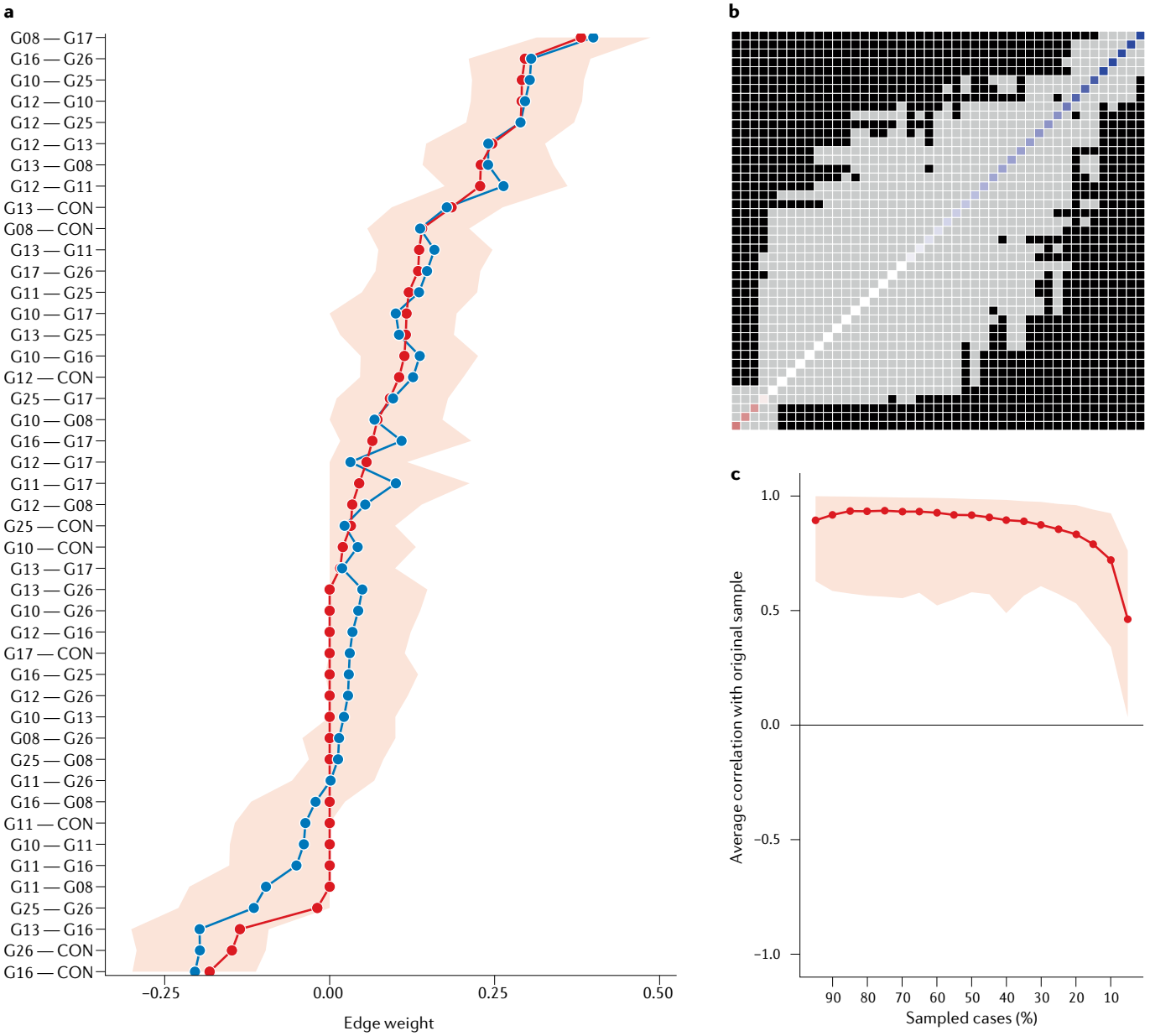


Fig. 7 | **Representation of robustness and stability of the trait-level personality network. a** | Sample value (red line), bootstrapped 95% intervals (shaded area) and average bootstrapped value (blue line) of edge weights. **b** | Whether the 95% bootstrapped interval of the differences between any two edges includes the value zero (grey squares) or not (dark squares) gives an indication of whether two edges are different from each other[17]. Diagonal visualizes magnitude of original edge; red indicates negative values, blue indicates positive values and colour saturation indicates absolute values (more saturated the colour, stronger the edge). **c** | Results of case-dropping bootstrap analysis showing average correlation between strength centrality estimated in the full sample and strength estimated on a random subsample, retaining only a certain portion of cases (from 90% to 10%). Shaded area indicates 95% bootstrapped confidence intervals of correlation estimates. Higher values indicate better stability of centrality estimates[17].

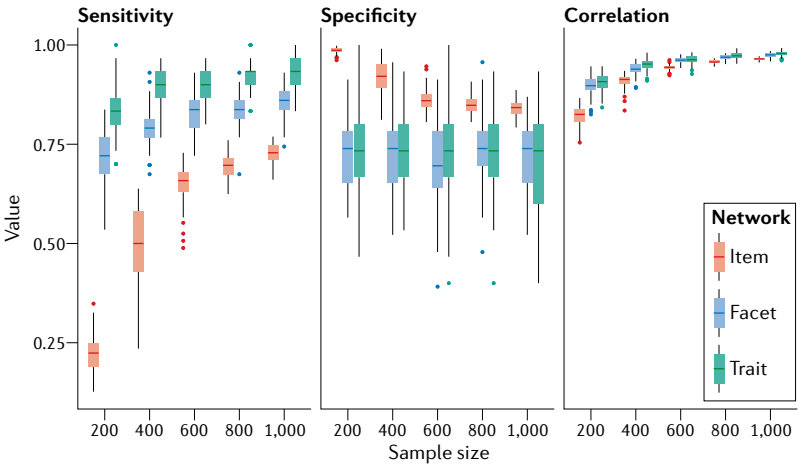


Fig. 8 | **Projected replicability for the personality network as assessed through the ReplicationSimulator function in the bootnet R package.** ReplicationSimulator generates multiple data sets from an estimated network to assess expected sensitivity (probability of including edges given that they are, in fact, present in the generating network) and specificity (probability of leaving out edges given that they are, in fact, absent in the generating network) as well as expected correlation between edge weights for two replication data sets generated from the network.

methods do not produce standard errors or confidence intervals around edge weight estimates, as the sampling distributions of regularized regression coefficients are unwieldy. This limits the interpretation of individual edges. In non-regularized networks, significance tests can be used, but this practice is not based on model selection and therefore inherits problems inherent in significance testing. New Bayesian approaches address these challenges, as they can quantify evidence for or against edge inclusion[97].

Second, network structures depend on which variables are included. Nodes that are highly central in one network may therefore be peripheral in another. In addition, if important nodes are missing, this can affect the structure of the network; for instance, it may lead to increased edge strengths among nodes that represent effects of an omitted common cause[98]. If nodes are essentially duplicates of each other — for example, if two nodes have topological overlap — this will influence the network architecture as well[99,100]. Thus, network interpretation depends on a judicious choice of which variables to include in the network, and more research is needed to develop theoretical frameworks to guide these choices.

Third, centrality metrics have been suggested to reflect the importance of nodes to the system that the network represents[33] and early literature interpreted nodes with high centrality as more plausible targets for intervention[101]. However, recent work has highlighted situations where centrality is not a good proxy for causal influence[102,103], and for certain networks, peripheral nodes may be more important in determining system behaviour[104]. In addition, in some areas such as psychopathology, interactions may occur at different timescales, which complicates the relation between association structure and causal dynamics. This has rendered the use of centrality measures a topic of debate, with some papers arguing that, because psychometric network models do not specify dynamics or flow, centrality metrics should not be interpreted in terms of causal dynamics at all. In addition, centrality metrics that concatenate paths between nodes (such as closeness and betweenness) are based on (absolute) conditional associations; these do not represent physical distances — they violate transitivity — and should not be interpreted as such. Finally, although network software indexes many types of centrality, including closeness, betweenness, degree, strength, eigenvalue and expected influence, there are no clear guidelines on which interpretations are licensed by each of these[105], so more research is needed to investigate the relation between theoretical properties of possible generating models and empirical estimates of centrality[106].

Topological overlap
A concept that expresses the degree to which two nodes have the same position in the network topology. Two nodes with high topological overlap have very similar connections to other nodes.

Causal inference

The constituent parts of PMRFs are purely statistical associations, so that direct causal inference based on network structures is not justified. Although the PMRF itself is typically unique — there are no alternative PMRFs that will generate the same set of joint probability distributions — the correspondence between the PMRF and generative causal systems is one to many: edges between nodes may arise owing to directed causal effects or feedback loops, but also owing to unobserved common causes[107], conditioning on common effects[102,108] and various other structures (FIG. 9). As is the case for causal inference in general, causal inference based on PMRFs requires the statistical structure to be augmented by substantively backed assumptions[53]. This motivates the articulation of strong network theories in addition to the development of network models, as for instance have been devised for intelligence[109,110], attitudes[61,111] and certain mental disorders[112].

Current directions in network estimation may assist in causal inference by developing better methodologies. For example, causal search algorithms may be effective in identifying a particular causal model in certain cases[18,113–115]. In addition, inclusion of interventions in network structures may facilitate causal interpretation[25,116,117]. Alternatively, researchers may revert to non-causal interpretation of network structures. In such cases, marginal associations can be preferred over conditional associations if the goal is purely to describe the patterns of association. For example, Schwaba et al.[118] opted to model a network of correlations rather than partial correlations, because of the descriptive nature of their goal.

Confirmatory testing

Most applications of network analysis use exploratory techniques to estimate network structures[20]. However, advances in network estimation allow one to constrain parameters (such as edge weights) to a specific value, constrain edges to have the same edge weight as each other or constrain edge weights to be equal across different groups[88,119]. The ability to test these constraints adds confirmatory data analysis approaches to the network analytic toolbox[120]. The psychonetrics R package[121] is an example of an implementation that allows for confirmatory testing of network constraints. There are also

Bayesian implementations available for testing constraints in networks that can be used to test whether an edge is positive, negative or null, and to test order constraints on edge weights[85].

One way of arriving at network hypotheses is on the basis of exploratory network analyses. For example, an initial data set may be used to estimate a network model exploratively. In the next step, all of the estimated zeros are included as constraints in a network model that is fitted to a new data set[122]. Similarly, one can use an exploratively estimated network to formulate different hypotheses about the order of the strengths of edge weights and test these hypotheses against each other using Bayes factors[123]. A second way of arriving at network hypotheses is from substantive theory about the phenomena being modelled, from which network structures implied by the theory can be deduced[124]. To test substantive hypotheses, future methodological research should provide tools that can help researchers express substantive hypotheses in constraints on network structures, which can subsequently be tested using confirmatory models.

Table 2 | **Overview of network analysis software packages**

R package	Functionality	Documentation and access
bootnet	General package for network estimation and stability analysis	https://cran.r-project.org/web/packages/bootnet
qgraph	Visualization of graphical models as networks	https://cran.r-project.org/web/packages/qgraph
IsingFit	Regularized estimation of Ising models	https://cran.r-project.org/web/packages/IsingFit
IsingSampler	Simulation and non-regularized estimation of Ising models	https://cran.r-project.org/web/packages/IsingSampler
GGMnonreg	Non-regularized estimation of Gaussian graphical models	https://cran.r-project.org/web/packages/GGMnonreg
graphicalVAR	Estimation of graphical vector autoregressive models	https://cran.r-project.org/web/packages/graphicalVAR
mlVAR	Estimation of multilevel vector autoregressive models	https://cran.r-project.org/web/packages/mlVAR
EstimateGroupNetwork	Joint estimation of Gaussian graphical models in different groups	https://cran.r-project.org/web/packages/EstimateGroupNetwork
gimme	Estimation of group-level and individual-level relations in time series	https://cran.r-project.org/web/packages/gimme
mgm	Estimation of mixed graphical models	https://cran.r-project.org/web/packages/mgm
psychonetrics	Confirmatory network analysis and latent variable extensions	https://cran.r-project.org/web/packages/psychonetrics
networktools	Extended tools for network analysis	https://cran.r-project.org/web/packages/networktools
BGGM	Bayesian estimation and testing of Gaussian graphical models	https://cran.r-project.org/web/packages/BGGM (previous version https://cran.r-project.org/src/contrib/Archive/BGGM/BGGM_2.0.3.tar.gz)
EGAnet	Dimensionality assessment through network models	https://cran.r-project.org/web/packages/EGAnet

All packages are freely available and implemented in the open source statistical computing program R[141].

Outlook

Network models are suited to estimate and represent patterns of conditional associations without requiring strong a priori assumptions on the generating model, which renders them well suited to exploratory data analysis and visualization of dependency patterns in multivariate data. As statistical analysis methods, the software routines for estimating, visualizing and analysing networks enhance existing exploratory data analysis methods, as they focus specifically on the patterns of pairwise conditional associations between variables. The resulting network representation of conditional associations between variables, as encoded in the PMRF, may be of interest in its own right, but can also function as a gateway that allows the researcher to assess the plausibility of different generating models that may produce the relevant conditional associations. This assessment may include latent variable models[29] and directed acyclic graphs[115] in addition to explanations based on network theories[80,123].

Because network models for multivariate data explicitly represent pairwise interactions between components in a system, they form a natural bridge from data analysis to theory formation based on network science principles[3]. In this respect, networks not only accommodate the multivariate architecture of systems but also offer a toolbox to develop formal theories of the dynamical processes that form and maintain them[61,124]. One successful example of such an approach is the mutualism model of intelligence[125], which proposes an explanation of the positive correlations between intelligence tests based on network concepts. This explanation quantifies how the structure of the cognitive network impacts the dynamic processes taking place in it. This model has been extended to explain various empirical phenomena reported in the intelligence literature[126,127]. Similar developments have taken place in clinical psychology[112,128] and attitude research[78], as featured in the current paper.

The combination of network representations in data analytics and theory formation is remarkably fruitful in forging connections between different fields and research programmes. One important connection is that between the study of inter-individual differences and intra-individual mechanisms. More than half a century ago, Cronbach famously diagnosed psychological science to be a deeply divided discipline[129]. With one camp of psychological scientists concerned with mechanistic explanations and another camp primarily focused on the study of individual differences, that dichotomy is still prevailing. Some argue that in order to overcome this division, psychological scientists should rethink their widespread practice of detaching statistical practice from substantive theory[130–132]. One reason for this detachment, however, has been the long-standing lack of an intuitive modelling framework that facilitates both theory construction and process-based computations and simulation, so that it can connect the two disciplines[129]. But this gap is exactly what makes network approaches fall on fertile soil. Networks readily accommodate the multivariate architecture of psychological systems and also offer a toolbox to develop formal theories of the dynamical processes that act on them. In this manner, models of intra-individual dynamics can serve as explanations

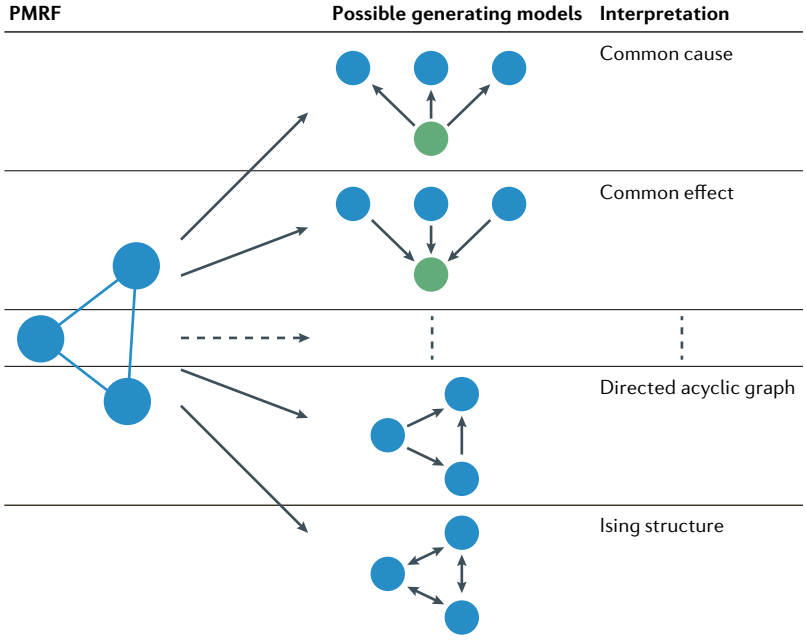


Fig. 9 | **From statistical model to causal inference.** Pairwise Markov random field (PMRF) (left) can be generated by alternative models (middle) that have different interpretations (right). Dashed lines represent range of models and interpretations not captured here.

of systems of inter-individual differences, bridging the gap between intra-individual and inter-individual modelling[129].

Network models are not only useful to create bridges from data analysis to theory formation but also to connect different scientific disciplines to each other. In recent years, network science and associated complex systems approaches have led to an active interdisciplinary research area in which researchers from many fields collaborate. Network approaches in psychology, as discussed here, have similarly broadened the horizon of relevant candidate methodologies relevant to psychological research questions; for instance, it is remarkable that the first network model fitted to psychopathology data[16] was based on modelling approaches developed to study atomic spins[133,134], whereas subsequent studies into the research dynamics of psychopathology[135] investigated sudden transitions using methodology developed in ecology[136] and, finally, recent studies of interventions in such networks are based on control theory[137]. Clearly, network representations create a situation where scientists with different disciplinary backgrounds find a common vocabulary.

This common vocabulary creates tantalizing possibilities for building bridges between research areas — particularly in cases where the systems studied are plausibly constituted by networks operating at different levels, such as human behaviour. For instance, largely independent of one another, neuroscience and psychology have both developed research traditions rooted in network science. With network models of the brain based on neuroimaging studies and network models of psychological responses, the bigger picture might no longer be obstructed by disciplinary fences[138,139]. This promise is by no means limited to psychology and its subdisciplines; the network fever is spanning many disciplines, such as physics, ecology and biology. In fact, the best cited network papers are concerned with universal network characteristics that can advance interdisciplinary theory and modelling[9,140]. We have only begun to chart the connections between disciplines that deal with complex networks, and we hope that network approaches to multivariate data can play a productive role in this respect.

Code availability

Code and data used in sample analyses are available from https://github.com/DennyBorsboom/NatureMethodsPrimer_NetworkAnalysis.

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