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Psychometric network analysis in educational sciences research: A methodological guideline for estimation, interpretation, and critical decision-making

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ABSTRACT

Psychometric network analysis has emerged as an alternative to the latent variable approach in modeling the structure of psychological and educational constructs. Rather than attributing the common variance among observed variables to a single latent common cause, the network perspective treats structures as systems composed of components that interact directly with one another. Although the approach has been widely applied in clinical psychology, its use in educational sciences remains limited and inconsistent. This study introduces the conceptual foundations of psychometric network analysis and, following the standard research article format, provides a structured analysis workflow for researchers working with educational data. In the methods section, the Gaussian graph model, regularized estimation, evaluation of network accuracy and stability, centrality interpretation, community detection via exploratory graph analysis (EGA), and group comparison are each addressed as decisions based on clear criteria. An application example based on a hypothetical dataset of 500 university students (measures of AI literacy, attitude, anxiety, and learning engagement) demonstrates each stage of the process. EGA recovered four dimensions, centrality emerged as a stable measure, and the network comparison test applied to a randomly assigned grouping showed the expected invariance. The findings reveal how predictive decisions, stability diagnostics, and caution in interpretation shape the possible outcomes. The discussion section addresses common pitfalls; such as overinterpreting centrality, confusing correlation with causation, and comparing groups without caution. An annotated R code is provided to support reproducible implementation.

Keywords: psychometric network analysis, Gaussian graphical model, centrality, exploratory graph analysis, educational measurement, reproducibility

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INTRODUCTION

In the field of educational science, measurement has long been conducted within the tradition of latent variables. This traditional approach interprets the common variation among observed items as a reflection of an underlying, directly unobservable common cause (Borsboom & Cramer, 2013). The interrelatedness of items on a motivation scale is explained by the fact that they all serve as indicators of the same motivational structure. In this reflective measurement logic, the latent trait gives rise to behavior and is measured indirectly through multiple observed indicators (Dumas & Edelsbrunner, 2023; Teo, 2011). This framework has formed the methodological backbone of educational research through tools such as confirmatory factor analysis and structural equation modeling (SEM) (Green, 2016; Yin & Huang, 2021). Indeed, in Turkish educational research, SEM has become one of the most widely used multivariate techniques (Karakaya-Ozyer & Aksu-Dunya, 2018).

While the explanatory power of the latent variable approach is undisputed, it is noted that it does not apply equally to all measurement situations. For some constructs, the relationship between items may stem not from a common cause but from the components directly influencing one another (Schmittmann et al., 2013). As an example of a student experiencing test anxiety whose sleep pattern is disrupted, and the disrupted sleep in turn reducing class participation, components may function not as passive indicators of a common cause but as active elements that trigger one another. This perspective finds a theoretical counterpart in the mutualism model, which attributes the positive relationship pattern in cognitive abilities not to a single hidden common cause but to mutually beneficial interactions among components throughout development (van der Maas et al., 2006). Educational data also support this model; Hofman et al. (2018) demonstrated that basic and advanced mathematical skills developed by mutually reinforcing each other over the course of an academic year, while Peng and Kievit (2020) showed that the relationship between academic achievement and cognitive abilities operates in a bidirectional manner. It is believed that modeling the structure as a causal system in such cases may be more informative than reducing it to a single latent dimension.

Psychometric network analysis was developed precisely to fill this gap. The approach represents a structure as a network consisting of nodes and the edges connecting them; nodes represent variables, while edges represent the statistical relationships between variables (Epskamp et al., 2018a). It was first rapidly adopted in clinical psychology to study the structure of psychopathology, and has been extended in other areas such as personality, attitudes and well-being (Costantini et al., 2015; Robinaugh et al., 2020).

The fundamental unit of estimate in the network model is the partial correlation between two variables. The weight of an edge indicates the association that remains between two nodes after the impacts of all other factors in the network have been accounted for. If (non-zero) edges between two items are found, they suggest a conditionally unique link, which cannot be accounted for indirectly by third variables (Epskamp & Fried, 2018). The absence of an edge, on the other hand, indicates conditional independence—that is, the two nodes become unrelated when other variables are held constant. This feature explains why network edges are more informative than simple correlations.

This conceptual difference is not superficial. In the latent variable model, the correlation between items is a byproduct that disappears when the common cause is controlled for. In the network model, however, the same correlation is preserved and examined as an indicator of the direct connection between components (Borsboom & Cramer, 2013). The two frameworks ask different questions of the same data and arrive at different inferences.

Most educational structures contain patterns of mutual interaction that naturally fit this framework; however, the use of the network approach in educational sciences is more recent compared to clinical psychology. It is worth distinguishing this approach from other, conceptually distinct methods that share the label “network” and are already used in education: social network analysis, which models relationships among individuals such as students or teachers (Grunspan et al., 2014); semantic network analysis, which maps the co-occurrence of concepts in textual material such as textbooks or student responses (Choi et al., 2017; Eskandari & Kim, 2022); and epistemic network analysis, which quantifies connections among coded elements in discourse data (Shaffer et al., 2016). Unlike these, psychometric network analysis estimates the partial correlations among measured variables and conflating it with the others can obscure what the resulting graph actually represents. Nevertheless, an increasing number of studies (Kadum & Karpudewan, 2026; Li & Bai, 2025; Rad & Roman, 2025; Sáez-Delgado et al., 2024) suggest that modeling educational topics as networks can be effective. Dalege et al. (2016) developed the causal attitude network model, which treats attitudes not as indicators of a single latent evaluation dimension but as a causal network composed of mutually influencing cognitive and emotional responses; this framework can be directly applied to the examination of students’ attitudes toward technology or artificial intelligence. In an educational context, Sachisthal et al. (2019) modeled students’ interest in science as a network, revealing that the pattern of connections between interest components varies across countries. Christensen et al. (2020), meanwhile, demonstrated that the network perspective can complement traditional factor-based approaches in assessing scale validity. These examples suggest that multi-component educational constructs (such as teacher competencies, academic motivation, burnout, or digital literacy) can also be better understood by mapping the bridges between their components.

The network approach should be positioned not as a rival replacing the latent variable model but as a complementary perspective. Some constructs may indeed be co-causal; in such cases, the factor model is more appropriate. Other constructs, however, are defined by the interactions among their components; in such cases, the network model is more explanatory. It is not possible to make a generalization about which structure belongs to which framework; this is as much an empirical question as it is a theoretical one and must be tested with data (Fried & Cramer, 2017).

Nevertheless, the visual output of network analysis presents a deceptive simplicity. A graph consisting of colored nodes and thick edges can be easily produced; however, the estimation, regularization, and stability decisions underlying this graph often remain invisible. Yet the estimated network is merely a sample estimate, and a structure that appears visually simple may conceal the uncertainty arising from sampling fluctuations (Epskamp et al., 2018a); failure to disclose this uncertainty in reporting, in turn, paves the way for researcher discretion and questionable practices (Burger et al., 2023). Hence, it is not surprising to see that published network studies often fail to report the stability of networks (Tomei et al., 2022), overinterpret centrality measures (Forbes et al., 2017; Steinley et al., 2017), and edges are presented as causal links (Fried & Cramer, 2017). Such issues stem not so much from the method itself as from a lack of understanding of the decision-making process behind it; indeed, it has been shown that the observed low reproducibility largely results from the method being applied inappropriately (Fried et al., 2021).

The aim of this study is to provide a guide that introduces educational researchers to psychometric network analysis, from its theoretical foundations to its practical applications. The study focuses on three questions: for which research questions is the network approach suitable in educational research, what critical decisions are made throughout the analysis, and how do these decisions limit the possible outcomes. To illustrate the process, a hypothetical dataset of five hundred university students was used; each step was demonstrated using this example, and explanatory R code was included in the appendix to ensure reproducibility. This study is an attempt not merely to demonstrate how the method is applied, but to highlight how it should be applied with caution.

METHOD

This section consists of three parts. First, the statistical framework and estimation models underlying psychometric network analysis are introduced. Next, the analysis is addressed step by step as a series of decisions, each of which shapes the interpretation. Finally, the hypothetical data, measurements, and analysis settings used in the application example are explained.

Network Models and Estimation

Since most educational data are collected on continuous or nearly continuous scales, the most commonly used model is the Gaussian graphical model (GGM). In this model, the network is defined via the partial correlation matrix among variables, and the edges carry the values of these partial correlations (Epskamp et al., 2018b). The partial correlation matrix is derived from the precision matrix, which is the inverse of the covariance matrix. Therefore, GGM estimation essentially reduces the problem of correctly estimating the precision matrix.

A problem arises in direct estimation. As the number of variables increases, the number of edges to be estimated grows rapidly, and when the sample size is limited, the matrix becomes unstable; small sample fluctuations can generate spurious edges. Regularization is used to solve this problem. The most common approach is to use the graphical lasso method to completely set weak edges to zero (Friedman et al., 2008). The result is a sparse and more reproducible network. The strength of regularization is controlled by a tuning parameter; the optimal model is determined using the extended Bayesian information criterion (EBIC) (Foygel & Drton, 2010). The hyperparameter within EBIC is typically set between 0 and 0.5; higher values produce sparser networks.

The model changes according to the data type. For binary items the Ising model is recommended and for a mixture of continuous and categorical variables a mixed graphical model is selected (Haslbeck & Waldorp, 2020). The selection of estimating method and correlation type is subject to data conditions. Isvoranu and Epskamp (2023) systematically compared the accuracy of various estimation methods and obtained practical rules of thumb that link the choice to the type of data, the sample size, and the density of the network. This study shows that, for continuous data, regularized GGM produces more accurate results, while, for ordinal data, poly-correlation-based estimation does so in most cases.

A different approach that is often used in conjunction with network analysis is exploratory graph analysis (EGA). EGA determines the number of dimensions of the data by applying community detection techniques on the network and provides an alternative to classic factor extraction approaches (Golino & Epskamp, 2017). Simulation experiments have demonstrated that EGA is competitive with existing approaches such as parallel analysis in the determination of the number of dimensions and can reach a level of accuracy that exceeds them under certain conditions (Golino et al., 2020). In this regard, EGA has become a direct application area of the network approach in scale development studies.

The Analytic Procedure: A Critical Decision Process

Psychometric network analysis is not a procedure that runs with a single command, but rather a process consisting of a series of decisions, each of which shapes the interpretation. The process is broken down into eight stages below; for each stage, the decision to be made is presented along with the available options and the rationale for the recommended default choice. The order of the stages is not rigid; however, it should be remembered that errors in early stages tend to contaminate all subsequent inferences.

Defining the research question and selecting nodes

The process begins with the question, not the method. Before proceeding to network analysis, the researcher must establish a theoretical rationale regarding whether the structure of interest behaves as a causal system or as a set of co-causal indicators. Node selection is also determined by this rationale. Nodes can be individual items or subscale scores; however, these two choices lead to different interpretations. Item-level networks provide a more detailed picture but are more sensitive to sample size; subscale-level networks are more robust but may obscure subtle relationships. Christensen et al. (2020) emphasized that item-level networks provide nuanced information regarding scale validity, but items that overlap conceptually may distort the structure. Fried and Cramer (2017) also note that the definition of the node set directly determines the network structure, and therefore this decision must be clearly justified.

Data preparation and assumption checks

The first issue in data preparation is sample size, and a frequently asked question here is whether there is a recommended practical ratio. In network models, the number of estimated parameters increases not linearly but quadratically with the number of nodes; in a Gaussian graph model with p nodes, there are p(p-1)/2 possible edges. In a network with ten nodes, 45 possible edges are estimated; in a network with twenty nodes, 190 possible edges are estimated. Therefore, as the number of variables increases, the required sample size grows significantly. The literature does not suggest a fixed participant-to-node ratio, as the required sample size depends not only on the number of nodes but also on the network's density and the strength of the edges; a dense network composed of weak edges requires a much larger sample size than a sparse network composed of strong edges (Epskamp et al., 2018a; Isvoranu & Epskamp, 2023). In practice, the recommended approach is to assess the adequacy of the sample based on the coefficient of determination calculated using bootstrap sampling, rather than relying on a fixed ratio; achieving acceptable stability in typical educational networks with ten to twenty nodes often requires several hundred participants.

The second issue is missing data; since network estimation requires a complete data matrix, missing data must be addressed using principled methods such as multiple imputation. The third and often overlooked issue is topological overlap between nodes. Two items asking the same thing are artificially linked by a strong edge, and this edge distorts the rest of the network. Therefore, it is recommended to screen for redundant nodes before estimation; the `goldbricker` function in the `networktools` package identifies item pairs with nearly identical correlation patterns, allowing them to be merged or one to be removed.

The fourth issue is the type of correlation, and this choice is particularly important for training data. Since educational measurements are largely collected using Likert-type ordinal items, treating these items as continuous and using Pearson correlation can lead to bias in edge estimation. In such a situation, poly-choric correlation should be preferred. Poly-choric correlation models the underlying continuous distribution of the ordinal items (Epskamp & Fried, 2018). Isvoranu and Epskamp (2023) investigated the effect of the estimate method and correlation type on the accuracy through a simulation and showed that the poly-coric based estimations resulted in less bias for ordinal data. The items' scores are transformed into aggregated subscale scores. The variables might be assumed to be continuous and estimated with methods based on Pearson.

Network estimation

The key decisions during the estimation phase are the model type and regularization strategy. For continuous data, the default choice is the graphical lasso method tuned with EBIC; this approach tends to produce networks that are both interpretable and reproducible (Epskamp & Fried, 2018). The researcher must select the EBIC hyperparameter here. High values produce conservative and sparse networks, thereby reducing the risk of false edges but potentially missing true yet weak edges. Low values, on the other hand, produce denser networks and increase sensitivity. In exploratory studies, a conservative value such as 0.5 is a reasonable starting point; however, the empirical results of this choice should be evaluated in a robustness analysis.

In recent years, criticisms regarding regularization-based estimation have also been raised. Williams and Rast (2020) argued that regularized networks can unnecessarily suppress true edges, particularly in large samples, and that selecting edges based on significance using an unregularized estimate yields more accurate results in some cases. This debate demonstrates that there is no single correct method; the choice of estimation method should be based on the data conditions and the research objective. Regardless of the method chosen, the study remains reproducible when the rationale and results are clearly reported.

Visualization and layout

Network visualization (Hevey, 2018) is the first step in interpretation, but it involves aesthetic decisions that can be misleading. In graphs generated using the qgraph package, edge thickness indicates the strength of the relationship, while edge color indicates its direction (Epskamp et al., 2012). Node placement is typically determined using the Fruchterman-Reingold algorithm; in this layout, strongly connected nodes are positioned closer to one another. Care must be taken when interpreting the layout, as position is merely a relative arrangement and different layouts can be generated from the same data. Fixing the layout when comparing multiple groups makes the visual comparison meaningful.

Centrality and node importance

Centrality measures quantify which nodes are more influential within the network. The most commonly used measure is strength; it is the sum of the absolute weights of all a node's edges. Closeness and betweenness are measures borrowed from social network analysis. However, Bringmann et al. (2019) demonstrated that these two measures are often unreliable and difficult to interpret in psychological networks because they rely on the short-path assumption, whereas psychological edges do not follow such a flow logic. Therefore, the strength measure is generally a more reliable indicator.

An important disadvantage of the strength metric in signed networks is that it aggregates positive and negative edges, therefore a node with strong but oppositely oriented connections may appear unnaturally weak. To solve this issue, the expected influence measure was created, which sums the edges while keeping their signatures (Robinaugh et al., 2020). For example, when there are negative edges in the educational networks, when there are inverse correlations between anxiety and involvement, reporting expected influence is more accurate than the power measure. Meanwhile, bridge centrality is utilized to find nodes that help transitions between distinct communities and is quite revealing in multidimensional architectures (Jones et al., 2021).

Community detection and dimensionality

Community detection algorithms are used to determine whether the nodes within a network form clusters that frequently connect to one another. EGA typically uses the walktrap or Louvain algorithm for this purpose (Golino & Epskamp, 2017). The choice between the two algorithms depends on the network's structure. Walktrap leverages the tendency of short random walks to remain within the same community and tends to accurately estimate the number of dimensions in relatively small to medium-density networks typically encountered in psychometrics; for this reason, it is the default algorithm in the EGAnet package. Louvain, on the other hand, scales better in networks with a large number of nodes or higher density because it directly optimizes modularity and is preferred for large-scale data structures. When comparing clustering algorithms under different settings, Golino et al. (2020) found that the walktrap-based EGA performed as well as standard approaches in identifying the number of dimensions. The bootEGA function allows you to assess the stability of the EGA output; this procedure illustrates the extent to which the dimensional structure is retained over repeated samples and which items consistently fall into the same dimension.

Network accuracy and stability

This step is the most critical yet most frequently overlooked step in network analysis. An estimated network is merely an estimate, and no interpretation can be trusted without evaluating the uncertainty of this estimate. The bootnet package performs this evaluation in two ways (Epskamp et al., 2018a). First, confidence intervals (CIs) for edge weights are calculated using nonparametric bootstrap. Wide CIs that include zero indicate that the value of the corresponding edge is uncertain; in this case, interpretations based on the magnitude order of the two edges should not be made.

Second, the stability of the centrality ranking is tested using case-dropping bootstrap. In this method, the network is re-estimated by progressively removing increasing proportions of the sample, and the correlation between the centrality ranking and the original ranking is tracked. The result is summarized by the correlation stability (CS) coefficient. The CS provides the highest case-dropping rate, at which the centrality ranking remains above 0.70 with 95% probability. The recommended criterion is that the CS value be at least 0.25, preferably above 0.50 (Epskamp et al., 2018a). Centrality interpretations below this threshold should be considered unreliable. Additionally, edge difference and centrality difference tests can be used to determine whether two edges or two nodes are statistically distinct.

Network comparison across groups

A common question in educational research is whether network structures differ across groups; for example, one might examine whether the artificial intelligence attitude network is similar among female and male students or across different country samples. This comparison should not be made visually, as networks estimated from different samples will always appear somewhat different due to sampling variation. The network comparison test (NCT) tests the statistical significance of this difference using authorized permutations (van Borkulo et al., 2023). The method is widely used in psychology, for example, in comparing symptom networks across different clinical diagnostic groups. It also finds direct application in educational contexts; Sachisthal et al. (2019) demonstrated that the network of science interest varies across countries using network-based comparisons, thereby highlighting the method's value in cross-cultural educational comparisons. The test compares the global strength of the network structure, individual edges, and the overall structure separately. Group comparisons conducted without applying NCT cannot distinguish whether observed differences are real or merely random.

Illustrative Data and Measures

To illustrate the process described above, a full analysis was conducted on a hypothetical dataset. The data was designed to simulate a sample of five hundred university students (N = 500) and includes thirteen continuous subscale scores representing four conceptual domains: artificial intelligence literacy (AIL1-AIL4), attitude toward artificial intelligence (ATT1-ATT3), anxiety regarding artificial intelligence (ANX1-ANX3), and learning engagement and intention to use (ENG1, ENG2, INT). Since nodes were defined at the subscale score level rather than at the item level, they were treated as continuous, and Pearson-based estimation was applied. A randomly assigned binary grouping variable (1 = female, 2 = male) was also included to illustrate the NCT; this variable does not represent a real group difference. The data was derived from a predefined sparse partial correlation structure; thus, the extent to which the estimated network recovered a known structure could be tracked.

Analysis

All analyses were conducted in the R environment. Before estimation, redundant nodes were screened using the goldbricker function, and the network was estimated using the graph lasso method (Pearson correlation, hyperparameter = 0.5) with EBIC tuning. The dimensional structure was examined using EGA based on the walktrap algorithm, and the stability of the structure was evaluated using bootEGA with 500 resampling iterations. Centrality measures—power, expected influence, proximity, and interconnectivity—were calculated in standardized form. Accuracy and stability were assessed using 1,000-repetition non-parametric bootstrapping (edge CIs and edge difference test) and case-dropout bootstrapping (centrality stability coefficient). Finally, the networks of the two groups were compared using an NCT with 1,000 permutations. The entire workflow is reproducible using the R code provided in the appendix (qgraph, bootnet, EGAnet, networktools, and NetworkComparisonTest packages).

Table 1. Descriptive statistics for the hypothetical data set

Indicator	Domain	M	SD	Skewness	Kurtosis
AIL1	Literacy	4.34	1.03	0.03	-0.29
AIL2	Literacy	4.43	0.99	-0.06	-0.14
AIL3	Literacy	4.38	1.06	0.00	-0.12
AIL4	Literacy	4.37	1.04	-0.12	0.00
ATT1	Attitude	4.34	1.04	-0.08	-0.06
ATT2	Attitude	4.40	1.01	0.10	-0.09
ATT3	Attitude	4.41	1.13	-0.03	-0.10
ANX1	Anxiety	4.40	1.03	-0.04	-0.15
ANX2	Anxiety	4.40	1.06	0.10	-0.10
ANX3	Anxiety	4.45	1.03	0.08	-0.07
ENG1	Engagement	4.36	1.04	-0.02	-0.12
ENG2	Engagement	4.37	1.07	-0.05	-0.51
INT	Engagement	4.34	1.02	-0.21	-0.06

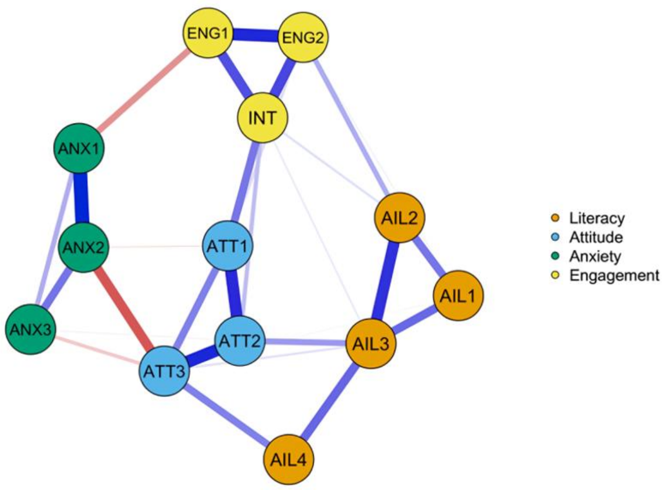

Figure 1. Psychometric network estimated using EBICglasso on hypothetical data (qgraph, colorblind theme) (blue edges represent positive partial correlations, and red edges represent negative partial correlations; edge thickness indicates the strength of the relationship & node colors represent theoretical domains [iteracy, attitude, anxiety, participation]) (created by the author)

RESULTS

Descriptive Statistics

Descriptive statistics for the variables are presented in **Table 1**. The means (Ms) for all items range from 4.34 to 4.45, with standard deviations of approximately 1.0. Skewness and kurtosis values fall within accepted normality limits; this supports the appropriateness of the Gaussian graph model based on Pearson correlation. The pre-estimation unnecessary node screening (goldbricker) did not suggest any node reductions for any item pair; therefore, all thirteen nodes were included in the network.

Estimated Network Structure

Of the 78 possible edges in the estimated network, 34 were non-zero (density = 0.44), and the average edge weight was calculated as 0.048. **Figure 1** shows the estimated network; nodes are colored according to their theoretical domains. The visual structure clearly presents the four conceptual domains as distinct clusters. Intra-domain edges are strong and positive (blue); for example, the connections ENG1-ENG2, ATT1-ATT2, ATT2-ATT3, AIL2-AIL3, and ANX1-ANX2 are among the thickest edges.

The inter-domain bridges are also theoretically meaningful. The ATT1-INT edge linking the attitude domain with the engagement domain aligns with the expectation that a positive attitude fosters the intention to use; the ATT2-AIL3 and ATT3-AIL3 edges linking the attitude and literacy domains also demonstrate the connection between these two domains. Two bridges, however, are negative (red): the ATT3-ANX2 edge linking attitude and anxiety suggests that trust in artificial intelligence is inversely related to the fear of job loss; the ANX1-ENG1 edge linking anxiety and engagement also suggests that anxiety is inversely related to engagement. Hence, it can be said that the network not only separates the domains but also reveals the theoretically interpretable bridges between them.

Dimensionality: Exploratory Graph Analysis

The dimensional structure was further tested using EGA. EGA identified four dimensions without any theoretical input and correctly placed the items into the domains of literacy, attitude, anxiety, and participation; this result aligns with the network's visual community structure. A 500-resampled bootEGA conducted to assess the stability of the structure supported a four-dimensional solution in 99.8% of the samples (only 0.2% showed three dimensions), with a median dimension count of 4 (95% CI: 3.91-4.09). When examining item-level placement stability, twelve items were present in their respective dimensions in all samples (100%); only the AIL4 item was repeated in its dimension 64% of the time (**Figure 2**). This indicates that AIL4 is the least stable item and may require review.

Centrality Analysis

The position of nodes within the network was evaluated using four centrality measures. **Figure 3** shows the values for normalized power, closeness, betweenness, and expected influence. A striking divergence emerges when power and expected effect values are compared. Although the ATT3 node is the most central node in the network in terms of power (z = 1.60), its expected influence value is negative (z = -0.57). This is due to the strong negative edge between ATT3 and ANX2; while this edge increases the

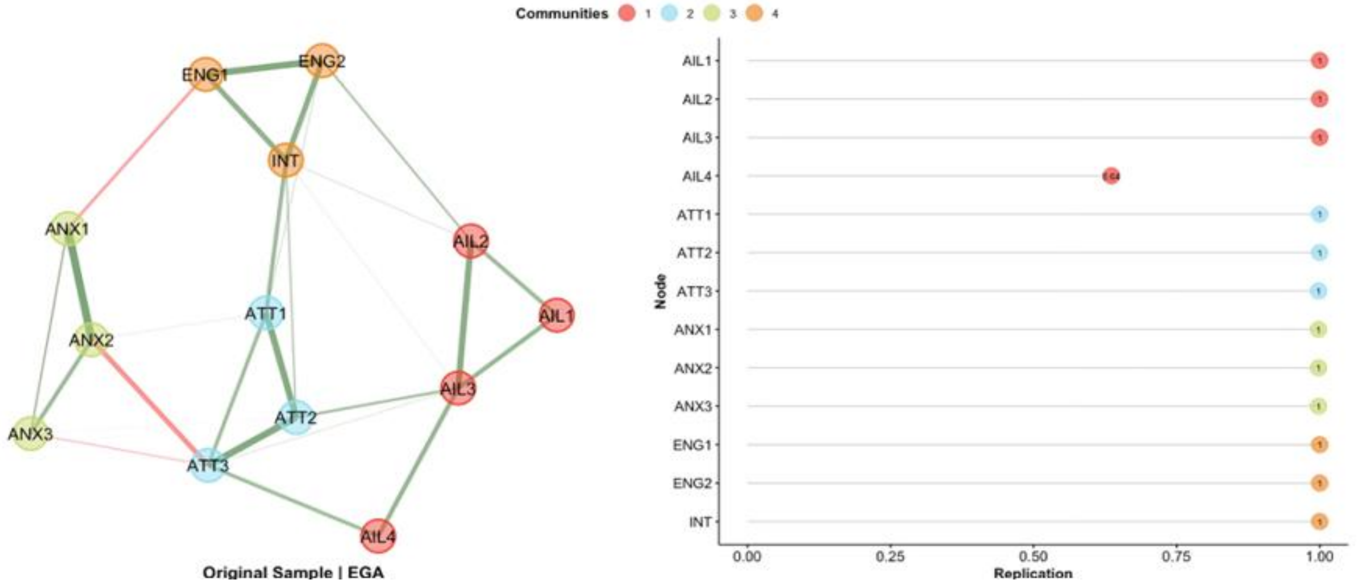

Figure 2. EGA (left: four-cluster solution in the original sample) and bootEGA item placement stability (right: the rate of item repetition within each dimension) (created by the author)

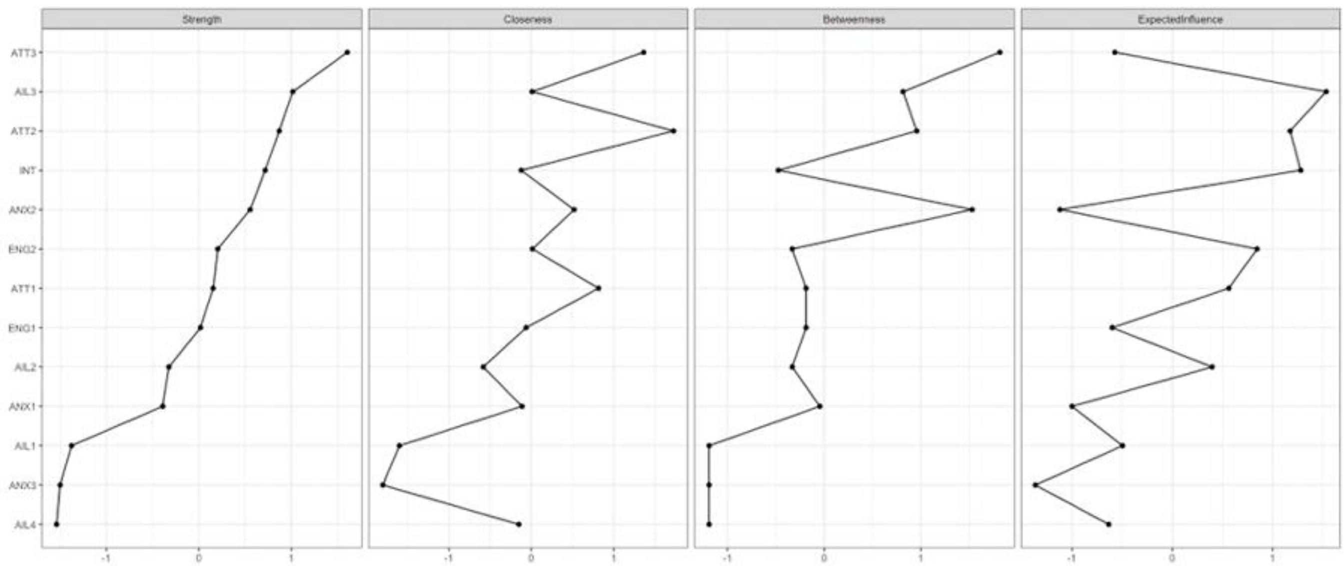

Figure 3. Standardized (z-score) centrality measures: strength, closeness, betweenness, and expected influence (created by the author)

node's absolute connectivity, it pulls down its signed sum. Similarly, all anxiety nodes have received a negative influence expected. This pattern concretely demonstrates that in signed networks, absolute power and signed expected influence can be distinctly separated from one another, and reporting both together provides a more accurate picture. The numerical values are provided in **Table 2**.

According to the power measure, the most central nodes are ATT3 (trust), AIL3 (evaluation literacy), ATT2 (perceived usefulness), and INT (intention to use); the nodes with the lowest centrality are AIL4, ANX3, and AIL1. The highest values in the expected impact measure belong to the AIL3, INT, and ATT2 nodes, while the three nodes in the anxiety domain (ANX3, ANX2, ANX1) received the most negative expected impact values.

Accuracy and Stability

Before proceeding to the interpretation, the network's accuracy and stability were tested.

Figure 4 shows the CIs for edge weights obtained from 1,000 non-parametric bootstrap repetitions. The CIs for strong edges are narrow and far from zero; these edges can be interpreted with confidence. In contrast, the CIs for many edges close to zero are wide and include zero; it would not be appropriate to draw definitive conclusions regarding the presence or order of these edges. The near-perfect overlap between the sample edge values and the bootstrap averages also suggests that there is no significant bias in the estimation.

Table 2. Standardized centrality measures (z-scores) at the node level

Indicator	Strength	Expected influence	Closeness	Betweenness
AIL1	-1.38	-0.50	-1.60	-1.19
AIL2	-0.32	0.40	-0.58	-0.33
AIL3	1.01	1.53	0.01	0.82
AIL4	-1.54	-0.63	-0.15	-1.19
ATT1	0.15	0.56	0.82	-0.19
ATT2	0.87	1.17	1.73	0.96
ATT3	1.60	-0.57	1.36	1.82
ANX1	-0.39	-1.00	-0.11	-0.04
ANX2	0.55	-1.12	0.52	1.53
ANX3	-1.50	-1.36	-1.80	-1.19
ENG1	0.02	-0.60	-0.06	-0.19
ENG2	0.20	0.84	0.01	-0.33
INT	0.72	1.28	-0.12	-0.47

Note.

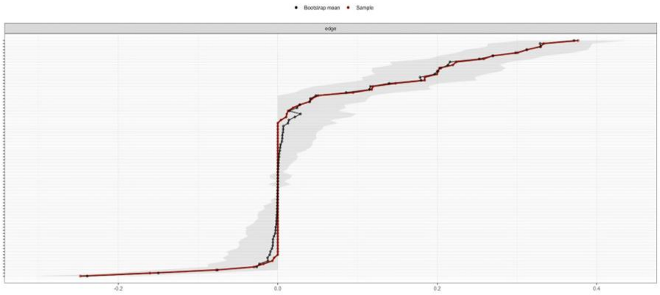

Figure 4. CIs for edge weights obtained via bootstrapping (the red line represents the sample edge values, the black line represents the bootstrap mean, and the gray band represents the 95% CI; the edges are sorted by sample weight) (created by the author)

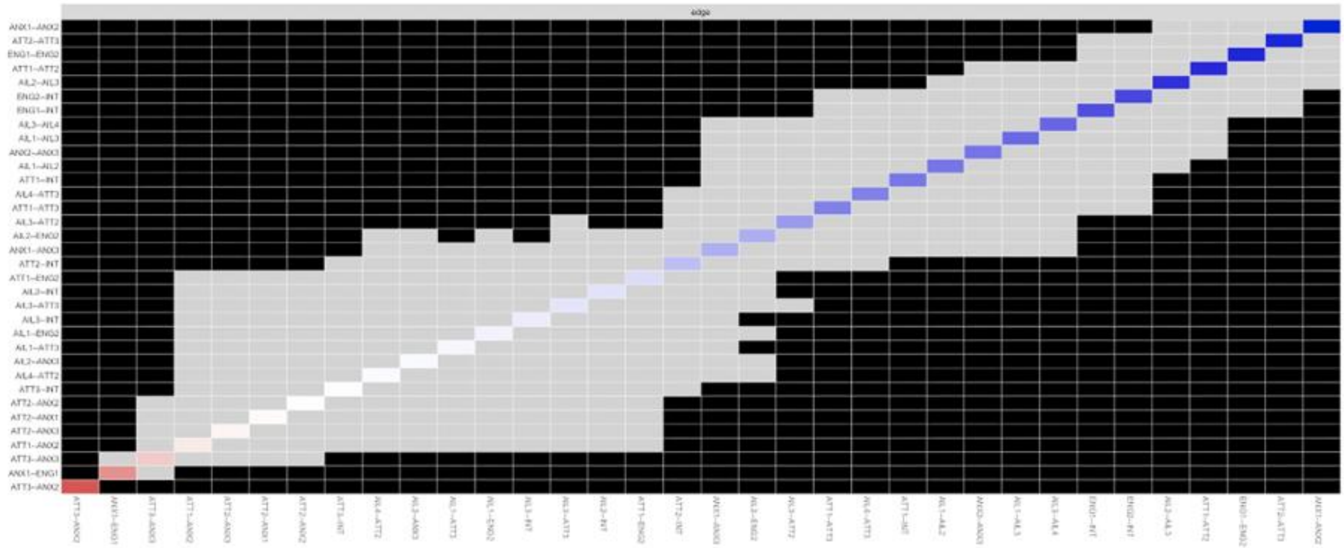

Figure 5. Edge difference test (black cells indicate pairs where the two edges are significantly different, while gray cells indicate pairs where they are not significantly different; the colored cells along the diagonal show the weights of the edges themselves) (created by the author)

The edge difference test (**Figure 5**) shows which edge pairs are statistically distinct. The strongest edges (ANX1-ANX2, ATT2-ATT3, ENG1-ENG2, ATT1-ATT2, and AIL2-AIL3) are significantly stronger than the vast majority of weak edges in the network. In contrast, a large number of weak edges with values close to zero cannot be meaningfully distinguished from one another; this once again underscores that interpretations based on the relative order of weak edges are unreliable.

The stability of the centrality ranking was assessed using a bootstrap method. **Figure 6** shows the correlation between the power ranking and the original ranking as progressively larger proportions of the sample are removed. The correlation remained at an average of 0.88 even when 75% of the sample was removed, and the lower limit of the CI remained above the 0.70 threshold. Accordingly, the CS coefficient for power reached the highest value examined (CS = 0.75); that is, power centrality exhibits high stability. It can be concluded that this result demonstrates that a sample size of N = 500 is sufficient to confidently interpret the centrality estimates for this network.

Network Comparison Across Groups

Finally, the networks of the two randomly assigned groups (women, men) were compared using an NCT. No significant difference was found in the general structure invariance test (M = 0.09, p = .994). There was also no significant difference between groups in the global power invariance test; global power values were calculated as 4.44 and 4.18, with a test statistic of S = 0.26, p = .561. At the edge level, only one of the seventy-eight edges (ANX2-INT) was nominally significant (p = .042); this will not survive multiple comparison correction. In the centrality invariance test, no significant differences were observed for power or expected influence at any node.

Since the grouping variable was randomly assigned, this lack of consistency is an expected result. The value of the finding is methodological rather than empirical: the NCT does not produce false differences when no real difference exists; thus, it provides an appropriate safeguard against the risk of false positives created by visually assessing group differences. In a real-world study, the same procedure

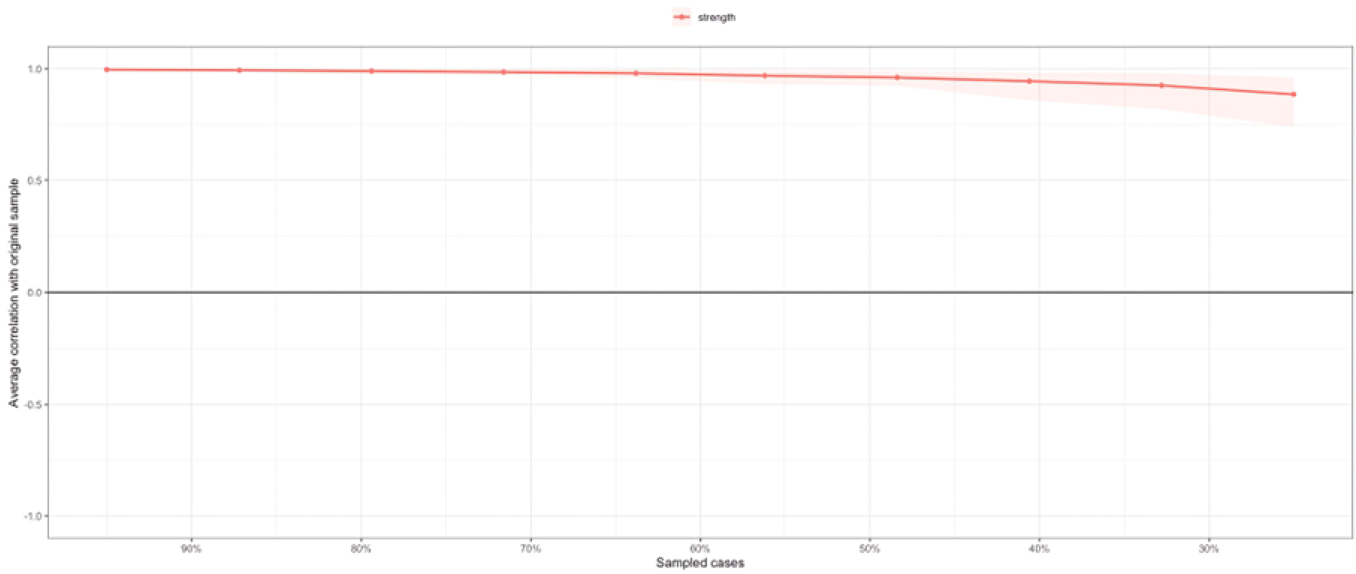

Figure 6. Stability of power centrality with case dropout (the vertical axis shows the correlation between the ranking and the original sample as proportion of samples removed increases) (created by the author)

could be used to test the invariance of an AI attitude network across samples of gender, educational level, or country.

DISCUSSION

This study, by demonstrating psychometric network analysis end-to-end in an educational context, has shown that the method's power is limited by the decision-making process behind it. The hypothetical example showed that a well-structured analysis recovered the known four-dimensional structure through both network communities and EGA; that centrality exhibited high stability (CS = 0.75); and that the NCT found invariance as expected in a randomly assigned grouping. Taken together, these findings demonstrate that the method can yield reliable results when executed with sound decisions; however, this reliability must be clearly demonstrated through stability and comparison diagnostics.

Common Challenges and Pitfalls

Researchers applying psychometric network analysis to educational data encounter a series of recurring issues. Most of these issues stem not from a technical flaw in the method but from interpretations that exceed the level of evidence supporting the inferences. The first pitfall is the interpretation of unstable networks in small samples. Networks estimated from limited samples can easily change in repeated studies; the presence of edges and the centrality rankings fluctuate from sample to sample. A network presented without a stability analysis should be considered unreliable, no matter how regular it may appear.

The second pitfall is the overinterpretation of centrality measures. The assumption that the most central node is automatically the most suitable target for intervention is widespread but incorrect. Centrality reflects a node's position within a cross-sectional pattern of relationships, not its causal importance. Furthermore, since proximity and intermediary measures have been shown to be unreliable in psychological networks, interpretations based on these measures should be made with particular caution (Bringmann et al., 2019). In the application example, while the power measure demonstrated high stability, the interpretations were based on this more reliable measure.

The third pitfall is interpreting edges as causal links. An edge indicates a conditional relationship between two variables; it does not specify which influences the other or whether a common third factor determines both. A network inferred from cross-sectional data is a map of non-directional relationships. Causal interpretations are valid only when supported by longitudinal or experimental designs.

The fourth pitfall is the artificial structure created by nodes that overlap in content. Two items asking nearly the same thing generate a strong edge between them, and this edge distorts both the network structure and centrality estimates. Failing to filter out redundant nodes before estimation is an error that often goes unnoticed but fundamentally affects the interpretation. The fifth pitfall is the generalization of cross-sectional networks to individual processes. A between-subject network reflects the average relationship pattern in the sample; it does not reflect the dynamics of a single individual over time. To understand how anxiety affects participation in a student, we need individual (idiographic) networks constructed from dense longitudinal data, not a network estimated from the group. Confusing these two levels leads to ecological bias.

The sixth pitfall is the careless comparison of groups. The fact that networks estimated from two samples look different is not, by itself, evidence of a meaningful difference, because sampling variation alone can produce this difference. The NCT in the application example is significant precisely for this reason: by failing to produce any meaningful difference in randomly assigned groups, it demonstrated that a valid comparison requires a statistical framework (van Borkulo et al., 2023).

Reporting Standards and Reproducibility

The reproducibility of network analysis is ensured only through transparent reporting. Burger et al. (2023) suggested a rigorous reporting standard for cross-sectional network studies. The key parts of this standard are equally relevant for research in education. The report should explain at least the sample size and characteristics, the reason for node selection, the way to deal with missing data, the type of correlation, the estimation method and the regularization value.

In addition, the version numbers of the software and packages used must be provided, as network packages are frequently updated and default settings may vary across versions. The results of stability analyses, particularly edge CIs and the centrality stability coefficient, should be reported alongside the findings. Whenever possible, the analysis code and data should be shared in an open repository. For detailed implementation recommendations and example code flows on this topic, the reference compiled by Isvoranu et al. (2022) provides a useful guide. Generally speaking, the value of network findings is directly proportional to the traceability of the decisions they inform.

Limitations and Future Directions

This study is based on the hypothetical example data provided and does not fully reflect the measurement error, missing data, and distribution issues that a real sample would carry. Additionally, since nodes in the example are defined as continuous subscale scores, the poly-coric estimation issues that arise when working with ordinal items have not been demonstrated. The grouping variable was also assigned randomly in a way that does not involve a real difference; therefore, the NCT serves only as a methodological demonstration. Since the example was conducted using a single dataset, the replicability of the findings in independent samples has not been tested. These limitations are consistent with the guide's purpose, as the example was designed to demonstrate the process rather than present actual findings.

Two directions can be suggested for future educational research. First, estimating individual networks using longitudinal and intensive measurement designs will allow for process-oriented questions that cross-sectional networks cannot address. Second, examining the invariance of network structure across different cultural samples using NCTs will provide new evidence regarding the cross-cultural validity of educational structures.

Conclusion

Psychometric network analysis offers a rich framework for examining the inner workings of educational structures. By treating structures as systems composed of directly interacting components, it reveals bridges and patterns that a causal model might overlook. However, the method's power is limited by the rigor of the decision-making process underlying it. It is not possible to generalize about the method's suitability for every educational question; however, when the structure is conceptualized as an interactive system and the analysis is conducted with sufficient methodological caution, network analysis can be considered a valuable tool.

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Ethics declaration: This study did not involve human participants, animals, or the collection of any personal data. The data set used throughout the worked example is entirely hypothetical and was generated by simulation, as documented in **Appendix A**. Accordingly, ethical approval and informed consent were not applicable.

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Data availability: No empirical data were collected or analyzed in this study. The data set used in the illustrative example is hypothetical and was generated by simulation; it is provided as supplementary material. The complete, annotated R code required to reproduce the simulated data and every analysis, figure, and result reported in this paper is provided in **Appendix A**. No additional data are associated with this article.

REFERENCES

Borsboom, D., & Cramer, A. O. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, 9(1), 91-121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T. W., & Snippe, E. (2019). What do centrality measures measure in psychological networks? *Journal of Abnormal Psychology*, 128(8), 892-903. https://doi.org/10.1037/abn0000446

Burger, J., Isvoranu, A. M., Lunansky, G., Haslbeck, J. M. B., Epskamp, S., Hoekstra, R. H. A., Fried, E. I., Borsboom, D., & Blanken, T. F. (2023). Reporting standards for psychological network analyses in cross-sectional data. *Psychological Methods*, 28(4), 806-824. https://doi.org/10.1037/met0000471

Choi, Y., Lim, Y., & Son, D. (2017). A semantic network analysis on the recognition of STEAM by middle school students in South Korea. *Eurasia Journal of Mathematics, Science and Technology Education*, 13(10), 6457-6469. https://doi.org/10.12973/ejmste/77950

Christensen, A. P., Golino, H., & Silvia, P. J. (2020). A psychometric network perspective on the validity and validation of personality trait questionnaires. *European Journal of Personality*, 34(6), 1095-1108. https://doi.org/10.1002/per.2265

Costantini, G., Epskamp, S., Borsboom, D., Perugini, M., Mõttus, R., Waldorp, L. J., & Cramer, A. O. (2015). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality*, 54, 13-29. https://doi.org/10.1016/j.jrp.2014.07.003

Dalege, J., Borsboom, D., van Harreveld, F., van den Berg, H., Conner, M., & van der Maas, H. L. J. (2016). Toward a formalized account of attitudes: The causal attitude network (CAN) model. *Psychological Review*, *123*(1), 2-22. https://doi.org/10.1037/a0039802

Dumas, D., & Edelsbrunner, P. (2023). How to make recommendations for educational practice from correlational data using structural equation models. *Educational Psychology Review*, 35, Article 48. https://doi.org/10.1007/s10648-023-09770-0

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, 23(4), 617-634. https://doi.org/10.1037/met0000167

Epskamp, S., Borsboom, D., & Fried, E. I. (2018a). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, 50(1), 195-212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, 48(4), 1-18. https://doi.org/10.18637/jss.v048.i04

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018b). The Gaussian graphical model in cross-sectional and time-series data. *Multivariate Behavioral Research*, 53(4), 453-480. https://doi.org/10.1080/00273171.2018.1454823

Eskandari, M., & Kim, Y. (2022). Semantic network analysis of the biotechnology domain in Iranian high school biology textbooks. *Eurasia Journal of Mathematics, Science and Technology Education*, 18(8), Article em2144. https://doi.org/10.29333/ejmste/12266

Forbes, M. K., Wright, A. G. C., Markon, K. E., & Krueger, R. F. (2017). Evidence that psychopathology symptom networks have limited replicability. *Journal of Abnormal Psychology*, *126*(7), 969-988. https://doi.org/10.1037/abn0000276

Foygel, R., & Drton, M. (2010). Extended Bayesian information criteria for Gaussian graphical models. *Advances in Neural Information Processing Systems*, 23, 604-612.

Fried, E. I., & Cramer, A. O. J. (2017). Moving forward: Challenges and directions for psychopathological network theory and methodology. *Perspectives on Psychological Science*, 12(6), 999-1020. https://doi.org/10.1177/1745691617705892

Fried, E. I., van Borkulo, C. D., & Epskamp, S. (2021). On the importance of estimating parameter uncertainty in network psychometrics: A response to Forbes et al. (2019). *Multivariate Behavioral Research*, 56(2), 243-248. https://doi.org/10.1080/00273171.2020.1746903

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, 9(3), 432-441. https://doi.org/10.1093/biostatistics/kxm045

Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS ONE*, 12(6), Article e0174035. https://doi.org/10.1371/journal.pone.0174035

Golino, H., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Sadana, R., Thiyagarajan, J. A., & Martinez-Molina, A. (2020). Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods*, 25(3), 292-320. https://doi.org/10.1037/met0000255

Green, T. (2016). A methodological review of structural equation modelling in higher education research. *Studies in Higher Education*, 41(12), 2125-2155. https://doi.org/10.1080/03075079.2015.1021670

Grunspan, D. Z., Wiggins, B. L., & Goodreau, S. M. (2014). Understanding classrooms through social network analysis: A primer for social network analysis in education research. *CBE—Life Sciences Education*, 13(2), 167-178. https://doi.org/10.1187/cbe.13-08-0162

Haslbeck, J. M. B., & Waldorp, L. J. (2020). mgm: Estimating time-varying mixed graphical models in high-dimensional data. *Journal of Statistical Software*, 93(8), 1-46. https://doi.org/10.18637/jss.v093.i08

Hevey, D. (2018). Network analysis: A brief overview and tutorial. *Health Psychology and Behavioral Medicine*, 6(1), 301-328. https://doi.org/10.1080/21642850.2018.1521283

Hofman, A. D., Kievit, R., Stevenson, C., Molenaar, D., Visser, I., & van der Maas, H. (2018). *The dynamics of the development of mathematics skills: A comparison of theories of developing intelligence*. OSF Preprints. https://doi.org/10.31219/osf.io/xa2ft

Isvoranu, A., & Epskamp, S. (2023). Which estimation method to choose in network psychometrics? Deriving guidelines for applied researchers. *Psychological Methods*, 28(4), 925-946. https://doi.org/10.1037/met0000439

Isvoranu, A., Epskamp, S., Waldorp, L. J., & Borsboom, D. (2022). *Network psychometrics with R: A guide for behavioral and social scientists*. Routledge. https://doi.org/10.4324/9781003111238

Jones, P. J., Ma, R., & McNally, R. J. (2021). Bridge centrality: A network approach to understanding comorbidity. *Multivariate Behavioral Research*, 56(2), 353-367. https://doi.org/10.1080/00273171.2019.1614898

Kadum, B. M. M., & Karpudewan, M. (2026). Psychometric network analysis of gendered patterns in experimental self-efficacy among Malaysian pre-university chemistry students. *Chemistry Education Research and Practice*. https://doi.org/10.1039/d6rp00083e

Karakaya-Ozyer, K., & Aksu-Dunya, B. (2018). A review of structural equation modeling applications in Turkish educational science literature, 2010-2015. *International Journal of Research in Education and Science*, 4(1), 279-291. https://doi.org/10.21890/ijres.383177

Li, J., & Bai, B. (2025). Mapping children's school readiness: Insights from network analysis. *Early Child Development and Care*, 195(15-16), 1651-1677. https://doi.org/10.1080/03004430.2025.2608074

Peng, P., & Kievit, R. A. (2020). The development of academic achievement and cognitive abilities: A bidirectional perspective. *Child Development Perspectives*, 14(1), 15-20. https://doi.org/10.1111/cdep.12352

Rad, D., & Roman, A. (2025). Mapping the motivational architecture of ai literacy: A network analysis of teachers' multidimensional work motivation. *Journal of Psychological and Educational Research*, 33(2), 203-222.

Robinaugh, D. J., Hoekstra, R. H. A., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: A review of the literature 2008-2018 and an agenda for future research. *Psychological Medicine*, 50(3), 353-366. https://doi.org/10.1017/s0033291719003404

Sachisthal, M. S. M., Jansen, B. R. J., Peetsma, T. T. D., Dalege, J., van der Maas, H. L. J., & Raijmakers, M. E. J. (2019). Introducing a science interest network model to reveal country differences. *Journal of Educational Psychology*, 111(6), 1063-1080. https://doi.org/10.1037/edu0000327

Sáez-Delgado, F., Mella-Norambuena, J., & López-Angulo, Y. (2024). Psychometric properties of the socioemotional skills instrument for teachers using network approach: English and Spanish version. *Frontiers in Psychology*, 15. https://doi.org/10.3389/fpsyg.2024.1421164

Schmittmann, V. D., Cramer, A. O., Waldorp, L. J., Epskamp, S., Kievit, R. A., & Borsboom, D. (2013). Deconstructing the construct: A network perspective on psychological phenomena. *New Ideas in Psychology*, 31(1), 43-53. https://doi.org/10.1016/j.newideapsych.2011.02.007

Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, 3(3), 9-45. https://doi.org/10.18608/jla.2016.33.3

Steinley, D., Hoffman, M., Brusco, M. J., & Sher, K. J. (2017). A method for making inferences in network analysis: Comment on Forbes, Wright, Markon, and Krueger (2017). *Journal of Abnormal Psychology*, 126(7), 1000-1010. https://doi.org/10.1037/abn0000308

Teo, T. (2011). Using structural equation modeling (SEM) in educational research: Practices and issues. *International Journal of Applied Educational Studies*, 10(1), 49-65.

Tomei, G., Pieroni, M. F., & Tomba, E. (2022). Network analysis studies in patients with eating disorders: A systematic review and methodological quality assessment. *International Journal of Eating Disorders*, 55(12), 1641-1669. https://doi.org/10.1002/eat.23828

van Borkulo, C. D., van Bork, R., Boschloo, L., Kossakowski, J. J., Tio, P., Schoevers, R. A., Borsboom, D., & Waldorp, L. J. (2023). Comparing network structures on three aspects: A permutation test. *Psychological Methods*, 28(6), 1273-1285. https://doi.org/10.1037/met0000476

van der Maas, H. L. J., Dolan, C. V., Grasman, R. P. P. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. J. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, 113(4), 842-861. https://doi.org/10.1037/0033-295x.113.4.842

Williams, D. R., & Rast, P. (2020). Back to the basics: Rethinking partial correlation network methodology. *British Journal of Mathematical and Statistical Psychology*, 73(2), 187-212. https://doi.org/10.1111/bmsp.12173

Yin, H., & Huang, S. (2021). Applying structural equation modelling to research on teaching and teacher education: Looking back and forward. *Teaching and Teacher Education*, 107, Article 103438. https://doi.org/10.1016/j.tate.2021.103438

APPENDIX A: ANNOTATED R CODE

The R code below reproduces the analysis workflow described in the article from start to finish. The code relies on the qgraph, bootnet, EGAnet, networktools, and NetworkComparisonTest packages. A hypothetical dataset that can be used in place of the actual data is also included in the introductory section.

```
# ======================================================================
# Psychometric network analysis in educational research
# Reproducible pipeline (R ≥ 4.2)
# ======================================================================
# ---- 0. Packages ----
# install.packages (c (“qgraph”, “bootnet”, “EGAnet”, “networktools”, “NetworkComparisonTest”, “mgm”, “psych”))
Library (qgraph); library (bootnet); library (EGAnet)
library (networktools); library (NetworkComparisonTest); library (psych)
set.seed (2026)
# ---- 1. Data (replace with data <- read.csv (“pna_hypothetical_data.csv”)) ----
p <- 13
labels <- c (“AIL1”,”AIL2”,”AIL3”,”AIL4”,”ATT1”,”ATT2”,”ATT3”, “ANX1”,”ANX2”,”ANX3”,”ENG1”,”ENG2”,”INT”)
Theta <- diag (p)
addE <- function (M, a, b, v) {M [a, b] <- M [b, a] <- -v; M}
pairs <- list (c (1, 2, .36), c (2, 3, .31), c (3, 4, .29), c (1, 3, .16), c (5, 6, .42), c (6, 7, .34), c (5, 7, .21), c (8, 9, .39), c (9, 10, .31), c (8, 10, .19), c (11, 12, .37), c (12, 13, .33), c (11, 13, .23), c (3, 6, .22), c (5, 13, .27), c(7, 9, -.24), c (8, 11, -.21), c(4, 7, .18), c (12, 2, .15))
for (e in pairs) theta <- addE (Theta, e [1], e [2], e[3])
Theta <- theta + diag (max (0,0 .06 – min (eigen (theta) $values)), p)
Sigma <- cov2cor (solve (theta))
data <- MASS::mvrnorm (500, rep (0, p), sigma)
data <- as.data.frame (pmin (pmax (4.4 + 1.05 * data, 1), 7))
colnames (data) <- labels
set.seed (99); data$group <- sample (1:2, nrow(data), replace = TRUE) # for NCT demo
# ---- 2. Descriptives & assumption checks ----
Describe (data [, labels]) [, c (“mean”, “sd”, “skew”, “kurtosis”)]
# Ordinal/Likert items -> use polychoric: corMethod = “cor_auto” or “spearman”
# ---- 3. Redundancy/topological overlap ----
Goldbricker (data [, labels], p = 0.05, threshold = 0.25)
# ---- 4. Estimation: EBICglasso (Pearson) ----
net <- estimateNetwork (data [, labels], default = “EBICglasso”, corMethod = “cor”, tuning = 0.5)
print (net)
# ---- 5. Visualization ----
groups <- list (literacy=1:4, attitude=5:7, anxiety=8:10, engagement=11:13)
plot (net, layout = “spring”, groups = groups, theme = “colorblind”, legend = TRUE, vsize = 7, label.cex = 1.1, filetype = “png”, filename = “figure1_network”)
# ---- 6. Centrality ----
centralityPlot (net, include = c (“Strength”, “Closeness”, “Betweenness”, “ExpectedInfluence”), scale = “z-scores”, orderBy = “Strength”)
centralityTable (net)
# ---- 7. Dimensionality (EGA + bootEGA) ----
ega <- EGA (data [, labels], model = “glasso”, algorithm = “walktrap”)
summary (ega)
bega <- bootEGA (data [, labels], iter = 500, type = “resampling”, model = “glasso”, seed = 2026)
summary (bega)
# ---- 8. Accuracy & stability ----
boot1 <- bootnet (net, nBoots = 1000, nCores = 4)
plot (boot1, order = “sample”, labels = FALSE)
# edge-weight CIs
plot (boot1, “edge”, plot = “difference”, onlyNonZero = TRUE, order = “sample”)
boot2 <- bootnet(net, nBoots = 1000, type = “case”, nCores = 4, statistics = c (“strength”,”expectedInfluence”))
plot (boot2, statistics = “strength”)
corStability (boot2)
# ---- 9. Group comparison (NCT) ----
g1 <- na.omit (data [which (data$group == 1), labels])
g2 <- na.omit (data [which (data$group == 2), labels])
nct <- NCT (g1, g2, it = 1000, test.edges = TRUE, test.centrality = TRUE,
 centrality = c (“strength”,”expectedInfluence”),
 estimatorArgs = list (corMethod = “cor”, gamma = 0.5))
summary (nct)
# ---- 10. Reproducibility ----
sessionInfo ()
```