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Iterated Community Detection in Psychological Networks

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Abstract

Psychological network models often feature communities: subsets of nodes that are more densely connected to themselves than to other nodes. The Spinglass algorithm is a popular method of detecting communities within a network, but it is a nondeterministic algorithm, meaning that the results can vary from one iteration to the next. There is no established method for determining the optimal solution or for evaluating instability across iterations in the emerging discipline of network psychometrics. We addressed this need by introducing and evaluating iterated community detection: Spinglass (IComDetSpin), a method for aggregating across multiple Spinglass iterations to identify the most frequent solution and quantify and visualize the instability of the solution across iterations. In two simulation studies, we evaluated (a) the performance of IComDetSpin in identifying the true community structure and (b) information about the fuzziness of community boundaries; information that is not available with a single iteration of Spinglass. In Study 1, IComDetSpin outperformed single-iteration Spinglass in identifying the true number of communities and performed comparably to Walktrap. In Study 2, we extended our evaluation to networks estimated from simulated data and found that both IComDetSpin and Exploratory Graph Analysis (a well-established community detection method in network psychometrics) performed well and that IComDetSpin outperformed Exploratory Graph Analysis when correlations between communities were high and number of nodes per community was lower (5 vs. 10). Overall, IComDetSpin improved the performance of Spinglass and provided unique information about the stability of community detection results and fuzziness in community structure.

Translational Abstract

Psychological network models can have communities: groups of nodes that are more strongly connected with each other than with other nodes. The Spinglass algorithm is a popular method of detecting these communities. Interestingly, Spinglass is a nondeterministic algorithm, which means that the algorithm's results can differ each time the algorithm is run. Researchers often report the results of one single Spinglass run, raising the question how stable the identified community solution is (i.e., how much it changes when the algorithm is run multiple times). This information is important because low stability poses a threat to the reliability and replicability of community detection. To address this challenge, we developed iterated community detection: Spinglass (IComDetSpin), a method that combines results from multiple Spinglass runs to identify the most reliable community structure and to quantify the stability of the detected communities. In two simulation studies, we found that IComDetSpin does a better job than single Spinglass runs and overall

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performs comparable to Exploratory Graph Analysis (a well-established community detection method in network psychometrics) at detecting the correct number of communities. In addition, IcomDetSpin also provides insight into how much communities in one network overlap with each other. That is, it provides information about the "fuzziness" of community boundaries, information that is not available with a single iteration of Spinglass. We conclude with a step-by-step tutorial for researchers who want to apply IComDetSpin to their own data.

Keywords: psychological networks, community detection, clustering, overlapping communities, Spinglass

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Network psychometrics has become an increasingly common means of exploring multivariate data in psychological science (Isvoranu et al., 2022). With this method, multivariate joint distributions are represented as networks (or graphs) in which nodes are variables and edges are relationships between these variables (Borsboom et al., 2021; Epskamp & Fried, 2018; Epskamp, Borsboom, & Fried, 2018; Epskamp, Waldorp, et al., 2018). Researchers then examine the topography of these networks. This method has been used to examine psychological constructs such as intelligence, personality, attitudes, and mental disorders as networks of interrelated components (Contreras et al., 2019; Costantini et al., 2019; Dalege et al., 2017; Fried & Cramer, 2017; Kan et al., 2019; Robinaugh et al., 2020).

As with other networks investigated in the field of network science (Danon et al., 2005; Fortunato & Hric, 2016; Newman & Girvan, 2004; Yang et al., 2016), psychometric networks often exhibit communities (Blanken et al., 2018; Bringmann & Eronen, 2018; Golino & Demetriou, 2017; Golino & Epskamp, 2017): subsets of nodes that show more or stronger connections to nodes within the subset than to nodes outside of the subset (Coscia et al., 2011; Fortunato & Hric, 2016). Several researchers have emphasized the importance of better understanding these communities as a means of better understanding the psychological phenomena under investigation in network psychometric studies. For example, Blanken et al. (2018) and Jones et al. (2021) both argued for the importance of examining communities in mental disorder symptom networks as a key to better understanding comorbidity in these disorders. Golino and Epskamp (2017) similarly called for further research on communities in the network psychometric literature and showed that network community detection is a powerful tool to detect and model dimensionality in psychological item covariation, even in unidimensional structures (Christensen et al., 2024; Golino et al., 2020).

Given its importance in network topography, it is unsurprising that many algorithms to detect communities have been developed. Some of these algorithms, such as Walktrap (Pons & Latapy, 2006) and the minimum average partial (Velicer, 1976) procedure, are deterministic: they always produce the same result when applied to the same network structure. Other algorithms are nondeterministic: they can produce different results when estimated on the same network structure. One such algorithm is known as Spinglass (Reichardt & Bornholdt, 2004, 2006a, 2006b). Although a popular means of estimating network structure, the nondeterministic nature of the algorithm presents a challenge. To our knowledge, there is no established method in the network psychometric literature for identifying the most appropriate solution from this nondeterministic algorithm. Moreover, to our knowledge, there is no established means of evaluating the stability of the findings across iterations. Such uncertainty poses a significant threat to the replicability of findings from this community detection algorithm in network psychometrics. Accordingly, there is a need for a method that identifies the best solution across iterations and quantifies the instability in the findings from the Spinglass community detection algorithm. In this article, we aim to address this need.

The second challenge we tackle in this article is one that extends beyond Spinglass. Many of the most used community detection algorithms in the network psychometric literature, such as Walktrap and Spinglass, assign each node to one community. That is, communities are mutually exclusive; there is no overlap in which some nodes belong to multiple communities. This lack of overlap is unrealistic in many fields (Javed, et al., 2018; Palla et al., 2005; e.g., Gavin et al., 2002; Onnela et al., 2003; Scott, 2000) and may be especially unrealistic in the complex and highly intercorrelated data commonly observed in psychology (i.e., "the crud factor"; Meehl, 1990). The high likelihood that there are fuzzy boundaries between communities in psychometric networks suggests the need for approaches that allow a variable to "cross-load" (to borrow a term from the latent variable literature) on multiple communities. That is, there is a need for methods that quantify the extent to which a given node may fit well in multiple communities. Although complex estimation algorithms exist to obtain community "cross-loadings," such as the Clique Percolation (CP; Barabási, n.d.; Lange, 2021) algorithm, it is not yet fully known how CP performs within smaller network structures common in network psychometrics since the overall size of a network affects the possible size of a clique (i.e., a clique is a fully connected group of nodes; Ribeiro Santiago et al., 2024), which the CP algorithm uses to identify communities.

The instability across iterations in the Spinglass algorithm suggests a potential opportunity to gain information about fuzzy community boundaries and nodes that may fit well in multiple communities. Because instability across Spinglass iterations suggests uncertainty about the community structure, including, for example, whether a given node fits best with one community or another, this instability may serve as an indicator of how fuzzy the boundaries are between communities. In other words, rather than merely a hindrance to be overcome, the nondeterministic nature of the Spinglass algorithm could potentially be leveraged to provide additional information about the community structure not available from many other community detection algorithms.

The Current Study

In this article, we present and evaluate iterated community detection: Spinglass (IComDetSpin) as a means of addressing these two challenges to community detection in psychometric networks: the need for methods to appropriately aggregate findings across multiple iterations of Spinglass and the need for more information about fuzzy community boundaries. The article will be structured as follows. First, we introduce the Spinglass algorithm on which IComDetSpin is based, provide an explanation of the nondeterministic approach the method takes to identifying communities, and use this background information to introduce IComDetSpin. Second, we use a simulation study to compare the performance of IComDetSpin relative to single iterations of Spinglass and to another commonly used community detection algorithm (Walktrap). In doing so, we focus both on the performance of these methods (i.e., on their ability to recover the appropriate number of communities and assign nodes to the correct community) and on the ability of IComDetSpin to provide information about fuzziness in community structure. Third, we use a second simulation study to further evaluate IComDetSpin with networks estimated from data, thereby evaluating the method in the context in which it is most likely to be used in empirical research. Finally, we conclude with a discussion of the findings from these simulation studies and their implications for the use and future development of IComDetSpin.

A Primer on IComDetSpin

Spinglass Community Detection

Community detection techniques aim to detect groups of nodes that have a higher likelihood to connect to nodes within their group compared to nodes outside of that group (Barabási, n.d.). Different techniques detect such groups through different formulations of community structure (Christensen et al., 2024). The Spinglass algorithm reformulates a network structure as a q-state Potts Spinglass energy function: also called a "Hamiltonian function," in which nodes are allowed to be in different "states." The optimal q spin-state configuration indicates community membership, with two nodes in the same state belonging to the same community.

Reichardt and Bornholdt (2006a, 2006b) formulated a Hamiltonian-like function that describes community structure in a Spinglass-like network model and showed that minimizing the Hamiltonian function is equivalent to finding the "best" community structure.[1] Their Hamiltonian function incorporates four important assumptions about community structure. First, existing intracommunity connections should be rewarded (i.e., decrease the energy for connections between nodes of the same spin-state). Second, missing intracommunity connections should be penalized (i.e., increase the energy for missing connections between nodes of the same spin-state). Third, existing intercommunity connections should be penalized. Fourth, missing intercommunity connections should be rewarded. The rewards and penalties depend on a weighting scheme that can be adjusted by a gamma parameter (when gamma = 1, existing and nonexisting connections are weighed equally) and a connection probability parameter, p_{ij}, of the null model to be used as a comparison. The null model either assumes equal connection probabilities for all nodes, the so-called configuration model, or adjusts the probability according to the degree distribution of the studied network, the so-called simple model.

To find the minimum of the Hamiltonian function (and, thus, the "best" community structure), Reichardt and Bornholdt (2004 for more detail; 2006a; 2006b) used simulated annealing as the optimization algorithm. Simulated annealing's optimization search pattern uses an analogy to annealing in metallurgy, in which a metal is heated and cooled down slowly to find the most stable metal configuration (i.e., the particle configuration with the lowest energy level or so-called ground state of the system). In the simulation of the annealing process, temperature refers to the "adventurousness" of the optimization algorithm: The algorithm starts off with a high temperature, where it explores the state space by accepting both decreases and increases in the energy. As more of the state space is explored, the temperature, that is, "adventurousness," slowly decreases and the algorithm only accepts decreases in energy. Through this funneled search pattern, the algorithm is more likely to find the global, rather than only local, energy minimum. The search pattern can be adjusted by defining the cooling-scheme parameters, with the start- and stop temperature and the cooling factor determining the range of temperature of the algorithm and the number of simulation runs, respectively. The lowest energy solution represents the best community structure found, with that solution's spin-state configuration encoding the community structure.

Previous simulation studies show that Spinglass performs well in recovering the true number and structure of communities (Fortunato, 2010; Hoffman et al., 2018; Orman & Labatut, 2009; Orman et al., 2013; Tripathi et al., 2016; Yang et al., 2016), until the algorithm reaches its resolution limit, at which it does not detect small communities in very large networks (Fortunato & Barthelemy, 2007). However, these prior studies do not address one important aspect of the Spinglass algorithm's performance: its tendency to produce different community solutions even when run on exactly the same network.

Because Spinglass utilizes simulations to detect community structure, the algorithm is nondeterministic: if we run the Spinglass algorithm repeatedly on the same network, we could retrieve different community solutions. As a result, there can be variability from one run of the algorithm to another: nodes may switch community membership, and small distinct communities may merge into a single broader community. Reichardt and Bornholdt (2009) studied the variability in Spinglass solutions and ran Spinglass several times on a real-world network to explore similarly optimal solutions; demonstrating the potential for multiple equally optimal solutions and the importance to consider a range of viable solutions rather than one optimum. Thus, when we cast the problem of detecting communities into finding the optimal modularity, that is, the optimal energy state of a system, we may leverage the fact that the system allows for comparably or equivalently optimal solutions, which we can find by iteratively running the algorithm. Importantly, such iterations simultaneously assure that we do not accept a nonoptimal solution as the final result since we run the algorithm more than once.

Iterated Community Detection Using Spinglass

With IComDetSpin, we implement a simple extension of the Spinglass algorithm of the R package igraph (Csárdi & Nepusz,

[1] Reichardt and Bornholdt (2006a) showed that, under certain parameters, their Hamiltonian function is equivalent to the Newman and Girvan (2004) network modularity function. Network modularity is a quality measure for the assignment of nodes to communities, where the higher the modularity (ranging from −1 to 1), the "better" the assignment of nodes into communities. From the established equivalence, it followed that minimizing the Hamiltonian function is equivalent to maximizing modularity.

2006; Reichardt & Bornholdt, 2006a): repeatedly run the Spinglass algorithm on the same network structure and then quantify and visualize the results across these iterations. With this extension, IComDetSpin provides the researcher with valuable information at both the network level and the node level that cannot be obtained via a single iteration of Spinglass.

First, addressing the challenge of quantifying stability across iterations, IComDetSpin provides network-level information showing all unique Spinglass solutions in descending order of frequency across iterations, as well as summarizing information on the number of detected communities across iterations and their frequency. An example of the network-level information provided by IComDetSpin appears in Figure 1. In this figure, the first community solution was produced in 94 of 100 iterations, and the second was produced in three of 100 iterations. The remaining community solutions were found twice and once across the 100 iterations.

This network-level information assists researchers in three ways. First, the information clearly identifies the most common solution provided by Spinglass, preventing the possibility of arriving at an idiosyncratic solution, which might occur when relying on a single iteration. Second, the information allows researchers to gain insight into the stability of community structure, thereby providing guidance about the level of confidence the researcher can have in each solution. For instance, the most common solution in Figure 1 was observed in 94% of iterations, suggesting a high degree of confidence in this solution. Third, the information allows researchers to see how community borders migrate across similarly frequent solutions. We can be confident in the first solution presented in Figure 1 not only because this specific constellation occurred in 94% of cases but also because these communities appeared with only minor variations in the remaining iterations, even in the solution with four instead of three communities.

Second, regarding the need for information about node "cross-loadings" across communities, IComDetSpin provides node-level information about which nodes tend to appear together in communities across all iterations, regardless of each individual community solution. IComDetSpin presents this information in a coappearance matrix: Nodes are listed on the *x*- and *y* axes, where each cell represents the frequency with which the corresponding nodes are assigned to the same community across all iterations (using the pheatmap package; Kolde, 2019). The coappearance matrix can be ordered according to node clustering (see Figure 2), summarizing which nodes frequently group together across all solutions. Together with the network-level information, this node-level information might help identify nodes that bridge particular communities. For example, a node that occurs with one community of nodes in 50% of the iterations and another in the remaining 50% of iterations might be considered to bridge those two communities.

For readers interested in additional information on IComDetSpin, we provide a tutorial on the use of IComDetSpin in the online supplemental materials. In the next two sections, we evaluate IComDetSpin to determine whether this iterated community detection approach improves upon the performance of single iterations of Spinglass and how it compares to another popular method of community detection both within and beyond the network psychometric literature, namely the Walktrap algorithm.

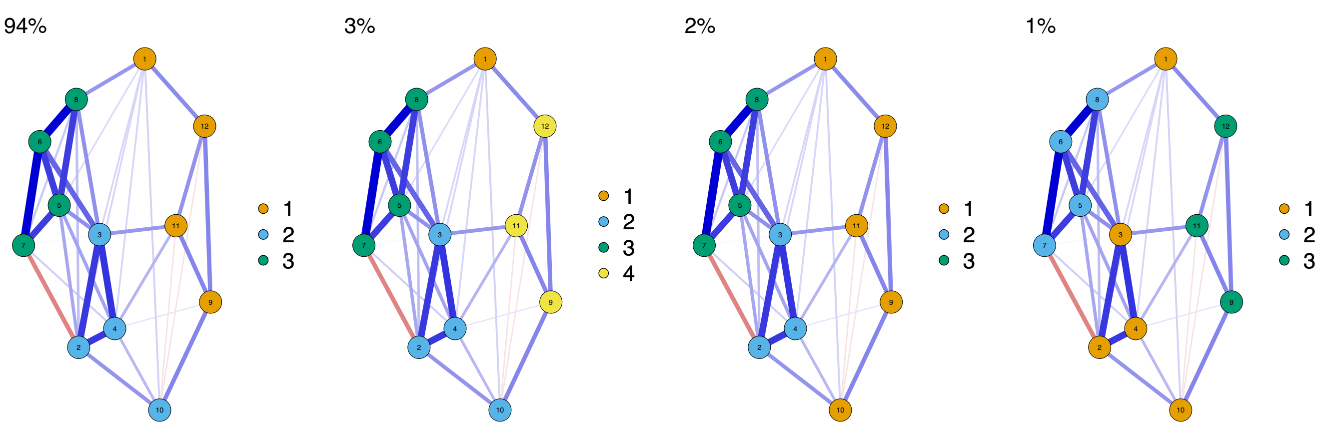
Simulation Study 1

In Study 1, we had two aims. First, we compared IComDetSpin's performance to traditional Spinglass and Walktrap community detection algorithms. We chose to compare IComDetSpin to Walktrap as Walktrap is used by the well-established community detection method Exploratory Graph Analysis (EGA; Golino et al., 2020; Golino & Epskamp, 2017). We could not compare IComDetSpin directly to EGA because EGA can only be applied to data and not to networks directly.

We focused especially on IComDetSpin's, Spinglass', and Walktrap's abilities to (a) identify the correct number of communities and (b) assign nodes to the correct communities. Given that IComDetSpin avoids potentially idiosyncratic results that may arise with single iterations of Spinglass, we anticipated that IComDetSpin would outperform Spinglass. We had no a priori hypotheses about the comparison between IComDetSpin and Walktrap. Second, we evaluated IComDetSpin's ability to detect fuzzy community boundaries. That is, we examined whether the instability in the IComDetSpin solution varied as a function of interconnectivity of the community

Figure 1

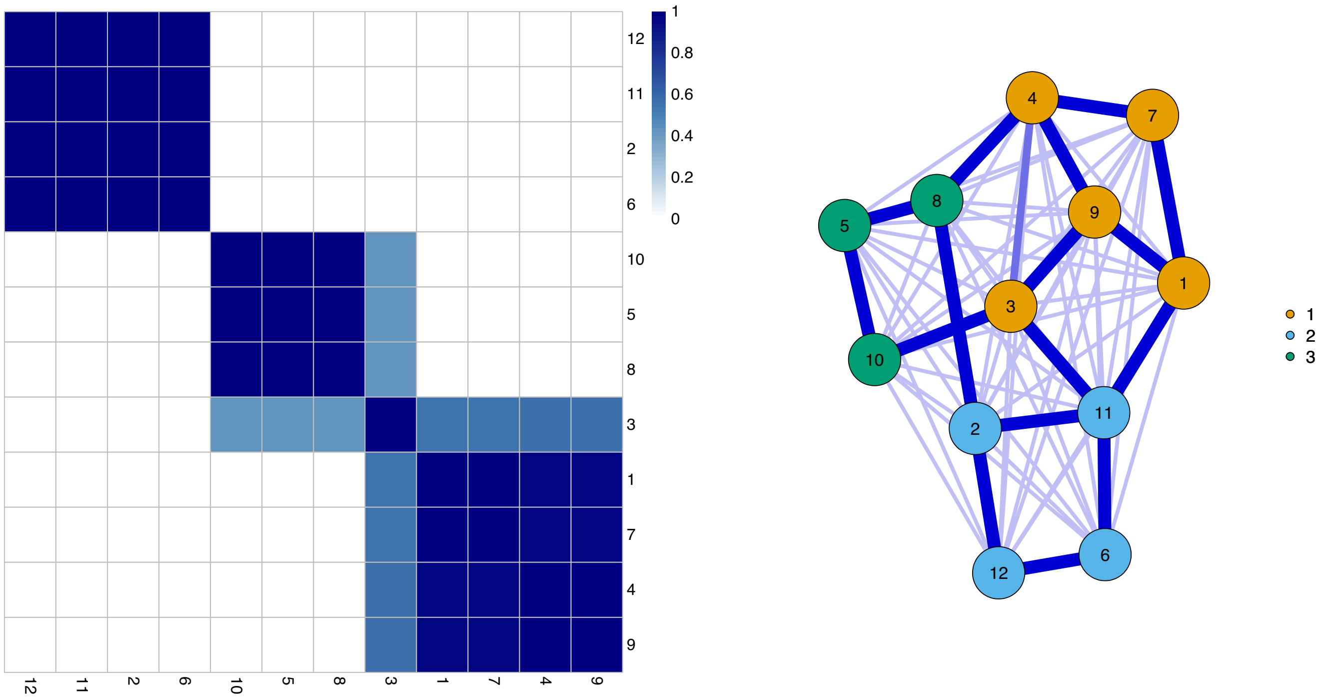
All Unique Spinglass Solutions in Order of Frequency (Left to Right) Across 100 Spinglass Iterations on a Simulated Network Structure



Note. See the online article for the color version of this figure.

Figure 2

An Example of a Coappearance Matrix and Community Structure of a Simulated Network



Note. Coappearance Matrix with nodes on the *x*- and *y* axes (left). The saturation of the boxes in the matrix indicates the frequency with which two nodes ended up in the same community across 100 Spinglass iterations on a simulated network structure (right). The example shows a community structure with a potential bridging node. See the online article for the color version of this figure.

structure and thereby might be used to provide information about the community structure in real-world networks. We expected IComDetSpin's ability to detect distinct communities to decrease as the connectivity between the communities increased.

We ran all techniques directly on networks in which the network characteristics (e.g., the number of nodes and the density of the network) were specified to resemble that of psychological networks. Importantly, for this study, we did not estimate networks from data. This allowed us to ensure that the performance measures reflected only the performance of the community detection algorithms rather than a mixture of community detection and network estimation.

Design Simulation

To generate "true" networks, we started with two communities, with six nodes in each community, where all possible connections within the community were present (i.e., full intracommunity connectivity). We varied three characteristics of the network. First, we varied the number of connections between the communities (i.e., intercommunity connectivity) by linking the nodes between communities at random. This resulted in 30 conditions, in which the number of between community connections increased from 1 to 30 (out of the possible 36 intercommunity connections). Second, we varied the strength of these between community connections resulting in nine conditions, in which the strength of each intercommunity edge increased from 0.1 to 0.9 in steps of 0.1 with all intercommunity edges having the same strength within conditions. Third, we varied the strength of the within-community connections in the same nine conditions (0.1–0.9 in steps of 0.1); again, all intracommunity connections had the same strength within conditions. The combination of conditions led to a total of 2,430 ($30 \times 9 \times 9$) conditions.

We want to stress that the specified community structure of the "true" networks is unclear despite calling the simulated structures "true" networks. For instance, in conditions with very strong intercommunity connections, there is arguably only a single community in the network, as the connections between the two sets of nodes are just as strong as the connections within a given set of nodes. In these circumstances, the techniques arguably perform more accurately if they detect one community rather than two or detect fuzzy community boundaries. So, for the first part of the study, where we focus on the performance in identifying the specified communities, we only investigated the 1,080 conditions with greater intra- than intercommunity community connections, which would suggest two distinguishable communities. When evaluating IComDetSpin's ability to detect fuzzy community boundaries, we included all 2,430 conditions.

We used five kinds of structural characteristics of the simulated networks to categorize conditions, of which the first three were based on the three simulation conditions mentioned: (a) the number of intercommunity connections, (b) the strength of intercommunity connections, and (c) the strength of intracommunity connections. We computed two additional statistics that characterize the network structure: the overall mixing parameter (MP) and the nodewise MP.

1. The MP is a statistic ranging from 0 to 1 that indicates the strength of clustering of a network, with a higher MP indicating a less clearly clustered network (Yang et al., 2016). The overall MP was computed as the ratio between the sum strength of all intercommunity connections and the sum strength of all connections in the network, $MP_{Overall} = \frac{\sum_{i=1}^{p} S_i^{inter}}{\sum_{i=1}^{p} S_i^{total}}$ (adapted from Yang et al., 2016), where p is the number of nodes in the network (community).
2. We computed a nodewise MP for each network by taking the ratio of the first node's intercommunity connection strength and its total connection strength: $MP_{Node} = \frac{S_i^{inter}}{S_i^{total}}$ (Yang et al., 2016). We limited the analysis to one node only since all nodes were eventually wired up equally across the simulated networks and should therefore lead to the same results.

We used qgraph (Epskamp et al., 2012) to create network structures based on each condition. Figure 3 shows three illustrative networks used in the simulation study, ranging from less clear (left side) to more distinct (right side) community structures, as indicated by the overall MP and nodewise MP values. We then analyzed these networks with IComDetSpin (specifying 100 iterations for each network structure), a single iteration of the Spinglass algorithm (using the same functional specifications as in IComDetSpin, namely the default settings where the null model is the configuration model and gamma is 1), and a single iteration of the Walktrap algorithm (using default settings; i.e., four steps). We conducted all simulations and data analyses in the statistical program R (R Core Team, 2022). The code can be found as the additional online materials (https://osf.io/mnued/).

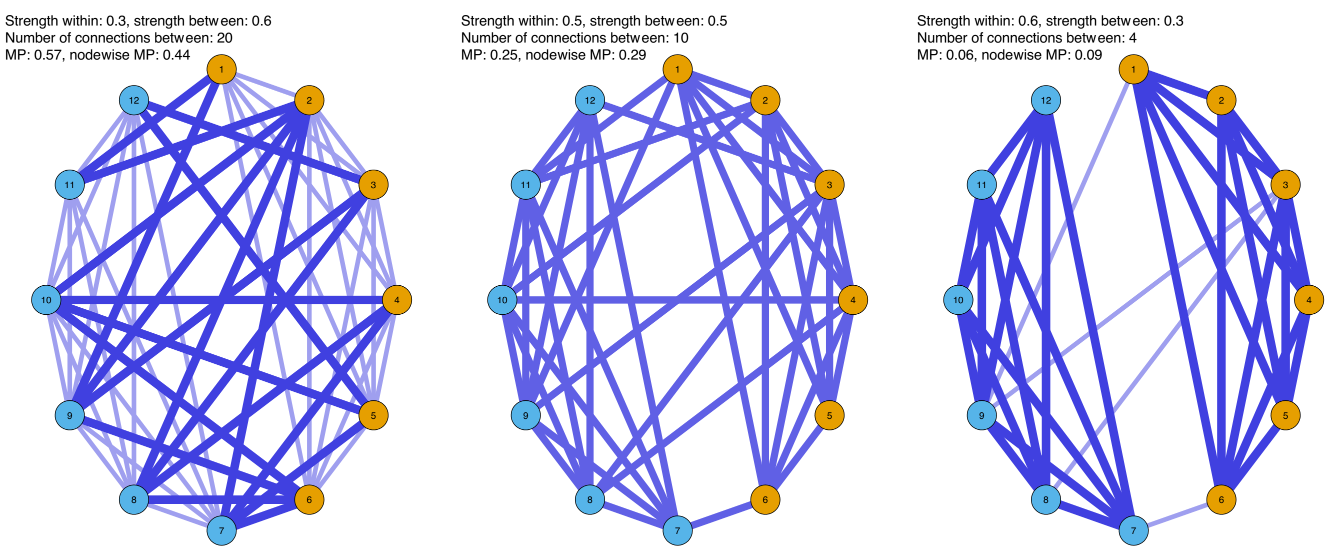
Performance Measures

We used six outcome statistics to summarize the community detection performance: accuracy, error, and absolute error in the number of detected communities (Garrido et al., 2016), the normalized mutual information (NMI), the average intracommunity allocation (AICA) and the nodewise AICA.

1. Accuracy in the number of detected communities summarizes whether a technique retrieved the specified number of communities from the data (i.e., two being considered the correct number of communities in Study 1). If the technique retrieved the specified number of communities, accuracy equals 1. If not, it equals 0.
2. Error in the number of detected communities summarizes whether the technique over- or underestimated the number of communities by subtracting the specified number of communities from the estimated number of communities. A positive error indicates overestimation, a negative error indicates underestimation. However, when averaging the error over multiple iterations, it converges to 0 in case the technique equally over- and underestimates the number of communities. The following performance measure circumvents this problem.

Figure 3

Three Examples of Network Structures That Were Used in Study 1



Note. The left network has 20 intercommunity connections with a strength of 0.6, and all intracommunity connections have a strength of 0.3. The MP is 0.57 and the nodewise MP is 0.44, indicating a less clearly clustered network. Note that because of its greater intercommunity than intracommunity connections, this network was not included when investigating Aim 1 of Study 1. The middle network has 10 intercommunity connections with a strength of 0.5, and all intracommunity connections have a strength of 0.5. The MP is 0.25 and the nodewise MP is 0.29. The right network has four intercommunity connections with a strength of 0.3 and all intracommunity connections have a strength of 0.6. The MP is 0.06 and the nodewise MP is 0.09, indicating a clearly clustered network. MP = mixing parameter. See the online article for the color version of this figure.

3. Absolute error in the number of detected communities summarizes how much the technique wrongly specifies the number of communities, by taking the absolute values during the calculations of the error.
4. We used the NMI as a performance measure that summarizes whether a technique correctly assigns nodes to its specified community. The NMI offers a more fine-grained view of the accuracy of the community detection as it summarizes whether nodes are assigned to their specified community irrespective of the accuracy of the detected number of communities. The NMI is a measure of similarity between two partitions (i.e., specification of which nodes belong to which community), namely the estimated and the specified node–community assignment. A value of 1 indicates perfect overlap between the two partitions and 0 indicating complete independence (Danon et al., 2005).
5. We computed the AICA, defined as the average coappearance of the nodes in each specified communities. We did so by summing up the coappearances across Spinglass iterations (information we retrieved from IComDetSpin's coappearance matrix) of all the nodes in their specified community divided by the number of nodes in the network.
6. We computed the nodewise AICA, defined as the average coappearance of the first node with the other nodes in its specified community. We did so by summing up the coappearance across Spinglass iterations at which the node appeared with the nodes of its specified community (information we retrieved from IComDetSpin's coappearance matrix) divided by the number of nodes of the specified community.

Results Study 1

Aim 1—Evaluating Community Detection Performance

Across the 1,080 conditions with greater intracommunity than intercommunity connection strength, IComDetSpin detected two communities in all cases, while Spinglass and Walktrap detected two communities in 92.4% and 99.9% of the cases, respectively (see Table 1).

Figure 4A depicts the mean accuracy for different levels of the overall MP, binned into 10 groups, to see at what level of clustering the techniques started to deviate from detecting two communities. For Spinglass, there was a slight overestimation of the number of communities across iterations, while Walktrap underestimated the number of communities for an overall MP of 0.5 (see Figure S1 in the online supplemental materials). Figure 4B–D shows the mean accuracy of the techniques on networks with different strengths of inter- and intracommunity connections and different number of intercommunity connections. We see that these three network characteristics did not affect Spinglass and IComDetSpin systematically. However, for Walktrap the strength (0.8) of the intercommunity connections decreased the mean accuracy to detect the specified number of communities.

Table 1
Frequency of Estimating Respective Number of Communities per Community Detection Technique Across 1,080 Conditions

Detection algorithm	1	2	3	4
IComDetSpin (%)		100		
Spinglass (%)		92.4	7.1	0.5
Walktrap (%)	0.1	99.9		

Note. IComDetSpin = iterated community detection: Spinglass.

Figure 5 depicts the performance of the different community detection techniques based on the mean absolute error (see Figure S2 in online supplemental materials for the mean error, which is in line with the presented results). Overall, the mean absolute error led to the same conclusion as stated for the accuracy. The mean absolute error also confirmed that all three techniques result in a similar magnitude of underestimation (mostly Walktrap) and overestimation (mostly Spinglass).

Figure 6 depicts the mean NMI for different MP levels, different intercommunity and intracommunity connection strength, and numbers of intercommunity connections. For Walktrap, we see that the node–community allocation dropped in accuracy around an MP of 0.4. As in these cases Walktrap detected one instead of two communities, it was heavily penalized in the computation of the NMI by placing six nodes in the wrong community.

Aim 2—Evaluating IComDetSpin as an Indicator of Community Overlap

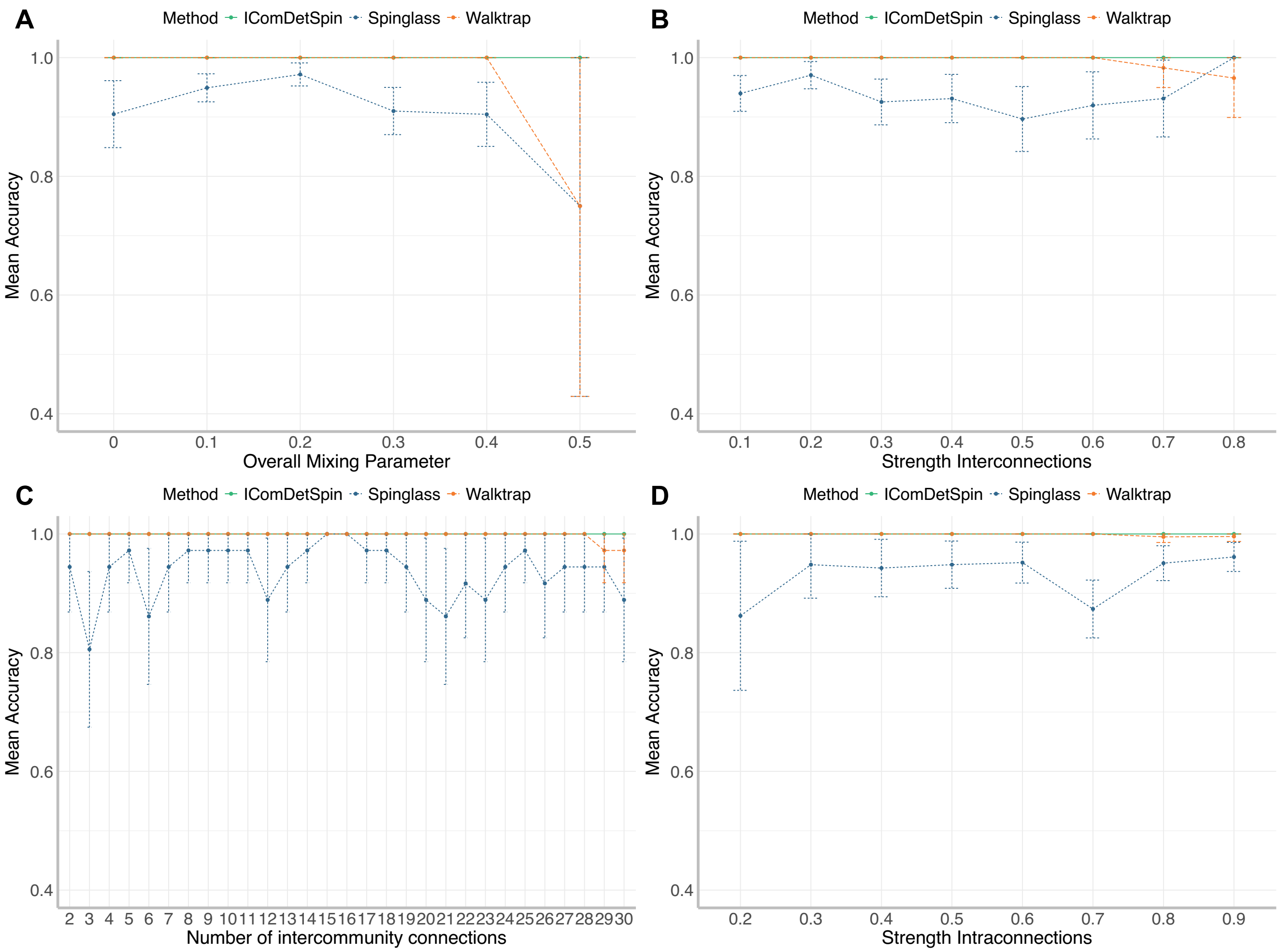
Figure 7 provides network-level (Figure 7A and 7B) and node-level (Figure 7C) information about the fuzziness of community boundaries detected by IComDetSpin. Figure 7A shows the proportion of the most common community solution across iterations by the overall MP. The correlation between the proportion of the most common solution and the overall MP was −0.53. We see a dropoff in the proportion of the most common community solution starting at an MP of 0.5. Figure 7B, which indicates AICA by the overall MP, shows a sharp drop-off in the AICA starting at an MP of 0.5. The correlation between these two measures is 0.82, indicating that low measures on the AICA reflect fuzzy boundaries between communities. Figure 7C shows the nodewise AICA, indicating the average coappearance of the first node with its specified community, by the nodewise MP. The correlation between these measures is −0.73. We see that around a nodewise MP of 0.25, IComDetSpin started to allocate the node to the other community. Around a nodewise MP of 0.50, the node was allocated either to its specified or the other community, suggesting that a node with such an interconnectivity pattern behaves as a "cross-loading" node and that IComDetSpin is sensitive to such interconnectivity patterns. Starting at a nodewise MP of 0.75, IComDetSpin allocated the node more frequently to the other compared to the specified community.

Study 1 Discussion

The findings from Study 1 suggest that IComDetSpin holds a small but consistent advantage over single iterations of Spinglass and performs comparably to Walktrap. The finding that the advantage of IComDetSpin was relatively minor is consistent with prior findings demonstrating that single iterations of the Spinglass algorithm consistently perform very well in recovering community structure (Christensen et al. 2024; Fortunato, 2010; Hoffman et al., 2018; Orman & Labatut, 2009; Orman et al., 2013; Tripathi et al., 2016;

Figure 4

The Mean Accuracy and 95% Confidence Interval Across Conditions



Note. (A) The mean accuracy and 95% confidence interval by the overall MP. Note that we binned the MP into 10 groups and that there is a difference in the number of networks per MP group (see the online supplemental materials for the exact number of networks per MP). (B–D) The mean accuracy and 95% confidence interval of community detection techniques on networks with different strengths of interconnections and intraconnections and different numbers of interconnections. Note that for the purpose of visualization, the *y* axis is limited to range from 0.4 to 1. IComDetSpin = iterated community detection: Spinglass; MP = mixing parameter. See the online article for the color version of this figure.

Yang et al., 2016). Nonetheless, the fact that IComDetSpin consistently demonstrated a small advantage suggests that this method provides meaningful added value, especially given the relative ease of performing this additional analysis.

Alongside this modest but consistent increase in performance, our findings demonstrate that IComDetSpin provides added information not available when relying on Walktrap or a single iteration of Spinglass. The variability identified in IComDetSpin solutions (represented by the proportion of the most common solution and the AICA) validly reflected fuzzy communities (represented by the [nodewise] MP).

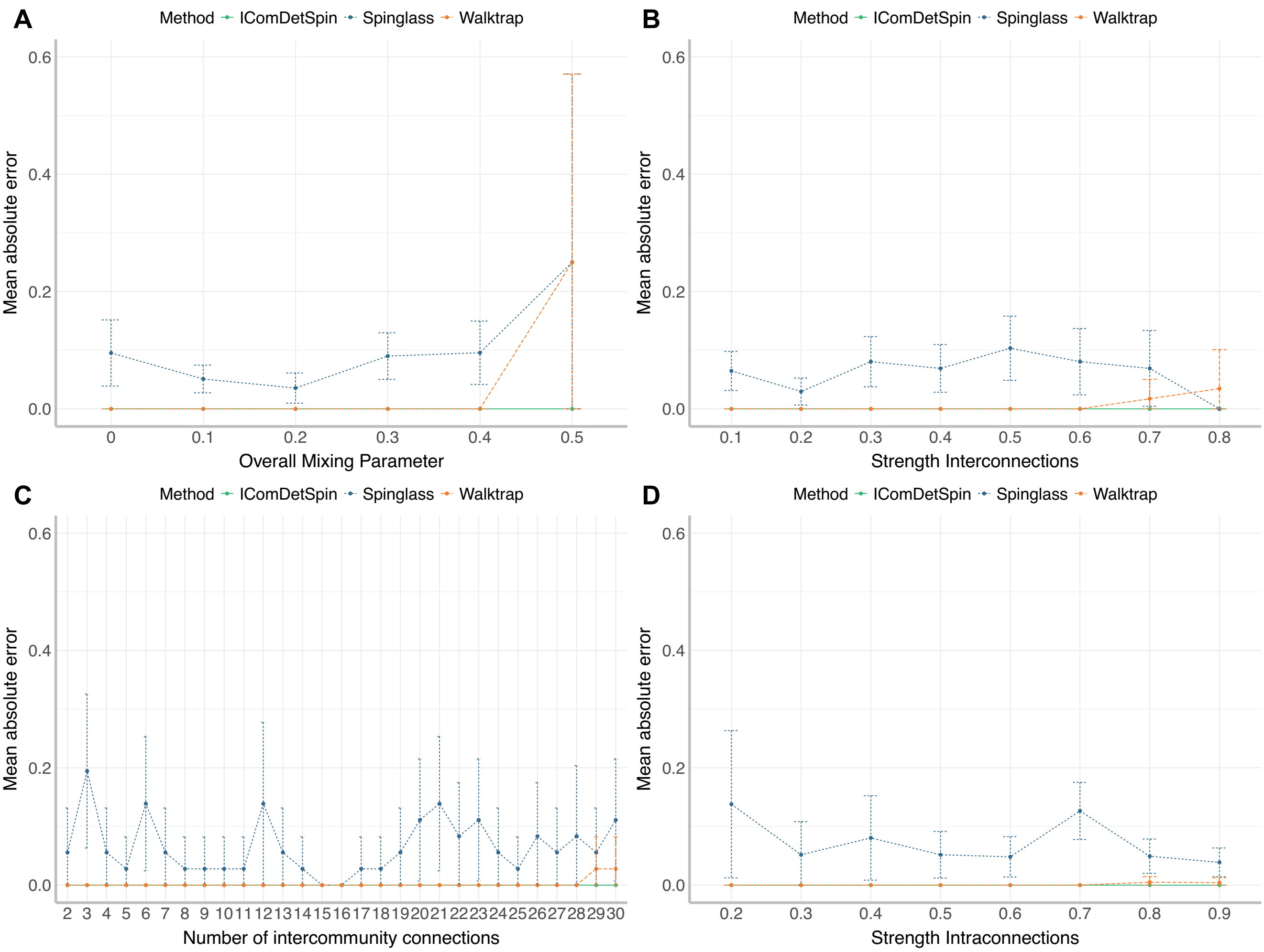
Together, these findings provide initial evidence that IComDetSpin may be a valuable addition to the growing set of tools available to examine the topography of psychometric networks. However, in this simulation, we examined networks in which the network structure was specified. In contrast, a critical step in the analysis of psychometric networks is the estimation of the network from data. Thus, it remains unclear from Study 1 alone how well IComDetSpin would perform in the kinds of real-world empirical studies it is most likely to be applied. It is this issue we address in Study 2.

Simulation Study 2

In Study 2, we investigated IComDetSpin's performance under the conditions it will most commonly be used in psychological research: on networks that have been estimated from data. Specifically, we analyzed IComDetSpin's performance to recover the community structure of networks estimated from simulated data where the structure from which data were simulated was the network community structure to be recovered. We further evaluated IComDetSpin by comparing its performance to EGA, which uses the Walktrap community detection algorithm (Golino et al., 2020; Golino & Epskamp, 2017). We closely

Figure 5

The Mean Absolute Error and 95% Confidence Interval Across Conditions



Note. (A) Mean absolute error and 95% confidence interval by overall MP. (B–D) The absolute error of community detection techniques on networks with different strengths of interconnections and intraconnections and different numbers of interconnections. Note that for the purpose of visualization, the *y* axis is limited to range from 0 to 0.6. IComDetSpin = iterated community detection: Spinglass; MP = mixing parameter. See the online article for the color version of this figure.

followed the rationale of Golino and Epskamp (2017) to be able to compare the results across simulation studies, especially since Golino and Epskamp (2017) also investigated the performance of other community detection algorithms, such as very simple structure, minimum average partial procedure, Kaiser-Gutmann's eigenvalue-greater-than-one-rule, and parallel analysis.

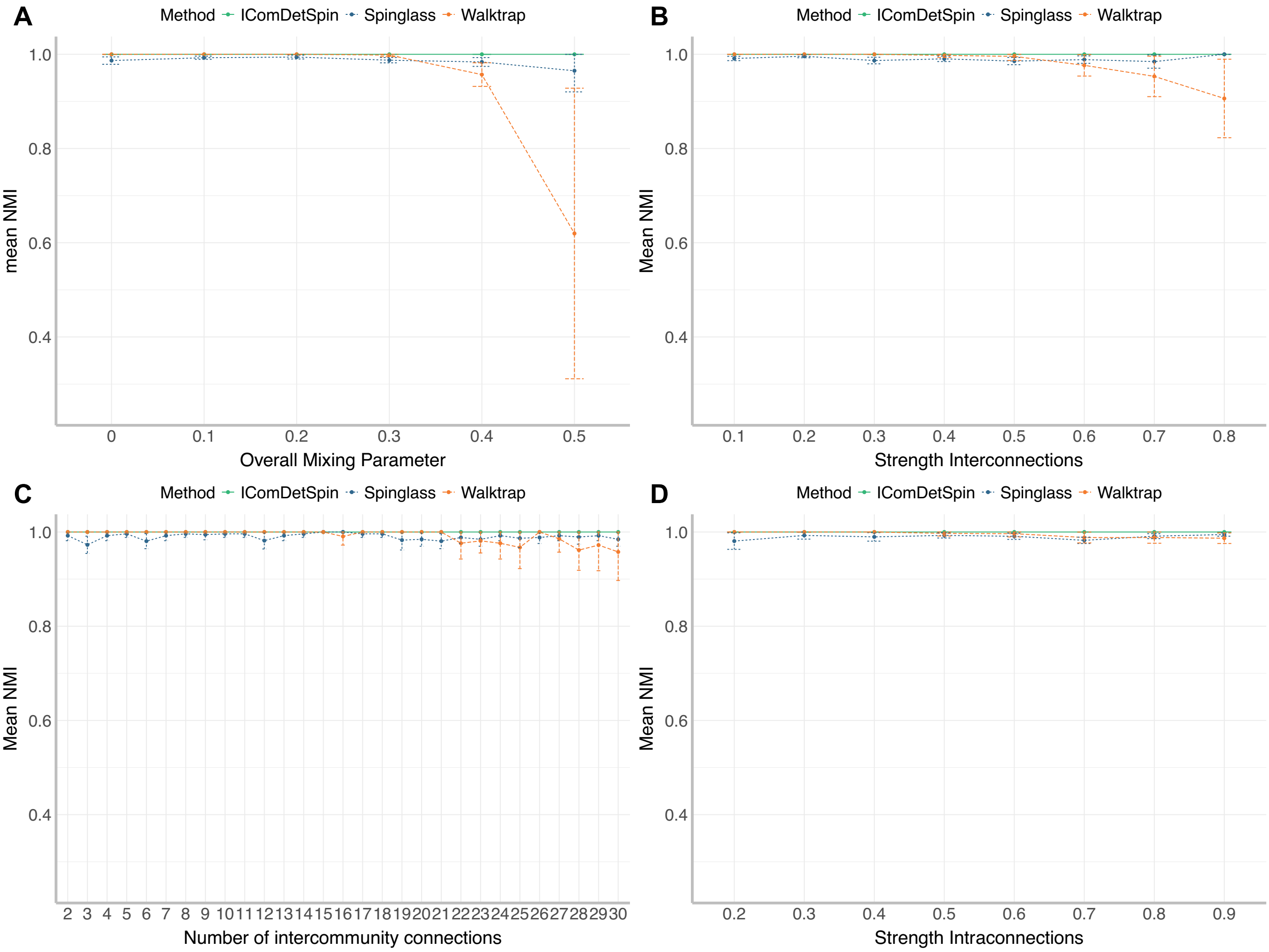
Design Simulation

Golino and Epskamp (2017) established the statistical equivalence between an n-latent factor model and an n-community network model. This equivalence allowed them to simulate data from structures with known community structure (n-factor models) and estimate networks from those simulated data. Taking this approach, we simulated 6,400 data sets based on specified factor structures in 64 conditions (i.e., 100 data sets per condition). We did so with the R package lavaan (Rosseel, 2012). In each condition, all factor structures had equal variances and factor loadings. Conditions were distinguished by four characteristics: (a) number of factors (2 and 4), (b) number of items per factor (5 and 10), (c) sample size (100, 500, 1,000, and 5,000), and (d) correlation between factors (orthogonal, 0.20, 0.50, and 0.70).

All data followed a multivariate normal distribution. In contrast to Golino and Epskamp (2017), who binarized items, we used an ordinal scale with six categories, which we argue is more in line with a partial correlation network estimated using glasso. For the remainder of this article, we will call the simulated correlational structures communities rather than factors and nodes rather than items because of the proven statistical equivalence and the focus on community detection rather than factor models. We ran two community detection algorithms on each data set: (a) IComDetSpin, using 100 iterations on glasso regularized partial correlation networks and (b) EGA (Golino et al., 2020; Golino & Epskamp, 2017) also with glasso regularization.

Figure 6

The Mean NMI and 95% Confidence Interval Across Conditions



Note. (A) The NMI and 95% confidence interval by overall mixing parameter. (B–D) The NMI for networks with different strengths of interconnections and intraconnections and different numbers of interconnections. Note that for the purpose of visualization, the *y* axis is limited to range from 0.25 to 1. IComDetSpin = iterated community detection: Spinglass; NMI = normalized mutual information. See the online article for the color version of this figure.

Performance Measures

We computed four of the same outcome statistics as in Study 1 to compare the performance of the techniques: the accuracy in the number of identified communities, the (absolute) error in the number of identified communities, and the NMI. We compared the accuracy between the techniques by plotting their mean accuracy, (absolute) mean error and mean NMI for all four levels of conditions and their sublevels (i.e., number of communities, number of nodes per community, sample size, and intercommunity correlation strength).

Results Study 2

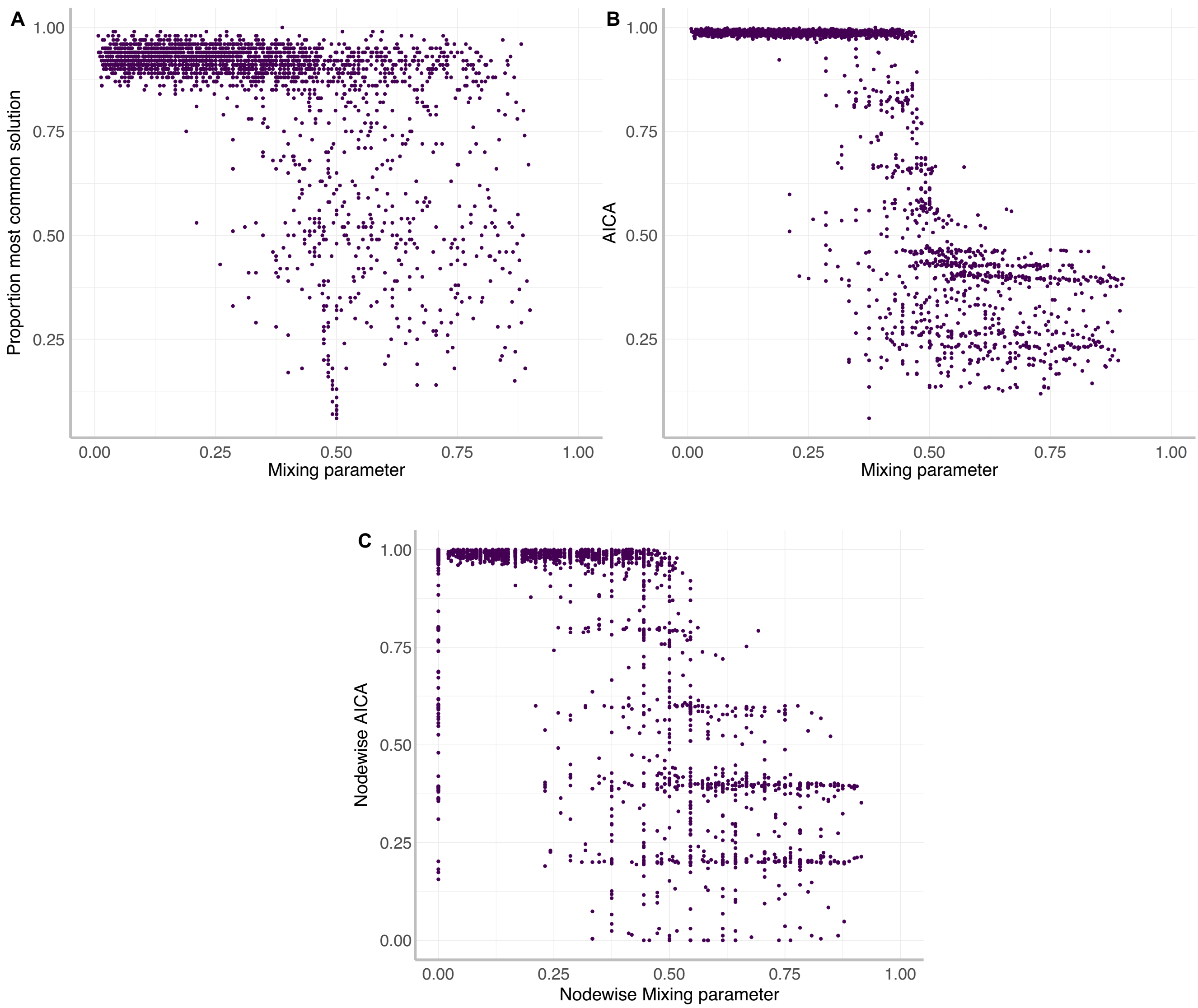
Aim 1—Evaluating Community Detection Performance

Figure 8 depicts the mean accuracy for the community detection techniques across all 64 simulated conditions subdivided by the number of communities, correlation between communities, number of nodes per community, and sample size conditions. Note that from the 6,400 data sets, applying IComDetSpin resulted in an error 961 times (15.01%): 509 times because IComDetSpin was fed an empty network (this happened only in conditions with a sample size of 100 and with four communities of 10 nodes each); 164 times because the qgraph function gave the error that the matrix was not positive definite; and 288 times because of IComDetSpin's inability to deal with networks that are not fully connected, that is, where there is at least one pair of nodes that is unable to reach each other (this only happened in conditions with a sample size of 100). In comparison to IComDetSpin, EGA demonstrates a notable advantage by only reporting three errors (0.0005%). To keep comparisons between algorithms fair, we only investigated the performance on network structures that could be analyzed by both community detection algorithms.

Across conditions, IComDetSpin showed high and robust accuracy in detecting the correct number of communities and

Figure 7

(A, B) Network-Level Information and (C) Node-Level Information About the Fuzziness of Communities (as Specified by the Mixing Parameters)



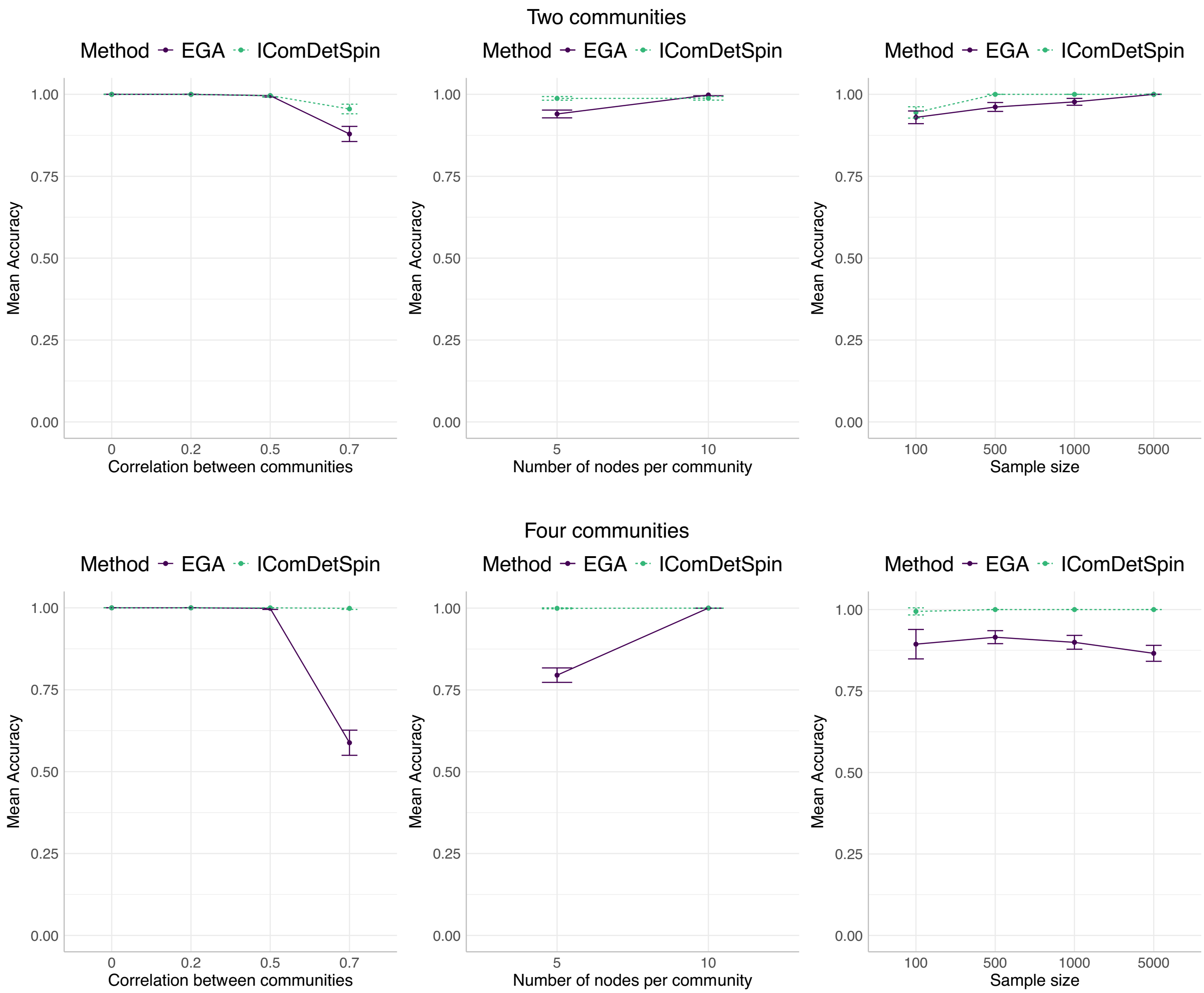
Note. Each dot represents one run of IComDetSpin (and thus, the summary of 100 spinglass iterations). Specifically, (A) The proportion of the most common community solution by the overall MP. (B) The AICA by the overall MP. (C) The nodewise AICA by the nodewise MP, which indicates how often the first node coappeared with the nodes of its specified community across the 100 Spinglass iterations (information we retrieved from IComDetSpin's coappearance matrix). IComDetSpin = iterated community detection: Spinglass; MP = mixing parameter; AICA = average intracommunity allocation. See the online article for the color version of this figure.

IComDetSpin and EGA performed comparably in most conditions of the two-community case. However, IComDetSpin performed slightly better than EGA with strong correlations between communities ($r = .7$) and when the number of nodes in a community was smaller (number of nodes = 5 vs. 10). These differences in performance between IComDetSpin and EGA were amplified in the four-community condition. EGA also showed a slight drop in accuracy with increasing sample size in the four-community condition.

Figure 9 depicts the mean absolute error (left) and mean error (right), which reiterates that EGA performs slightly worse than IComDetSpin in conditions with high correlations between communities and a low number of nodes per community and higher sample size in the four-community condition. When inaccurate, EGA tended to underestimate the number of communities, while IComDetSpin tended to overestimate (see also Figure S3–S5 in the online supplemental materials). Taken together, Figures 8 and 9 suggest that both IComDetSpin and EGA perform accurately in most of the studied conditions but are sensitive to the strength of community interconnections, with EGA being more sensitive to such interconnections as well as being sensitive to the ratio of nodes to the number of communities and sample size.

Figure 8

Mean Accuracy and 95% Confidence Interval of Community Detection Techniques for Data Conditions Separately (Two-Community Structure on the Top and Four-Community Structure on the Bottom)



Note. IComDetSpin = iterated community detection: Spinglass; EGA = exploratory graph analysis. See the online article for the color version of this figure.

Figure 10 shows the performance of the community detection techniques in terms of the NMI. Even though NMI is concerned with node allocation and not with the number of communities, the pattern of results follows those of the overall accuracy results in Figure 7. The NMI shows that inaccuracies in terms of the number of detected communities did not lead to large inaccuracies in terms of node-to-community assignment, except for those cases in which EGA underestimates the number of communities in conditions with high correlations between communities.

Aim 2—Evaluating IComDetSpin as an Indicator of Community Overlap

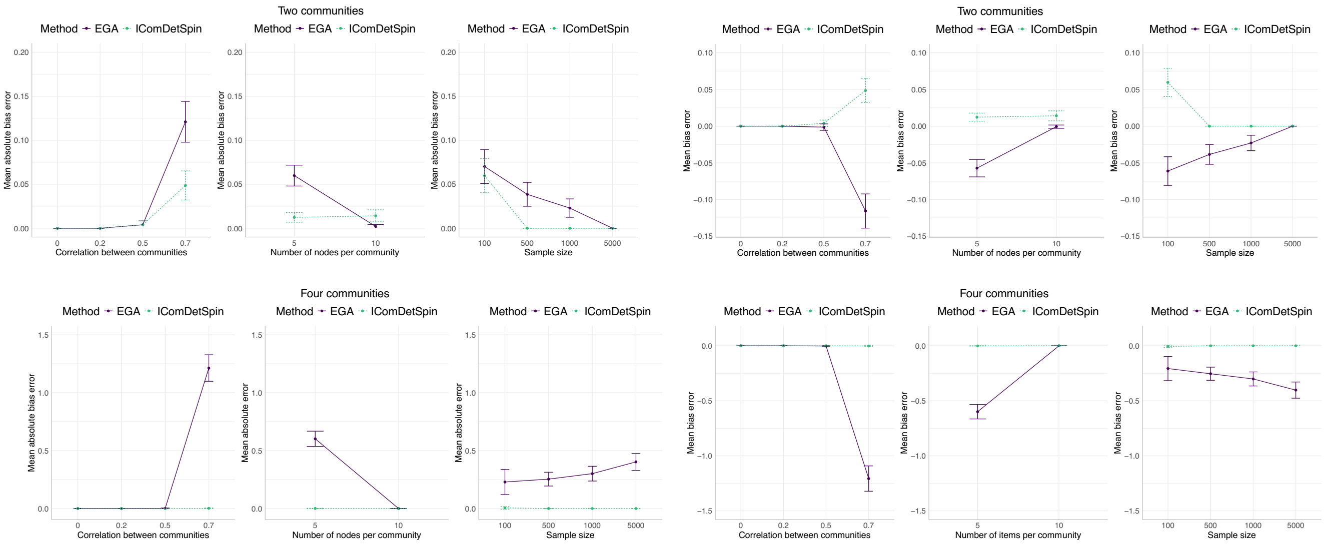
Figure 11 shows the proportion of the most common community solution (Figure 11A) and the AICA (Figure 11B) across 100 Spinglass iterations by the specified correlation between communities. Although the effect is minimal, for both outcome measures, we see that the higher the correlation between communities, the lower the mean AICA.

Study 2 Discussion

IComDetSpin performs better than EGA when the correlation between communities is high, especially when there are four communities instead of two. This aligns with our result in Study 1, in which we found that Walktrap's mean accuracy, the algorithm used by EGA, decreased with a high strength (0.8) of the intercommunity connections. However, in Study 2, IComDetSpin showed considerably more errors than EGA because of its inability to

Figure 9

Mean Absolute (Left) and Mean Error (Right) and 95% Confidence Interval of Community Detection Techniques for Data Conditions Separately (Two-Community Structure on the Top and Four-Community Structure on the Bottom)



Note. EGA = exploratory graph analysis; IComDetSpin = iterated community detection: Spinglass. See the online article for the color version of this figure.

deal with networks where the network is not fully connected. Taken together, this suggests that Walktrap, and therefore EGA, appear to more readily detect smaller numbers of communities with increasing community interconnection, that is, they are more sensitive to "lower dimensional" structures. For those instances in which IComDetSpin showed no errors, it performed accurately in almost all conditions.

Discussion

In this article, we introduced and evaluated IComDetSpin, an openly accessible community detection method which combines information on and visualizations of stability and fuzziness of community structure. We described IComDetSpin's rationale and functionality, provided a tutorial on how to use IComDet Spin (see the online supplemental materials), and examined its performance on psychological networks in two simulation studies. In the first simulation study, we analyzed IComDetSpin's performance on prespecified network structures (i.e., not estimated from data) and compared its performance to that of the traditional Spinglass and Walktrap algorithm. In the second study, we analyzed its performance on network structures estimated from simulated data and compared its performance to EGA, which uses the Walktrap algorithm (Golino et al., 2020; Golino & Epskamp, 2017).

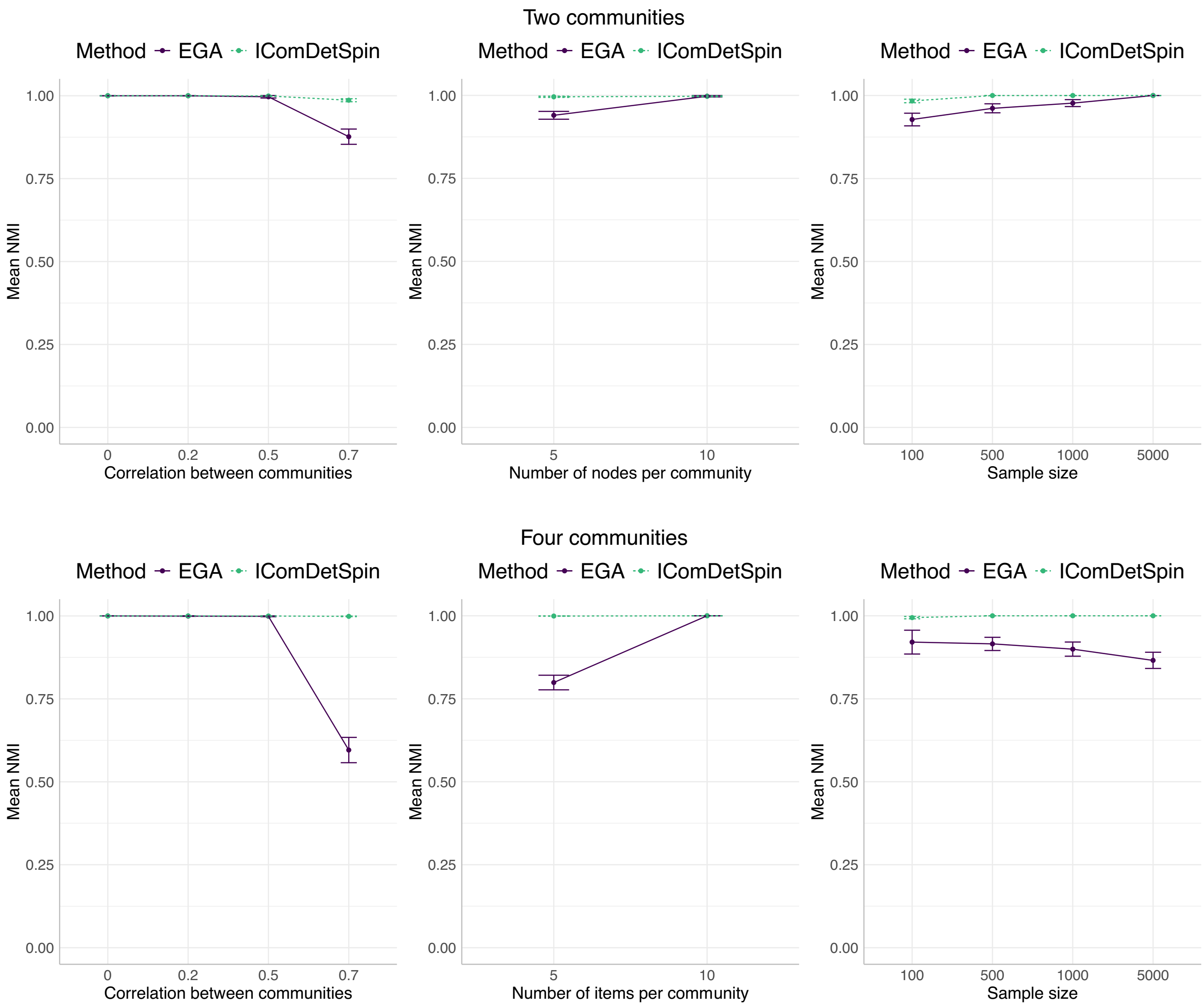
The first study showed that IComDetSpin performed well in detecting the number of communities in most conditions with its performance slightly improving on the source algorithm Spinglass when it comes to detecting the number of communities. Furthermore, IComDetSpin allows researchers to judge whether the Spinglass solution they retrieve is the most stable in their studied context. Around an MP of 0.5, Walktrap's solutions resulted in underestimation more frequently compared to IComDetSpin and Spinglass.

In addition, we examined IComDetSpin's ability to detect fuzzy community boundaries in less clearly clustered community structures. At an MP of 0.5, IComDetSpin's percentage of iterations in which the most popular community structure was chosen starkly dropped. Furthermore, at a nodewise MP of 0.25, the quantification of the coappearance matrix became fuzzier. That is, IComDetSpin started to allocate nodes to the other community rather than its specified community. As such, we argue that the "misallocation" of nodes to other communities reflects growing fuzziness in the boundary between communities. This suggests that the variability across iterations visualized with IComDetSpin provides meaningful information about overlapping community boundaries and, potentially, bridging nodes.

The second study showed that IComDetSpin performed accurately and robustly in terms of detecting the number of communities and allocating nodes to specified communities across investigated conditions in simulated data resembling data on which it will most frequently be used. IComDetSpin and EGA performed equally well in cases of moderate community intercorrelations (<0.5), but IComDetSpin outperformed EGA on all performance measures when correlations between communities were high and number of nodes per community were low, suggesting that EGA is more sensitive to strong interconnections and to the ratio of nodes to the number of communities. Golino and Epskamp (2017) and Golino et al. (2020) also showed that the correlations between communities affects EGA's accuracy which is in line with our findings, and Golino and Epskamp's results (2017; Figure 1 vs. Figure 4) suggest that EGA is sensitive to the ratio of nodes to the number of communities in the case of high community intercorrelations. Overall, we conclude that IComDetSpin demonstrates promising performance in detecting the number of specified communities, robustly allocates nodes correctly in the case of networks estimated from data, and offers information on the instability and fuzziness of community structure.

Figure 10

Mean NMI and 95% Confidence Interval of Community Detection Techniques for Data Conditions Separately (Two-Community Structure on the Top and Four-Community Structure on the Bottom)



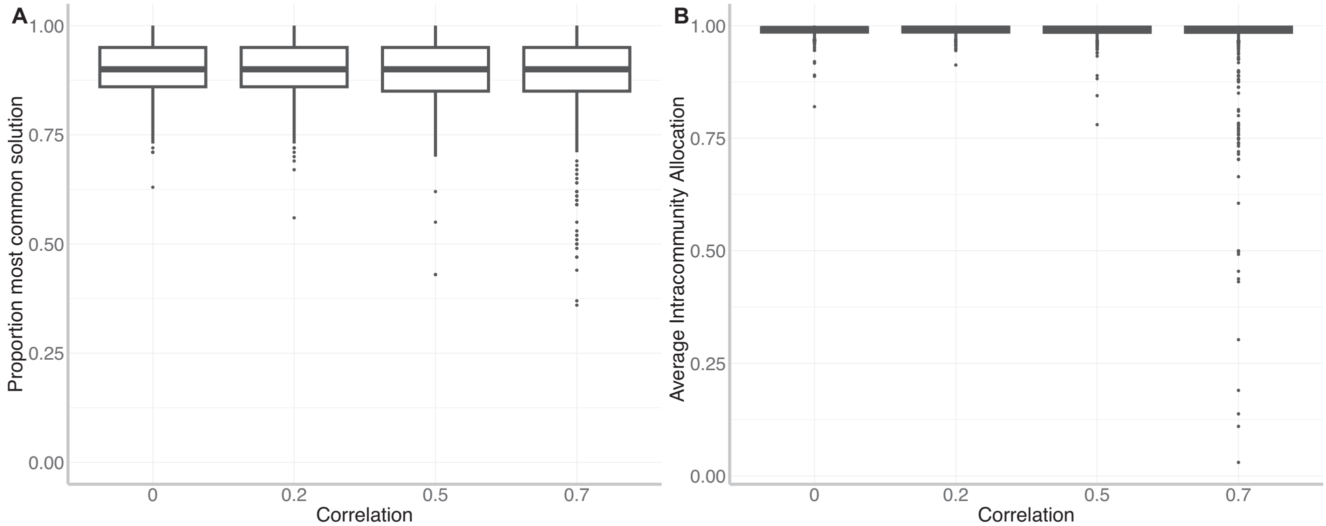
Note. NMI = normalized mutual information; IComDetSpin = iterated community detection: Spinglass; EGA = exploratory graph analysis. See the online article for the color version of this figure.

Practical Considerations

In practice, there are five aspects to consider when using IComDetSpin. First, IComDetSpin will generally find stable and strongly demarcated communities in networks with densely and strongly intraconnected communities, even in the presence of intercommunity connections. Second, IComDetSpin as investigated in this article (with default Spinglass settings) is capable to detect single (i.e., "unidimensional") community structures. However, if a researcher expects to find only one community, EGA might be more sensitive to detect such structures (especially EGA's latest version; Christensen et al., 2024; Golino et al., 2020). Third, IComDetSpin should be used cautiously on networks estimated from small sample sizes ($n = \sim 100$). Fourth, researchers should consider whether under- or overestimation of the number of communities presents a greater risk for one's study, as EGA tended to underestimate the number of communities, while IComDetSpin tended to overestimate. Finally, we recommend the users of IComDetSpin to think beforehand about how potential negative edges should be treated in their network. When considering negative edges (which can be specified in the algorithm), the Spinglass algorithm aims to find communities with strong positive interactions while minimizing the impact of negative interactions within a community. However, in psychological data, two nodes that belong to the same community may have a negative connection because of inversely coded questionnaire items, potentially impacting the community results of the Spinglass algorithm (see also the example in the tutorial in the online supplemental materials).

Figure 11

The Proportion of the Most Common Community Solution and the Average intracommunity Allocation by the Correlation Between Communities



Note. (A) The proportion of the most common community solution across 100 Spinglass iterations by the correlation between communities. (B) The average intracommunity allocation by the correlation between communities. Average intracommunity allocation indicates how often the first node coappeared with the nodes of its specified community across the 100 Spinglass iterations (information we retrieved from IComDetSpin's coappearance matrix). IComDetSpin = iterated community detection: Spinglass.

Limitations

The main limitation of our simulation studies is that we only examined a limited selection of both network and algorithm specifications. First, we varied the number of connections between communities, but not the number of nodes nor connections within a community (we only investigated fully connected communities with a set number of nodes) in Study 1, and we did not investigate the strength of intracommunity connections in Study 2. Also, we only investigated network structures with a "multidimensional" community structure in Studies 1 and 2. Second, we used networks with positive edge weights only. We could have studied the effect of negative connections on community detection, especially because Spinglass, and therefore IComDetSpin, is not specifically designed to work with psychometric networks in which negative edges could be an intracommunity rather than intercommunity, connection. Given that many psychological networks could have communities that contain both positive and negative edges, an important avenue for future research is to vary the settings of IComDetSpin in relation to both positively and negatively connected networks. Third, the simulation study only investigates the null model setting "config." During initial simulation, we found that it is more common for densely connected networks to find a single community with the "config" null model than with the "simple" null model, which has important implications when used on dense network models to be expected within psychology. Fourth, we should investigate the effect of adjusting the algorithm's gamma parameter (gamma changes the ratio with which existing and nonexisting intra- and intercommunity connections are penalized and rewarded in the simulation) in future simulation studies. By adjusting the gamma parameter across IComDetSpin runs, we might better zoom in and out of the hierarchical structure of a network (Reichardt & Bornholdt, 2006a).

Future Outlook

Two main questions remain unanswered. First, we need to further assure whether it is sensible to exploit the variability of the Spinglass algorithm in order to find bridging nodes, overlapping community boundaries, and hierarchical organization in psychological community structure. For this purpose, we need to construct psychological benchmark networks with prespecified bridging nodes, overlap and/or hierarchies to vet the detection of such structures by the algorithm in future simulation studies, and compare its performance to other algorithms which are capable to detect such structures (Lange, 2021). Second, regarding psychological community detection in general, we need to establish ways to judge the quality and/or statistical significance of different community partitions. At this time, community detection is an exploratory tool. With IComDetSpin, we offer insights into the stability of community structure by leveraging the functionality of the Spinglass simulation. Network scientists are also working on establishing the statistical significance of community partitions (Fortunato & Hric, 2016; Reichardt & Bornholdt, 2006a, 2006b). Unfortunately, the modularity statistic should not be used to evaluate the general significance of a partition. Even random graphs can show high modularity, making it difficult to establish absolute comparison values for modularity (Fortunato, 2010; Fortunato & Hric, 2016). EGA uses confirmatory factor analysis to assess the model fit of the structure suggested by the community partition (Golino & Epskamp, 2017). IComDetSpin returns the modularity statistic for each found community structure, and in future implementations, we might offer significance levels or other fit statistics of partitions, but such information will need to be integrated with the user's domain knowledge to vet different solutions.

Conclusion

Community detection is a relatively novel tool in the network psychometric toolbox. IComDetSpin's builds on the popular Spinglass algorithm by (a) allowing researchers to identify the most robust community solution, (b) quantify instability in the estimation of communities, and (c) leverage the estimated instability to gauge the fuzziness of boundaries between communities at the network- and the node level, that is, the extent to which a given node may be a member of multiple communities. Together, this information can help researchers in providing much needed context and nuance to their network community findings and, in doing so, equips researchers to better investigate the role of communities in psychometric networks.

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