

Applying network analysis to measure organizational behaviors using R software

Igor Menezes, Jeremy Zwiigelaar, Elton Moraes, John Mendy, Pedro Pires dos Santos

Abstract

The amount of research investigating psychological networks has grown substantially over the last decade but to our knowledge this is the first study applying network analysis methodology to the fields of OB/HRM. As such, this study aims to provide researchers and practitioners with an easy-to-use syntax to conduct network analysis for the exploration of relationships among organizational behaviors. Unlike the mainstream techniques used in psychometrics (e.g., principal component analysis and structural equation modelling), which are constrained by the number of associations among variables or assumptions regarding dimensionality, network analysis is able to analyze the whole set of items at once in order to find the most representative associations among them. A step-by-step guide is provided with an example showing how to test potential relationships between engagement and authentic leadership using the R package *bootnet*. Besides information on edge-weights and centrality measures, this paper covers a bootstrapping procedure to test their accuracy and stability when small sample sizes are used. The possibilities of applications of psychological networks to organizational behavior and HRM practices are endless and can help overcome some of the limitations of the traditional statistical techniques applied to these fields.

Keywords: psychological networks, organizational behavior, human resource management practices, R software, bootnet package

Introduction

In mainstream organizational behavior research, the investigation of psychological constructs has been mostly carried out under the common factor approach. For instance, by carrying out their typically annual organizational climate research, organizations usually choose the dimensions that fit their own business strategies and that may provide information on employee's satisfaction regarding different aspects deemed important for them, their teams and the organization as a whole. Despite its relevance this approach does not provide further insights on how variables from different dimensions relate to one another. For instance, the worker's dissatisfaction with the organization leadership might affect the individual's sense of collaboration, which could negatively impact on the perception of how products and services have been delivered to customers. Or the lack of resources and poor infra-structure could prevent organizational innovation and eventually hinder the organization's image. These types of associations have been addressed more recently by a new field of investigation called *psychological networks*, *network analysis* or *network psychometrics*. This is defined in the literature as a complex interplay of psychological variables that offer a different conceptual interpretation of the data by explaining co-occurrences via direct relationships between variables (Epskamp, Borsboom & Fried, 2018; van der Maas et al, 2006).

The amount of research exploring psychological networks has grown substantially over the last decade, though to our knowledge, this is the first study applying this methodology to the field of organizational behavior. The study introduces the procedures to estimate psychological networks using the most updated techniques implemented in the R statistical package.

Network models are conceived as a network of mutually reinforcing elements connected by causal relations (Marsman et al, 2018; van der Maas et al., 2006) so that they can better explain how complex interactions among different psychological variables occur (Epskamp et al, 2018). The way psychological networks are designed differs from latent causal models, such as unidimensional Item Response Theory (IRT) and Structural Equation Modelling (SEM), since they do not model the dependencies among the observable variables (Borsboom, 2008). Hence, while latent trait models will seek a common causal representation of the psychological variable by creating for instance a separate dimension for *role clarity* and another for *communication*, psychological networks will explore the interactions between the elements of these two dimensions all together. In order to create and consequently understand a psychological network, two elements are needed: *nodes*, represented by the observable behaviors or the items of a psychological instrument, and *edges*, the associations formed among them.

A few studies on psychological networks (e.g., Briganti et al, 2018; Hoffman, Curtiss & McNally, 2016) have also paid particular attention to the detection of communities, which cluster nodes with a great number of edges among themselves and a few edges with nodes from other communities. When comparing psychological networks and principal component analysis, clustered nodes could be interpreted as components or as enclosed variables that are able to share information in a sensible way (Constantini & Perugini, 2014; Dalege, Borsboom, van Harreveld & van der Maas, 2017), though the applications of these two techniques in psychological research are not interchangeable.

While applied to research in organizational behaviour, psychological networks can create an interconnected system of reinforcing behaviours that are able to show how different variables influence one another and which ones are more central for explaining the

psychological trait under investigation. In spite of the fact that the field of organizational behavior mostly makes use of nonexperimental designs, psychological networks may suggest potential causal structures in a pathway. For example, workers might not rely on the organizational leadership, which in turn will impinge on the team morale and consequently increase turnover intentions. This causal structure indicates that we would be able to predict *turnover intentions* by knowing the attitudes towards the leadership that could lead a worker to leave his or her organization. Nonetheless, we can also predict turnover intentions from team morale, making the knowledge about attitudes towards leadership no longer necessary for the prediction of turnover intentions. Consequently, the correlation estimated between leadership and turnover intentions is estimated to be zero, making these two variables conditionally independent from each other.

This property will be generalized to all relationships established among the items of a network, which will be calculated using partial correlation coefficients when data is assumed to be continuous or ordinal. Partial correlation networks are a subclass of undirected networks called Markov random field in which edges connect nodes by solid lines with no arrows, showing that the edge (x, y) is identical to the edge (y, x) .

Using R software for the estimation of psychological networks

In the following, we illustrate how to conduct a network analysis based on a data set comprised of 238 workers who responded to eleven items. Seven items were chosen from the Intellectual Social Affective (ISA) Engagement Scale (Soane et al, 2012), and four items measuring the transparency dimension were selected from the Authentic Leadership Questionnaire (Walumbwa, Avolio, Gardner, Wernsing & Peterson, 2008). The items are listed in Table 1 and further information on how to download the data set can be found at the end of this paper.

Table 1.

ISA Engagement Scale items and Authentic Leadership Questionnaire's transparency items.

ISA Engagement Scale	Authentic Leadership Questionnaire (Transparency dimension)
ENG01 - I feel positive about my work.	TRANSP1 - I let others know who I truly am as a person.
ENG02- I share the same work values as my colleagues.	TRANSP2 - I admit my mistakes to others.
ENG03- I concentrate on my work.	TRANSP3- I seek others' opinions before making up my own mind.
ENG04 - I pay a lot of attention to my work.	TRANSP4 - I openly share my feelings with others
ENG05 - I share the same work goals as my colleagues.	
ENG06 – I focus hard on my work.	
ENG07 - I feel energetic in my work.	

The application of network analysis to measure organizational behaviors can be performed in R in two parts: firstly, the networks are estimated regardless of the sample size in use, and secondly, accuracy and stability of the estimates are calculated for studies with small sample sizes.

Part 1: Network estimation

Step 1. To start off, you should import the data file to R, as follows:

```
Data <- read.csv(file="network tutorial.csv", header=TRUE, sep=",")
```

When the argument *header* is set to TRUE, it will allow the first row of values in the .csv file to be transformed into column names. Also, as the data file has a .csv extension, the *sep* argument will separate the columns by comma.

The *bootnet* package (Epskamp & Fried, 2018) was chosen for network estimation since it performs well with complex data and small sample sizes. Parameter estimates are reliable when a weight matrix has at least as many observations as the number of parameters, calculated by $P(P-1)/2$, where P is the number of nodes (Epskamp, Kruis & Marsman, 2017). As such, in our example, we have $11*10/2 = 55$ parameters to be estimated. The more items are used in a network analysis, the larger the sample size needed for an accurate estimate.

In psychological networks, the strength of the relationship between two variables is a parameter estimated from data. One of the most popular techniques for the estimation of network models based on continuous or ordinal data is the Gaussian graphical model, a pairwise Markov random field (PMRF) that calculates the partial correlation coefficient for the edges by conditioning on all other variables in the network. In order to enhance the prediction accuracy, interpretability and generalizability, a regularization technique called LASSO (Least Absolute Shrinkage and Selection Operator) is further adopted, mainly when small samples are used (Epskamp et al., 2017). By using LASSO, the usual sum of squared errors is minimized due to a penalty being applied that bounds the total sum of the absolute values of the edges. As a result, some of the edge estimates are reduced to zero, while only a subset of covariates are selected in the final model. This type of network is called *sparse*, as opposed to a *dense* network where each node is linked to every node in the network.

Step 2. The main function of the *bootnet* package is the *estimateNetwork*, which automatically calculates the correlation matrix, employs LASSO to shrink some edge-weights to zero and choose the tuning parameter using EBIC. Whenever ordinal variables have seven or less intervals (e.g., Likert scale), they are detected as ordinal and polychoric correlation is used instead.

```
require(bootnet)
Groups <- c(rep("Transparency",4), rep("Engagement",7))
Model <- estimateNetwork(Data, default = "EBICglasso", corMethod="cor_auto")
Model$graph
```

```
plot(Model, edge.labels=T, title="EBICglasso Network", groups=Groups, palette='pastel')
```

Although the choice of groups is not required, it allows a clear visualization of how items from different dimensions are grouped together and how they related to items from other dimensions. If you however do not want to have items from different dimensions coloured, the argument *groups* should be removed from the *plot* function. Also, when a large number of variables are in place, the visualization of edge weights may be confusing due to overlapping edge weights crossing different variables. In such cases it is recommended to set *edge.labels* to FALSE.

Figure 1 shows the graphical representation of a psychological network with the aforementioned eleven items. The thickness of the edges represent the strength of the association between two nodes, controlled by all other variables through partial correlation (Epskamp et al, 2018). The thicker an edge (solid line) is, the stronger the association between two nodes (circles). *Blue edges* represent positive associations, whereas negative associations are depicted as *red edges*. Since LASSO estimation penalizes near zero edges, the interpretation of the regularized partial correlations cannot be done in the same way as in traditional correlation coefficients, by creating thresholds based on their absolute values. That is to say that the most significant edges or pairwise comparisons are those with stronger associations while compared against the remaining model edge coefficients.

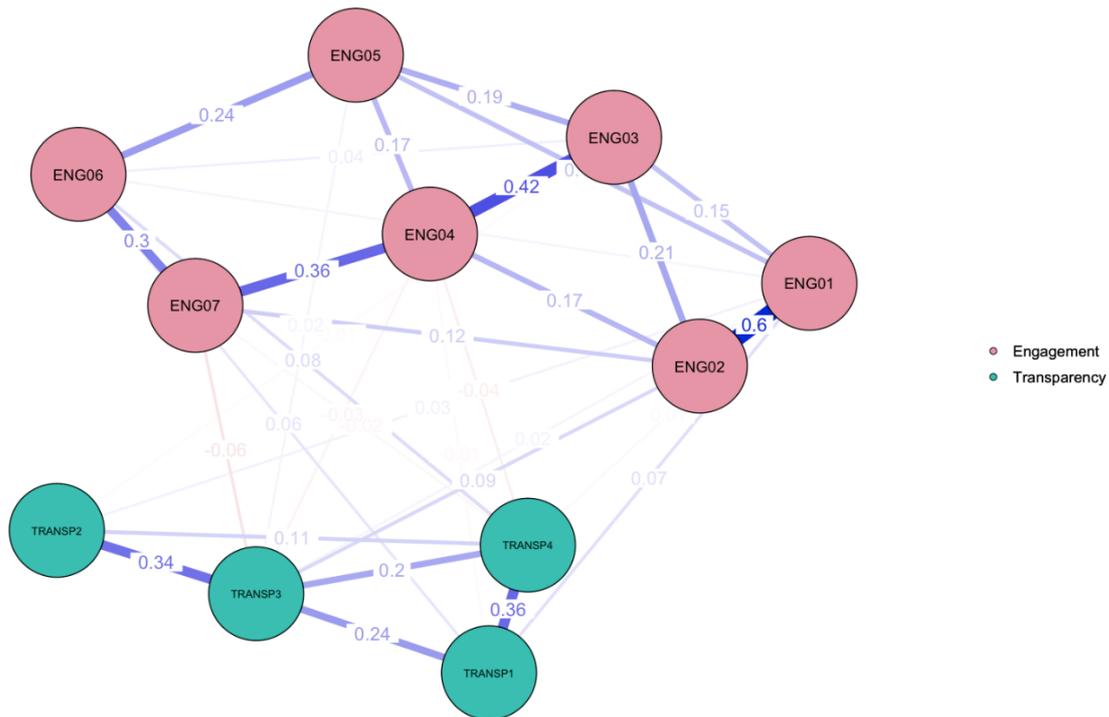


Figure 1: A graphical representation of a psychological network showing relations among items measuring engagement and transparency.

As can be seen in Figure 1, *feeling positive about the work* (ENG01) is strongly related to *sharing the same work values as other colleagues* (ENG02), which in turn can motivate leaders to *seek others' opinions before making up their own minds* (TRANSP03). As such, rather than test a few independent comparisons between the items of these two dimensions via regression models, a psychological network would assume that leadership develops from the complex interaction among all variables under measurement. It follows that the more variables a construct has, the greater the chance of identifying significant relations among them, making the application of psychological networks to the investigation of organizational behaviors an important methodological advance.

In addition to the estimation of psychological networks, it is important to analyze the predictability of the nodes, that is how much of the variance of a node can be predicted by the edges connected to it (Haslbeck & Waldorp, 2018). This analysis can confer weight to the edges

and include information regarding interactions between variables from different dimensions, which would not be otherwise determined by traditional methods of data analysis. The importance of the nodes, or how influential in a network they are, can therefore be assessed via centrality indices of the network structure (Constantini et al., 2015; Opsahl, Agneessens & Skvoretz, 2010). The three main measures are *strength*, which shows how well a node is directly connected to other nodes, *closeness*, which shows how well a node is indirectly connected to other nodes, and *betweenness*, which quantifies the number of times a node acts as a bridge along the shortest path between two other nodes (Epskamp et al., 2018). Recent studies have revealed that *strength* is the most stable centrality index when cases are removed from the data set, while *betweenness* and *closeness* were not reliably estimated (Epskamp et al., 2017; Fried et al., 2018).

Figure 2 shows the three Centrality Indices (CI) for the aforementioned network relating to the items of engagement and leadership transparency. The interpretation is quite straightforward as the farther right an index is positioned, the higher the node centrality, with the leftmost values representing the least central nodes. Centrality measures are shown as standardized z-scores in most of the statistical packages in order to provide interpretability. As can be seen in Figure 2, sharing the same work values as other colleagues (ENG02) is the most important variable for explaining how leadership is perceived as it scores high in all of the three centrality measures. By being directly (*strength*) and indirectly (*closeness*) connected to other variables as well as representing a bridge variable (*betweenness*), ENG02 occupies a central position in the interactions among the variables in the network. It is also worth mentioning that engagement items scored higher for *strength*, which is likely a result of the clustering of items from the engagement measure which has seven items. The findings are relatively similar for *closeness*, though ENG02 remains the highest value. For *betweenness*, most of the items seem to lose centrality, with TRANSP03 scoring as high as ENG02. Accordingly, the position of each item depends upon the aspects considered by each centrality index as relevant.

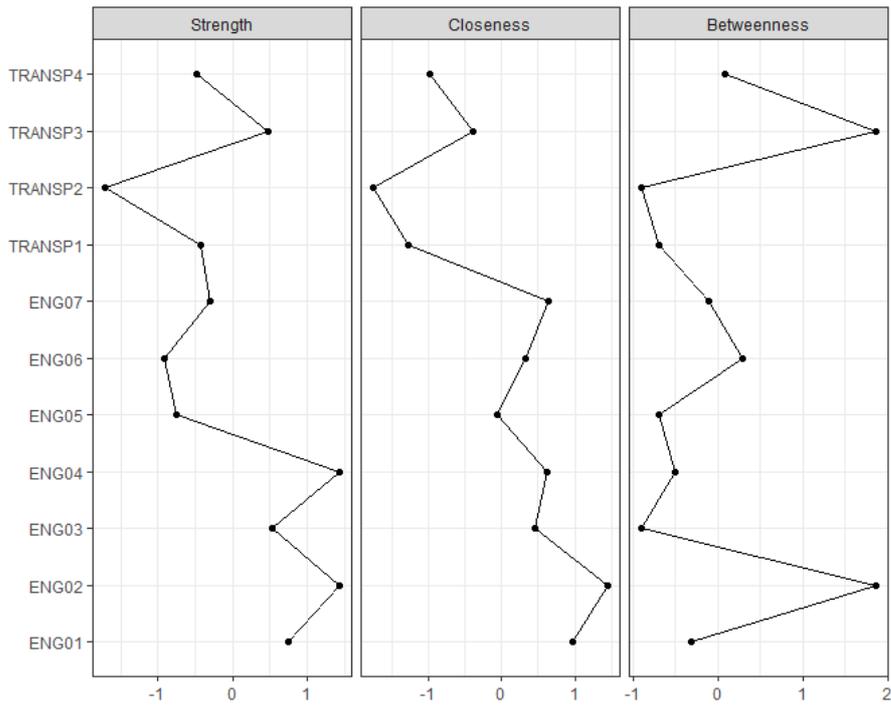


Figure 2: Centrality indices (CI) of a psychological network showing relations among items measuring engagement and transparency.

Step 3. In R, the command to calculate the centrality indices is quite straightforward:

```
centralityPlot(Model)
```

Notwithstanding the importance of the network estimated and its respective centrality indices, for cross-sectional network models using small sample sizes, Epskamp et al (2017) recommend to calculate the stability of centrality indices and the accuracy of edge-weights.

Part 2: Bootstrapped network and its accuracy

As the collection of large sample sizes is a common problem in organizational behavior due to the complexity involved in data collection or availability of targeted subjects,

some techniques were developed by Epskamp et al (2017) to test the robustness of a network after estimation. These techniques are based on bootstrap sampling procedures which involve resampling or performing simulations while estimating parameters for a model multiple times and finally assigning measures of accuracy to the sample estimates. Accordingly, some additional functions from the package *bootnet* were therefore designed to: (1) estimate the accuracy of edge weights, (2) test the stability of the centrality measures through portions of the original data set, and (3) through the resulting CIs for both edge-weights and centrality measures, make comparisons to ascertain that differences are not just relative, but also statistically significant.

For the estimation of edge-weights accuracy, a 95% confidence interval (CI) containing the true value of the parameter is calculated so that values lie within the interval $1/2\alpha$ and $1 - 1/2\alpha$. This interval is known as *bootstrapped CI*. While applied to edge-weights, bootstrapping can be either *non-parametric*, with observations in the data resampled with replacement to create new datasets, or *parametric*, with new observations sampled from the parametric model estimated from the original data. The higher the number of bootstrapped samples, the better the consistency of estimated parameters for both types of bootstrapping.

Non-parametric bootstrapping is data-driven and requires no theory, whereas the samples drawn from the parametric bootstrapping must follow a multivariate normal distribution and all assumptions that follow from it. To handle ordinal data, as in Likert-type scales, Epskamp et al (2017) recommend the use of non-parametric bootstrapping, mainly when LASSO regularization is used for network estimation. As this is the case for this study, R syntax on parametric bootstrapping will not be provided.

While bootstrapped CI sheds light on edge-weight accuracy, bootstrapped results should not be used to test the significance of an edge being different from zero since the regularization and consequent shrinkage process done by LASSO already indicates that a non-zero edge will be different from zero (Constantini et al, 2015). To derive the edge-weight

stability, researchers are advised to assess the width of the bootstrapped CIs, as the wider they are, the poorer the accuracy of the edge weight. Besides, the width of the CIs can be used to compare edges to one another. Non-overlapping CIs suggest there is a significant difference between the edge weights, though overlapping CIs might still show significant differences.

Step 4. In R, the syntax is quite similar to the one used earlier since it starts with the raw data as an object. However, there are a few arguments to be added. The first one is the number of bootstraps for the argument *nBoot*. Recommendations for the number of minimum bootstraps range from approximately 600 (Wilcox, 2010) to 1500 (Davidson & MacKinnon (2000)). Although a higher number of repetitions brings more robustness, it may be computationally intensive, mainly for larger sample sizes and more complex models. The additional argument *nCores*, for Windows users, indicates the number of CPU cores to be allocated for bootstrapping. If the amount of cores on your CPU is unknown, remove this argument and leave it as the default. Finally, the argument *type* will allow you to choose the type of bootstrap method, whether parametric or nonparametric. As this study uses ordinal data, the option “nonparametric” was chosen, as follows:

```
resboot1 <- bootnet(Data, default = c("EBICglasso"), tuning=.5, corMethod="cor_auto",  
  nBoots = 1000, nCores = 8, type = c("nonparametric"))
```

Firstly, information that can be assessed is the edge-weight accuracy, for which there is information on all of the estimated edges' 95% confidence interval. As the number of edges increase it might be difficult to read the direct plot output, in this case change the argument “labels=F” or read the output of confidence intervals directly.

```
plot(resboot1, labels = T, order = "sample")
```

Figure 3 shows both bootstrap (black dots) and sample mean (red dots), from which we can confirm that the edge connecting ENG01 ↔ ENG02 has the best accuracy. As

aforementioned, for an edge to be significant, it should have a narrow bootstrapped CI, which in turn could not contain zero. From the edge ENG03 \leftrightarrow ENG05 downwards, zero is included in the CI resulting in a reduced estimate accuracy. It is also possible to check some of the bridging pairs between measures, which were faint in the network. Also, several CIs do not overlap (e.g., ENG01 \leftrightarrow ENG02, ENG03 \leftrightarrow ENG04 and ENG04 \leftrightarrow ENG07), suggesting that their estimated means are significantly different from each other.

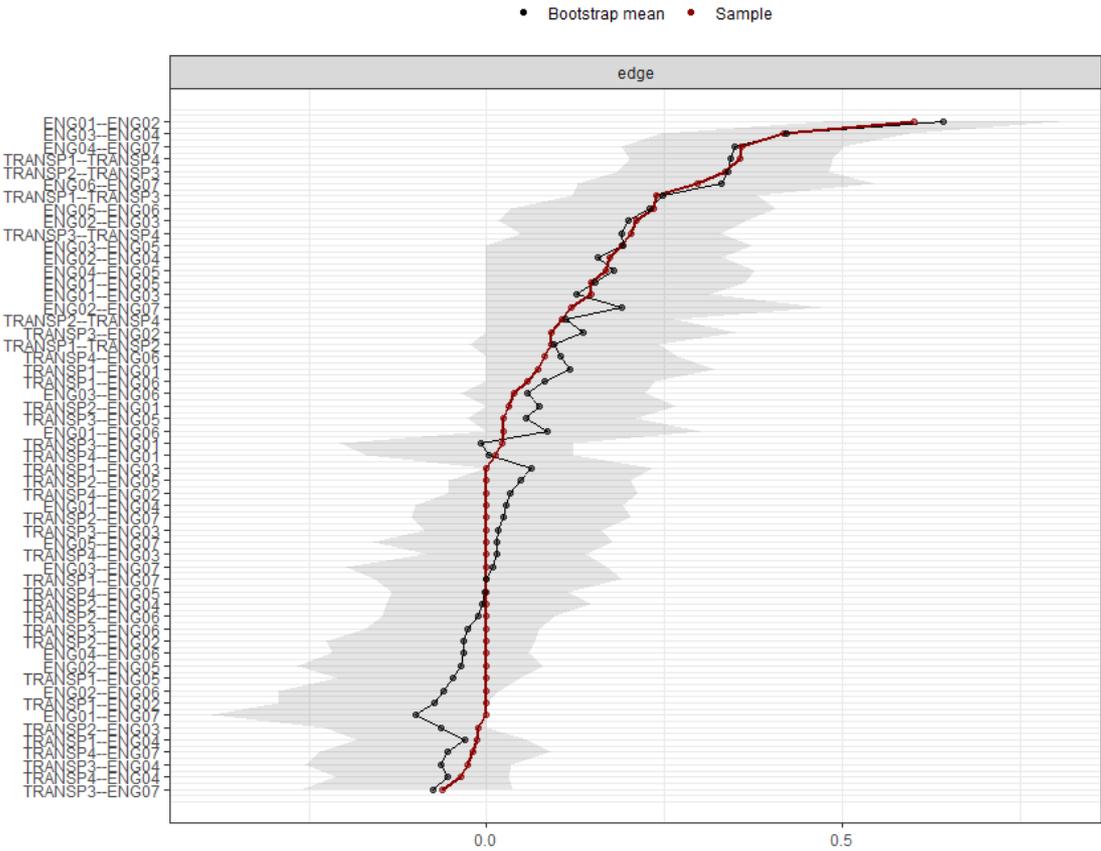


Figure 1. Bootstrapped values for the edge weights. The red line shows the sample means. Black line shows bootstrapped means. The grey area represents the 95% bootstrapped confidence interval.

The second bootstrapping strategy implemented in the *bootnet* package requires a case-drop estimation to test the centrality stability (*case-dropping subset bootstrap*). In other words, bootstrapping is performed with subsets of the data, and after every case drop, the

stability is assessed through the correlation between the original sample's estimated centrality values and the ones calculated for the subsets. Centrality measures are expected to be unstable when the correlations among different subsamples drop significantly. Epskamp et al (2017) named it as the *correlation stability coefficient* or *CS-coefficient*. For a significance level of $\alpha=0.05$, the *CS-coefficient* should be greater than or equal to 0.70, representing the maximum proportion of cases that can be dropped. Additionally, Epskamp et al (2017) suggest that *CS-coefficients* should not be below 0.25, and preferably above 0.5 for the interpretation of centrality differences, though further research is needed in order to define more reliable cutoff scores for interpretation.

Step 5. To compute the *CS-coefficient* in R, the same *bootnet* function and its argument *type* should be used, replacing the “nonparametric” option used for estimating edge-weights accuracy with the option “case”, which implies the use of case-dropping subset bootstrap. As the following syntax looks similar to the object *resboot1* created above, it is recommended to create a second object to assign the *bootnet* function. Also, the object *resboot1* will be used for an additional analysis shown below.

```
resboot2 <- bootnet(Data, default = c("EBICglasso"), tuning=.5,  
                  corMethod="cor_auto", nBoots = 1000,  
                  nCores = 8, type = c("case"))  
plot(resboot2, labels = T, order = "sample")
```

The change in the option of the argument *type* allows for the investigation of the correlation between the original centrality measures and the resulting estimate after the case-dropping process. The *CS-coefficient* is obtained for each of the three centrality measures, as can be seen in Figure 4 generated by using the function *plot(resboot2...)*. As indicated in Epskamp's et al. (2017) and Fried's et al., 2018 studies, the measure of strength is relatively more stable when compared to betweenness and closeness. For the current study, the measure

of betweenness dropped steadily, being the least reliable centrality measure. The CS-coefficient can be computed using the following function:

```
corStability(resboot2)
```

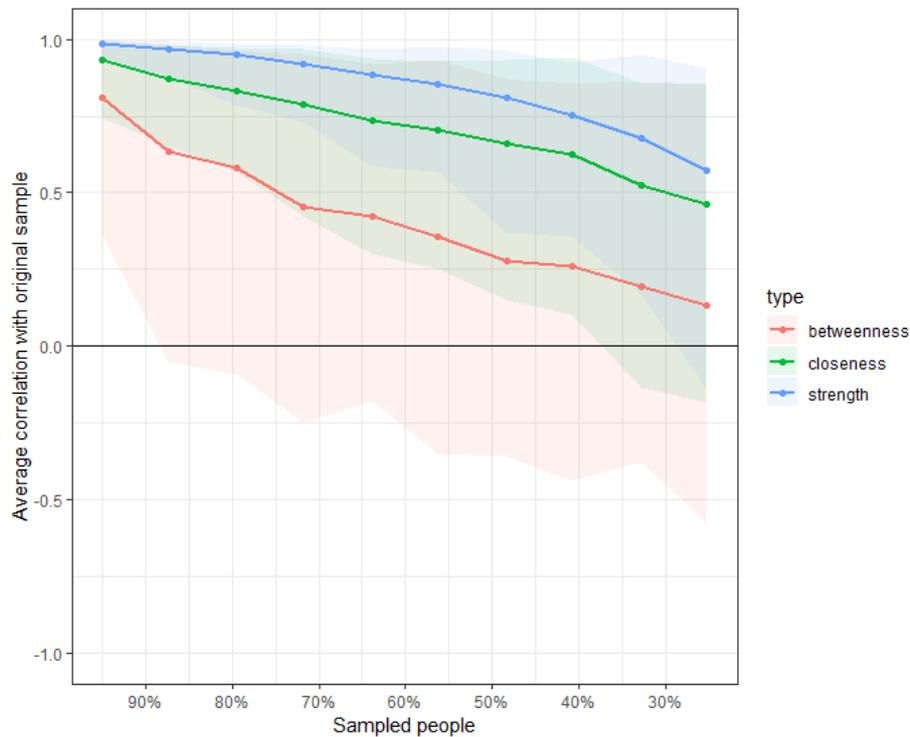


Figure 2. Graphic for the stability of centrality measures.

The results suggest that the strength ($CS(\text{cor}=.7)=.361$) is the most stable statistic while compared to betweenness ($CS(\text{cor}=.7)=0$) and closeness ($CS(\text{cor}=.7)=.126$), though all of them are under the expected cutoff 0.5.

The last test carried out by the *bootnet* function is the *bootstrapped difference test*, which checks whether there are differences between estimated edges-weights as well as between centrality nodes (variables). These differences are analyzed by using a bootstrapped CI around those difference scores (Epskamp et al., 2017). If zero is included in the bootstrapped CI, differences cannot be considered significant (Chernick, 2011).

Step 6. In R, the function *differenceTest* performs the bootstrapped difference tests. As shown in Figure 3, it is not clear whether the edges $ENG01 \Leftrightarrow ENG02$ and $ENG03 \Leftrightarrow ENG04$ are significantly different. If one would like to test whether these differences are really significant, the bootstrapped object *resboot1* used for testing edge-weight accuracy should be used again. After that, the names of the variables forming the edges should be added (e.g., "ENG01--ENG02", "ENG03--ENG04"). Finally, the option "edge" should be included to determine that the difference test should be carried out per edges:

```
differenceTest(resboot1, "ENG01--ENG02", "ENG03--ENG04", "edge")
```

The output indicates that the estimated mean for the edge "ENG01--ENG02" is significantly higher than for the edge "ENG03--ENG04" (significant=TRUE, C.I.-.46,-.01). If one is interested in plotting every pairwise comparison between edges, the following command should be used:

```
plot(resboot1, "edge", plot = "difference", onlyNonZero = TRUE, order = "sample")
```

If the *onlyNonZero* argument equals TRUE, only the estimated edges which are nonzero are shown. Finally, the argument *order* = "sample" will place the edges in descending order, from the most positive to the most negative edge-weights.

Very similar procedure should be performed for testing the differences between centrality measures. As shown in Figure 2, items ENG02 and ENG04 seem to have similar values for strength. By using the same function *differenceTest*, but adding the names of the variables (e.g., "ENG02" and "ENG04") along with the centrality measure under testing ("strength"), the significance of the differences can be computed:

```
differenceTest(resboot1, "ENG02", "ENG04", "strength")
```

The result showed that the bootstrapped difference between "ENG02" and "ENG04" included zero (C.I.-.95,.30), suggesting that their locations in the z-scale are not significantly different (significant=FALSE). For plotting all edge-weight pairwise comparisons, similar syntax should be used, except for the *onlyNonZero* argument, which has to be removed as it does not apply for centrality measures, and the option "edge" that must be replaced with the name of the centrality measure under testing, in our case "strength":

```
plot(resboot1, "strength", plot = "difference", order = "sample")
```

These commands produce Figures 5 and 6 respectively, for which gray boxes indicate non-significant differences and black colored boxes indicate significant differences. The diagonal in Figure 5 represents the color of the edges; negative edges show shades of red, whereas positive edges show shades of blue. Figure 6 shows the centrality index measured, in our case "strength".

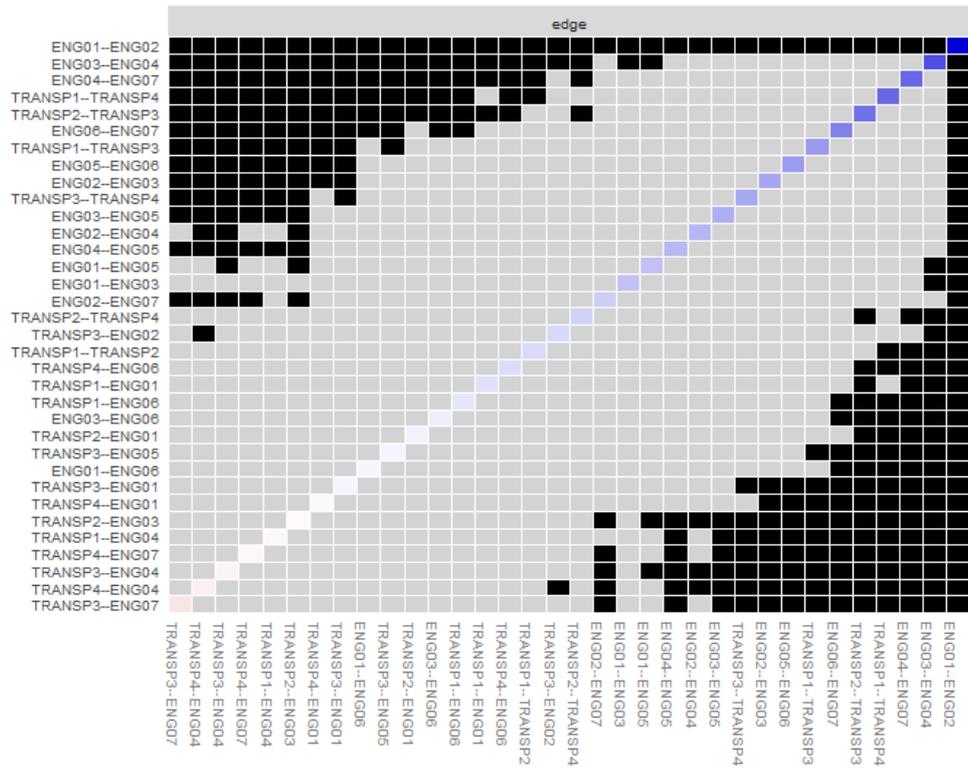


Figure 5. Plot of the difference test for edge-weights. Diagonal indicates the edge colors with the corresponding direction and magnitude of the associations. Gray colored boxes represent non-significant differences, while black boxes represent significant differences.

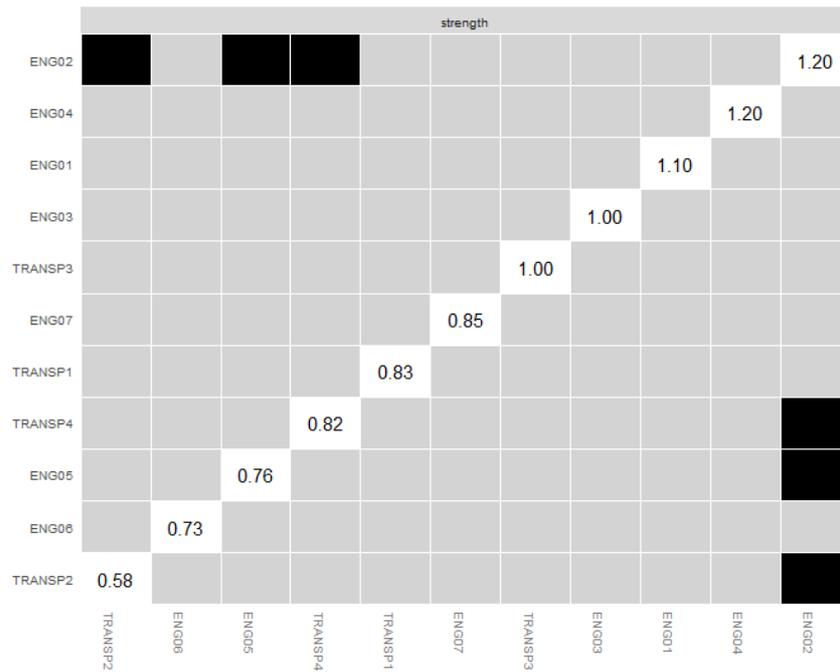


Figure 6. Plot for difference test of the strength centrality measures for every node. Diagonal represent strength coefficients. Grey colored boxes represent non-significant differences, while black boxes represent significant differences.

This study used the *bootnet* package, but it is also possible to estimate psychological networks with the *qgraph* and *igraph* packages, though they do not calculate edge-weights accuracy and centrality measures stability. For large samples sizes in which the estimation process is expected to be highly accurate, making the use of bootstrapping procedures irrelevant, these packages could be used instead, generating similar outputs.

Conclusions

The possibilities of applications of psychological networks to organizational behavior and HRM practices are endless. Unlike Organizational Network Analysis (ONA), a well-known technique for visualizing and analyzing formal and informal observed relationships

among individuals or objects, psychological networks enable organizations to investigate complex and high-dimensional data that can better explain how psychological variables from different dimensions are related to one another. In contrast to the traditional common cause model (e.g., structural equation modelling), in which the correlations are due to a latent variable underlying the test items, the observed correlations between the items of a psychological network are the result of their direct causal influence on one another (Marsman et al, 2018). Moreover, psychological networks differ from between-item multidimensional models (e.g., principal component analysis), allowing correlations between items from different dimensions. Therefore, exploratory models with multiple dimensions or even different psychological constructs may be designed in order to show how multifaceted behaviors may emerge from the interactions among various distinct factors. Based on a theory-driven approach, the formulation of more complex hypotheses involving causal associations between multiple variables are also one of the advantages of using psychological networks. The fields of OB/HRM typically use structural equation models for causal modelling but testing all associations between observable and latent variables is not possible as the increasing number of parameters to be estimated would lead to under-identified and consequently useless models.

In spite of the many advantages of using psychological networks in OB/HRM research, there are a few limitations . First of all, for a network to be estimated, the number of observations must be at least the same as the number of parameters in the model. This has a direct implication for studies in organizational behavior, which oftentimes are conducted with small samples sizes. Secondly, despite the developments in graph theory and social network analysis, the generalization of these techniques for the investigation of psychological constructs is not quite straightforward. Psychological networks are contemporary psychometric models that contrast with more traditional approaches such as component analysis and structural equation modelling, whose techniques have been refined over the

years. As such, the number of methodological studies aimed at testing for instance new estimation algorithms and network accuracy is still very limited. Most of the studies on psychological networks have been developed in the last five years, with applications primarily focused on clinical psychology and personality. This study's novelty is in showing how psychological networks can be deployed for the investigation of constructs in HRM/OB and can help researchers and practitioners to easily apply these techniques in their research and professional practice.

N.B. The dataset used in this study can be downloaded on <https://compsocialsciences.com/datasets/>

References

- Barber, R.F. and Drton, M., 2015. High-dimensional Ising model selection with Bayesian information criteria. *Electronic Journal of Statistics*, 9(1), pp.567-607.
- Borsboom D., 2008. Latent variable theory. *Measurement*, 6, pp.25-53.
- Briganti, G., Kempnaers, C., Braun, S., Fried, E.I. and Linkowski, P., 2018. Network analysis of empathy items from the Interpersonal Reactivity Index in 1973 young adults. *Psychiatry Research*, 265, pp.87-92.
- Chen, J. and Chen, Z., 2008. Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*, 95(3), pp.759-771.
- Chernick, M.R., 2011. *The essentials of biostatistics for physicians, nurses, and clinicians*. John Wiley & Sons.
- Costantini, G. and Perugini, M., 2014. Generalization of clustering coefficients to signed correlation networks. *PloS one*, 9(2), p.e88669.

- Costantini, G., Epskamp, S., Borsboom, D., Perugini, M., Möttus, R., Waldorp, L.J. and 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, pp.13-29.
- Dalege, J., Borsboom, D., van Harreveld, F. and van der Maas, H.L., 2017. Network analysis on attitudes: a brief tutorial. *Social psychological and personality science*, 8(5), pp.528-537.
- Davidson, R. and MacKinnon, J.G., 2000. Bootstrap tests: How many bootstraps?. *Econometric Reviews*, 19(1), pp.55-68.
- Epskamp, S., Borsboom, D. and Fried, E.I., 2018. Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, 50(1), pp.195-212.
- Epskamp, S., Kruis, J. and Marsman, M., 2017. Estimating psychopathological networks: Be careful what you wish for. *PloS one*, 12(6), p.e0179891.
- Fried, E.I., Eidhof, M.B., Palic, S., Costantini, G., Huisman-van Dijk, H.M., Bockting, C.L., Engelhard, I., Armour, C., Nielsen, A.B. and Karstoft, K.I., 2018. Replicability and generalizability of posttraumatic stress disorder (PTSD) networks: a cross-cultural multisite study of PTSD symptoms in four trauma patient samples. *Clinical Psychological Science*, 6(3), pp.335-351.
- Haslbeck, J.M. and Waldorp, L.J., 2018. How well do network models predict observations? On the importance of predictability in network models. *Behavior research methods*, 50(2), pp.853-861.
- Hofmann, S.G., Curtiss, J. and McNally, R.J., 2016. A complex network perspective on clinical science. *Perspectives on Psychological Science*, 11(5), pp.597-605.
- Marsman, M., Borsboom, D., Kruis, J., Epskamp, S., van Bork, R., Waldorp, L.J., Maas, H.V.D. and Maris, G., 2018. An introduction to network psychometrics: Relating Ising network models to item response theory models. *Multivariate behavioral research*, 53(1), pp.15-35.

- Opsahl, T., Agneessens, F. and Skvoretz, J., 2010. Node centrality in weighted networks: Generalizing degree and shortest paths. *Social networks*, 32(3), pp.245-251.
- Soane, E., Truss, C., Alfes, K., Shantz, A., Rees, C. and Gatenby, M., 2012. Development and application of a new measure of employee engagement: the ISA Engagement Scale. *Human Resource Development International*, 15(5), pp.529-547.
- Van Borkulo, C.D., Borsboom, D., Epskamp, S., Blanken, T.F., Boschloo, L., Schoevers, R.A. and Waldorp, L.J., 2014. A new method for constructing networks from binary data. *Scientific reports*, 4, pp.5918.
- Van Der Maas, H.L., Dolan, C.V., Grasman, R.P., Wicherts, J.M., Huizenga, H.M. and Raijmakers, M.E., 2006. A dynamical model of general intelligence: the positive manifold of intelligence by mutualism. *Psychological review*, 113(4), pp.842.
- Walumbwa, F.O., Avolio, B.J., Gardner, W.L., Wernsing, T.S. and Peterson, S.J., 2008. Authentic leadership: Development and validation of a theory-based measure. *Journal of management*, 34(1), pp.89-126.
- Wilcox, R.R., 2010. *Fundamentals of modern statistical methods: Substantially improving power and accuracy*. Springer.