NETWORK PSYCHOMETRICS BASED VALIDATION OF ACADEMIC EMOTIONAL REGULATION QUESTIONNAIRE (AERQ)

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Abstract

The academic emotional regulation questionnaire (AERQ), developed by Buric et al. (2016), measures the trait based emotional regulation ability in academics in University students. The present study applied network psychometrics analysis to validate the scale in the Indian context. 496 students from the School of Mechanical engineering, School of Computer Science engineering and the School of Hotel Management and Tourism of Lovely Professional University, Phagwara, Punjab, India, were the sample subjects. Mahalanobis distance was computed to detect outliers, removal of which lead to the final sample size of the study being 443. Exploratory graph analysis (EGA) using the package eganet in R/RStudio, lead to the extraction of the original eight dimensions of the scale, with one item from social support dimension showing anomaly. As per the rules of (EGA), it was removed the test was re-run to obtain the graph of the network. The package lavaan was used to conduct confirmatory factor analysis using the estimator "WLSMV" for ordinal data, and robust CFI, TLI, RMSEA and SRMR were 0.962, 0.958, 0.026 and 0.048, well below the desired benchmarks, indicating excellent fit. Under network inference analysis, the state-of-the-art edge weight accuracy using non-parametric bootstrap confidence interval, correlation stability coefficient and bootstrapped difference tests were conducted to study the significance of the obtained estimates using the package bootnet. Structural consistency is computed under reliability analysis instead of internal consistency using the packages bootega, eganet and psych. The plots are generated using the package qgraph. The significance of this research exercise in the Indian context is discussed.

Keywords: *Academic Emotional Regulation Questionnaire (AERQ), Exploratory Graphical Analysis, eganet, lavaan, bootnet, Network Psychometrics, Edge-weight accuracy, Correlation stability coefficient, bootstrapped difference test, WLSMV estimator, Structural consistency, bootega, Psych, qgraph.*

INTRODCTION:

The academic emotional regulation questionnaire (AERQ) developed by Buric et al. (2016) is an instrument to measure the emotional strategies employed by students in various academic situations. The scale identified eight dimensions using 37 items when administered on Croatian undergraduate students. These eight dimensions are "situation selection, developing competence, redirecting attention, reappraisal, suppression, respiration, venting and social support", with details shown below:

Dimension. No.	Dimension Label	No. of Items	Description
1.	Redirecting Attention	6	"attempts to refocus one's attention in order to avoid or to block the emotional experience"
2.	Venting	5	"students' behavioural manifestations and expressions of unpleasant emotions as a way of releasing the negative energy"
3.	Situation selection	4	"circumventing academic situations that can trigger unpleasant emotions"
4.	Developing competencies	5	"behaviours and actions students implement to develop capabilities and competences which will prevent or lessen unpleasant emotional experiences"

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5.	Reappraisal	5	“students' attempts to undermine the relevance of a situation that evokes unpleasant emotions”
6.	Respiration	3	“students' attempts to reduce subjective feelings of tension accompanied by unpleasant emotions through deep breathing”
7.	Seeking Social Support	4	“sharing unpleasant emotions and seeking comfort from close members of the student's social milieu”
8.	Suppression	5	“students' attempts to suppress subjective and behavioural manifestations of unpleasant emotions in academic situations in order to hide them from others”

The scale was adapted and validated in the Indian context by Chakraborty and Chechi (2020) which reported the extraction of the original eight dimensions with moderate goodness of fit estimates while confirming the factor structure on a sample size of 496 students pursuing the programs of Mechanical engineering and Hotel management. This study applied Hong’s Parallel analysis conducted using Watkins (2000) Monte Carlo PCA Parallel Analysis software during exploratory factor analysis (EFA) under Varimax rotation. The factor loadings of the items on their respective factors are shown below:

Table 1: Standardized Regression Weights:

			Estimate
DevCom1	<---	Dev_Comp	.372
DevCom2	<---	Dev_Comp	.605
DevCom3	<---	Dev_Comp	.397
DevCom4	<---	Dev_Comp	.616
DevCom5	<---	Dev_Comp	.529
Venting1	<---	Venting	.607
Venting2	<---	Venting	.718
Venting3	<---	Venting	.762
Venting4	<---	Venting	.682
Venting5	<---	Venting	.763
Supp1	<---	Supp	.525
Supp2	<---	Supp	.526
Supp3	<---	Supp	.562
Supp4	<---	Supp	.561
Supp5	<---	Supp	.534
Reapp1	<---	Reapp	.519
Reapp2	<---	Reapp	.605
Reapp3	<---	Reapp	.707
Reapp4	<---	Reapp	.627
Reapp5	<---	Reapp	.580
SitSelec1	<---	Sit_selec	.569
SitSelec2	<---	Sit_selec	.533
SitSelec3	<---	Sit_selec	.609
SitSelec4	<---	Sit_selec	.410
ReAtt2	<---	ReAtt	.600
ReAtt3	<---	ReAtt	.609

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			Estimate
ReAtt4	<---	ReAtt	.640
ReAtt5	<---	ReAtt	.610
Respi1	<---	Respi	.738
Respi2	<---	Respi	.725
Respi3	<---	Respi	.734
SocSupp1	<---	Soc_Supp	.622
SocSupp2	<---	Soc_Supp	.773
SocSupp3	<---	Soc_Supp	.331
SocSupp4	<---	Soc_Supp	.700

The confirmatory factor analysis CFA revealed better estimation of the goodness of fit when compared to original study results as shown below:

Table 2: Goodness of Fit Estimates of the AERQ:

Estimate	"P Value"	"CMIN/DF"	"RMR"	"RMSEA"	"GFI"	"IFI"	"TLI"	"CFI"
Benchmark	"> 0.05"	"<3"	"<0.08"	"<0.05"	">0.9"	">0.9"	">0.9"	">0.9"
Recent Study (2020) Result	0.000	1.943	0.093	0.044	0.884	0.872	0.86	0.87
Original Study (2016) Result	0.01	2.09	0.07	0.06	-	-	-	0.85

But, Golino and Demetriou (2017) presented a robust technique of factor or dimension extraction from psychological data over the traditional techniques of parallel analysis PA (Horn, 1965) and minimum average partial procedure MAP (Valicer et al, 2000), especially in situations when the inter-dimenisonal correlation is above 0.7 and the indicators per factor are low. This new and powerful state of the art dimension extraction technique is called Exploratory Graph Analysis (EGA; Golino and Epskamp, 2016).

The exploratory graph analysis originated from the area of Network Psychometrics, which involves the estimation of undirected network models (Lauritzen, 1996a,b) obtained from psychological data. These network models, such as the popular pairwise Markov random field (PMRF, van Borkulo et al., 2014, Costantini et al, 2015a) consist of "*Nodes*" which represent the items of a questionnaire and "*Edges*" which are the connections between the nodes with no arrow heads and hence termed undirected, representing the statistical relationship between them (Epskamp and Fried, 2016).

Factors are formed when the nodes are strongly connected (through edge weights) to each other forming "*Clusters*". According to Golino and Epskamp (2016), there are two principals associated with clusters. The first principal says that orthogonal factors are represented in the network models through unconnected clusters and the second principal says that with each extracted factor there will be an associated weighted cluster in the model estimated from the variance-covariance matrix. This matrix would make use of partial correlation coefficient to measure the relationship between two nodes after controlling the influence of other nodes on this relationship. However, sampling variations can cause spurious correlations to emerge (Epskamp and Fried, 2016), as is often seen in the traditional exploratory factor analysis (EFA) technique.

To address this issue, EGA employs a regularization technique called the least absolute shrinkage and selection operator (LASSO; Tibshirani, 1996) which is one of the most famous tool available with the administration of network analysis on psychological data (van Borkulo et al., 2014; Kossakowski et al., 2015; Fried et al., 2015). LASSO reduces the small partial correlation coefficients between weakly related nodes to exact zero (Golino and Epskamp, 2016; Epskamp and Fried, 2016), without allowing the estimation of spurious correlation and split loading of items. As a result, there is conditional independence between nodes allowing for the interpretation of the network model, with lesser number of edges explain the covariance between the nodes of the dataset (Epskamp and Fried, 2016). In this way,

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according to Golino and Epskamp (2016), the EGA employs the estimation of correlation matrix of the variables of interest, LASSO to get the sparse inverse correlation matrix for employing regularization using EBIC and finally the walktrap algorithm (Pons and Latapy, 2005) to obtain the weighted clusters or the extracted factors from the partial correlation matrix. The LASSO technique also addresses the problem of small sample size in psychological research.

While extracting the number of dimensions, the EGA is recursively run based on two rules. Rule one says that if there is only one item loading on a dimension, it is deleted. Every dimension should have at least two items loading on it. Rule two says that if two items of a dimension cross load on another dimension, then they are deleted and the EGA is run again. However, it is suggested that EGA be run until every dimension has three items loading on it (Tabachnick and Fidell, 2001). The exploratory graph analysis is later followed by confirmatory factor analysis to establish the validity of the factor structure.

Epskamp et al. (2018) mention that once weighted network between observed variables are obtained, they are analyzed using the measures called most central nodes of the graph theory(Newman, 2010), based on the concept of centrality (Borgatti, 2015; Costantini et al., 2017; Freeman, 1978), for making inferences. The significance of a node in the entire network model is measured quantitatively using three centrality indices (Costantini et al., 2015a; Newman, 2010; Opsahl et al.,2010), namely the *node strength, closeness and betweenness*. When a node makes direct and strong connections with other nodes a network, it is its node strength (Barrat, Barthelemy, Pastor-Satorras and Vespignani, 2004) which is a stable and prominent index of centrality representing strength centrality of the node (Epskamp et al, 2017). When the paths, both direct and indirect, connect a node to the other nodes are short, it represents the closeness centralilty, which is sensitive to the changes in the network model (Borgatti, 2005). Moreover, a node can lie in between the shortest path connecting two other nodes, representing the betweenness centrality. Also, clustering coefficient (Saramaki, Kivela, Onnela, Kaski and Kertesz, 2007; Watts and Strogatz, 1998) represents the extent to which certain nodes come together through direct connections and represent their redundancy. Removal any node from such a cluster should not influence the validity of the instrument. Clustering coefficient is used in the estimation of the parameter edge weight's strength and sign (Saramaki, Kivela, Onnela, Kaski and Kertesz, 2007; Costantini and Perugini, 2014). Proper interpretation of edge-weight parameter, as the measure of the casual relationships between nodes, through partial correlation coefficients, is made possible the implementation of conditional independence of multivariate normal data through pairwise Markov random field, PMRF, network model. For multivariate normal data, the appropriate PMRF is the Gaussian graphical model (GGM; Constantini et al., 2015a, Lauritzen, 1996) where the connections between the nodes are directly measured in terms of the strength of partial correlation coefficients. This model requires a correlation matrix as its input computed using polychoric correlations for ordinal data (Epskamp, 2016).

However, the accuracy of edge weights is a function of sample size, with higher the sample size, higher the accuracy. Since most of the psychological research is conducted using moderate sample size, it becomes important to assess the accuracy of the network parameters. Very few studies addressed the accuracy of the estimates of network analysis owing to the lack of a proper methodology (Fried, 2016), which was ultimately developed by Epskamp et al. (2018). This methodology involved the estimation of *confidence interval (CIs)* within which the true edge weights of the nodes exist with 95% confidence, using bootstrapping, measuring the stability or the order of the centrality indices using the measure *Correlation stability coefficient (CS)* and testing the significance difference between edge weights and centrality indices using bootstrapping.

During the calculation variability of the edge-weights using confidence interval (CI), knowledge of the sampling distribution is required. It is easily done using bootstrapping (Efron, 1979), a technique in which the sample data is repeatedly utilized to generate multiple samples by changing the order of the data randomly and hence obtain multiple sampling distributions forming non-parametric bootstrapping. Parametric bootstrapping generates new samples using fresh observations and the parametric model of the original data (Bollen and Stine, 1992). In network psychometrics, bootstrapping is implemented using LASSO (Hastie et al., 2015). Epskamp, Borsboom and Fried (2018) recommend using non-parametric bootstrapping over parametric bootstrapping in network analysis, because the former is purely data driven and the latter is theory driven. Also, when parametric bootstrapping is selected, the GGM model samples

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multivariate continuous normal data over the categorical ordinal response data of the Likert scale requiring polychoric correlation matrix estimation as its input. LASSO also produces biased estimates during regularization when parametric bootstrapping is chosen. The presence of zero in the non-parametric bootstrapped confidence interval is observed here to check for the accuracy of the edge-weights and compare each other, and not conducting any significance testing, although when zero is present in the obtained CI (with a negative and a positive abscissa and ordinate), it shows that the nodes do not differ in strength from each other accepting the null hypothesis.

Neither parametric sampling nor non-parametric bootstrapping technique can be extended to the centrality indices estimation as biased sampling distributions results are produced. As a result, the stability of the order of the centrality indices in various sub-sets of the data is studied. It is measured by calculating the correlation stability coefficient, *CS-coefficient*, which is the measure of the relationship between the order of the centrality indices in the original network data and a re-estimated network data with lesser cases or rows of original dataset. This represents *m out of n bootstrap* technique, where n are the cases in the original dataset and m are the cases in the re-estimated dataset with fewer cases than the original data. This technique of *case dropping subset bootstrap* addresses several limitations of the regular bootstrap (Chernick, 2011). If nodes are dropped instead of cases, the interpretation of the results will be difficult. CS-coefficient of 0.7 and above between original centrality indices and the subsets network centrality indices represents a very large effect size (Cohen, 1977). It should be preferably at 0.5 and never less than 0.25.

Finally, the centrality of a node differing significantly over another or the edge weight between two nodes differing from another two nodes is significantly is tested by estimating the bootstrapped confidence interval and checking whether zero lies in that interval, the null hypothesis being the absence of any such significant difference.

When it comes to reliability analysis of the instruments, network psychometrics computes structural consistency instead of internal consistency reliability estimates (Christensen et al., 2019). While internal consistency is evaluated and homogeneity is assumed in the traditional techniques of reliability estimates, structural consistency combines both of these aspects of a scale. It is because there is an inherent incompatibility in the estimation of internal consistency is network psychometrics. Internal consistency is a ratio between the common variance shared by the items and variance of an item (McNeish, 2018). During the estimation of networks, the common-variance is mostly removed and a measure of relationship between only variance specific to items is left over (Forbes, Wright, Markon and Krueger, 2017, 2019). Also, in the network, the items in the form of nodes are cross-connected all along. This leads to requirement to not only know whether certain items are related casually but also remain intact coherently, displaying their unidimensionality, in the entire network. In this way, structural consistency as a concept marries internal consistency between items and their homogeneity all along the network to which they belong. Two estimates, namely structural consistency and item stability are conceived to quantitative measure and report reliability under network psychometrics.

Structural consistency is estimated using bootstrapping technique and ranges from 0 to 1. Several samples are generated under this technique. Then, the intactness of certain items which are internally consistent, is observed by estimating the presence of number of items of the original dimension in the replicate sample dimension as it is. If items of a scale are internally consistent and homogeneous, they would be found to remain so when searched in multiple samples generated using bootstrapping. Otherwise, items would show cross loading or splitting when searched in different samples. For a scale with 10 items, structural consistency of 0.8 implies that its 8 items consistently are found to be intact in multiple samples. The items which are responsible for this consistency in the structure are found using item stability estimation.

The present study is an attempt to extend the above mentioned new techniques in the revalidation of the academic emotional regulation questionnaire on the same sample data as collected in the recent study validation of AERQ (Chakraborty and Chechi, 2020). The seminal study on psychometrics by Golino and Demetriou (2017) mentioned under its limitations to extend their research to instruments with Likert scales higher threshold or response categories. This study addresses the mentioned limitation by

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revalidating the five point Likert scale AERQ in the Indian context using the state of the art techniques of network psychometrics.

METHODOLOGY

Sample:

The present study applied network psychometrics analysis to validate the scale in the Indian context. 496 students from the School of Mechanical engineering, School of Computer Science engineering and the School of Hotel Management and Tourism of Lovely Professional University, Phagwara, Punjab, India, were the sample subjects. Mahalanobis distance was computed to detect outliers, removal of which lead to the final sample size of the study being 443.

Statistical Analysis

Mahalanobis distance was computed using SPSS Statistics Ver. 23.0, to detect outliers, removal of which lead to the final sample size of the study being 443. R Ver. 3.6.3 and RStudio Ver. 6.1.7601 were used to conduct the rest of statistical analysis. The exploratory graph analysis was conducted using the package *eganet* (Golino et al., 2020), which lead to the extraction of the original eight dimensions of the scale, with one item from social support dimension showing anomaly. As per the rules of (EGA), it was removed the test was re-run to obtain the graph of the network. Confirmatory factor analysis was conducted using package *lavaan* (Rossel, 2012), and the package *Psych* (Revelle,2019), using the estimator "WLSMV" for ordinal data, and for estimating robust goodness of fit estimates. Under network inference analysis, the state-of-the-art edge weight accuracy using non-parametric bootstrap confidence interval, correlation stability coefficient and bootstrapped difference tests were conducted to study the significance of the obtained estimates using the package *bootnet*. Structural consistency is computed along with item stability under reliability analysis instead of internal consistency using the packages *bootega*, *eganet* (Golino and Christensen, 2020) and *psych*. The plots are generated using the package *qgraph*.

RESULT

R Codes / Results for Conducting Exploratory Graph Analysis – Trail 1

1. Read the data file in RStudio, say, AERQ_37_ALL.
2. Install the package eganet.
3. Library (eganet) - Activate the package eganet.
4. Define the data frame ega.aerq to store the result of exploratory graph analysis
5. Display the results using summary command

```
View(AERQ_37_ALL)
> ega.aerq<-EGA(AERQ_37_ALL, plot.EGA = TRUE)
Variables detected as ordinal: SitSelec1; SitSelec2; SitSelec3; SitSelec4; DevCom1; DevCom2;
DevCom3; DevCom4; DevCom5; ReAtt1; ReAtt2; ReAtt3; ReAtt4; ReAtt5; ReAtt6; Reapp1; Reapp2;
Reapp3; Reapp4; Reapp5; Supp1; Supp2; Supp3; Supp4; Supp5; Respi1; Respi2; Respi3; Venting1;
Venting2; Venting3; Venting4; Venting5; SocSupp1; SocSupp2; SocSupp3; SocSupp4
Network estimated with gamma = 0.5
> summary(ega.aerq)
EGA Results:

Number of Dimensions:
[1] 8
```

Items per Dimension:

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	items	dimension
Vn1	Venting1	1
Vn2	Venting2	1
Vn3	Venting3	1
Vn4	Venting4	1
Vn5	Venting5	1
ScS3	SocSupp3	1
DC1	DevCom1	2
DC2	DevCom2	2
DC3	DevCom3	2
DC4	DevCom4	2
DC5	DevCom5	2
StS1	SitSelec1	3
StS2	SitSelec2	3
StS3	SitSelec3	3
StS4	SitSelec4	3
Rs1	Respi1	4
Rs2	Respi2	4
Rs3	Respi3	4
Sp1	Supp1	5
Sp2	Supp2	5
Sp3	Supp3	5
Sp4	Supp4	5
Sp5	Supp5	5
Rp1	Reapp1	6
Rp2	Reapp2	6
Rp3	Reapp3	6
Rp4	Reapp4	6
Rp5	Reapp5	6
ScS1	SocSupp1	7
ScS2	SocSupp2	7
ScS4	SocSupp4	7
RA1	ReAtt1	8
RA2	ReAtt2	8
RA3	ReAtt3	8
RA4	ReAtt4	8
RA5	ReAtt5	8
RA6	ReAtt6	8

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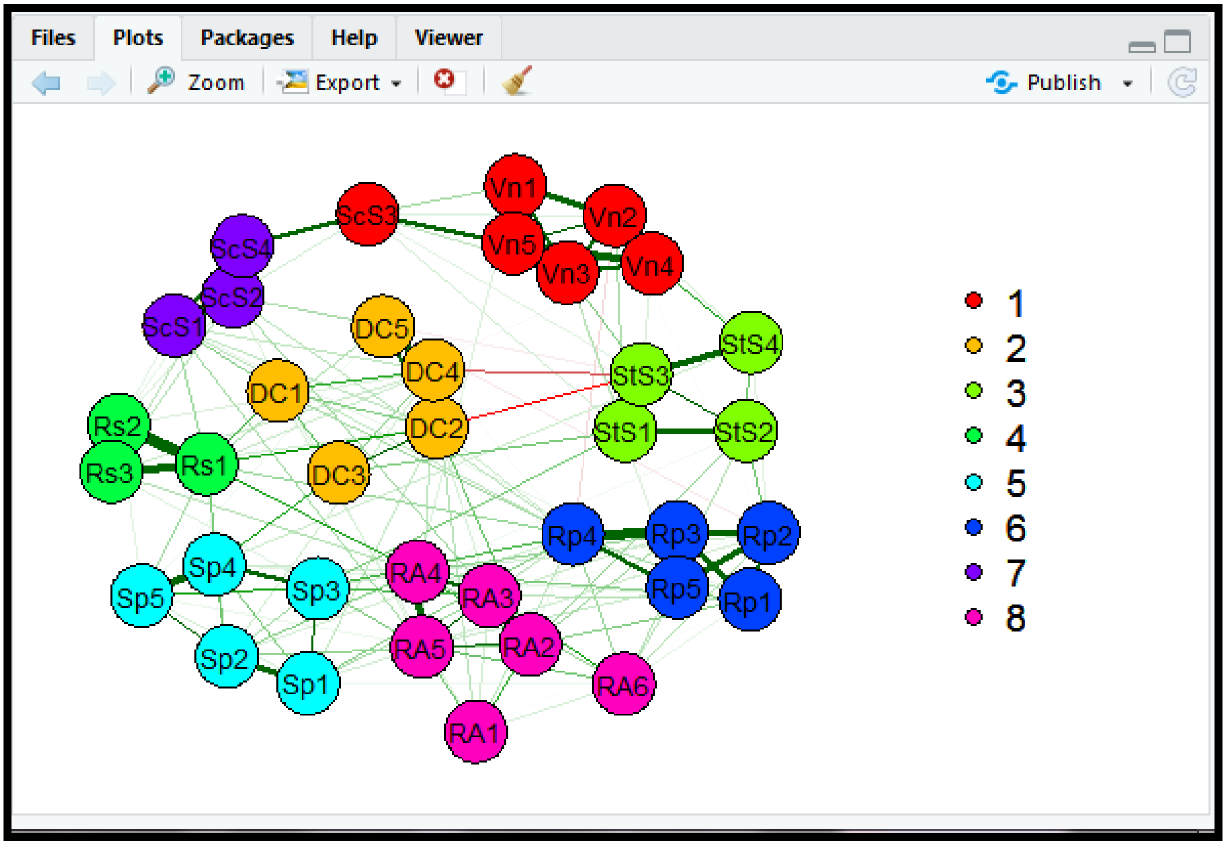

Fig. 1: Network of partial correlations, estimated using graphical lasso, showing the pattern of AERQ items per cluster. Cluster 1 = Venting, Cluster 2 = Developing competencies, Cluster 3 = Situation Selection, Cluster 4 = Respiration, Cluster 5 = Suppression, Cluster 6 = Reappraisal, Cluster 7 = Social Support, Cluster 8 = Redirecting Attention

Interpretation: All the 36 items clustered as per the theoretical structure, except the items 3 of social support dimension, which showed anomaly. It is deleted and EGA is run again to obtain the final factor structure.

R Codes / Results for Conducting Exploratory Graph Analysis – Final Trail

```
> View(AERQ_37_ALL_Without_Outliers_and_Item_SocSup3)
> ega.aerq<-EGA(AERQ_37_ALL_Without_Outliers_and_Item_SocSup3, plot.EGA = TRUE)

Variables detected as ordinal: SitSelec1; SitSelec2; SitSelec3; SitSelec4; DevCom1; DevCom2; DevCom3; DevCom4; DevCom5; ReAtt1; ReAtt2; ReAtt3; ReAtt4; ReAtt5; ReAtt6; Reapp1; Reapp2; Reapp3; Reapp4; Reapp5; Supp1; Supp2; Supp3; Supp4; Supp5; Respi1; Respi2; Respi3; Venting1; Venting2; Venting3; Venting4; Venting5; SocSupp1; SocSupp2; SocSupp4
Network estimated with gamma = 0.5
> summary(ega.aerq)
EGA Results:

Number of Dimensions:
[1] 8
```


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Items per Dimension:

items		dimension
DC1	DevCom1	1
DC2	DevCom2	1
DC3	DevCom3	1
DC4	DevCom4	1
DC5	DevCom5	1
StS1	SitSelec1	2
StS2	SitSelec2	2
SS3	SitSelec3	2
StS4	SitSelec4	2
Sp1	Supp1	3
Sp2	Supp2	3
Sp3	Supp3	3
Sp4	Supp4	3
Sp5	Supp5	3
Rs1	Respi1	4
Rs2	Respi2	4
Rs3	Respi3	4
Rp1	Reapp1	5
Rp2	Reapp2	5
Rp3	Reapp3	5
Rp4	Reapp4	5
Rp5	Reapp5	5
ScS1	SocSupp1	6
ScS2	SocSupp2	6
ScS4	SocSupp4	6
RA1	ReAtt1	7
RA2	ReAtt2	7
RA3	ReAtt3	7
RA4	ReAtt4	7
RA5	ReAtt5	7
RA6	ReAtt6	7
Vn1	Venting1	8
Vn2	Venting2	8
Vn3	Venting3	8
Vn4	Venting4	8
Vn5	Venting5	8

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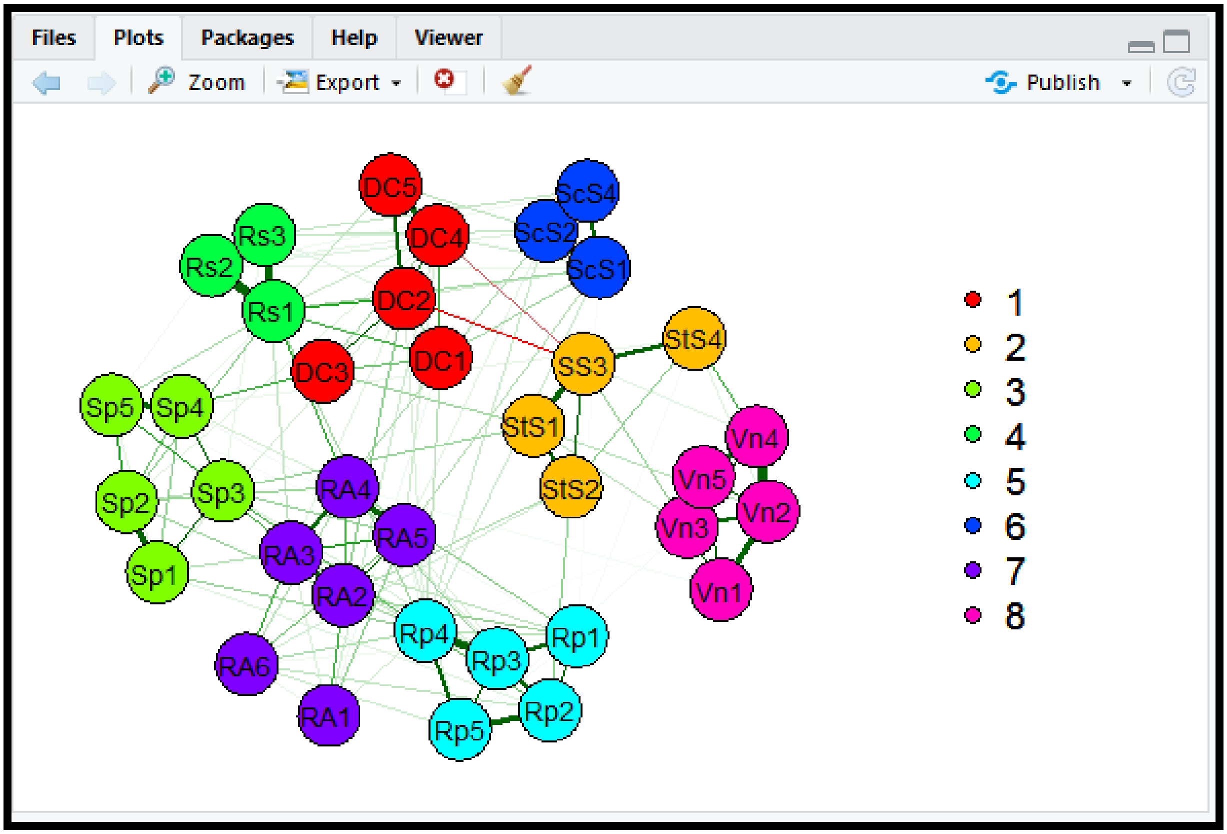

Fig. 2: Network of partial correlations, estimated using graphical lasso, showing the final pattern of AERQ items per cluster. Cluster 1 = Venting, Cluster 2 = Developing competencies, Cluster 3 = Situation Selection, Cluster 4 = Respiration, Cluster 5 = Suppression, Cluster 6 = Reappraisal, Cluster 7 = Social Support, Cluster 8 = Redirecting Attention

R Codes / Results for Conducting WLSMV Estimator based Confirmatory Factor Analysis for Ordinal Data to obtain Factor Loadings and Goodness of Fit Measures:

```
> cfa.aerq <- CFA(ega.obj = ega.aerq, estimator = 'WLSMV', plot.CFA = TRUE, data =
AERQ_37_ALL_Without_Outliers_and_Item_SocSup3)
[1] DevCom1 DevCom2 DevCom3 DevCom4 DevCom5
36 Levels: DevCom1 DevCom2 DevCom3 DevCom4 DevCom5 Reapp1 Reapp2 Reapp3 ... Venting5
[1] SitSelec1 SitSelec2 SitSelec3 SitSelec4
36 Levels: DevCom1 DevCom2 DevCom3 DevCom4 DevCom5 Reapp1 Reapp2 Reapp3 ... Venting5
[1] Supp1 Supp2 Supp3 Supp4 Supp5
36 Levels: DevCom1 DevCom2 DevCom3 DevCom4 DevCom5 Reapp1 Reapp2 Reapp3 ... Venting5
[1] Respi1 Respi2 Respi3
36 Levels: DevCom1 DevCom2 DevCom3 DevCom4 DevCom5 Reapp1 Reapp2 Reapp3 ... Venting5
[1] Reapp1 Reapp2 Reapp3 Reapp4 Reapp5
36 Levels: DevCom1 DevCom2 DevCom3 DevCom4 DevCom5 Reapp1 Reapp2 Reapp3 ... Venting5
[1] SocSupp1 SocSupp2 SocSupp4
36 Levels: DevCom1 DevCom2 DevCom3 DevCom4 DevCom5 Reapp1 Reapp2 Reapp3 ... Venting5
[1] ReAtt1 ReAtt2 ReAtt3 ReAtt4 ReAtt5 ReAtt6
36 Levels: DevCom1 DevCom2 DevCom3 DevCom4 DevCom5 Reapp1 Reapp2 Reapp3 ... Venting5
[1] Venting1 Venting2 Venting3 Venting4 Venting5
36 Levels: DevCom1 DevCom2 DevCom3 DevCom4 DevCom5 Reapp1 Reapp2 Reapp3 ... Venting5
Warning message:
```


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In lav_samplestats_from_data(lavdata = lavdata, missing = lavoptions$missing, :
  lavaan WARNING: number of observations (443) too small to compute Gamma

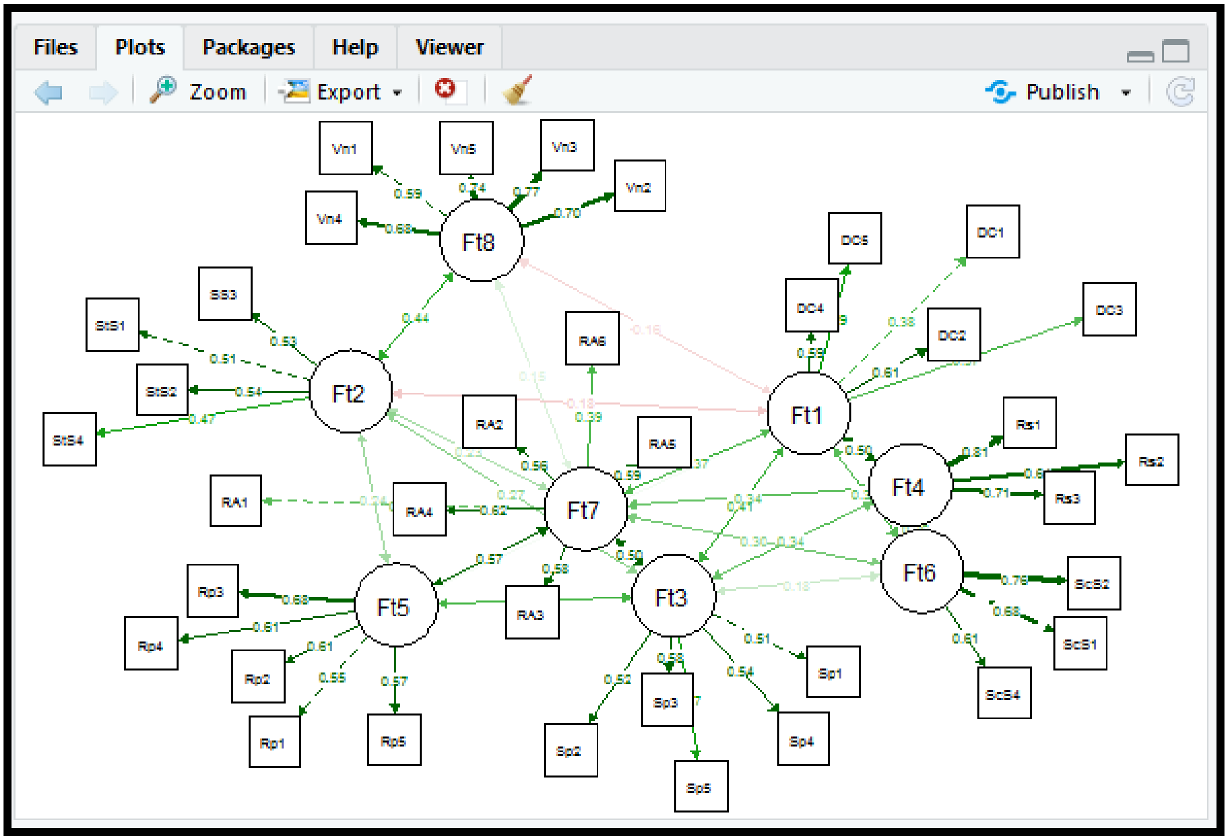

Fig. 3: Standardized weights of the CFA model from the Structure Suggested by EGA in the AERQ Data.

>>lavaan::fitMeasures(cfa.aerq$fit, fit.measures = "all")

npar	fmin
100.000	0.639
chisq	df
565.982	566.000
pvalue	chisq.scaled
0.492	819.833
df.scaled	pvalue.scaled
566.000	0.000
chisq.scaling.factor	baseline.chisq
0.690	5287.523
baseline.df	baseline.pvalue
630.000	0.000
baseline.chisq.scaled	baseline.df.scaled
5287.523	630.000
baseline.pvalue.scaled	baseline.chisq.scaling.factor
0.000	1.000
cfi	tli
1.000	1.000
nnfi	rfi

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1.000	0.881
nfi	pnfi
0.893	0.802
ifi	rni
1.000	1.000
cfi.scaled	**tli.scaled**
0.946	**0.939**
cfi.robust	**tli.robust**
0.962	**0.958**
nnfi.scaled	nnfi.robust
0.939	0.958
rfi.scaled	nfi.scaled
0.827	0.845
ifi.scaled	rni.scaled
0.946	0.946
rni.robust	**rmsea**
0.962	**0.000**
rmsea.ci.lower	rmsea.ci.upper
0.000	0.015
rmsea.pvalue	rmsea.scaled
1.000	0.032
rmsea.ci.lower.scaled	rmsea.ci.upper.scaled
0.026	0.037
rmsea.pvalue.scaled	**rmsea.robust**
1.000	**0.026**
rmsea.ci.lower.robust	rmsea.ci.upper.robust
0.022	0.030
rmsea.pvalue.robust	rmr
NA	0.063
rmr_nomean	**srmr**
0.063	**0.048**
srmr_bentler	srmr_bentler_nomean
0.048	0.048
crmr	crmr_nomean
0.049	0.049
srmr_mplus	srmr_mplus_nomean
0.048	0.048
cn_05	cn_01
487.102	506.425
gfi	**agfi**
0.964	**0.958**
pgfi	mfi
0.819	1.000

ecvi
1.733

Table 1: Result of WLSMV Estimator based Confirmatory Factor Analysis for Ordinal Data:

S.No.	Estimate	Benchmark of the Estimate	Standard MI based Estimate	Robust WLSMV based Estimate	Remark on Goodness of Fit
1.	CFI	0.95	0.946	0.962	Excellent

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2.	TLI	0.95	0.939	0.958	Excellent
3.	GFI / AGFI	0.95	NA	0.964 / 0.958	Excellent
4.	RMSEA	0.08	0.000	0.026	Excellent
5.	SRMR	0.05	0.048	0.048	Excellent

```
> View(ega.aerq$dim.variables)
> net.loads(ega.aerq$network, ega.aerq$wc)$std
              1      2      3      4     5      6      7     8
SitSelec1  0.040  0.033  0.262  0.000 0.033  0.000  0.000 0.000
SitSelec2  0.000  0.000  0.261  0.000 0.003  0.031  0.000 0.038
SitSelec3  0.037 -0.124  0.362  0.000 0.000  0.000 -0.005 0.000
SitSelec4  0.055  0.000  0.165  0.000 0.012  0.006  0.000 0.000
DevCom1    0.000  0.132  0.000  0.058 0.000  0.020  0.033 0.008
DevCom2    0.000  0.297 -0.087  0.081 0.014  0.011  0.018 0.040
DevCom3    0.000  0.149  0.038  0.000 0.057  0.000  0.000 0.000
DevCom4    0.000  0.314 -0.050  0.038 0.011  0.002  0.018 0.028
DevCom5    0.000  0.234 -0.003  0.022 0.004 -0.005  0.024 0.000
ReAtt1     0.000  0.027  0.000  0.000 0.000  0.015  0.000 0.095
ReAtt2     0.000  0.037  0.029  0.000 0.027  0.052  0.000 0.285
ReAtt3     0.000  0.009  0.000  0.020 0.069  0.044  0.028 0.320
ReAtt4     0.006  0.000  0.000  0.067 0.042  0.064  0.000 0.269
ReAtt5     0.000  0.015  0.000  0.000 0.034  0.026  0.037 0.309
ReAtt6     0.000  0.000  0.020  0.000 0.004  0.058  0.000 0.112
Reapp1     0.000  0.000  0.000  0.000 0.007  0.203  0.006 0.077
Reapp2     0.001 -0.006  0.047  0.000 0.011  0.319  0.000 0.037
Reapp3     0.000  0.000  0.000  0.000 0.012  0.404  0.000 0.055
Reapp4    -0.007  0.036  0.000  0.028 0.086  0.281  0.037 0.057
Reapp5     0.007  0.000  0.000  0.000 0.000  0.276  0.000 0.027
Supp1      0.000  0.015  0.000  0.000 0.240  0.036  0.000 0.022
Supp2      0.000  0.011  0.003  0.037 0.248  0.010  0.000 0.050
Supp3      0.000  0.000  0.038  0.009 0.250  0.053  0.000 0.069
Supp4      0.000  0.058  0.014  0.007 0.293  0.006  0.000 0.011
Supp5      0.000  0.004  0.000  0.033 0.269  0.000  0.000 0.004
Respi1    -0.001  0.150  0.000  0.343 0.063  0.023  0.030 0.050
Respi2     0.000  0.009  0.000  0.402 0.006  0.000  0.025 0.000
Respi3     0.000  0.023  0.000  0.372 0.008  0.000  0.040 0.020
Venting1   0.257  0.000  0.000  0.000 0.000  0.000  0.000 0.007
Venting2   0.382  0.000  0.034  0.000 0.000  0.009  0.000 0.000
Venting3   0.388  0.000  0.055  0.000 0.000  0.008  0.000 0.000
Venting4   0.310  0.000  0.074 -0.002 0.000  0.000  0.000 0.000
Venting5   0.460  0.000  0.000  0.000 0.000  0.000  0.000 0.000
SocSupp1   0.000  0.059  0.000  0.036 0.000  0.018  0.310 0.020
SocSupp2   0.009  0.021 -0.005  0.030 0.000  0.015  0.439 0.028
SocSupp3   0.120  0.000  0.020  0.000 0.000  0.000  0.128 0.000
SocSupp4   0.082  0.000  0.000  0.025 0.000  0.000  0.357 0.0
```

R Codes / Results for Computing the Centrality Indices Under Edge-weight Accuracy Estimation:

1. Install boot net
2. Library(bootnet)
3. Network <- estimateNetwork(AERQ_37_ALL_Without_Outliers_and_Item_SocSup3,default = "EBICglasso")

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4. Install qgraph
5. Library (qgraph)
6. plot(Network, layout = "spring",labels = TRUE)

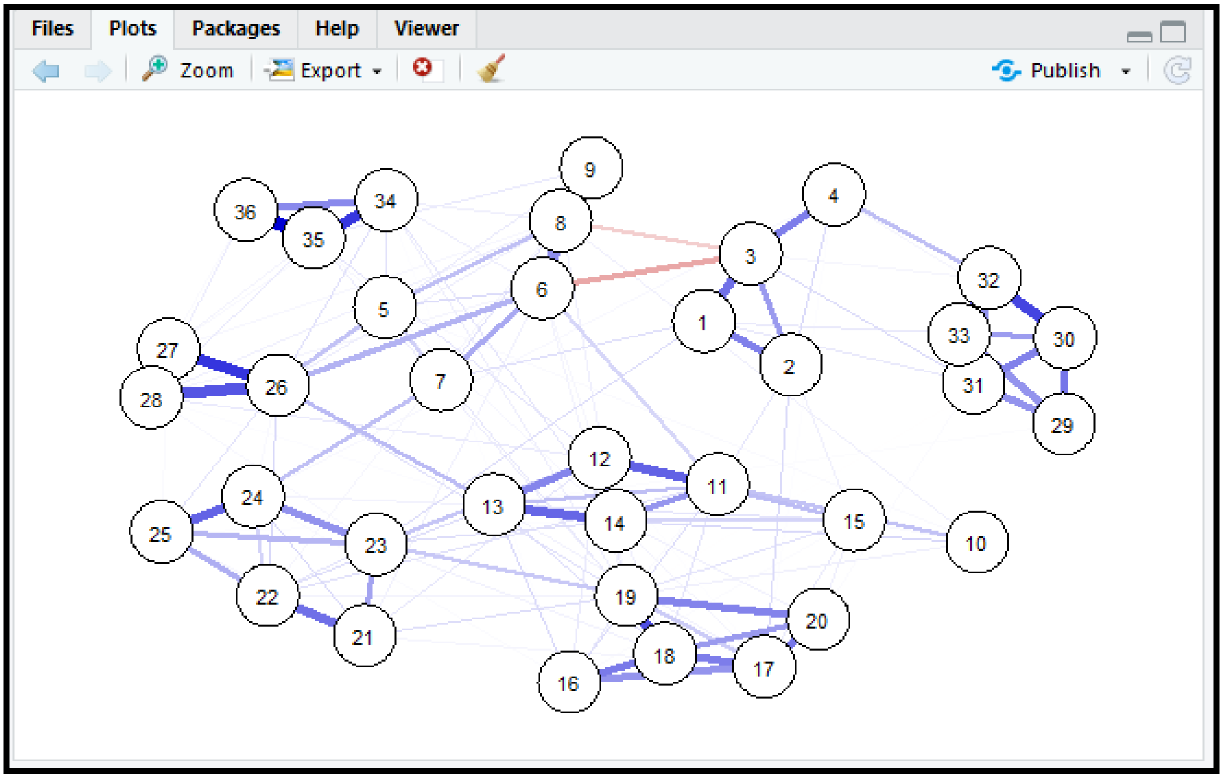

Fig. 3: Estimated Network Structure of AERQ. The network structure is a Gaussian graphical model, which is a network of partial correlation coefficients.

Interpretation: Strong connections emerge between the nodes 34,35 and36, 26,27 and 28, 11,12,13 and 14, 21 and 22, 24 and 25, 1,3 and 4, 6 and 8, 30 and 32. Negative relationship exists between the nodes 3 and 6. For the rest of the nodes, the edges are either relatively weak or absent representing statistical independence or no sufficient power to detect any relationship between them.

R Codes / Results for Obtaining Centrality Indices – Strength-wise

```
>centralityPlot(Network)
```

Note: z-scores are shown on x-axis rather than raw centrality indices.

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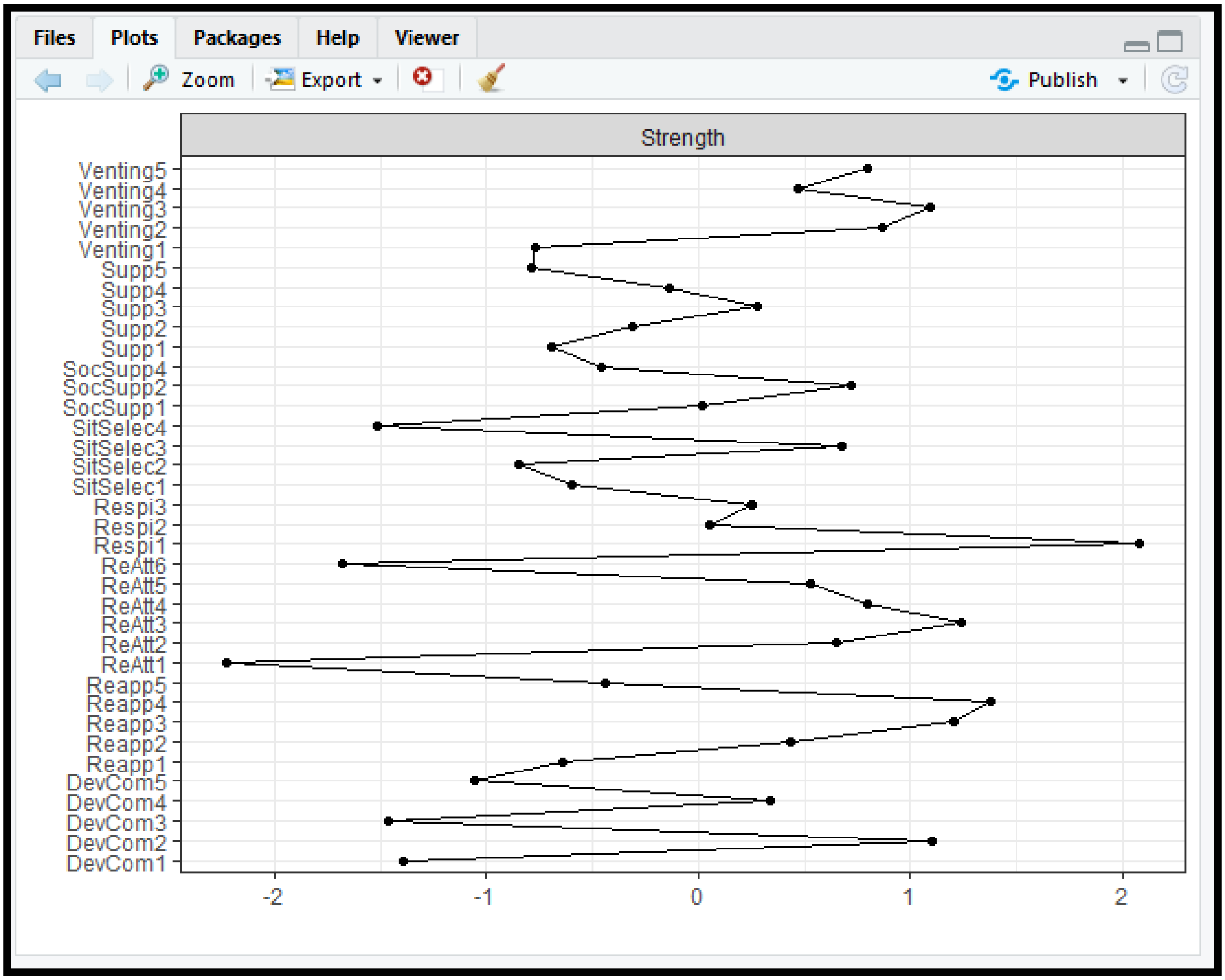

Fig. 5 Centrality Indices – Strength

Interpretation: The strength of the nodes differs significantly in their centrality index, strength-wise as seen in the graph above. The node Respi2 has the highest strength. However, accuracy of the network structure and the stability of the centrality estimates must be checked before interpreting the differences of centrality indices.

R Codes / Results for Obtaining Edge weight Accuracy

```
boot1 <- bootnet(Network, nBoots = 100,nCores = 8)
```

```
plot(boot1, labels = FALSE, order = "sample")
```


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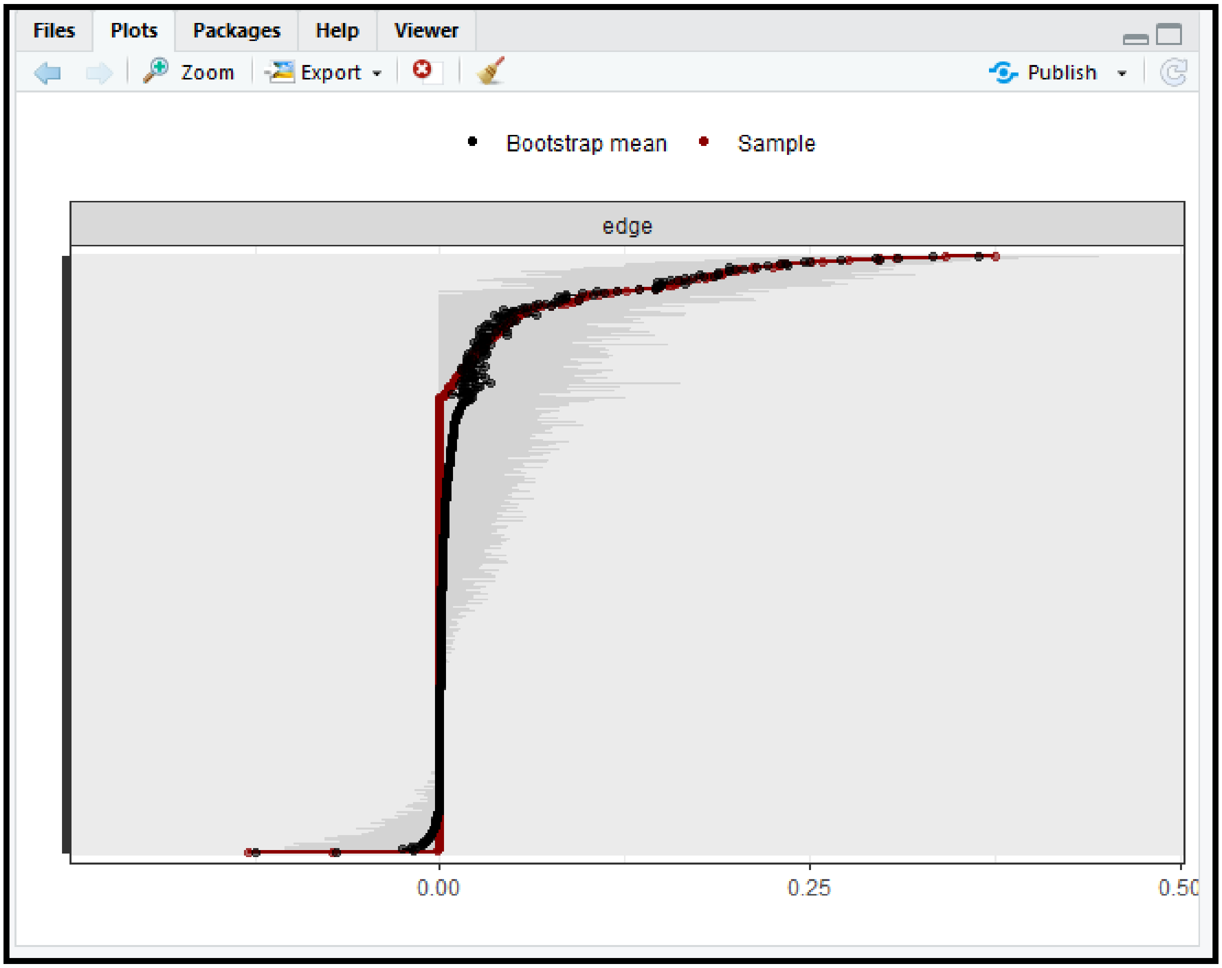

Fig.6 Bootstrapped confidence interval of estimated edge-weights for the estimated network of AERQ. The red line indicates the sample values and the gray area the boot strapped CIs. Each horizontal line represents one edge of the network, ordered from the edge with the highest edge-weight to the edge with the lowest edge-weight.

Interpretation: The nodes of AERQ don't differ significantly with respect to strength because the bootstrapped confidence interval contains zero (0, 0.5).

R Codes / Results for Obtaining Centrality Stability – CS Coefficient Estimation

boot2 < - bootnet(Network, nBoots = 100,type = "case", nCores = 8)

Plot(boot2)

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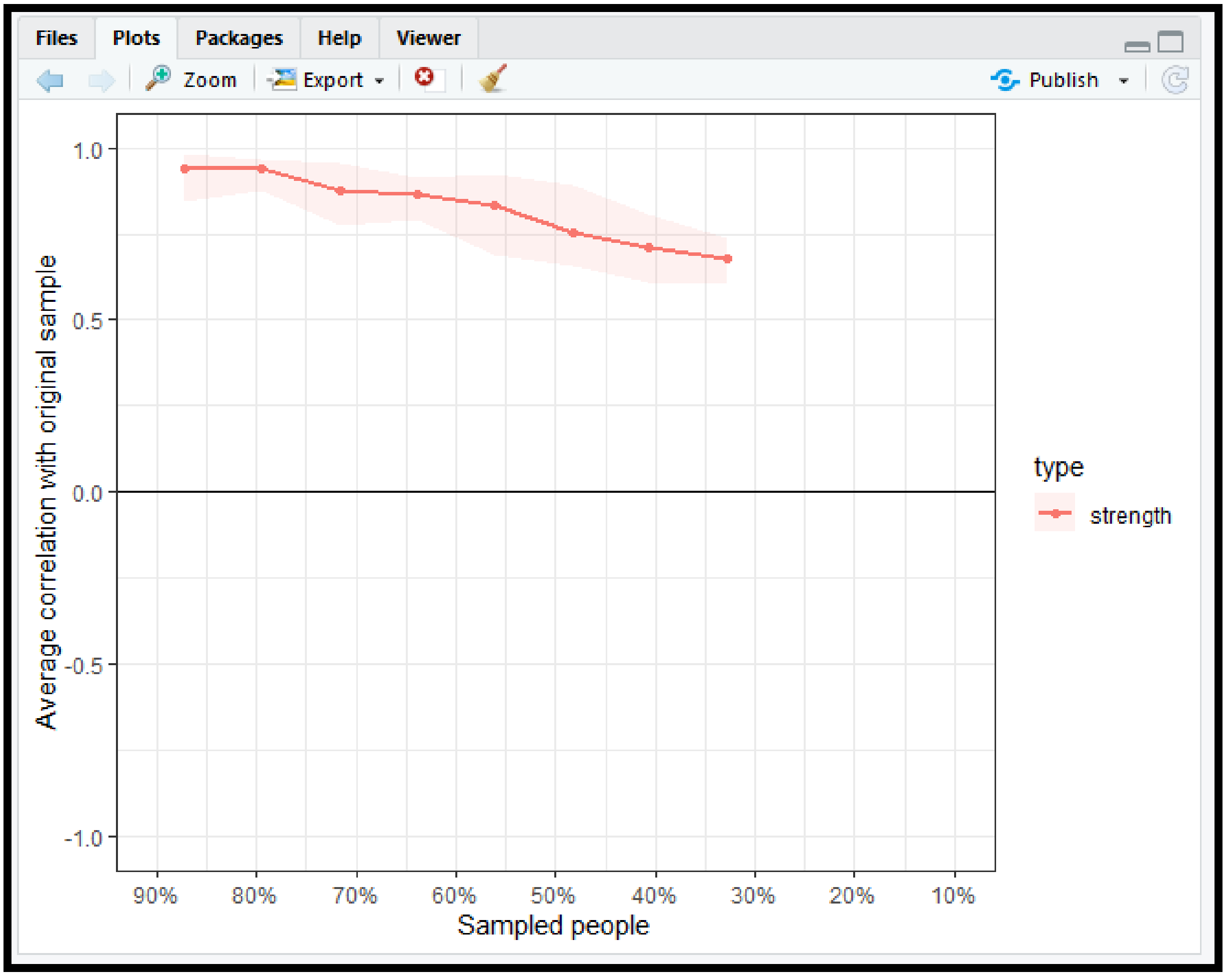

corStability(boot2)

=== Correlation Stability Analysis ===

Sampling levels tested:

	nPerson	Drop%	n
9	145	67.3	6
2	180	59.4	12
3	214	51.7	20
4	249	43.8	9
5	283	36.1	8
6	317	28.4	10
7	352	20.5	16
8	386	12.9	13
9	421	5.0	6

Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:

edge: 0.673 (CS-coefficient is highest level tested)

- For more accuracy, run bootnet(…, caseMin = 0.594, caseMax = 1)

strength: 0.361

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- For more accuracy, run bootnet(…, caseMin = 0.284, caseMax = 0.438)

Accuracy can also be increased by increasing both ‘nBoots’ and ‘caseN’.

Interpretation: The stability falls down steeply and it is quantified using the CS- coefficient of 0.673, which is above the cutoff value of 0.5. This implies that the order of the node strength is fairly accurate, owing to its stability across samples generated through bootstrapping technique of n=100 run.

R Codes / Results for Conducting Significance Difference Test:

```
differenceTest(boot1, 3, 17, "strength")
```

```
Expected significance level given number of bootstrap samples is approximately: 0.05
       id1    id2  measure      lower      upper significant
1 SitSelec3 Reapp2 strength -0.3422148 0.3161339       FALSE
```

Interpretation: The above test is conducted to check for any significant difference in the node strength centrality between nodes 3 and 17. The result FALSE indicate that there is no significance difference between the nodes 3 and 17 with respect to strength.

R Codes / Results for Estimating the Structural Consistency Reliability of each of the Dimensions of AERQ:

```
> library(haven)
> AERQFinal <- read_sav("D:/Ph.D/10. Ph.D. Article Publications and Paper Presentations/18. NP Based AERQ Validation/AERQFinal.sav")
> View(AERQFinal)
> ega.aerq<-EGA(AERQFinal, model = 'glasso')
> View(ega.aerq$dim.variables)
> net.loads(ega.aerq, ega.aerq$wc)$std
```

	1	2	3	4	5	6	7	8
DevCom1	0.128	0.000	0.000	0.057	0.017	0.031	0.004	0.000
DevCom2	0.300	-0.087	0.011	0.080	0.009	0.017	0.037	0.000
DevCom3	0.142	0.031	0.054	0.000	0.000	0.000	0.000	0.000
DevCom4	0.315	-0.048	0.008	0.036	0.000	0.016	0.023	0.000
DevCom5	0.236	0.000	0.000	0.020	0.000	0.021	0.000	0.000
SitSelec1	0.027	0.265	0.029	0.000	0.000	0.000	0.000	0.032
SitSelec2	0.000	0.261	0.000	0.000	0.028	0.000	0.030	0.000
SitSelec3	-0.119	0.366	0.000	0.000	0.000	0.000	0.000	0.033
SitSelec4	0.000	0.164	0.006	0.000	0.002	0.000	0.000	0.055
Supp1	0.012	0.000	0.239	0.000	0.033	0.000	0.018	0.000
Supp2	0.008	0.000	0.248	0.037	0.008	0.000	0.048	0.000
Supp3	0.000	0.033	0.251	0.006	0.052	0.000	0.068	0.000
Supp4	0.055	0.007	0.293	0.006	0.003	0.000	0.010	0.000
Supp5	0.000	0.000	0.268	0.030	0.000	0.000	0.002	0.000
Respi1	0.152	0.000	0.062	0.344	0.023	0.031	0.050	0.000
Respi2	0.007	0.000	0.003	0.402	0.000	0.024	0.000	0.000
Respi3	0.021	0.000	0.006	0.373	0.000	0.040	0.018	0.000
Reapp1	0.000	0.000	0.003	0.000	0.203	0.002	0.073	0.000
Reapp2	0.000	0.039	0.009	0.000	0.321	0.000	0.035	0.000
Reapp3	0.000	0.000	0.011	0.000	0.408	0.000	0.056	0.000
Reapp4	0.031	0.000	0.085	0.028	0.283	0.035	0.056	-0.001

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```
Reapp5     0.000  0.000 0.000 0.000  0.276 0.000 0.023  0.003
SocSupp1   0.055  0.000 0.000 0.035  0.014 0.325 0.019  0.000
SocSupp2   0.018  0.000 0.000 0.029  0.013 0.464 0.026  0.000
SocSupp4   0.000  0.000 0.000 0.023  0.000 0.379 0.000  0.000
ReAtt1     0.018  0.000 0.000 0.000  0.011 0.000 0.087  0.000
ReAtt2     0.036  0.025 0.025 0.000  0.051 0.000 0.287  0.000
ReAtt3     0.008  0.000 0.069 0.020  0.044 0.027 0.323  0.000
ReAtt4     0.000  0.000 0.040 0.065  0.064 0.000 0.271  0.003
ReAtt5     0.013  0.000 0.031 0.000  0.024 0.034 0.311  0.000
ReAtt6     0.000  0.015 0.000 0.000  0.052 0.000 0.106  0.000
Venting1   0.000  0.000 0.000 0.000  0.000 0.000 0.003  0.262
Venting2   0.000  0.031 0.000 0.000 -0.001 0.000 0.000  0.409
Venting3   0.000  0.056 0.000 0.000  0.003 0.000 0.000  0.412
Venting4   0.000  0.073 0.000 0.000  0.000 0.000 0.000  0.337
Venting5   0.000  0.000 0.000 0.000  0.000 0.000 0.000  0.427

boot <- bootEGA(AERQFinal, n = 100, model = "glasso", type = "resampling", plot.typicalStructure =
FALSE)

Generating data...done

Computing correlation matrices...
  |++++++++++++++++++++++++++++++++++++++++++++++++++| 100% elapsed=02m 15s
Estimating networks...
  |++++++++++++++++++++++++++++++++++++++++++++++++++| 100% elapsed=08s
Computing results...done
> sc <- dimStability(boot, orig.wc = ega.aerq$wc)
> sc$dimensions
    1     2     3     4     5     6     7     8
0.910 0.902 0.906 0.680 0.738 0.960 0.932 1.000
```

Table 2: Structural Consistency Reliability of each of the Dimensions of AERQ:

S.No.	Dimension	Items	Structural Consistency Reliability Estimate	Items displaying Structural Consistency
1.	Developing Competencies	5	0.910	4
2.	Situation Selection	4	0.902	4
3.	Suppression	5	0.906	4
4.	Respiration	3	0.68	2
5.	Reappraisal	5	0.738	4
6.	Social Support	3	0.96	3
7.	Redirecting Attention	6	0.932	5
8.	Venting	5	1.000	5

Interpretation: All the five items of the dimension venting consistently display intactness when searched in 100 samples generated from the original data set using bootstrapping technique. Five out of the six items of the dimension redirecting attention show structural consistency. This estimate is calculated for the rest of the dimensions as shown above. The dimension respiration has the least structural consistency estimate showing a tendency of falling apart.

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DISCUSSION:

The traditional approaches of factor analysis are primarily based on the assumption that the data is continuous and make use of Pearson's product moment correlation matrix along with its maximum likelihood estimator for validating the factor structure using the goodness of fit indices. Also, the reliability estimation takes into account internal consistency and assumes homogeneity. In reality, the questionnaires used to gather data have ordinal responses in their Likert scale requiring polychoric correlation for estimation of the goodness of fit estimates based on WLSMV estimator.

To address these genuine limitations of the traditional approaches, a new area of psychometrics research under network psychometrics was proposed by Golino and Epskamp in 2016. This study extended the adaptation study of the AERQ scale by Chakraborty and Chechi (2020) by applying the techniques of this area on it. Except item3 of the dimension social support, all the 36 items of the scale, displayed the theoretical factor structure by loading on the eight original dimensions. The result was further validated by the tests to establish the centrality index – strength of the scale.

The study also estimated structural consistency reliability for each of the dimensions of the AERQ scale which is a novel exercise in the Indian context. However, the results of this study can show improvement for increased sample size. There is no mechanism to conduct power analysis, as this topic is a subject of future research in this field (Epskamp, Borsboom and Fried, 2018).

Further studies can be conducted on this scale by gathering data on samples of different demographic instances like gender, locality and socio-economic status for assessing the stability of the factor structure and the structural consistency of the items. This study only conducted the essential accuracy of the estimated edge-weights test (Epskamp, Borsboom and Fried, 2018). Estimation of the left over centrality indices like closeness and betweeness must be taken up in the future studies for AERQ along with the estimation of item stability plot across dimensions.

CONCLUSION:

The awareness on the state of the art techniques of network psychometrics for validating psychological scales using freeware like R/RStudio is the need of the hour to clean the edifice of psychological literature that is filled with faulty and sub-standard estimates of statistical estimands on application of erroneous estimators. The present study applied these new techniques on the items of AERQ instrument and obtained results which are way better than the results of the original study in Croatia and its adaptation study in India. However, there is room for improvement in the techniques used under inferential statistics of these results, as the field of network psychometrics is relatively young.

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