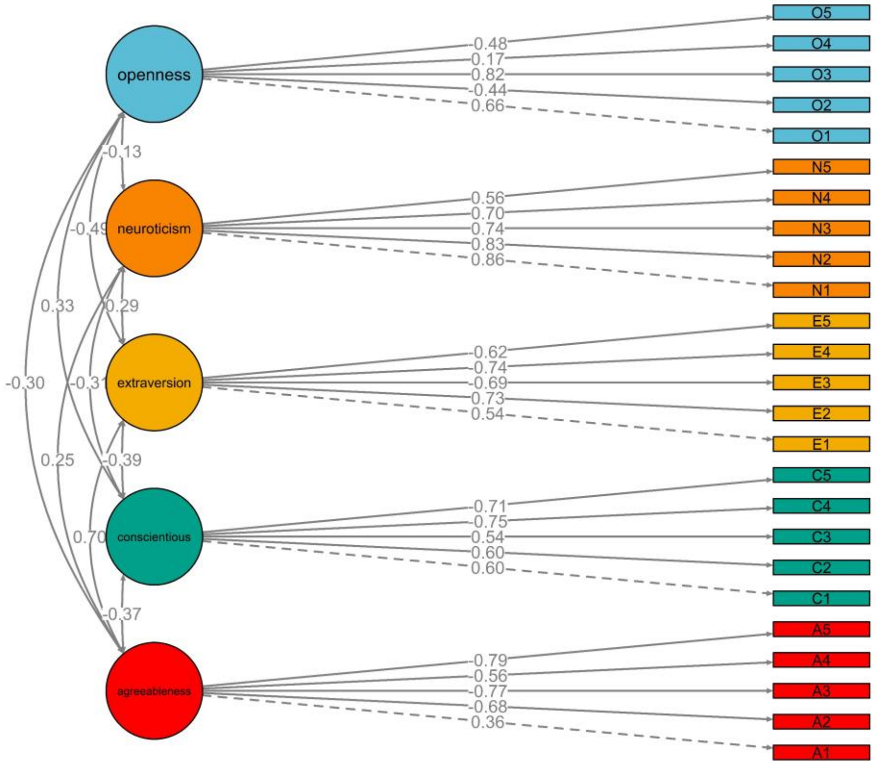
ANÁLISIS DE REDES:

Una nueva forma de examinar las relaciones entre variables en psicología

Dr. José Ventura-León
Docente Investigador

De como llegué a los modelos de redes…

SEM



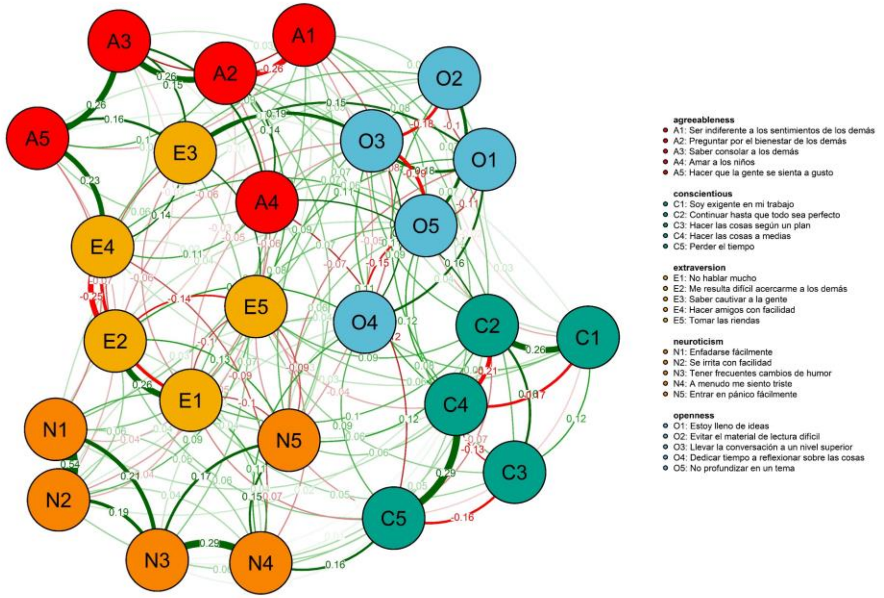
Carga varianza-covarianza

$$\Sigma = \Lambda \Psi \Lambda^{T} + \Theta$$

Carga Factorial

Residual varianza-covarianza

Network Analysis



Matriz de escalado diagonal

$$\Sigma = \Delta (I - \Omega)^{-1} + \Delta$$

Matriz de varianza-covarianza

Red de correlación parcial

frontiers in Psychology

CONCEPTUAL ANALYSIS
published: 18 May 2017
doi: 10.3389/fpsyg.2017.00798

Check for updates

Modeling Psychological Attributes in Psychology – An Epistemological Discussion: Network Analysis vs. Latent Variables

Hervé Guyon[1,2], Bruno Falissard[1] and Jean-Luc Kop[3]*

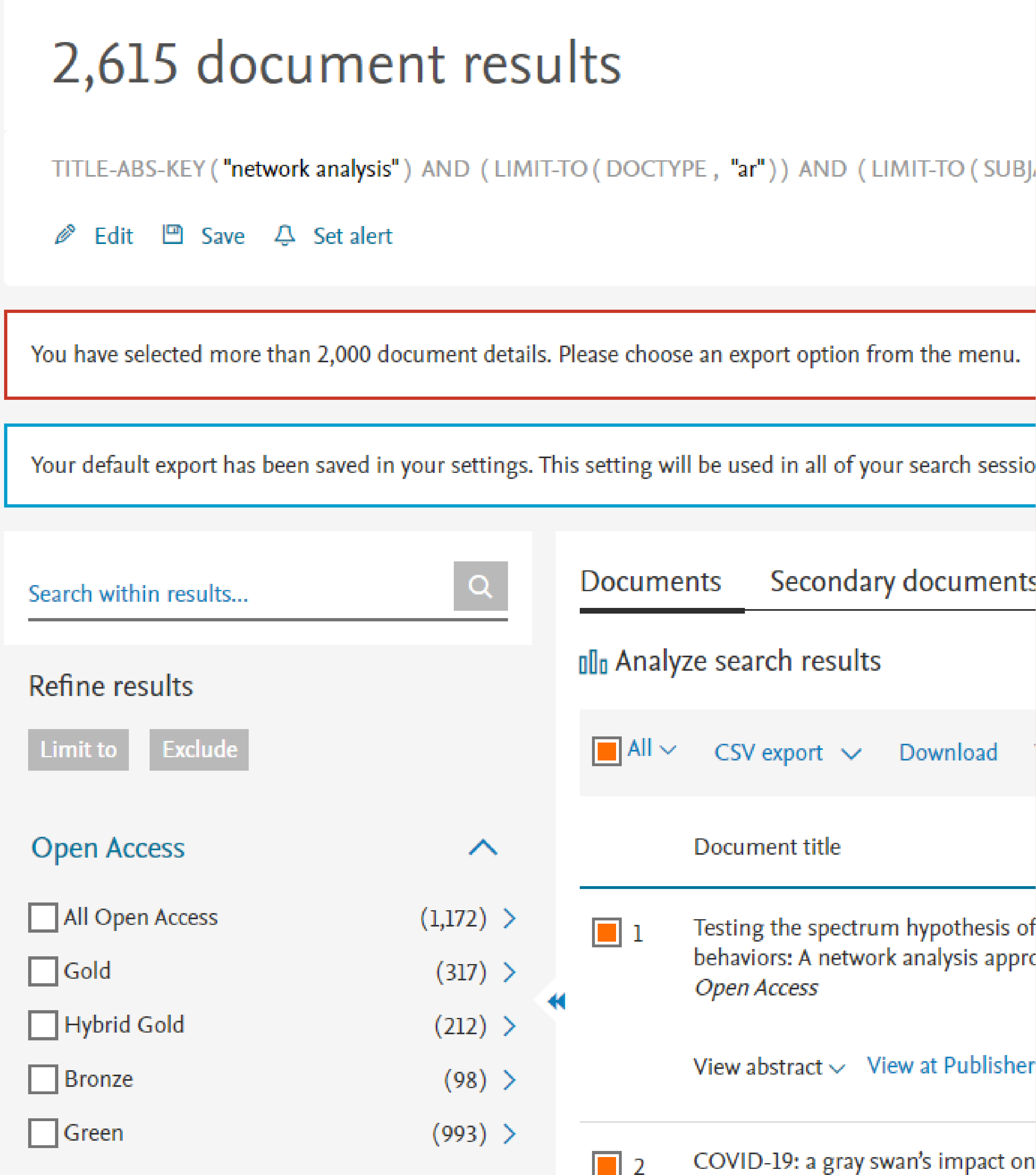
[1] INSERM U1018, CESP, APHP, Université Paris-Sud, UVSQ, Université Paris-Saclay, Villejuif, France, [2] IUT de Sceaux – Université Paris-Sud, Sceaux, France, [3] Laboratoire Interpsy – 2LPN (CEMA), Université de Lorraine, Nancy, France

Network Analysis is considered as a new method that challenges Latent Variable models in inferring psychological attributes. With Network Analysis, psychological attributes are derived from a complex system of components without the need to call on any latent variables. But the ontological status of psychological attributes is not adequately

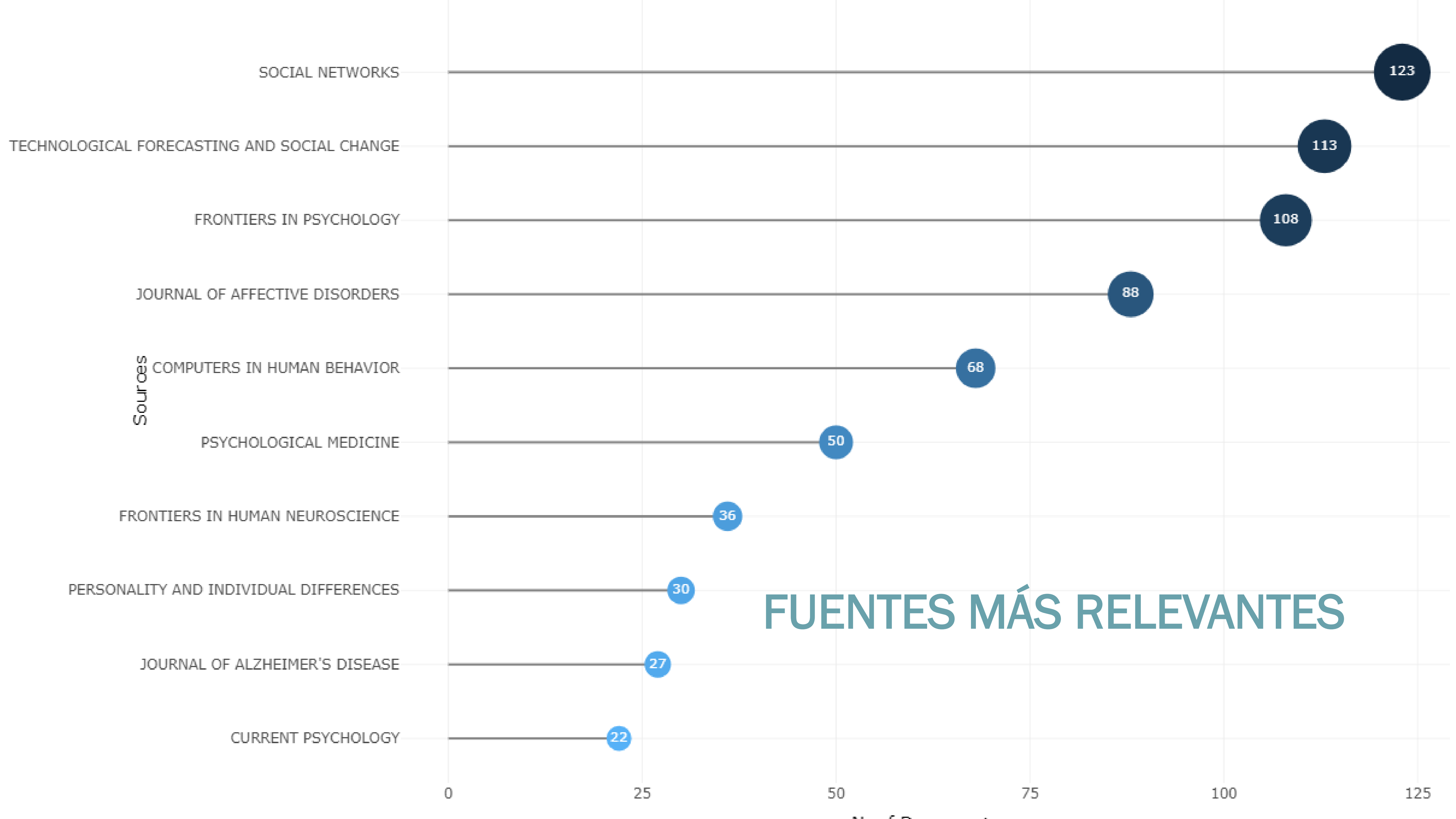
El análisis de redes parece poseer un interés real en la psicopatología (Bringmann et al., 2015 ; Fried et al., 2017). Pero más allá de los aspectos metodológicos, plantea una cuestión epistemológica más general para la psicología (Dalege et al., 2016 ; Borsboom, 2017). Con el Análisis de Redes, un atributo psicológico no se considera como una causa común subyacente que explica las manifestaciones perceptibles. Aquí, un atributo psicológico es un sistema complejo de componentes perceptibles[1] , es decir, un sistema en el que cada componente interactúa entre sí sin que estos componentes perceptibles estén vinculados a una causa común subyacente (Cramer et al., 2010 , 2012a ; Borsboom y Cramer, 2013 ; Bringmann et al., 2013 ; Schmittmann et al. al., 2013 ; De Schryver et al., 2015 ; Fried, 2015 ; McNally et al., 2015 ; Dalege et al., 2016). Abandonar las variables latentes plantea la cuestión de la ontología de los atributos psicológicos.

PANORAMA GENERAL DEL ANÁLISIS DE REDES

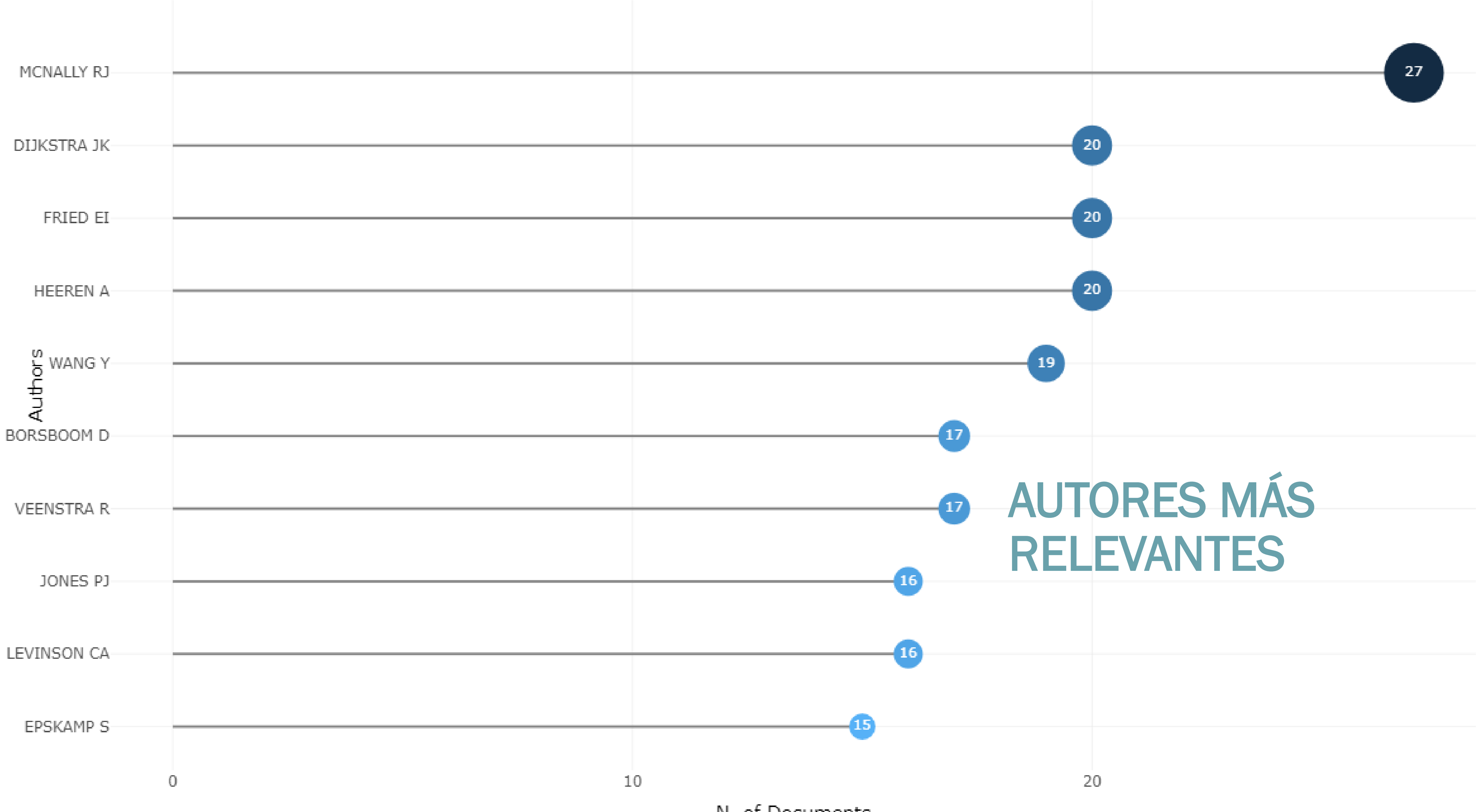
CUANTAS PUBLICACIONES ACERCA DE REDES HAY EN SCOPUS



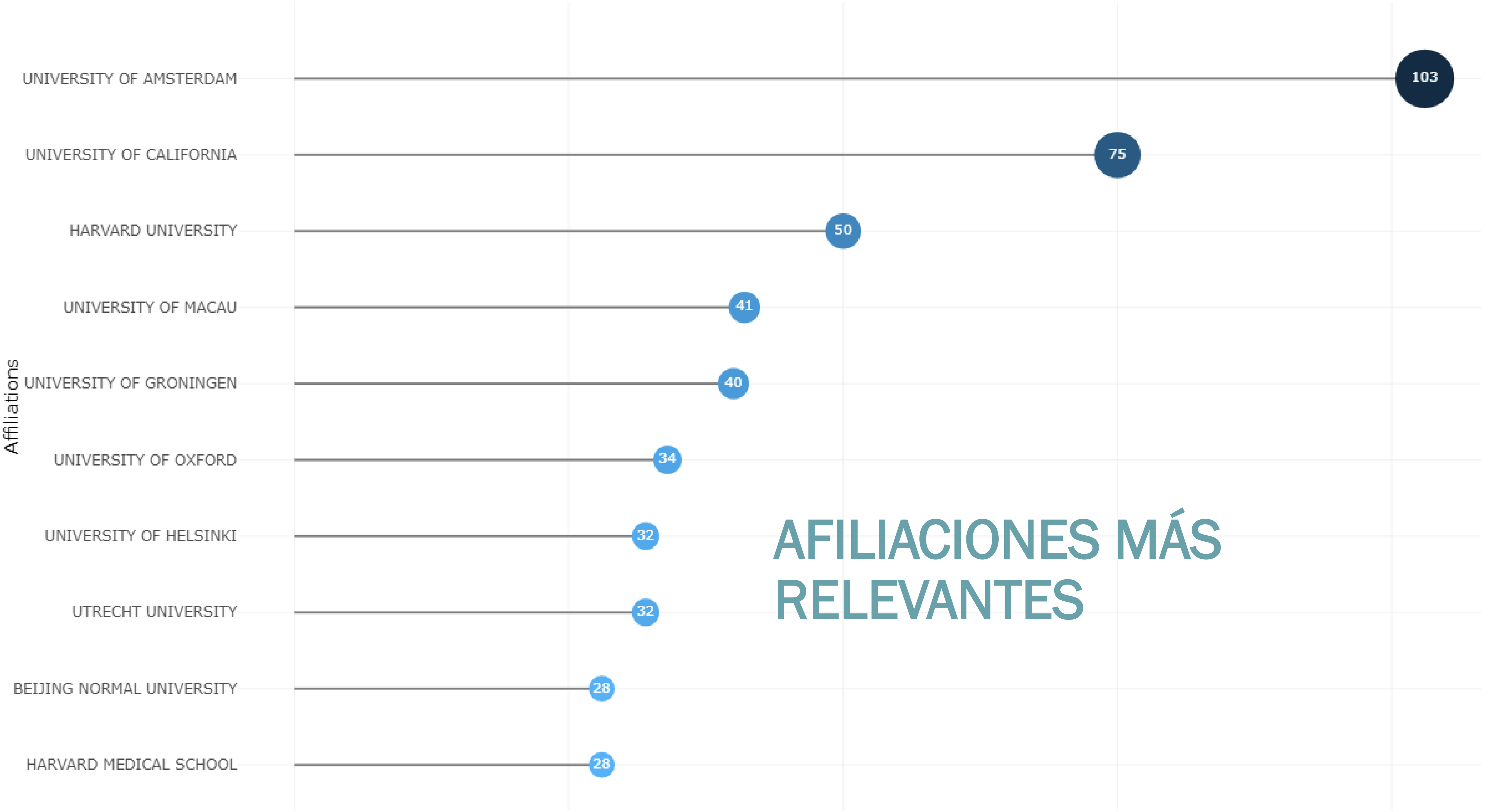
FUENTES MÁS RELEVANTES



AUTORES MÁS RELEVANTES

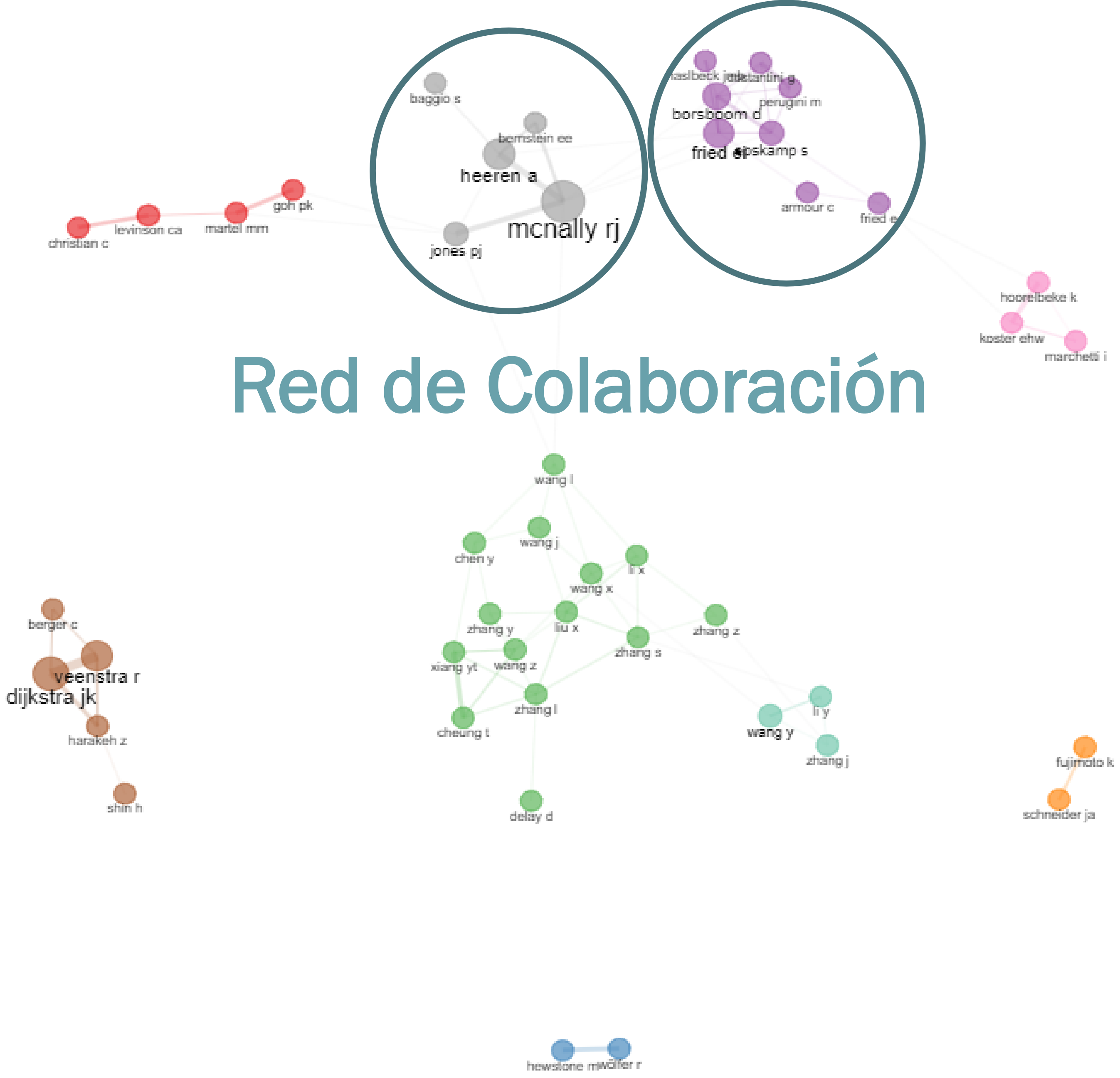


AFILIACIONES MÁS RELEVANTES



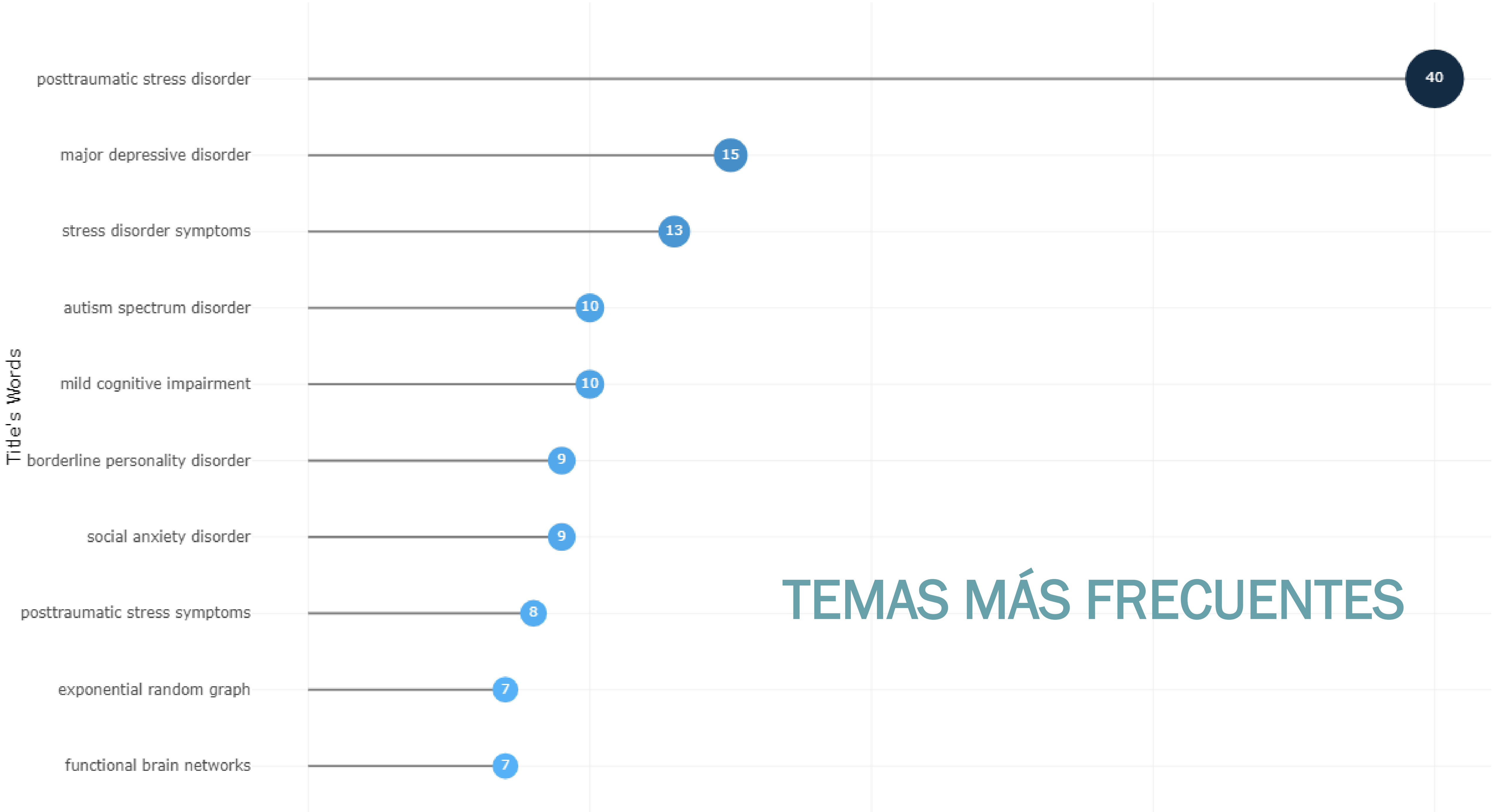
Edit

Red de Colaboración



REFERENCIAS MÁS CITADAS A NIVEL LOCAL

Document	DOI	Year	Global Citations	Title
EPSKAMP S, 2018, PSYCHOL METHODS	10.1037/met0000167	2018	564	A tutorial on regularized partial correlation networks
COSTANTINI G, 2015, J RES PERS	10.1016/j.jrp.2014.07.003	2015	372	State of the aRt personality research: A tutorial on network analysis of personality data in R
BEARD C, 2016, PSYCHOL MED	10.1017/S0033291716002300	2016	261	Network analysis of depression and anxiety symptom relationships in a psychiatric sample
ARMOUR C, 2017, J ANXIETY DISORD	10.1016/j.janxdis.2016.11.008	2017	161	A network analysis of DSM-5 posttraumatic stress disorder symptoms and correlates in U.S. military veterans
HASLBECK JMB, 2017, PSYCHOL MED	10.1017/S0033291717001258	2017	123	How predictable are symptoms in psychopathological networks? A reanalysis of 18 published datasets
BRINGMANN LF, 2015, PSYCHOL MED	10.1017/S0033291714001809	2015	190	Revealing the dynamic network structure of the Beck Depression Inventory-II
HASLBECK JMB, 2018, BEHAV RES METHODS	10.3758/s13428-017-0910-x	2018	126	How well do network models predict observations? On the importance of predictability in network models
COSTANTINI G, 2019, PERS INDIVID DIFFER	10.1016/j.paid.2017.06.011	2019	112	Stability and variability of personality networks. A tutorial on recent developments in network psychometrics
RODEBAUGH TL, 2018, J CONSULT CLIN PSYCHOL	10.1037/ccp0000336	2018	85	Does centrality in a cross-sectional network suggest intervention targets for social anxiety disorder?
HEEREN A, 2018, J AFFECTIVE DISORD	10.1016/j.jad.2017.12.003	2018	69	Mapping network connectivity among symptoms of social anxiety and comorbid depression in people with social anxiety disorder



TEMAS MÁS FRECUENTES

Red de co-citación

› Psychol Methods. 2018 Dec;23(4):617-634. doi: 10.1037/met0000167. Epub 2018 Mar 29.

A tutorial on regularized partial correlation networks

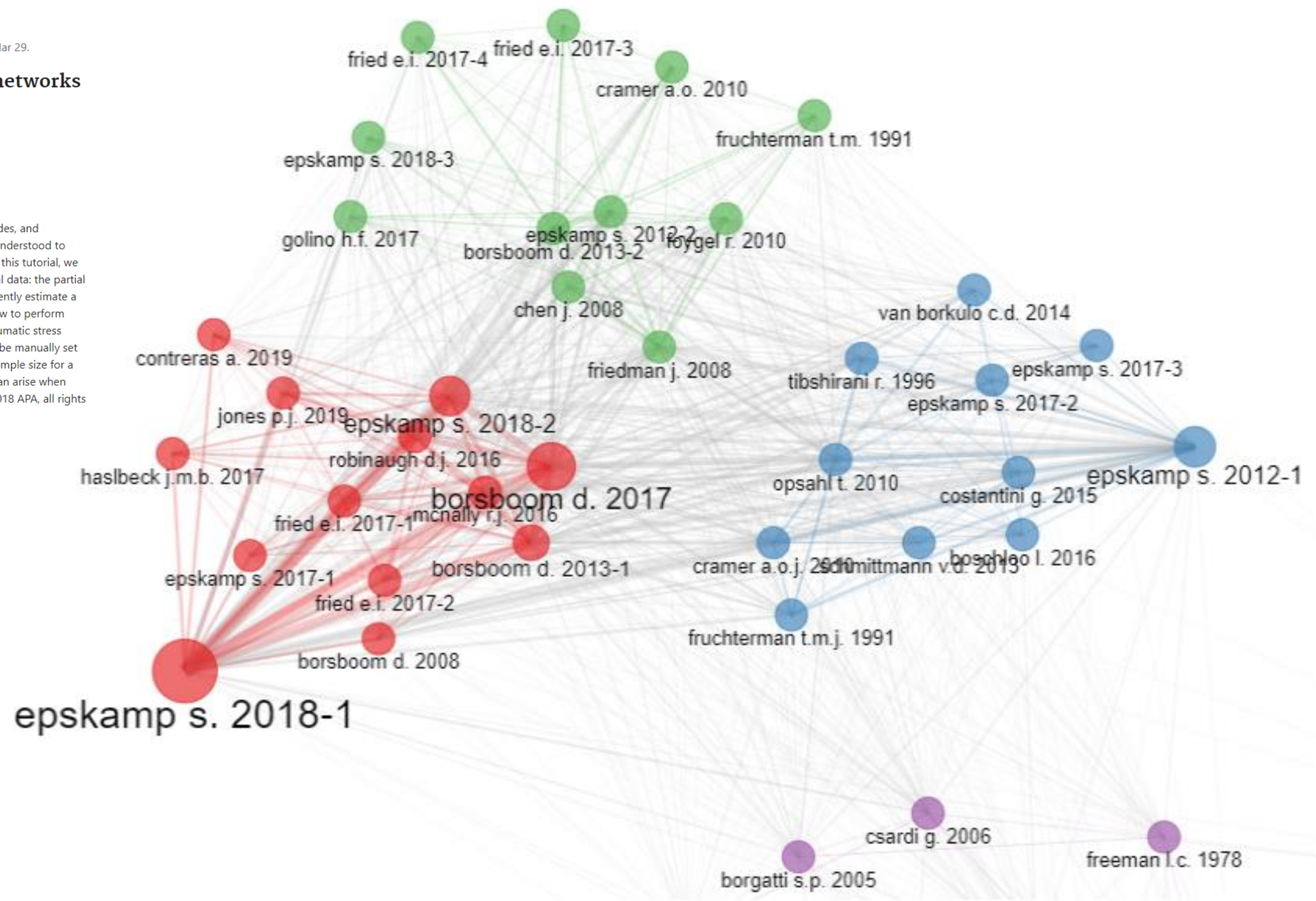
Sacha Epskamp [1], Eiko I Fried [1]

Affiliations + expand

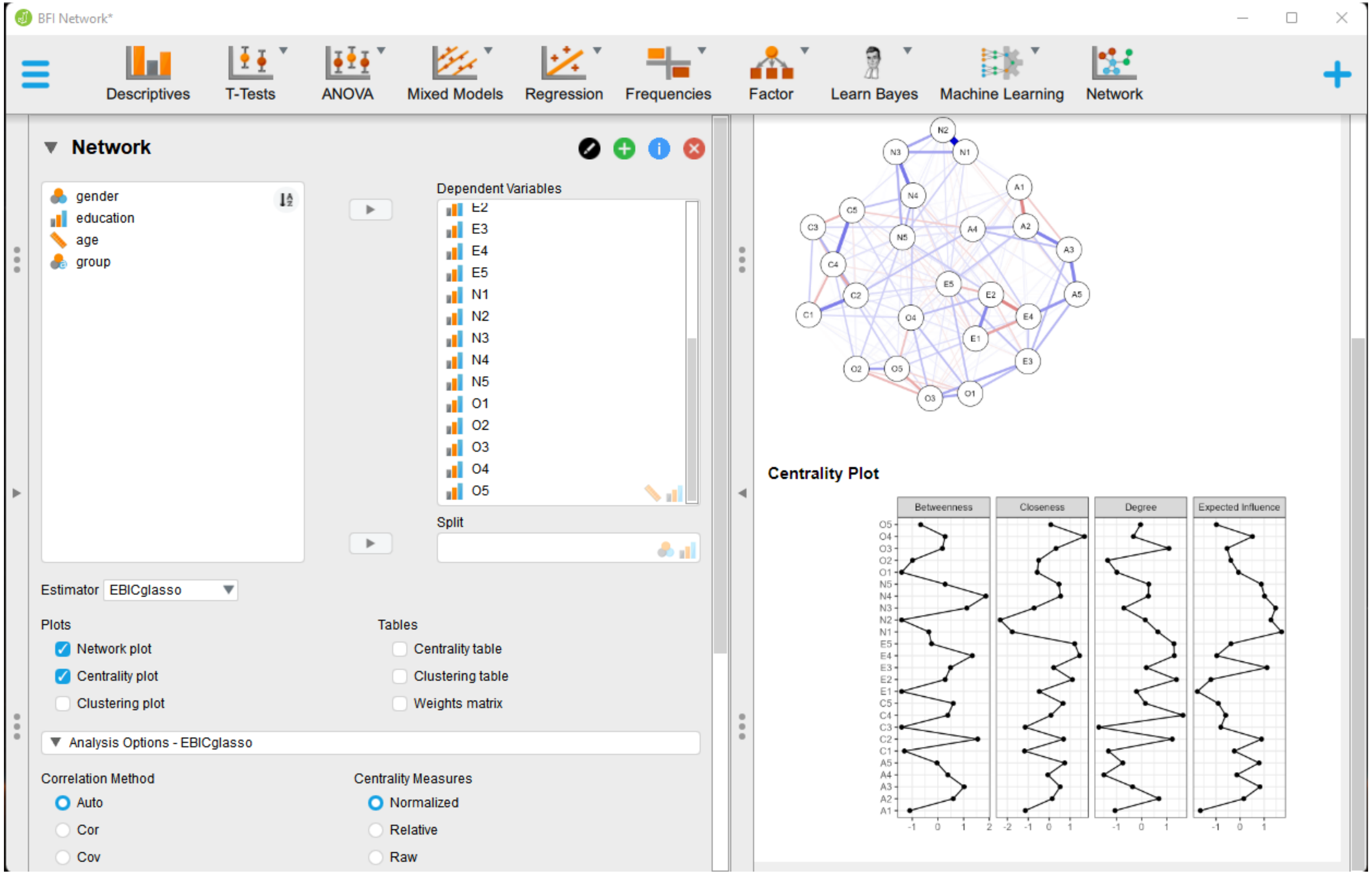
PMID: 29595293 DOI: 10.1037/met0000167

Abstract

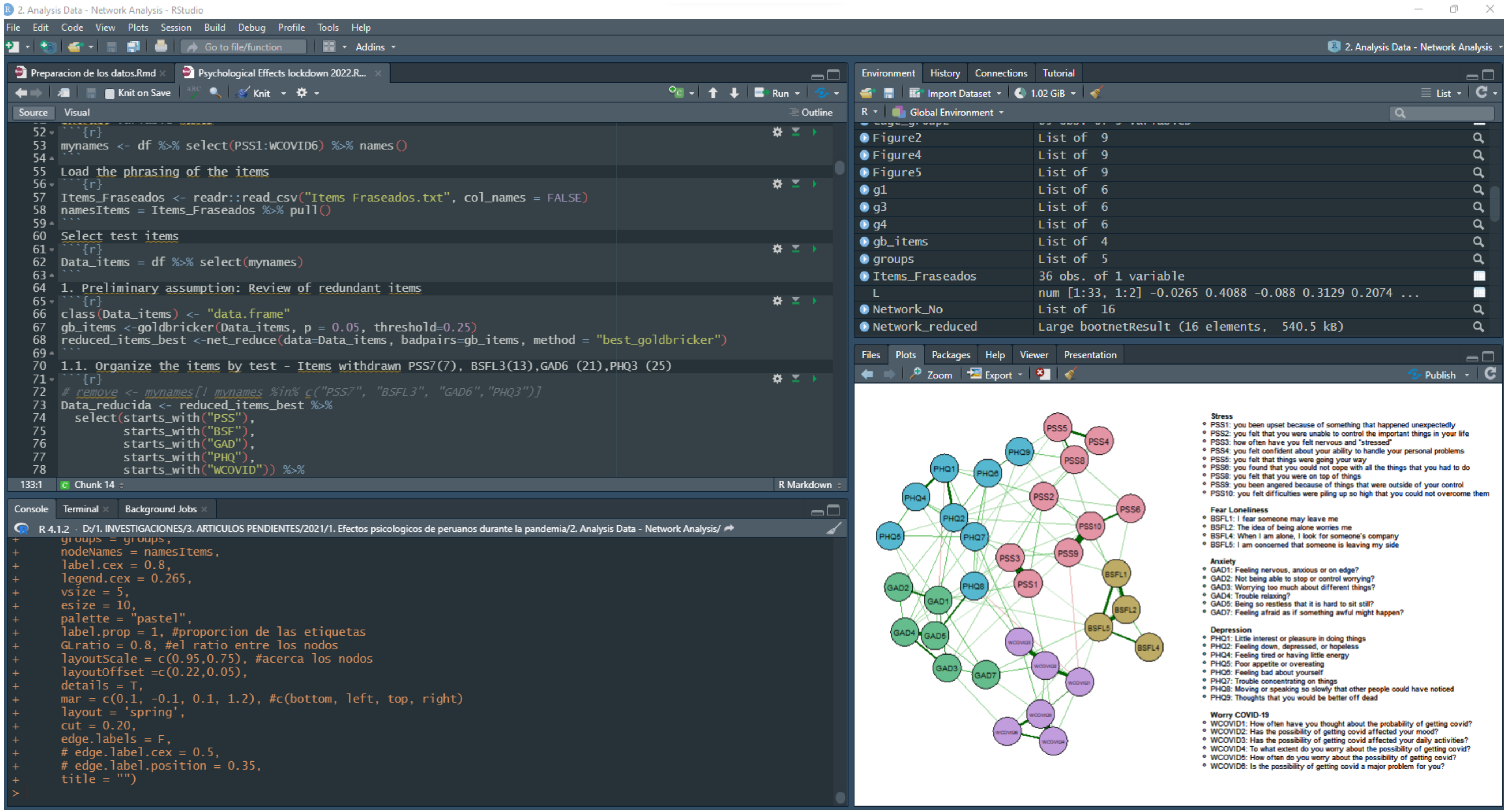
Recent years have seen an emergence of network modeling applied to moods, attitudes, and problems in the realm of psychology. In this framework, psychological variables are understood to directly affect each other rather than being caused by an unobserved latent entity. In this tutorial, we introduce the reader to estimating the most popular network model for psychological data: the partial correlation network. We describe how regularization techniques can be used to efficiently estimate a parsimonious and interpretable network structure in psychological data. We show how to perform these analyses in R and demonstrate the method in an empirical example on posttraumatic stress disorder data. In addition, we discuss the effect of the hyperparameter that needs to be manually set by the researcher, how to handle non-normal data, how to determine the required sample size for a network analysis, and provide a checklist with potential solutions for problems that can arise when estimating regularized partial correlation networks. (PsycINFO Database Record (c) 2018 APA, all rights reserved).



PROGRAMAS PARA EL ANÁLISIS DE REDES


BFI Network*
Descriptives
T-Tests
ANOVA
Mixed Models
Regression
Frequencies
Factor
Learn Bayes
Machine Learning
Network
Network
gender
education
age
group
Dependent Variables
E2
E3
E4
E5
N1
N2
N3
N4
N5
O1
O2
O3
O4
O5
Split
Estimator
EBICglasso
Plots
Network plot
Centrality plot
Clustering plot
Tables
Centrality table
Clustering table
Weights matrix
Analysis Options - EBICglasso
Correlation Method
Auto
Cor
Cov
Centrality Measures
Normalized
Relative
Raw
Centrality Plot
Betweenness
Closeness
Degree
Expected Influence

RStudio


2. Analysis Data - Network Analysis - RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Go to file/function
Addins
Preparacion de los datos.Rmd
Psychological Effects lockdown 2022.R...
Knit on Save
Knit
Run
Source Visual
Outline
mynames <- df %>% select(PSS1:WCOVID6) %>% names()
Load the phrasing of the items
Items_Fraseados <- readr::read_csv("Items Fraseados.txt", col_names = FALSE)
namesItems = Items_Fraseados %>% pull()
Select test items
Data_items = df %>% select(mynames)
1. Preliminary assumption: Review of redundant items
class(Data_items) <- "data.frame"
gb_items <-goldbricker(Data_items, p = 0.05, threshold=0.25)
reduced_items_best <-net_reduce(data=Data_items, badpairs=gb_items, method = "best_goldbricker")
1.1. Organize the items by test - Items withdrawn PSS7(7), BSFL3(13),GAD6 (21),PHQ3 (25)
# remove <- mynames[! mynames %in% c("PSS7", "BSFL3", "GAD6","PHQ3")]
Data_reducida <- reduced_items_best %>%
select(starts_with("PSS"),
starts_with("BSF"),
starts_with("GAD"),
starts_with("PHQ"),
starts_with("WCOVID")) %>%
133:1
Chunk 14
R Markdown
Console Terminal Background Jobs
R 4.1.2 · D:/1. INVESTIGACIONES/3. ARTICULOS PENDIENTES/2021/1. Efectos psicologicos de peruanos durante la pandemia/2. Analysis Data - Network Analysis/
nodeNames = namesItems,
label.cex = 0.8,
legend.cex = 0.265,
vsize = 5,
esize = 10,
palette = "pastel",
label.prop = 1, #proporcion de las etiquetas
GLratio = 0.8, #el ratio entre los nodos
layoutScale = c(0.95,0.75), #acerca los nodos
layoutOffset =c(0.22,0.05),
details = T,
mar = c(0.1, -0.1, 0.1, 1.2), #c(bottom, left, top, right)
layout = 'spring',
cut = 0.20,
edge.labels = F,
# edge.label.cex = 0.5,
# edge.label.position = 0.35,
title = "")
Environment History Connections Tutorial
Import Dataset
1.02 GiB
List
Global Environment
Figure2 List of 9
Figure4 List of 9
Figure5 List of 9
g1 List of 6
g3 List of 6
g4 List of 6
gb_items List of 4
groups List of 5
Items_Fraseados 36 obs. of 1 variable
L num [1:33, 1:2] -0.0265 0.4088 -0.088 0.3129 0.2074 ...
Network_No List of 16
Network_reduced Large bootnetResult (16 elements, 540.5 kB)
Files Plots Packages Help Viewer Presentation
Zoom
Export
Publish
Stress
PSS1: you been upset because of something that happened unexpectedly
PSS2: you felt that you were unable to control the important things in your life
PSS3: how often have you felt nervous and "stressed"
PSS4: you felt confident about your ability to handle your personal problems
PSS5: you felt that things were going your way
PSS6: you found that you could not cope with all the things that you had to do
PSS8: you felt that you were on top of things
PSS9: you been angered because of things that were outside of your control
PSS10: you felt difficulties were piling up so high that you could not overcome them
Fear Loneliness
BSFL1: I fear someone may leave me
BSFL2: The idea of being alone worries me
BSFL4: When I am alone, I look for someone's company
BSFL5: I am concerned that someone is leaving my side
Anxiety
GAD1: Feeling nervous, anxious or on edge?
GAD2: Not being able to stop or control worrying?
GAD3: Worrying too much about different things?
GAD4: Trouble relaxing?
GAD5: Being so restless that it is hard to sit still?
GAD7: Feeling afraid as if something awful might happen?
Depression
PHQ1: Little interest or pleasure in doing things
PHQ2: Feeling down, depressed, or hopeless
PHQ4: Feeling tired or having little energy
PHQ5: Poor appetite or overeating
PHQ6: Feeling bad about yourself
PHQ7: Trouble concentrating on things
PHQ8: Moving or speaking so slowly that other people could have noticed
PHQ9: Thoughts that you would be better off dead
Worry COVID-19
WCOVID1: How often have you thought about the probability of getting covid?
WCOVID2: Has the possibility of getting covid affected your mood?
WCOVID3: Has the possibility of getting covid affected your daily activities?
WCOVID4: To what extent do you worry about the possibility of getting covid?
WCOVID5: How often do you worry about the possibility of getting covid?
WCOVID6: Is the possibility of getting covid a major problem for you?

ACERCA DE LA TÉCNICA

Estimadores

Isvoranu, A., & Epskamp, S. (2021, January 26). Which Estimation Method to Choose in Network Psychometrics? Deriving Guidelines for Applied Researchers. https://doi.org/10.31234/osf.io/mbycn

Table 1. Estimation methods used in the simulation study

Method	R package	Functions	Settings	Ordinal/Categorical
EBICglasso	*qgraph*	EBICglasso	$\gamma = 0.5$	polychoric correlations as input
ggmModSelect	*qgraph*	ggmModSelect	stepwise = TRUE	polychoric correlations as input
ggmModSelect_stepwise	*qgraph*	ggmModSelect	stepwise = FALSE	polychoric correlations as input
FIML_prune	*psychonetrics*	ggm %>% prune	$\alpha = 0.01$	N/A
FIML_prune_modelsearch	*psychonetrics*	ggm %>% prune %>% modelsearch	$\alpha = 0.01$	N/A
WLS_prune	*psychonetrics*	ggm %>% prune	$\alpha = 0.01$	three-stage WLS (Muthén, 1984)
WLS_prune_stepup	*psychonetrics*	ggm %>% prune %>% stepup	$\alpha = 0.01$	three-stage WLS (Muthén, 1984)
mgm_CV	*mgm*	mgm	Selection via 10-fold cross-validation	variables treated categorical
mgm_EBIC	*mgm*	mgm	Selection via EBC ($\gamma = 0.5$)	variables treated categorical
BGGM_explore	BGGM	explore %>% select	BF cutoff = 3	variables treated as ordinal
BGGM_estimate	BGGM	estimate %>% select	95% credibility interval	variables treated as ordinal
GGM_bootstrap	GMMnonreg	GGM_bootstrap	$\alpha = 0.01$	N/A
GGM_regression	GMMnonreg	GGM_regression	BIC optimization	N/A

Network Estimation for Applied Researchers Isvoranu & Epskamp, 2021

Which Estimation Method to Choose in Network Psychometrics? Deriving Guidelines for Applied Researchers

Adela-Maria Isvoranu[1] & Sacha Epskamp[1,2]

[1]Department of Psychology, Psychological Methods, University of Amsterdam, Amsterdam, The Netherlands

[2]Centre for Urban Mental Health, University of Amsterdam, Amsterdam, the Netherlands

1

Con un tamaño de muestra bajo (n = 300), si el objetivo es descubrir una estructura de red que se asemeje a una red verdadera y descubrir las **edge más fuertes**, deben preferirse los estimadores **regularizados**; sin embargo, si el objetivo es centrarse en el descubrimiento individual de cada edge, deben evitarse los estimadores regularizados.

2

Cuando la expectativa era que existieran muchas **edge puente** y menos fuertes, lo que suele ser el caso de las estructuras de red más densas, encontramos que los **estimadores ggmModSelect (stepwise = TRUE, gamma = 0)** y mgm (EBIC; gamma =0,25) eran los que mejor funcionaban.

3

Al investigar la centralidad, con un tamaño de muestra bajo pero común en las ciencias sociales (n = 600), el uso del estimador EBICglasso o de los estimadores escalonados no regularizados **ggmModSelect dio la mayor confianza para interpretar los índices de centralidad**.

Network Estimation for Applied Researchers Isvoranu & Epskamp, 2021

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4

La fuerza como medida de centralidad mostró los mejores resultados, seguida de la cercanía. Cabe destacar que, en el caso de los datos **categóricos ordenados** de forma sesgada, hay que tener más **cuidado al interpretar las medidas de centralidad.**

5

Para el caso de la betweenness, nuestros resultados mostraron que las propiedades globales de la betweenness son probablemente difíciles de estimar, y como tal **no recomendaríamos el uso e interpretación de la betweenness en** los estudios de redes.

Which Estimation Method to Choose in Network Psychometrics? Deriving Guidelines for Applied Researchers

Adela-Maria Isvoranu[1] & Sacha Epskamp[1,2]

[1]Department of Psychology, Psychological Methods, University of Amsterdam, Amsterdam, The Netherlands

[2]Centre for Urban Mental Health, University of Amsterdam, Amsterdam, the Netherlands

Finally, when data were Gaussian, applying a non-paranormal on rank-transformation (Spearman correlations as input) did not impact performance of the estimators. When data were skewed, a non-paranormal or rank-transformation improved the performance in the majority of estimators across most datasets. Since the latter worked well on all data types and comparably to the more complicated nonparanormal transformation, we recommend Spearman correlations as input in the case of skewed data. Surprisingly, for ordered categorical data, data transformation did not make a substantial difference.

What do centrality measures measure in psychological networks?

Laura F. Bringmann[1,6], Timon Elmer[2], Sacha Epskamp[3], Robert W. Krause[4], David Schoch[5], Marieke Wichers[6], Johanna Wigman[6], Evelien Snippe[6]

[1] Department of Psychometrics and Statistics, Heymans Institute, University of Groningen, Netherlands

[2] Chair of Social Networks, Department of Humanities, Social and Political Sciences, ETH Zürich, Switzerland

[3] Department of Psychological Methods, University of Amsterdam, Netherlands

[4] Department of Sociology/ICS, University of Groningen, Netherlands

[5] Department of Sociology, University of Manchester, UK

[6] Interdisciplinary Center Psychopathology and Emotion Regulation (ICPE), Department of Psychiatry (UCP), University of Groningen, University Medical Center Groningen, Netherlands

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Phone: +31 50 36 39737

Pagina 17.

- Sin embargo, es cuestionable que la idea de flujo tenga algún sentido en las redes psicológicas. Originalmente, las redes de flujo se conceptualizaban como redes dirigidas que describían procesos de transporte, como el tráfico o los fluidos en las tuberías (Newman, 2010).

Pagina 18.

- Esto significa que la medida sólo es aplicable a redes totalmente conectadas (cuando todos los nodos pueden ser alcanzados por los demás nodos; Wasserman y Faust, 1994, p. 203).

Pagina 19.

- Por lo tanto, aunque se utilizan ampliamente en las redes sociales, la mayoría de las veces los índices de betweenness y closeness no son adecuados para detectar los nodos centrales en absoluto (Borgatti, 2005).

- Y lo que es más importante, no está claro qué entidad de una red de síntomas o de afectos seguiría un camino en absoluto, ya que estas redes se refieren a las fuerzas de conexión entre los síntomas y no a la transmisión de algo de un síntoma a otro.

- Lo que se añade a este enigma es que en las redes psicológicas las aristas son a menudo negativas, mientras que degree, closeness, y betweenness se desarrollaron teniendo en cuenta la distancia o la longitud de los caminos, y la longitud no puede ser negativa

Multivariate Behav Res. Author manuscript; available in PMC 2022 Mar 1.
Published in final edited form as:
Multivariate Behav Res. 2021 Mar-Apr; 56(2): 199–223.
Published online 2019 Aug 12. doi: 10.1080/00273171.2019.1640103
PMCID: PMC7012663
NIHMSID: NIHMS1534037
PMID: 31401872

Problems with centrality measures in psychopathology symptom networks: Why network psychometrics cannot escape psychometric theory

Michael N. Hallquist, Aidan G. C. Wright, and Peter C. M. Molenaar

Associated Data

▸ Supplementary Materials

Table 1.

Correspondence between nodal centrality statistics and fitted factor loadings

Model	M r with strength (SD_{bw}, SD_{wi})	M r with closeness (SD_{bw}, SD_{wi})	M r with betweenness (SD_{bw}, SD_{wi})
One-factor CFA	0.98 (.005, .01)	0.94 (.01, .03)	0.74 (.05, .13)
Two-factor CFA, Orthogonal	.98 (.007, .01)	.42 (.06, .31)	0.37 (.08, .27)
Two-factor CFA, Correlated	0.97 (.007, .01)	.51 (.07, .27)	.44 (.07, .25)
Three-factor CFA, Orthogonal	0.98 (.007, .01)	.42 (.06, .31)	.31 (.07, .28)
Three-factor CFA, Correlated	0.97 (.009, .01)	.55 (.06, .26)	.41 (.06, .26)

Psychol Methods. 2018 Dec;23(4):617-634. doi: 10.1037/met0000167. Epub 2018 Mar 29.

A tutorial on regularized partial correlation networks

Sacha Epskamp [1], Eiko I Fried [1]

Affiliations + expand

PMID: 29595293 DOI: 10.1037/met0000167

Abstract

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Pagina 2

La regularización consiste en estimar un modelo estadístico con una penalización adicional por la complejidad del modelo. Al hacerlo, el modelo que se estima es disperso: se estima que muchos parámetros son exactamente cero.
Al estimar las redes, *esto significa que los bordes que probablemente sean espurios se eliminan del modelo*, lo que lleva a redes más sencillas de interpretar.

EATING DISORDERS

ORIGINAL ARTICLE

Social anxiety and eating disorder comorbidity and underlying vulnerabilities: Using network analysis to conceptualize comorbidity

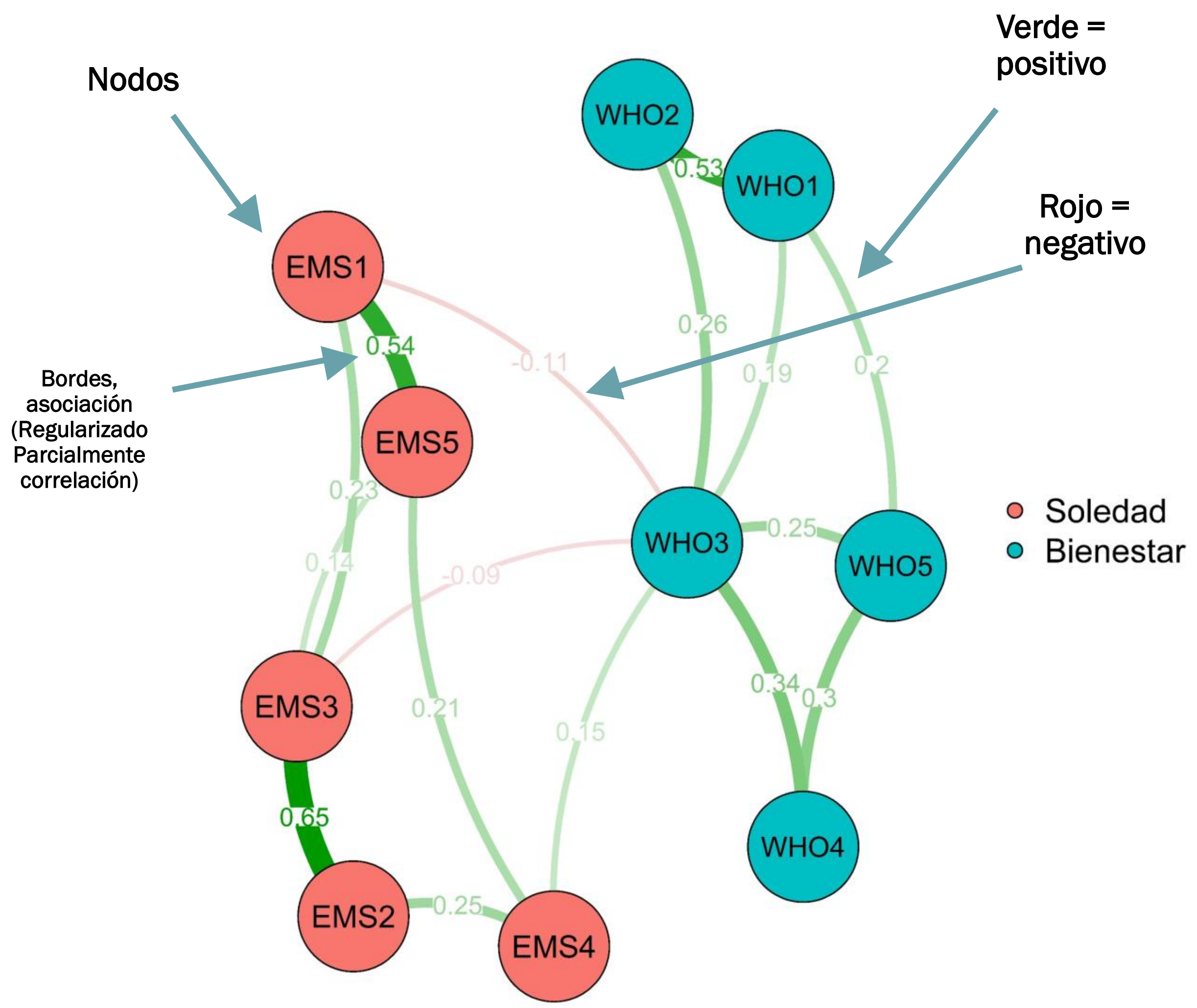
Cheri A. Levinson[1] | Leigh C. Brosof[1] | Irina Vanzhula[1] | Caroline Christian[1] | Payton Jones[2] | Thomas L. Rodebaugh[3] | Julia K. Langer[3] | Emily K. White[4] | Cortney Warren[5] | Justin W. Weeks[6] | Andrew Menatti[6] | Michelle H. Lim[3] | Katya C. Fernandez[3]

goldbricker

Usage

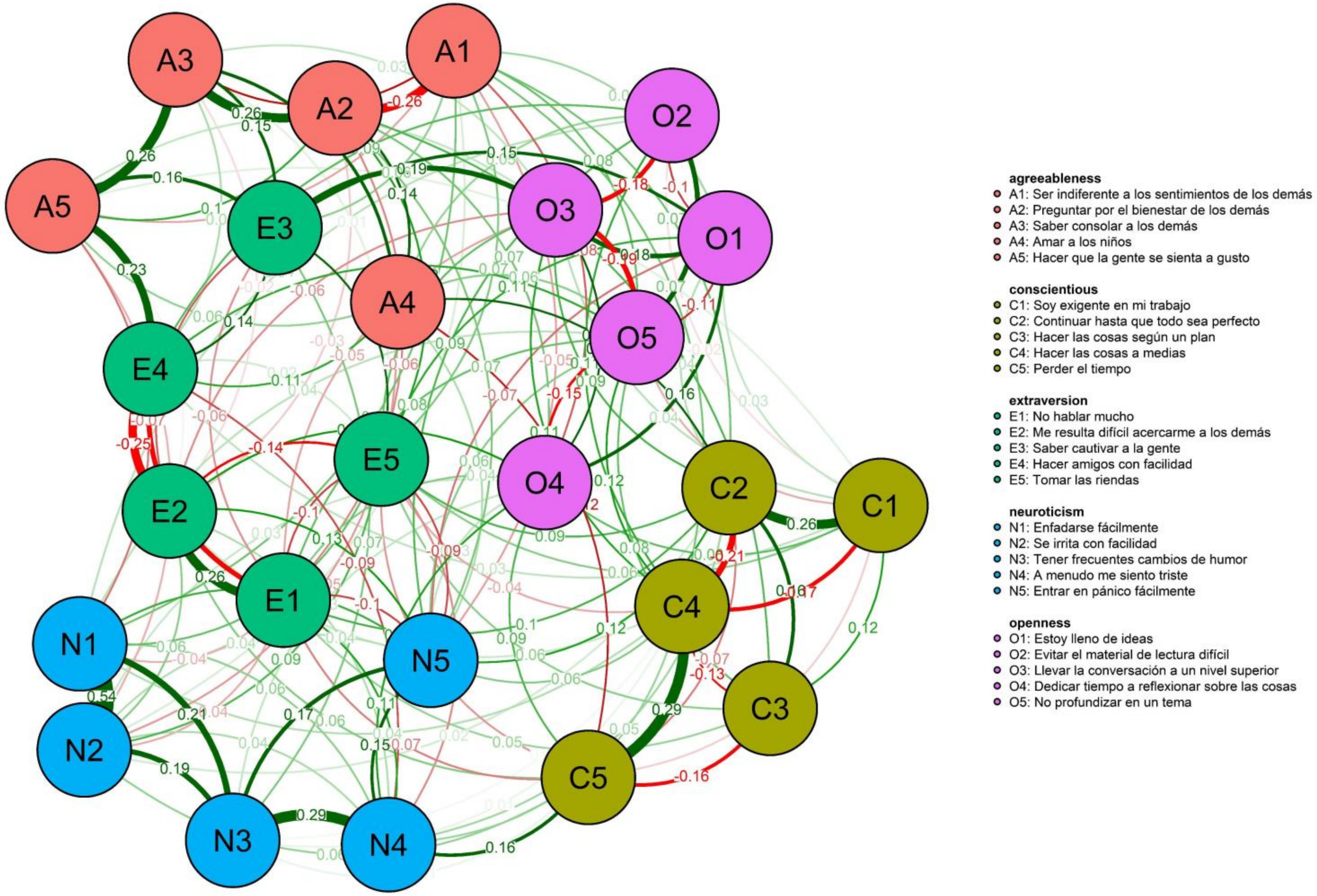
```
goldbricker(
  data,
  p = 0.05,
  method = "hittner2003",
  threshold = 0.25,
  corMin = 0.5,
  progressbar = TRUE
)
```

INTERPRETACIÓN DE LAS REDES



Nodos
Verde = positivo
Rojo = negativo
Bordes, asociación (Regularizado Parcialmente correlación)
EMS1
EMS2
EMS3
EMS4
EMS5
WHO1
WHO2
WHO3
WHO4
WHO5
0.54
0.65
0.25
0.23
0.14
0.21
-0.11
-0.09
0.15
0.53
0.26
0.19
0.2
0.25
0.34
0.3
Soledad
Bienestar

Fruchterman–Reingold algorithm (*spring* command)



PROCEDIMIENTO DE ANÁLISIS

Procedimiento de análisis

- Network estimation
- Computing centrality índices
- Edge-weight accuracy
- Centrality stability

Preparación de los datos

```r
#librerias
library("bootnet")
library("psych")
library("dplyr")
library("qgraph")
```

```r
# Organizar los grupos para poder generar el grafico

groups <- structure(list(`agreeableness` = c(1:5),
                         `conscientious` = c(6:10),
                         `extraversion` = c(11:15),
                         `neuroticism` = c(16:20),
                         `openness` = c(21:25)),
                    Names = c("agreeableness",
                              "conscientious",
                              "extraversion",
                              "neuroticism",
                              "openness"))
```

```r
#Insertar el fraseo de los ítems

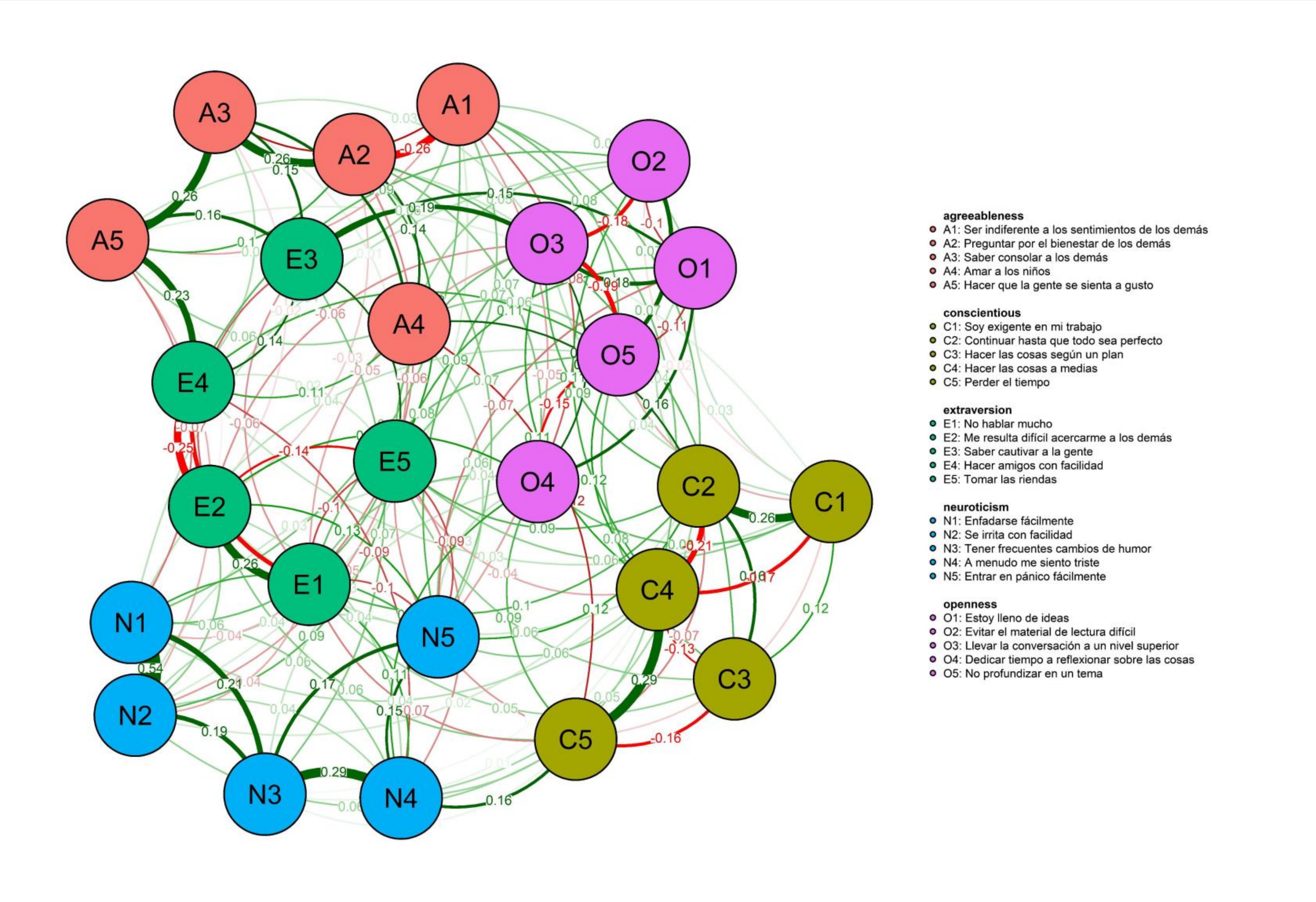
items <- c(
  "Ser indiferente a los sentimientos de los demás",
  "Preguntar por el bienestar de los demás",
  "Saber consolar a los demás",
  "Amar a los niños",
  "Hacer que la gente se sienta a gusto",
  "Soy exigente en mi trabajo",
  "Continuar hasta que todo sea perfecto",
  "Hacer las cosas según un plan",
  "Hacer las cosas a medias",
  "Perder el tiempo",
  "No hablar mucho",
  "Me resulta difícil acercarme a los demás",
  "Saber cautivar a la gente",
  "Hacer amigos con facilidad",
  "Tomar las riendas",
  "Enfadarse fácilmente",
  "Se irrita con facilidad",
  "Tener frecuentes cambios de humor",
  "A menudo me siento triste",
  "Entrar en pánico fácilmente",
  "Estoy lleno de ideas",
  "Evitar el material de lectura difícil",
  "Llevar la conversación a un nivel superior",
  "Dedicar tiempo a reflexionar sobre las cosas",
  "No profundizar en un tema")
```

Network estimation

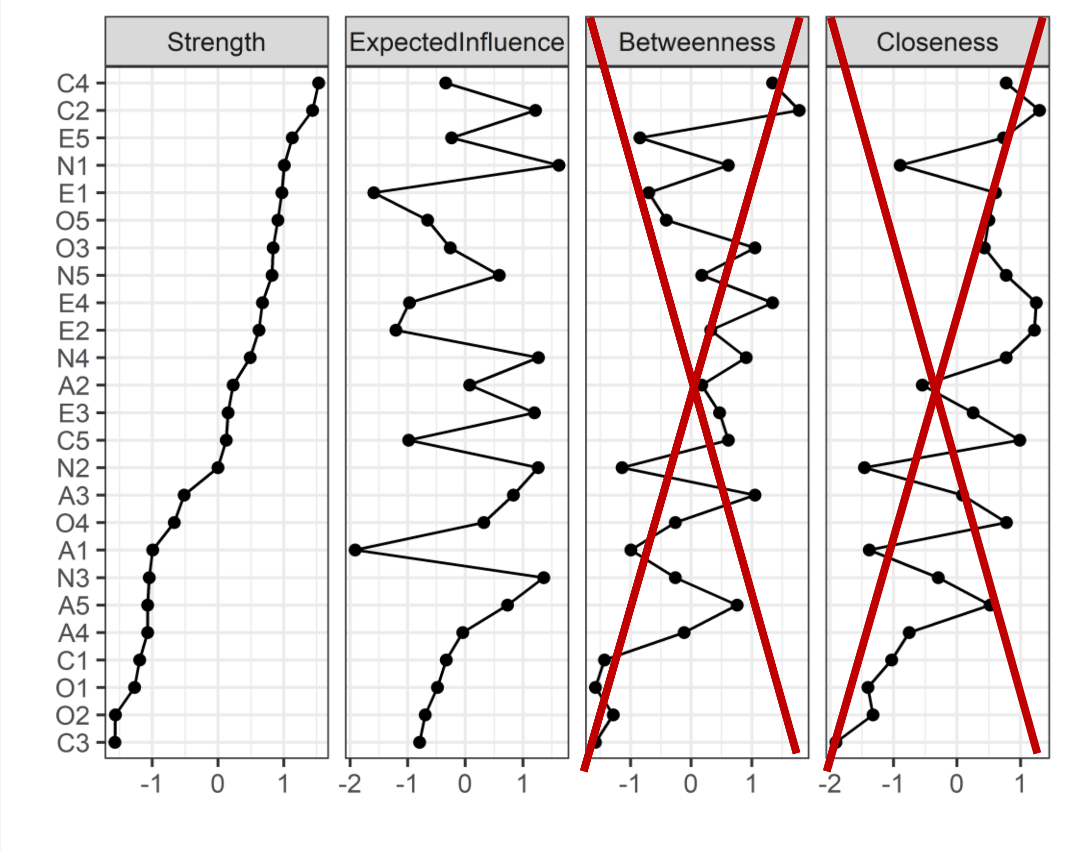
```
network     <- estimateNetwork(bfi[,1:25] %>% na.omit(),
                                default = "ggmModSelect",
                                stepwise = TRUE,
                                tuning = 0,
                                corMethod = "spearman")
```

plot

- ```
  g1 <- qgraph(network$graph,
               groups = groups,
               nodeNames = items,
               curveAll = 2,
               palette = "ggplot2",
               layout = 'spring',
               edge.labels = T,
               legend.cex = 0.25,
               legend = T,
               edge.label.cex = 0.5)
  ```

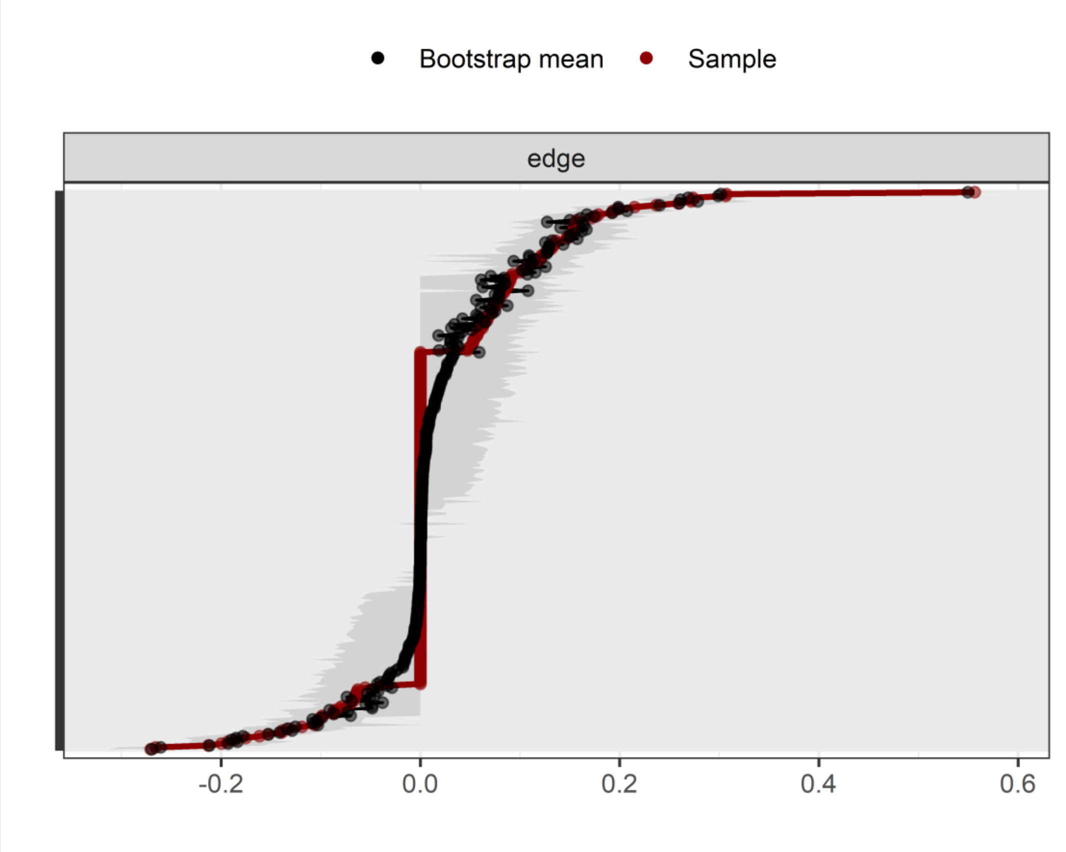

  ```

Computing centrality índices



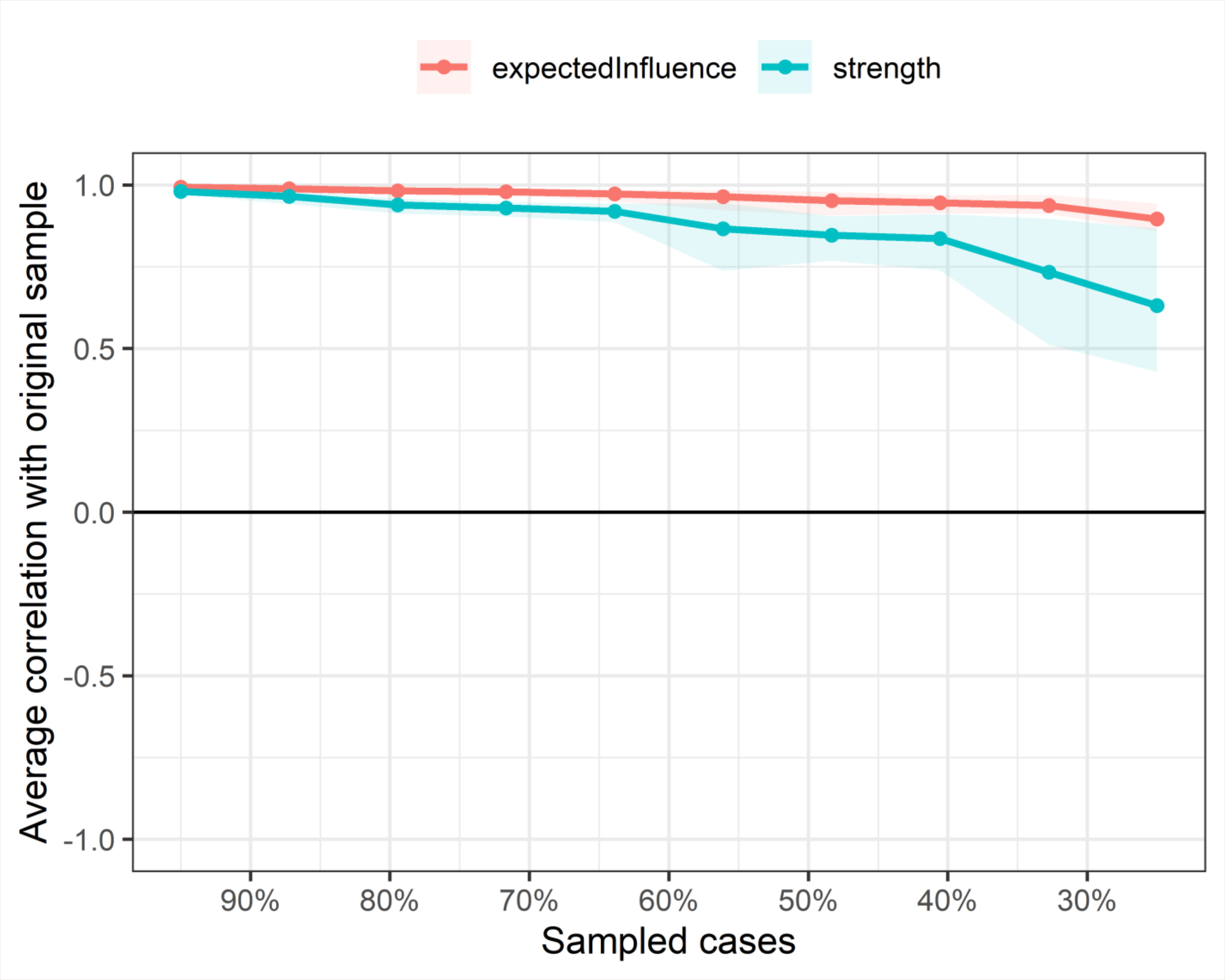

```
centralityPlot(network,
        include = c("Strength","ExpectedInfluence","Betweenness","Closeness"),
        orderBy ="Strength", scale = c("z-scores"))
```

Edge-weight accuracy




```
boot1 <- bootnet(network, nBoots = 100,
nCores = 12)

# Plot results:
plot(boot1, labels = FALSE, order = "sample")
```



Centrality stability

```
boot2 <- bootnet(network,
             nBoots = 100,
             type = "case",
             nCores = 12,
             statistics = c('strength',
'ExpectedInfluence'))
plot(boot2, 'all')
```

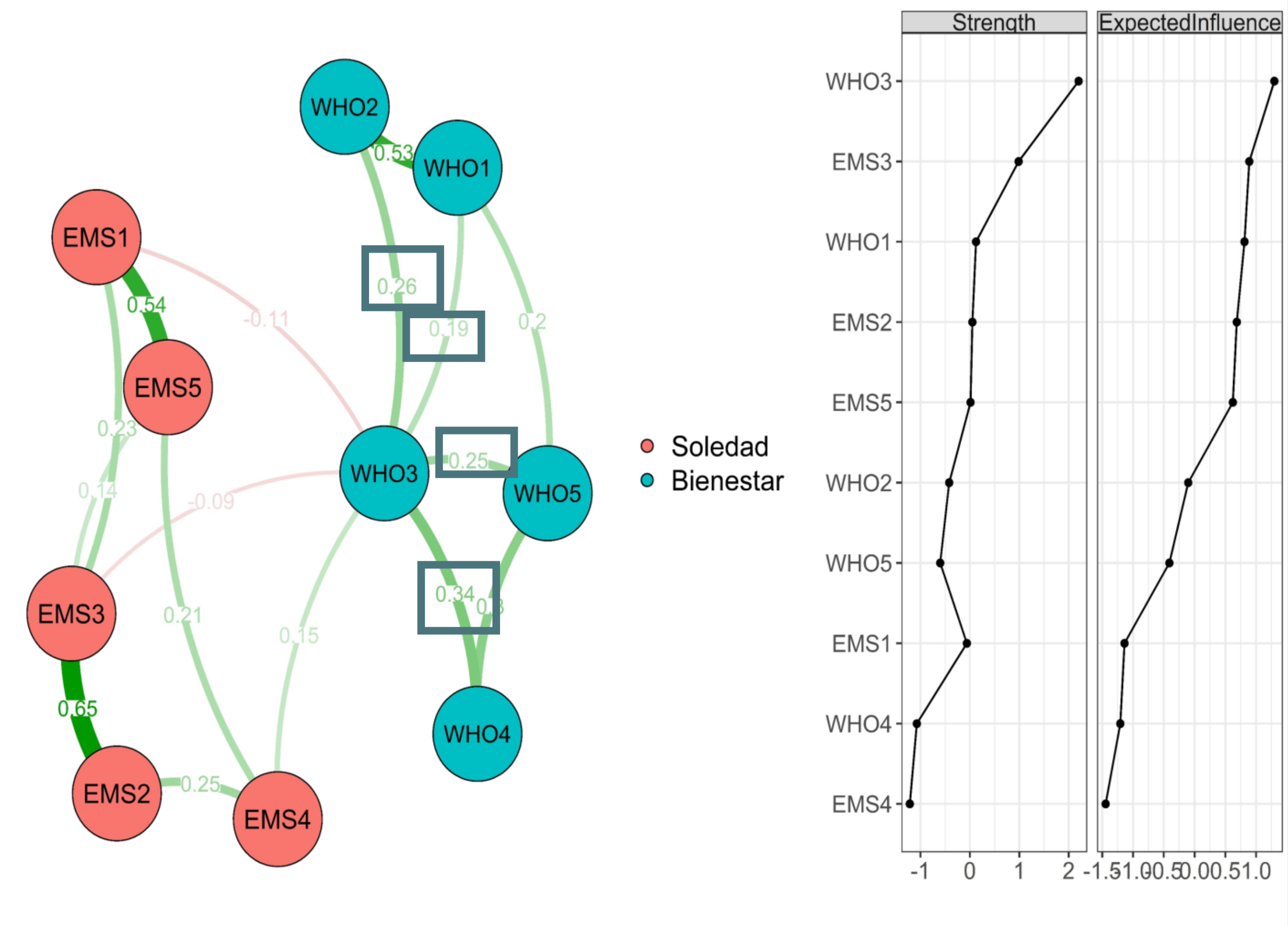
Índices Centralidad

Fuerza = la suma de los pesos absolutos de las aristas entre un nodo focal y todos los demás otros nodos a los que está conectado en la red.

$$\text{Strength centrality} = |r_1| + |-r_2| + |r_3| + |r_4| + |r_5|$$

Influencia esperada = suma de los pesos de las aristas(tiene en cuenta las aristas negativas)

$$\text{Expected influence} = r_1 + (-r_2) + r_3 + r_4 + r_5$$



Coeficiente de estabilidad (CS)

```
corStability(boot2)
## === Correlation Stability Analysis ===
##
## Sampling levels tested:
##    nPerson Drop%  n
## 1      609  75.0 10
## 2      798  67.2 10
## 3      988  59.4 13
## 4     1177  51.7 10
## 5     1367  43.9 16
## 6     1556  36.1  6
## 7     1746  28.3  5
## 8     1935  20.6 12
## 9     2125  12.8 10
## 10    2314   5.0  8
##
## Maximum drop proportions to retain correlation of 0.7 in at least 95% of the samples:
##
## expectedInfluence: 0.75 (CS-coefficient is highest level tested)
##   - For more accuracy, run bootnet(..., caseMin = 0.672, caseMax = 1)
##
## strength: 0.594
##   - For more accuracy, run bootnet(..., caseMin = 0.517, caseMax = 0.672)
##
## Accuracy can also be increased by increasing both 'nBoots' and 'caseN'.
```

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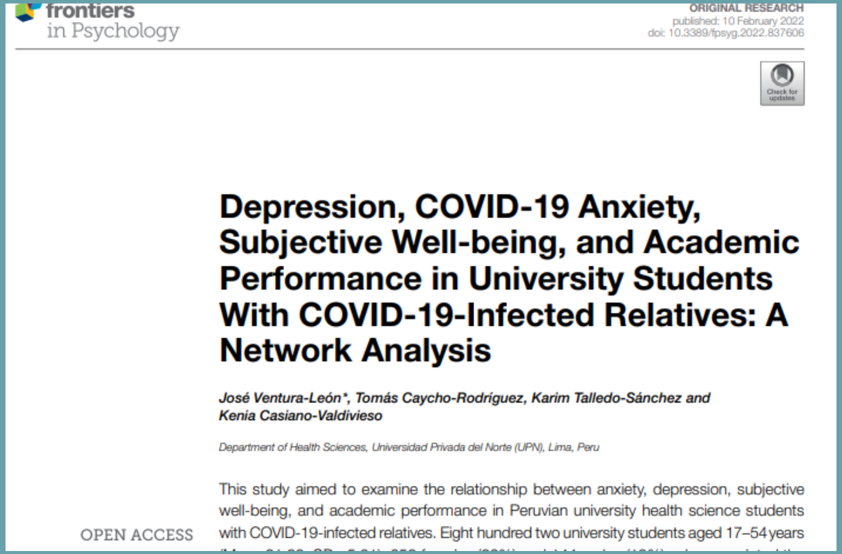
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Depression, COVID-19 Anxiety, Subjective Well-being, and Academic Performance in University Students With COVID-19-Infected Relatives: A Network Analysis

José Ventura-León, Tomás Caycho-Rodríguez, Karim Talledo-Sánchez and Kenia Casiano-Valdivieso*

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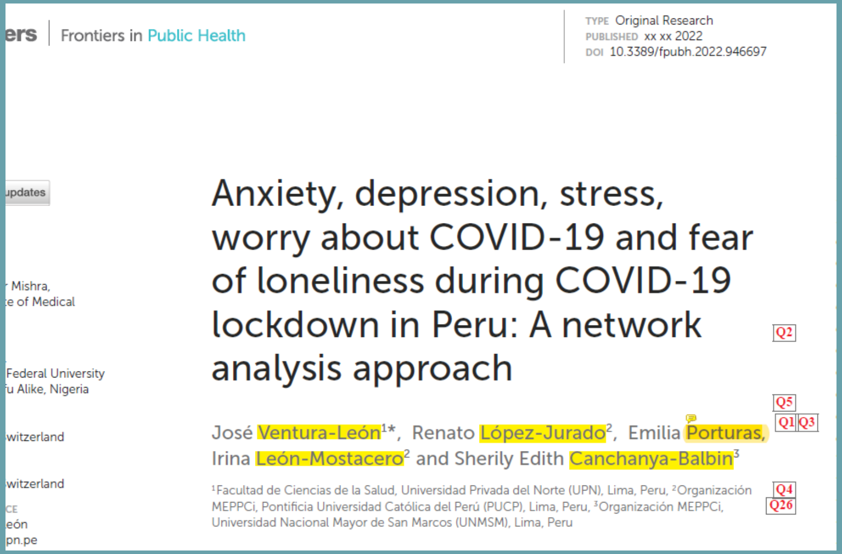
OPEN ACCESS

This study aimed to examine the relationship between anxiety, depression, subjective well-being, and academic performance in Peruvian university health science students with COVID-19-infected relatives. Eight hundred two university students aged 17–54 years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Anxiety, depression, stress, worry about COVID-19 and fear of loneliness during COVID-19 lockdown in Peru: A network analysis approach

Q2

Q5
Q1 Q3

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Q4
Q26

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