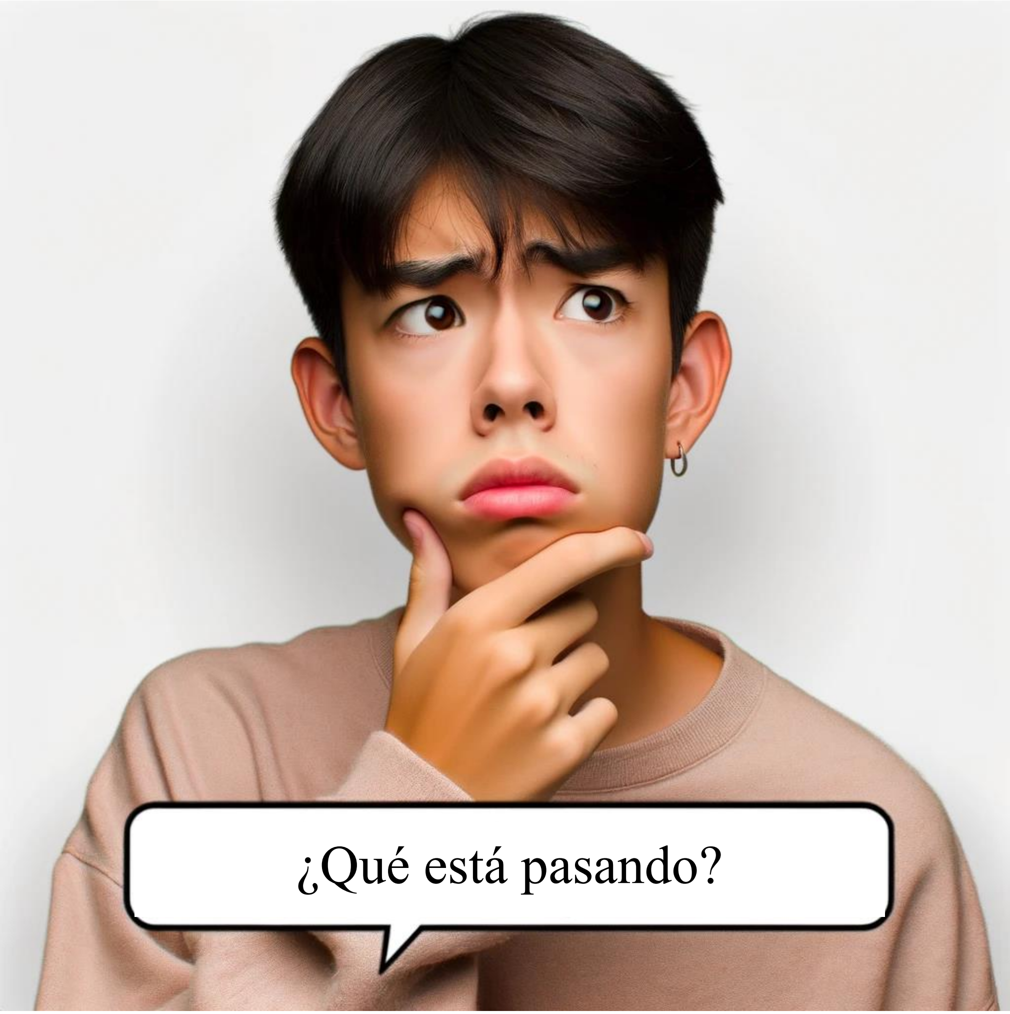
Análisis de Redes:

Nueva perspectiva para examinar los fenómenos psicológicos

Dr. José Ventura-León
Docente investigador


W



Revista de Investigación en Psicología, Vol.7 No.2, Diciembre 2004

EL ESTATUS MULTIPARADIGMÁTICO DE LA PSICOLOGÍA

THE ESTATUS MULTIPARADIGMÁTICO OF PSYCHOLOGY

MANUEL CAMPOS ROLDÁN [1]
Universidad Nacional Mayor de San Marcos, Facultad de Psicología

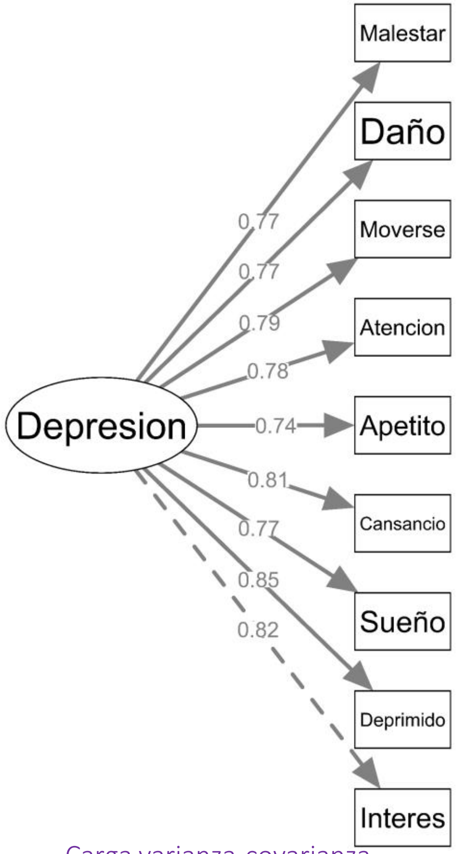
RESUMEN
El trabajo examina el estado multiparadigmático de la psicología contemporánea en nuestro medio. Se revisa los conceptos epistemológicos de ciencia, ideología, modelo teórico-metodológico y paradigma.

Palabras clave: Epistemología, metodología, ciencia, ideología, paradigma.

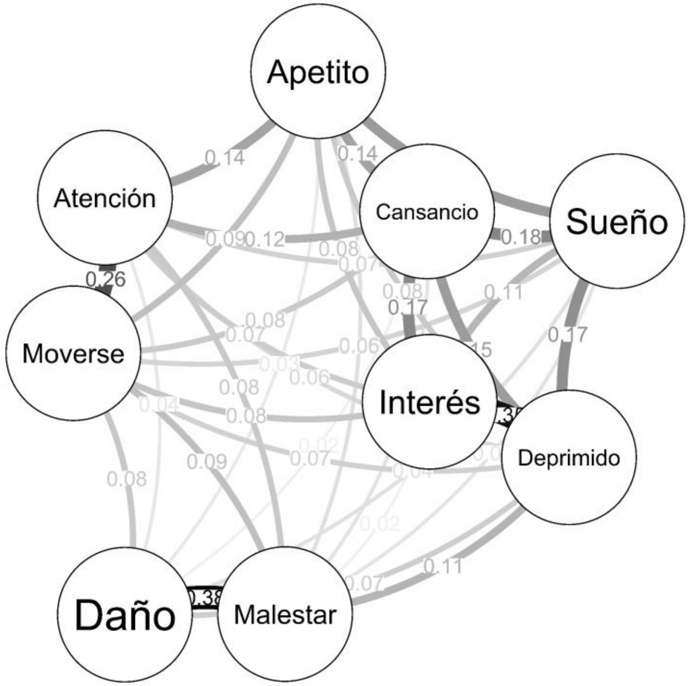
ABSTRACT
The paper examines the paradigmatic situation in contemporary Psychology. It reviews science, ideology, model and paradigm as epistemological concepts.

Keywords: Epistemology, Methodology, Science, Ideology, Paradigm.

Cambio en la manera de entender las relaciones:



Análisis de redes



Carga varianza-covarianza

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

Carga Factorial

Residual varianza-covarianza

Matriz de escalado diagonal

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

Matriz de varianza-covarianza

Red de correlación parcial

Epskamp, S., Rhemtulla, M., & Borsboom, D. (2017). *Generalized Network Psychometrics: Combining Network and Latent Variable Models. Psychometrika, 82(4), 904–927.* doi:10.1007/s11336-017-9557-x

Psychological Review
2006, Vol. 113, No. 4, 842–861

0033-295X/06/$12.00 DOI: 10.1037/0033-295X.113.4.842

A Dynamical Model of General Intelligence: The Positive Manifold of Intelligence by Mutualism

Han L. J. van der Maas, Conor V. Dolan, Raoul P. P. P. Grasman, Jelte M. Wicherts, Hilde M. Huizenga, and Maartje E. J. Raijmakers
University of Amsterdam

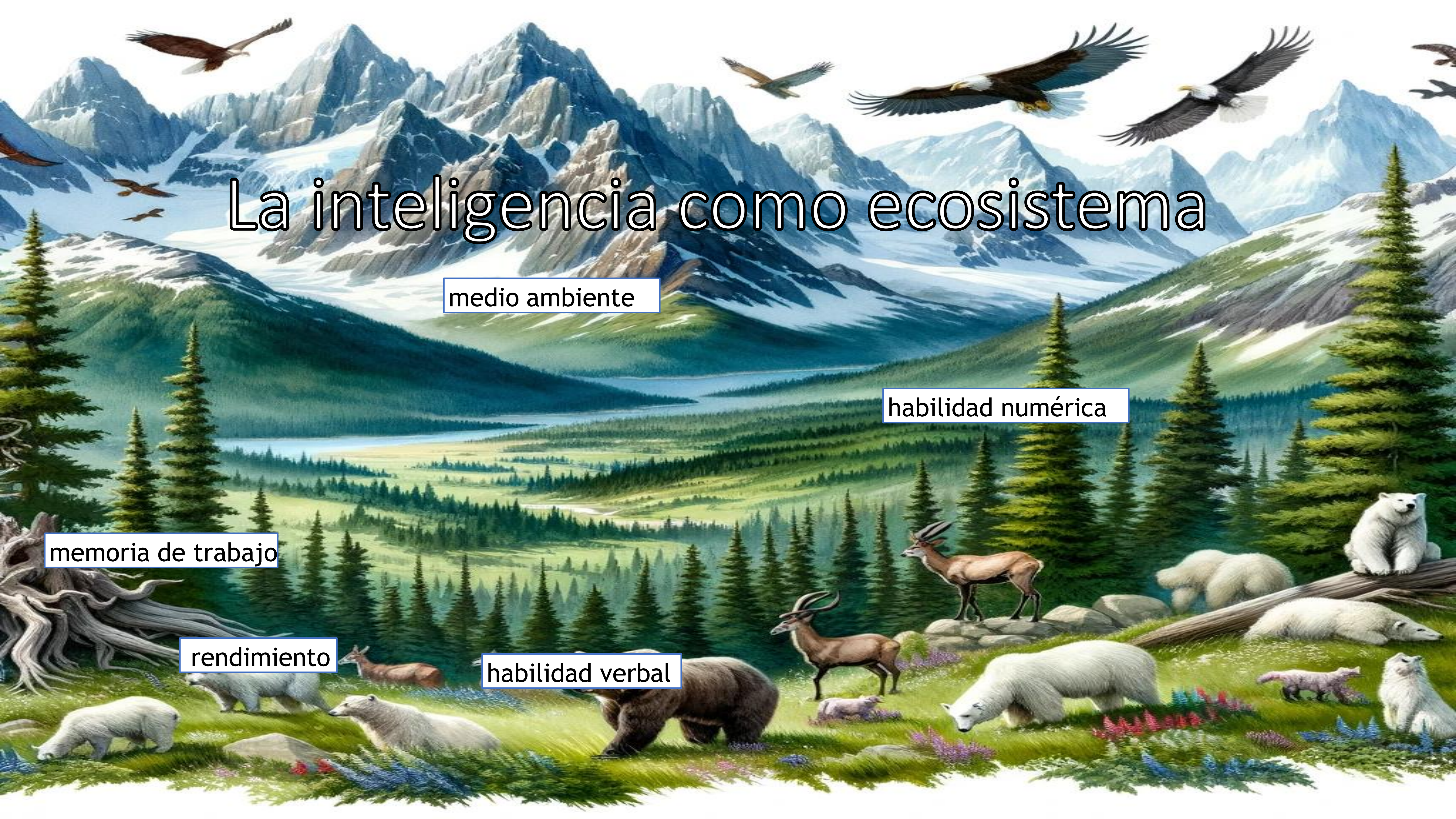
Scores on cognitive tasks used in intelligence tests correlate positively with each other, that is, they display a positive manifold of correlations. The positive manifold is often explained by positing a dominant latent variable, the *g* factor, associated with a single quantitative cognitive or biological process or capacity. In this article, a new explanation of the positive manifold based on a dynamical model is proposed, in which reciprocal causation or mutualism plays a central role. It is shown that the positive manifold emerges purely by positive beneficial interactions between cognitive processes during development. A single underlying *g* factor plays no role in the model. The model offers explanations of important findings in intelligence research, such as the hierarchical factor structure of intelligence, the low predictability of intelligence from early childhood performance, the integration/differentiation effect, the increase in heritability of *g*, and the Jensen effect, and is consistent with current explanations of the Flynn effect.

Keywords: intelligence, *g* factor, dynamical systems, mutualism, reciprocal causation

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

El objetivo de este artículo es esbozar una tercera posibilidad, una nueva explicación de la matriz positiva. Esta explicación se basa en un modelo de desarrollo formulado matemáticamente con **mutualismo o relaciones beneficiosas positivas entre procesos cognitivos**. Esta explicación identifica un mecanismo plausible **que da origen a la matriz positiva, pero que no incluye "g" como una variable cuantitativa latente**. Al menos, esto demuestra que una variable latente, que está establecida de manera psicométrica (es decir, en análisis de factores), **no necesariamente tiene que corresponder a una variable cuantitativa real,** como la velocidad de procesamiento o el tamaño del cerebro. Este modelo también sugiere explicaciones de otros fenómenos empíricos importantes en la investigación de la inteligencia (Van Der Maas et al., 2006, p. 843).

La inteligencia como ecosistema



Comorbidity: A network perspective

Angélique O. J. Cramer
Department of Psychology, University of Amsterdam, 1018 WB Amsterdam, The Netherlands
A.O.J.Cramer@uva.nl
www.aojcramer.com

Lourens J. Waldorp
Department of Psychology, University of Amsterdam, 1018 WB Amsterdam, The Netherlands
L.J.Waldorp@uva.nl
http://users.fmg.uva.nl/lwaldorp

Han L. J. van der Maas
Department of Psychology, University of Amsterdam, 1018 WB Amsterdam, The Netherlands
H.L.J.vanderMaas@uva.nl
http://users.fmg.uva.nl/hvandermaas/

Denny Borsboom
Department of Psychology, University of Amsterdam, 1018 WB Amsterdam, The Netherlands
D.Borsboom@uva.nl
http://sites.google.com/site/borsboomdenny/dennyborsboom

Abstract: The pivotal problem of comorbidity research lies in the psychometric foundation it rests on, that is, *latent variable theory*, in which a mental disorder is viewed as a latent variable that *causes* a constellation of symptoms. From this perspective, comorbidity is a (bi)directional relationship between multiple latent variables. We argue that such a latent variable perspective encounters serious problems in the study of comorbidity, and offer a radically different conceptualization in terms of a *network approach*, where comorbidity is hypothesized to arise from direct relations between symptoms of multiple disorders. We propose a method to visualize comorbidity networks and, based on an empirical network for major depression and generalized anxiety, we argue that this approach generates realistic hypotheses about pathways to comorbidity, overlapping symptoms, and diagnostic boundaries, that are not naturally accommodated by latent variable models: Some pathways to comorbidity through the *symptom space* are more likely than others; those pathways generally have the same direction (i.e., from symptoms of one disorder to symptoms of the other); overlapping symptoms play an important role in comorbidity; and boundaries between diagnostic categories are necessarily fuzzy.

Keywords: comorbidity; complex networks; generalized anxiety; latent variable models; major depression

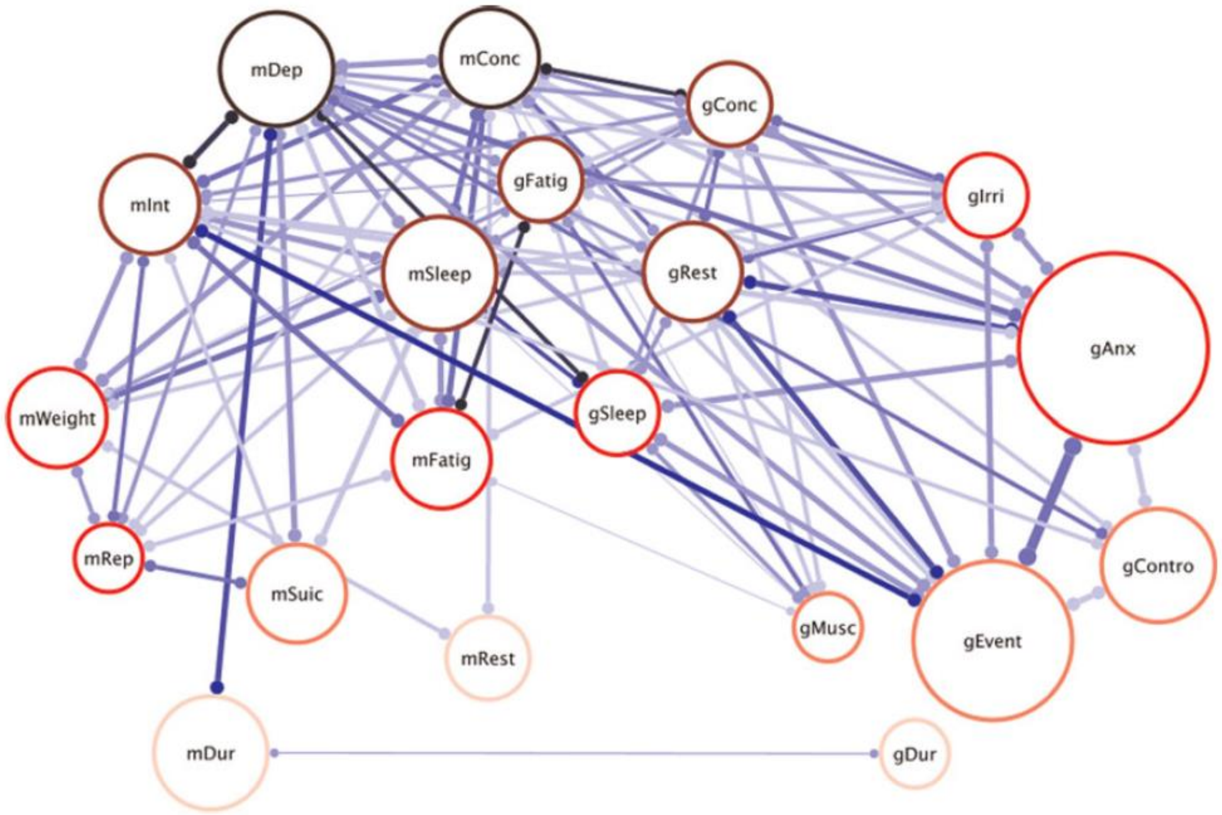


Figure 4. A comorbidity network for major depressive disorder (MDD) and general anxiety disorder (GAD). Larger nodes represent more frequent symptoms, darker circumference represents higher centrality, thicker edges represent higher frequency of co-occurrence, and darker edges represent stronger associations. Only edges with a log odds ratio higher than (+ or -)0.60 are represented. Centrally positioned nodes (*mConc*, *gConc*, *mSleep*, *gSleep*, *mFatig*, *gFatig*, *mRest*, and *gRest*) represent overlapping symptoms. Non-overlapping MDD symptoms are displayed on the *left* of the figure, and non-overlapping GAD symptoms on the *right*.

Cramer, A., Waldorp, L., Van der Maas, H., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences, 33*(2-3), 137-150. doi:10.1017/S0140525X09991567

ANNUAL REVIEWS **Further**

Click here for quick links to Annual Reviews content online, including:

- Other articles in this volume
- Top cited articles
- Top downloaded articles
- Our comprehensive search

Network Analysis: An Integrative Approach to the Structure of Psychopathology

Denny Borsboom and Angélique O.J. Cramer

Department of Psychology, University of Amsterdam, Amsterdam 1018 XA, The Netherlands; email: D.Borsboom@uva.nl

Annu. Rev. Clin. Psychol. 2013. 9:91–121

The *Annual Review of Clinical Psychology* is online at http://clinpsy.annualreviews.org

This article's doi: 10.1146/annurev-clinpsy-050212-185608

Keywords

network analysis, psychopathology, latent variable models, psychometrics, measurement, philosophy of science

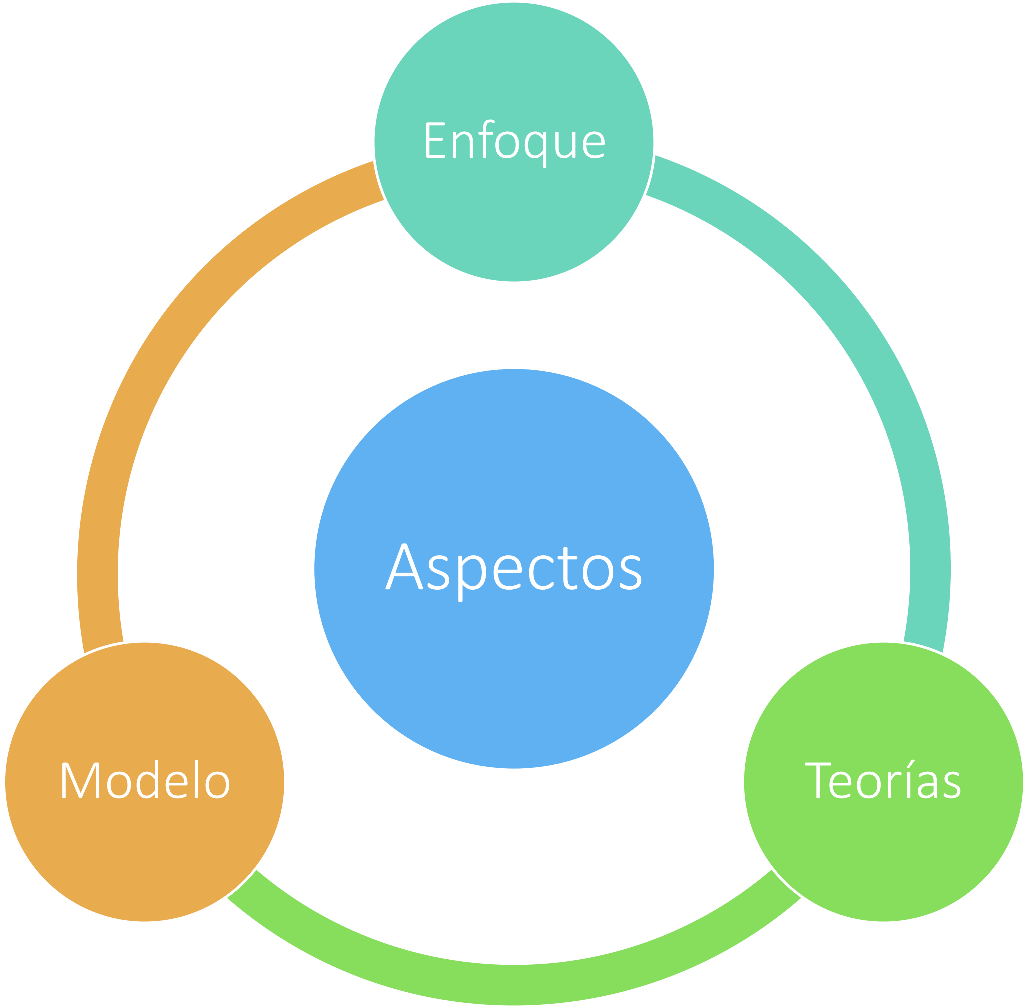
Abstract

In network approaches to psychopathology, disorders result from the causal interplay between symptoms (e.g., worry → insomnia → fatigue), possibly involving feedback loops (e.g., a person may engage in substance abuse to forget the problems that arose due to substance abuse). The present review examines methodologies suited to identify such symptom networks and discusses network analysis techniques that may be used to extract clinically and scientifically useful information from such networks (e.g., which symptom is most central in a person's network). The authors also show how network analysis techniques may be used to construct simulation models that mimic symptom dynamics. Network approaches naturally explain the limited success of traditional research strategies, which are typically based on the idea that symptoms are manifestations of some common underlying factor, while offering promising methodological alternatives. In addition, these techniques may offer possibilities to guide and evaluate therapeutic interventions.

Las apariencias sugieren que, en psicopatología, un proceso análogo está en funcionamiento. Se presenta un ejemplo en la Figura 1, en el que la DM es la causa raíz de sus síntomas observables (ver Tabla 1 para la leyenda correspondiente). Sin embargo, esta similitud entre la psicopatología y la medicina moderna es solo superficial. **Ciertamente, los clientes son diagnosticados con un trastorno en función de un conjunto de síntomas, después de lo cual el diagnóstico se utiliza para elegir un protocolo de tratamiento.** Esto sugiere la **identificación y el tratamiento de una causa raíz.** Sin embargo, aunque en las últimas décadas se ha hecho mucho de la sugerencia de que los síntomas en psicopatología tienen tales causas raíz (se ha sugerido diversas bases en deseos reprimidos, indefensión aprendida, desequilibrios hormonales, anomalías neurales o defectos genéticos), hasta ahora ha sido **imposible identificar estos empíricamente**. De hecho, es imposible identificar cualquiera de los **trastornos mentales comunes como condiciones que existen independientemente de sus síntomas**. En nuestra opinión, es poco probable que esto cambie; es decir, consideramos poco probable que, en el futuro, con equipos de detección mejores y tamaños de muestra más grandes, **podamos identificar tales condiciones independientemente de sus síntomas** (Borsboom & Cramer. 2013, pp.94-95).

Borsboom, D., & Cramer, A. O. (2013). Network analysis: an integrative approach to the structure of psychopathology. *Annual review of clinical psychology*, *9*, 91-121.

Importante recordar…



Borsboom, D., Cramer, A. O. J., Fried, E. I., Isvoranu, A. M., Robinaugh, D. J., Dalege, J., & van der Maas, H. L. J. (2022). Chapter 1. Network perspectives. In Isvoranu, A. M., Epskamp, S., Waldorp, L. J., & Borsboom, D. (Eds.). *Network psychometrics with R: guide for behavioral and social scientists*. Routledge, Taylor & Francis Group.

Términos de los modelos de redes

Redes

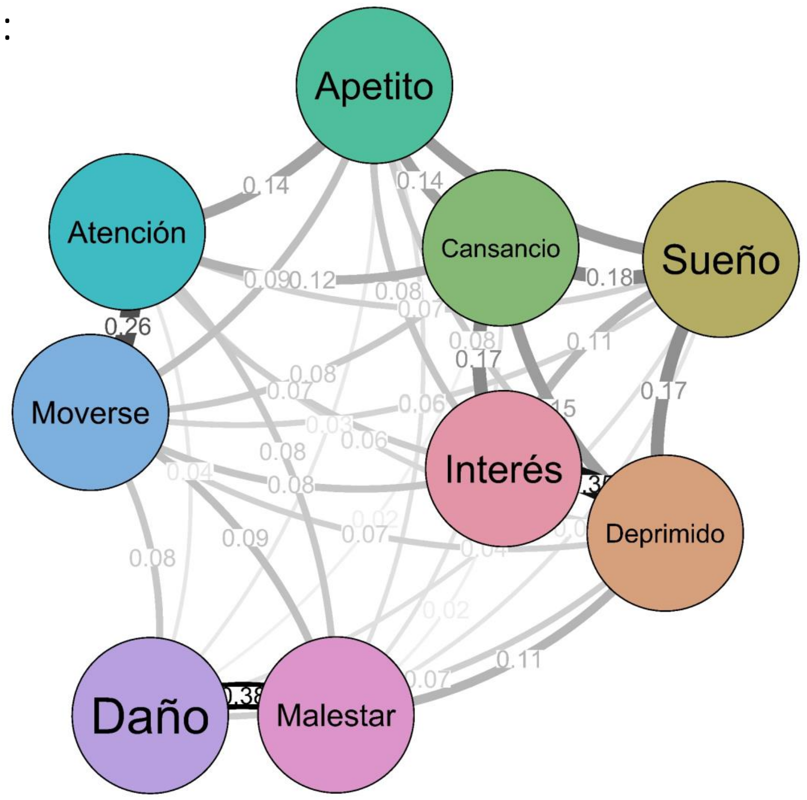
Una red es un conjunto de nodos conectado por un conjunto de bordes:

- Los nodos también son llamados vértice.
- Los bordes también son llamados Edges o conexiones.
- Las redes también son llamadas grafos

grafos ≠ red

Objeto matemático

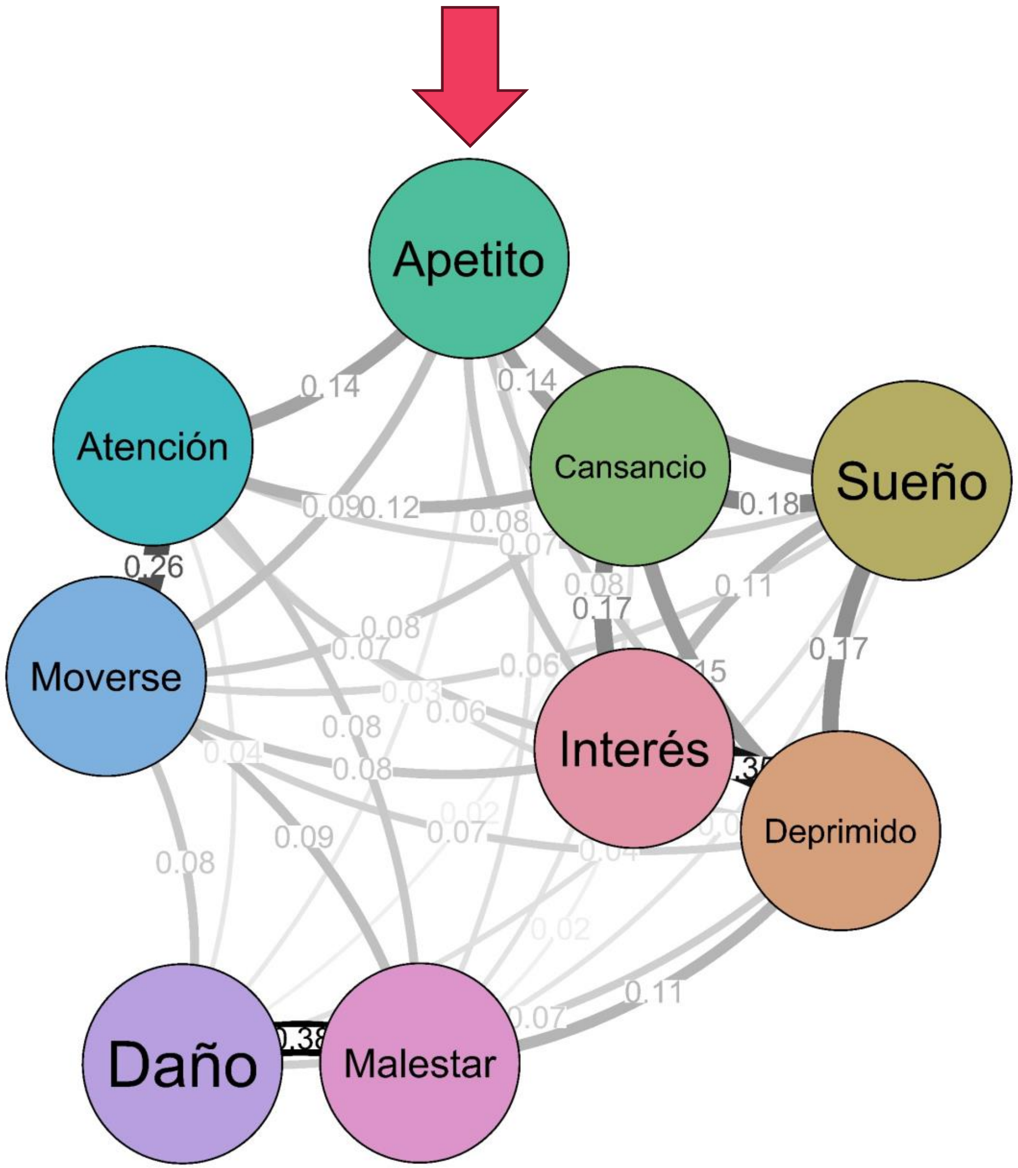
Cuando mostramos una imagen



Nodo

Pueden ser:

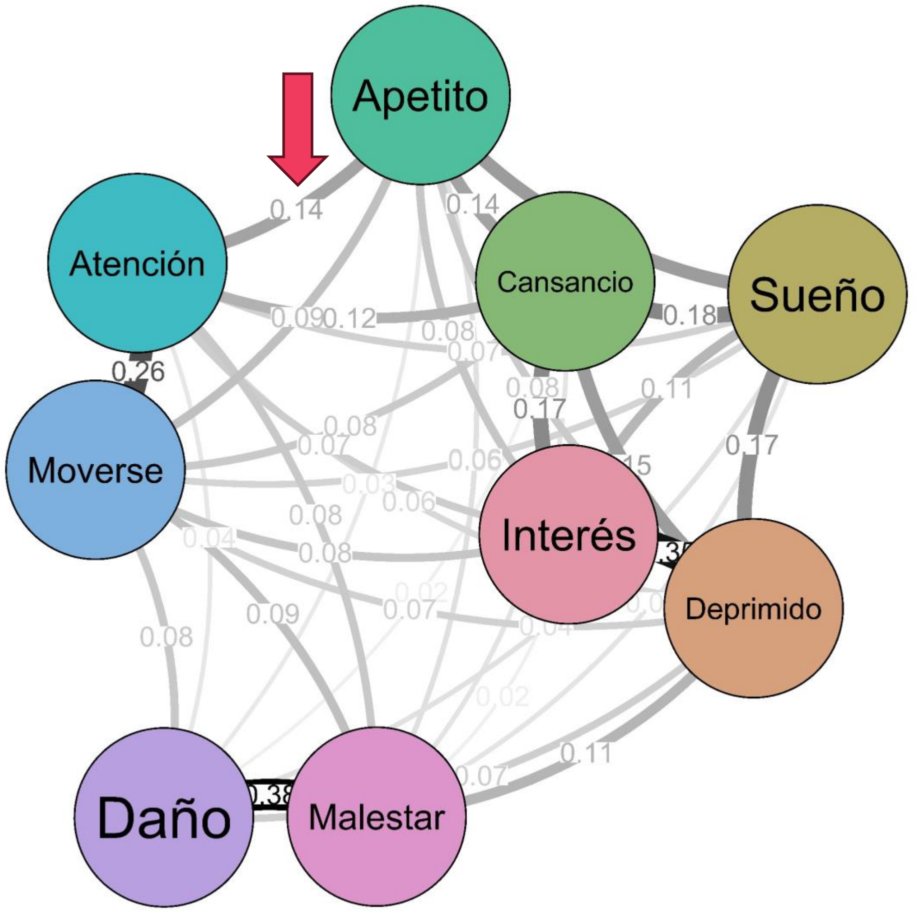
- Personas
- Ciudades
- Síntomas
- Constructos psicológicos



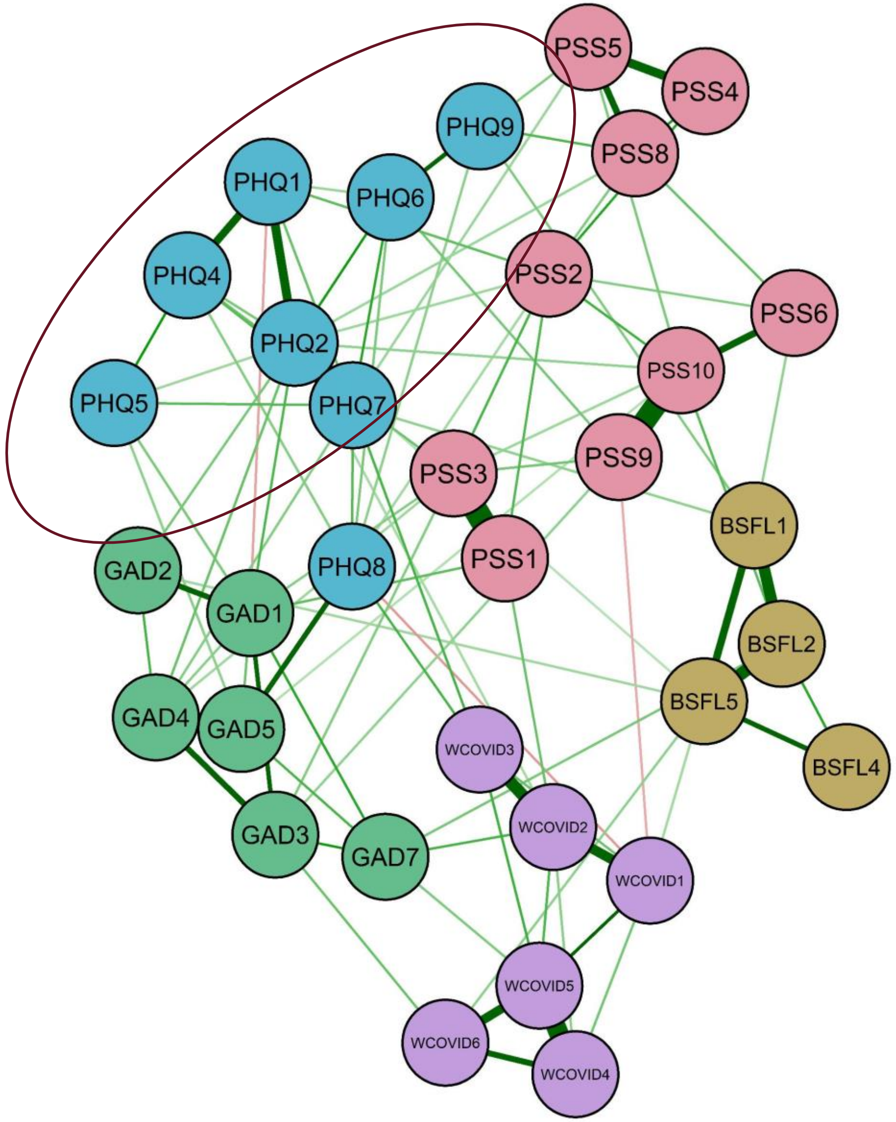
Borde (Edge)

Representa la conexión entre dos nodos

- Amigos/contactos
- Distancia
- Comorbilidad
- Causalidad
- Interacción



Comunidad



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

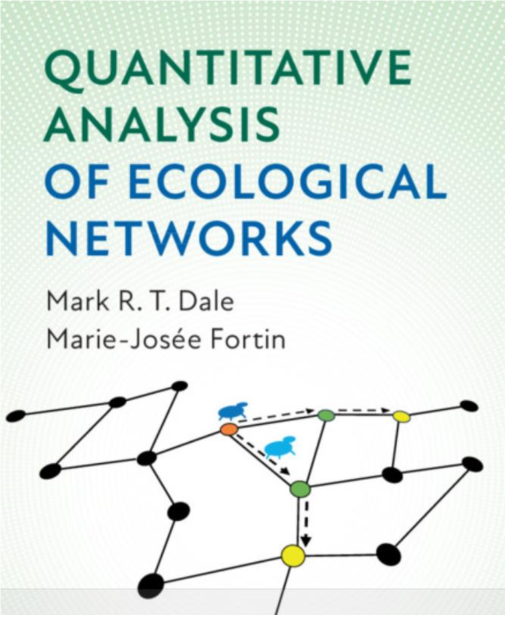
- GAD1: Feeling nervous, anxious or on edge?
- GAD2: Not being able to stop or control worrying?
- GAD3: Worrying too much about different things?
- GAD4: Trouble relaxing?
- GAD5: Being so restless that it is hard to sit still?
- GAD7: Feeling afraid as if something awful might happen?

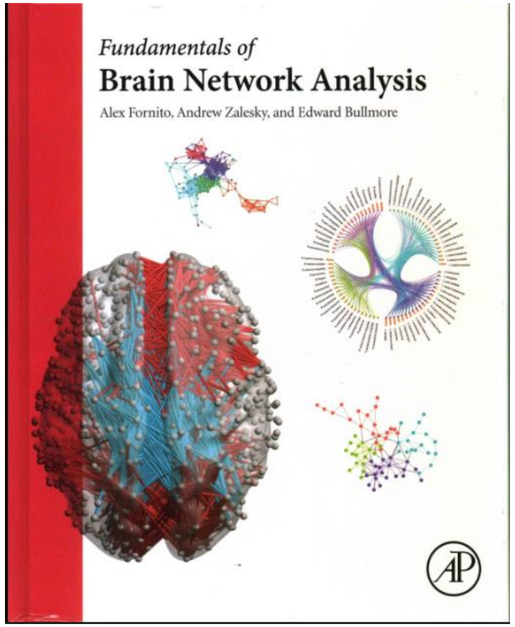
Depression

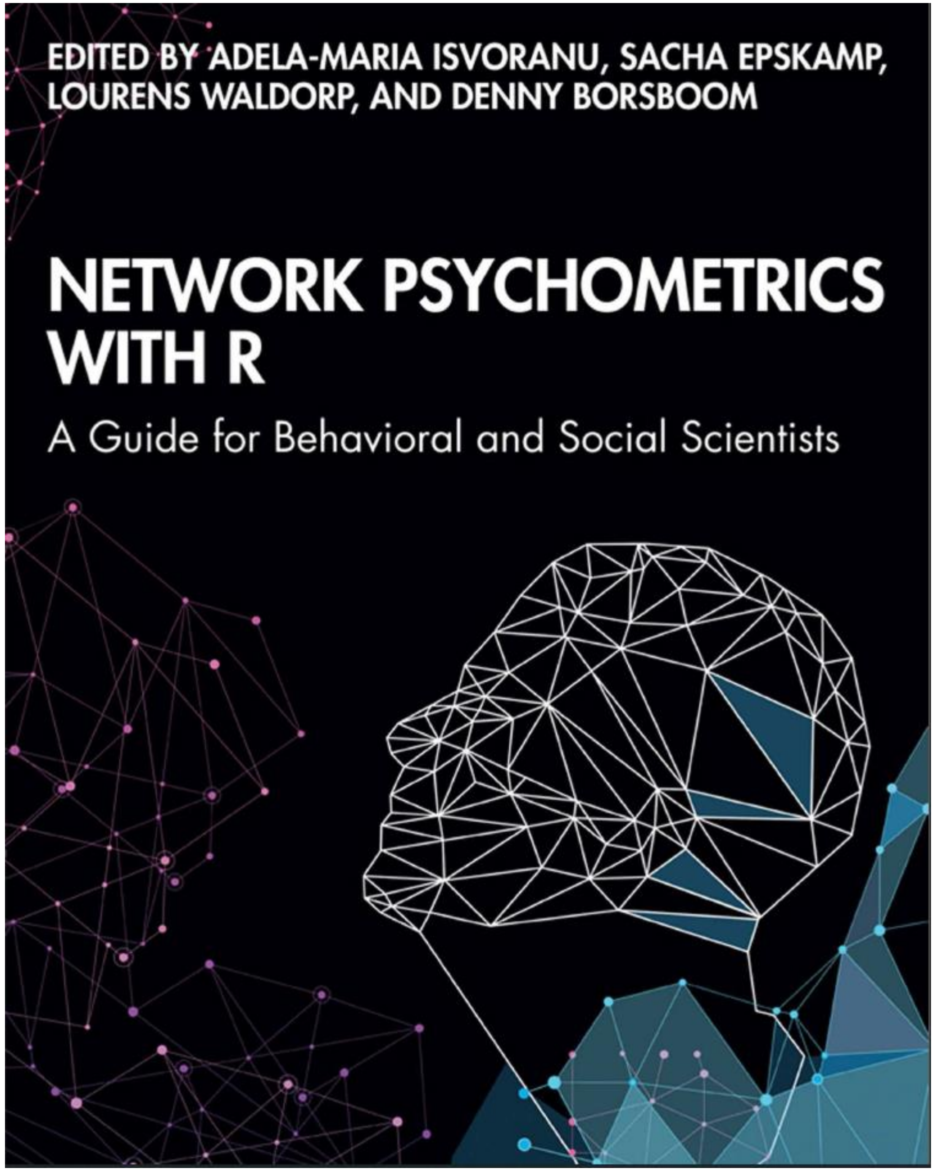
- PHQ1: Little interest or pleasure in doing things
- PHQ2: Feeling down, depressed, or hopeless
- PHQ4: Feeling tired or having little energy
- PHQ5: Poor appetite or overeating
- PHQ6: Feeling bad about yourself
- PHQ7: Trouble concentrating on things
- PHQ8: Moving or speaking so slowly that other people could have noticed
- PHQ9: Thoughts that you would be better off dead

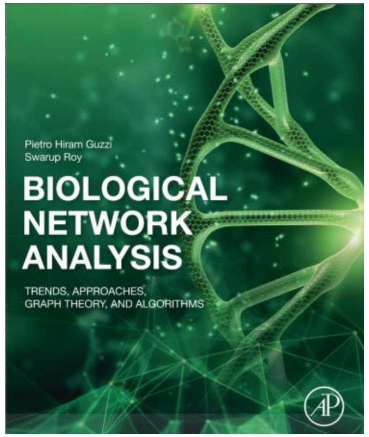
Worry COVID-19

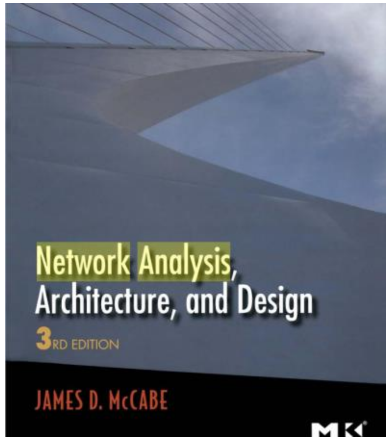
- WCOVID1: How often have you thought about the probability of getting covid?
- WCOVID2: Has the possibility of getting covid affected your mood?
- WCOVID3: Has the possibility of getting covid affected your daily activities?
- WCOVID4: To what extent do you worry about the possibility of getting covid?
- WCOVID5: How often do you worry about the possibility of getting covid?
- WCOVID6: Is the possibility of getting covid a major problem for you?


QUANTITATIVE ANALYSIS OF ECOLOGICAL NETWORKS
Mark R. T. Dale
Marie-Josée Fortin


Fundamentals of
Brain Network Analysis
Alex Fornito, Andrew Zalesky, and Edward Bullmore


EDITED BY ADELA-MARIA ISVORANU, SACHA EPSKAMP, LOURENS WALDORP, AND DENNY BORSBOOM
NETWORK PSYCHOMETRICS WITH R
A Guide for Behavioral and Social Scientists


Pietro Hiram Guzzi
Swarup Roy
BIOLOGICAL NETWORK ANALYSIS
TRENDS, APPROACHES, GRAPH THEORY, AND ALGORITHMS

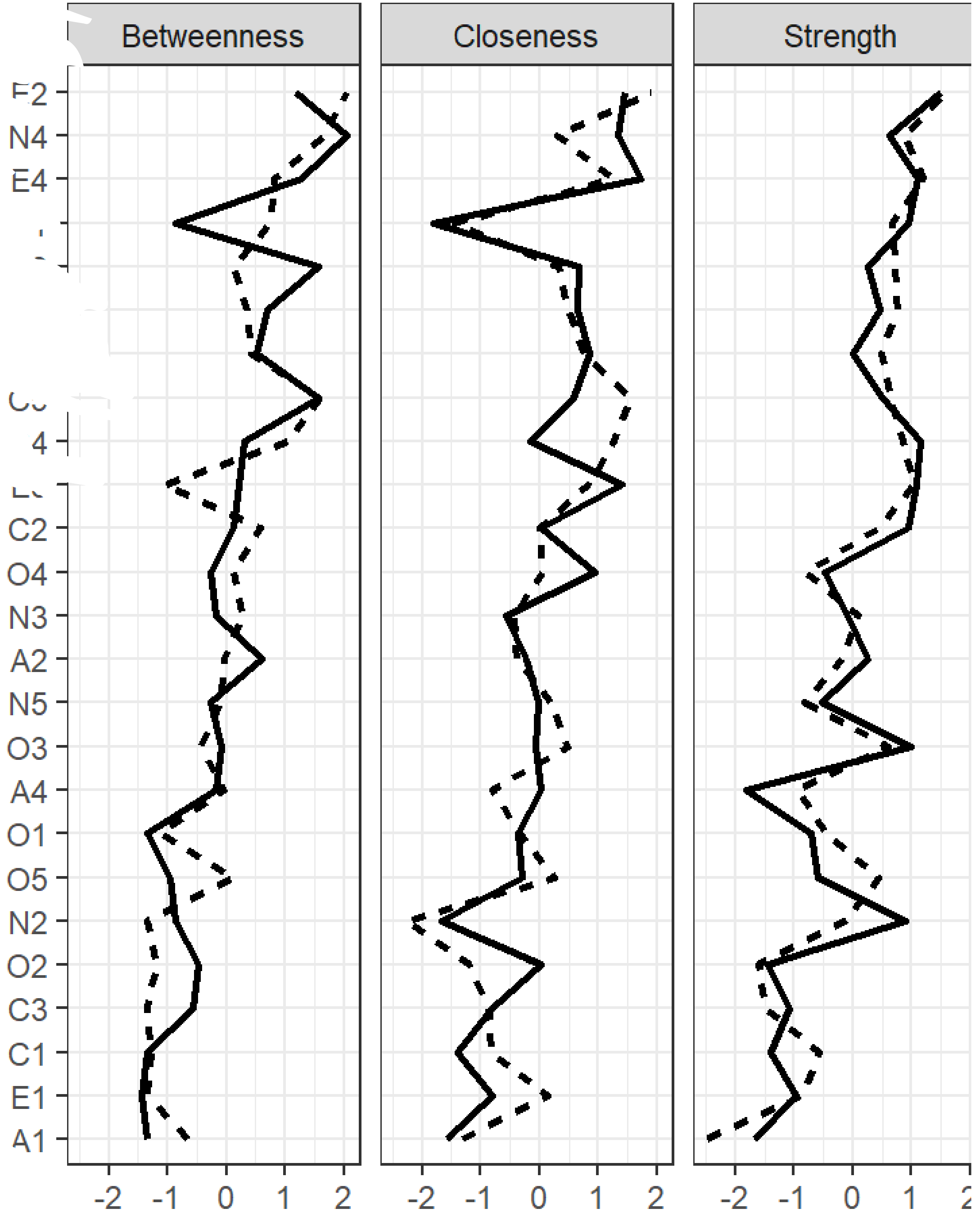

Network Analysis, Architecture, and Design
3RD EDITION
JAMES D. McCABE

Centralidad

Strength

Closeness

Betweenness



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

Address correspondence to:
Laura Bringmann, PhD
Department of Psychometrics and Statistics
Grote Kruisstraat 2/1
University of Groningen
9712 TS Groningen
Netherlands
Email: l.f.bringmann@rug.nl
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)

Comparison of latent variable and psychological network models in PROMIS data: output metrics and factor structure

Joshua Starr[1] · Carl F. Falk[1]

Accepted: 23 June 2023

Abstract

Purpose Much research is still needed to compare traditional latent variable models such as confirmatory factor analysis (CFA) to emerging psychometric models such as the Gaussian graphical model (GGM). Previous comparisons of GGM centrality indices with factor loadings from CFA have discovered redundancies, and investigations into how well a GGM-based alternative to exploratory factor analysis (i.e., exploratory graph analysis, or EGA) is able to recover the hypothesized factor structure show mixed results. Importantly, such comparisons have not typically been examined in real mental and physical health symptom data, despite such data being an excellent candidate for the GGM. Our goal was to extend previous work by comparing the GGM and CFA using data from Wave 1 of the Patient Reported Outcomes Measurement Information System (PROMIS).

Methods Models were fit to PROMIS data based on 16 test forms designed to measure 9 mental and physical health domains. Our analyses borrowed a two-stage approach for handling missing data from the structural equation modeling literature.

Results We found weaker correspondence between centrality indices and factor loadings than found by previous research, but in a similar pattern of correspondence. EGA recommended a factor structure discrepant with PROMIS domains in most cases yet may be taken to provide substantive insight into the dimensionality of PROMIS domains.

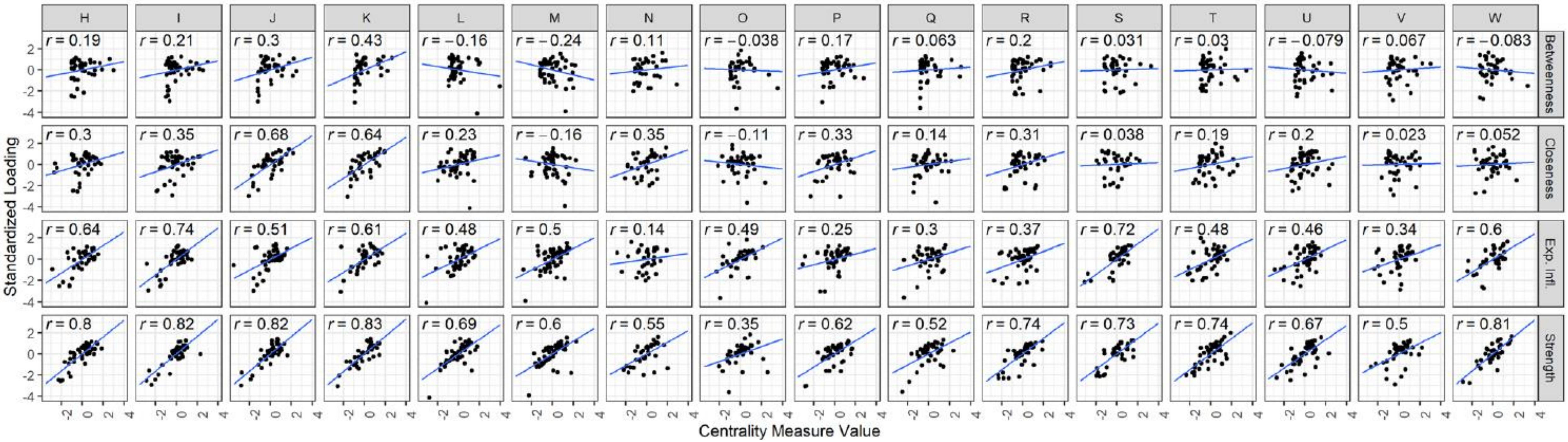
Conclusion In real mental and physical health data, the GGM and EGA may provide complementary information to traditional CFA metrics.

Keywords PROMIS · Network analysis · Centrality indices · Exploratory graph analysis · Mental and physical health · Measurement

Starr, J., & Falk, C. F. (2023). Comparison of latent variable and psychological network models in PROMIS data: output metrics and factor structure. *Quality of Life Research*, 1-9.

Comparing centrality indices and factor loadings

Correspondence of centrality indices with standardized loadings was assessed with Pearson correlations separately for each test form but across all factors within a given form. Results showed similar patterning compared to Hallquist et al. [14] yet overall weaker associations (see Fig. 1). Average correlations per centrality index were computed by applying Fisher's z-transformation to all correlations in a given row of Fig. 1, taking the unweighted average, and then backtransforming to r. Recall that Hallquist et al. [14] found that strength was highly correlated with factor loadings ($r \geq .97$), and that closeness and betweenness were less so ($r \leq .55$ when models had multiple factors). In our case, correspondence with loadings was strongest on average for strength ($r = .70$), less strong for expected influence ($r = .49$), weaker still for closeness ($r = .24$), and near zero for betweenness ($r = .08$). If we compute correlations separately for each test form *and* each factor, correspondence becomes stronger for strength ($r = .91$), expected influence ($r = .79$), and betweenness ($r = .27$), yet remains the same for closeness. Thus, within a given factor, items with stronger loadings were typically also high on strength, though correspondence remained notably weaker than found by Hallquist et al. [14].



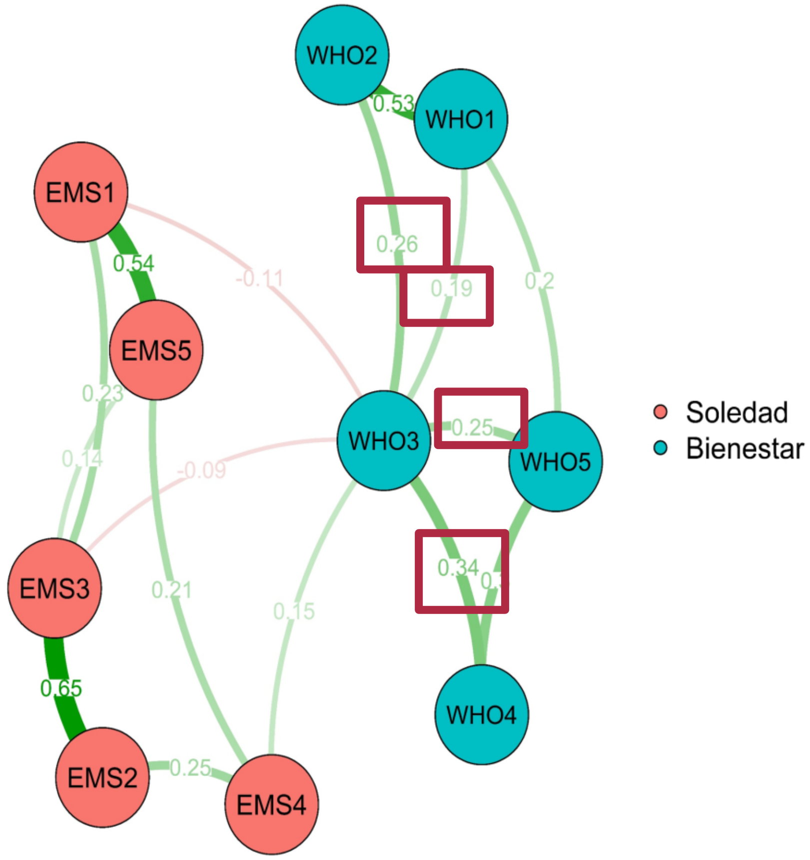
- Starr, J., & Falk, C. F. (2023). Comparison of latent variable and psychological network models in PROMIS data: output metrics and factor structure. *Quality of Life Research*, 1-9.

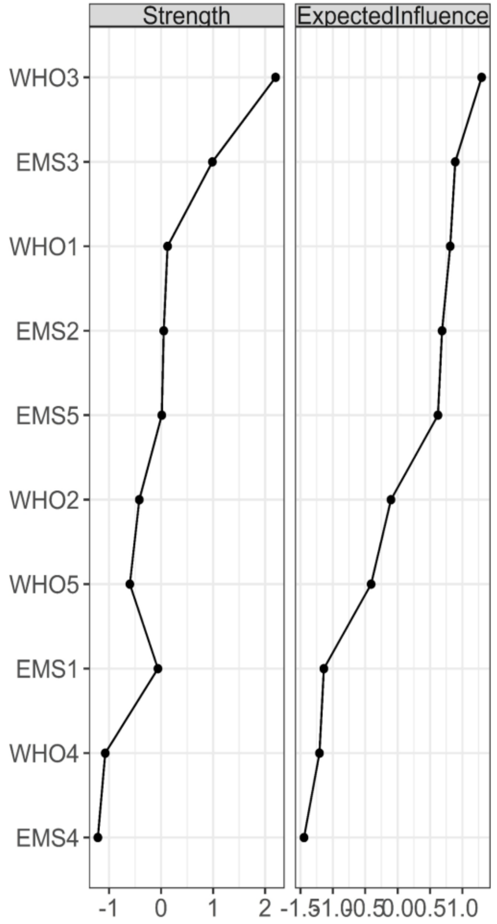
Fuerza del nodo

$$Strength(i) = \sum_{j=1}^{n} |\omega_{ij}|$$

Strength centrality = $|r_1| + |-r_2| + |r_3| + |r_4| + |r_5|$

La variante ponderada típica se denomina fuerza de nodo, que suma sobre la matriz de pesos absolutos en lugar de la matriz de adyacencia:





J Abnorm Psychol. Author manuscript; available in PMC 2017 Aug 1.
Published in final edited form as:
J Abnorm Psychol. 2016 Aug; 125(6): 747–757.
Published online 2016 Jun 16. doi: 10.1037/abn0000181
PMCID: PMC5060093
NIHMSID: NIHMS788995
PMID: 27505622

Identifying Highly Influential Nodes in the Complicated Grief Network

Donald J. Robinaugh,[1,2] Alexander J. Millner,[3] and Richard J. McNally[3]

Associated Data

▸ Supplementary Materials

Abstract

Go to: ▸

The network approach to psychopathology conceptualizes mental disorders as networks of mutually reinforcing nodes (i.e., symptoms). Researchers adopting this approach have suggested that network topology can be used to identify influential nodes, with nodes central to the network having the greatest influence on the development and maintenance of the disorder. However, because commonly used centrality indices do not distinguish between positive and negative edges,

Table 1

Mean correlations among centrality and expected influence indices in randomly generated Erdős-Rényi networks

	Closeness	Betweenness	Strength	EI_1
Positive Edges				
Betweenness	.80 (.09)			
Strength	.89 (.06)	.81 (.09)		
EI_1	.89 (.06)	.81 (.09)	1.00 (.00)	
EI_2	.91 (.06)	.78 (.10)	.99 (.01)	.99 (.01)
5% Negative Edges				
Betweenness	.81 (.08)			
Strength	.89 (.06)	.81 (.09)		
EI_1	.75 (.18)	.68 (.20)	.84 (.17)	
EI_2	.79 (.16)	.68 (.18)	.86 (.14)	.99 (.01)
10% Negative Edges				
Betweenness	.80 (.08)			
Strength	.89 (.06)	.80 (.10)		
EI_1	.65 (.20)	.59 (.21)	.74 (.19)	
EI_2	.70 (.18)	.61 (.19)	.77 (.16)	.98 (.01)
25% Negative Edges				
Betweenness	.80 (.07)			
Strength	.89 (.06)	.81 (.09)		
EI_1	.39 (.30)	.36 (.31)	.44 (.30)	
EI_2	.47 (.29)	.42 (.28)	.52 (.27)	.97 (.02)

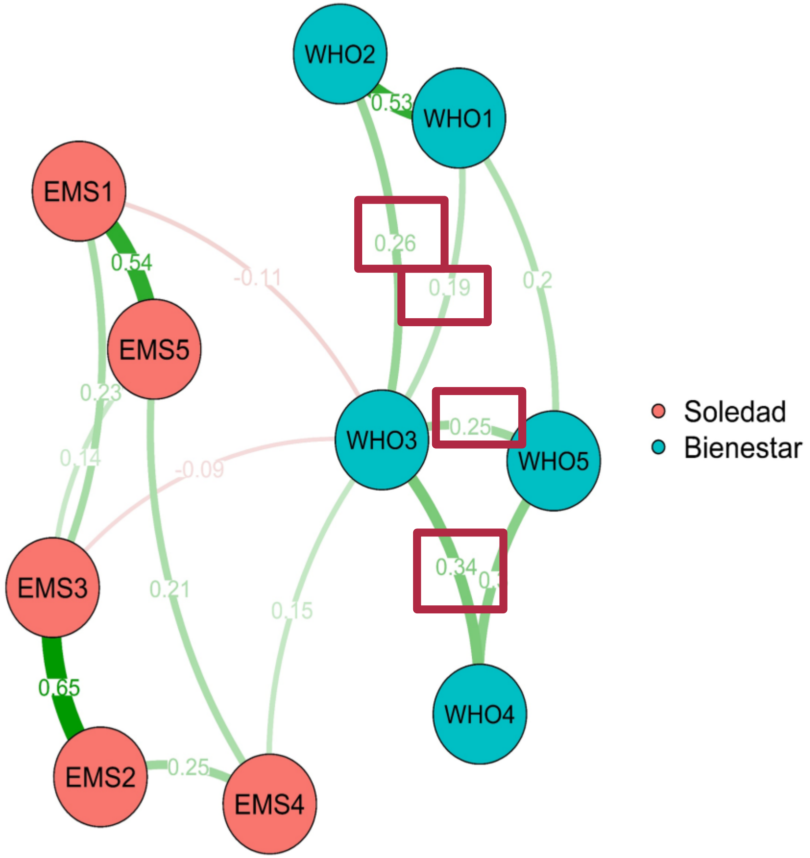
Open in a separate window

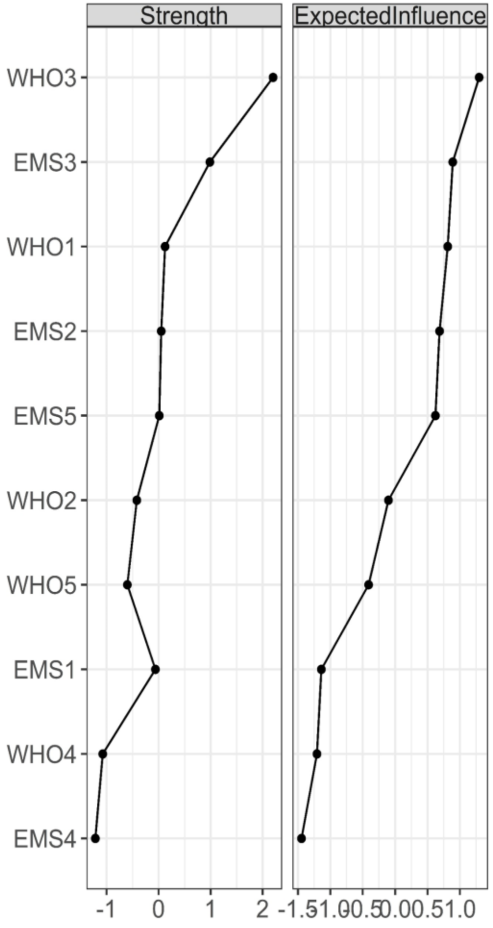
Expected Influence

$$ExpectedInfluence_1(i) = \sum_{j=1}^{n} a_{ij}\omega_{ij}$$

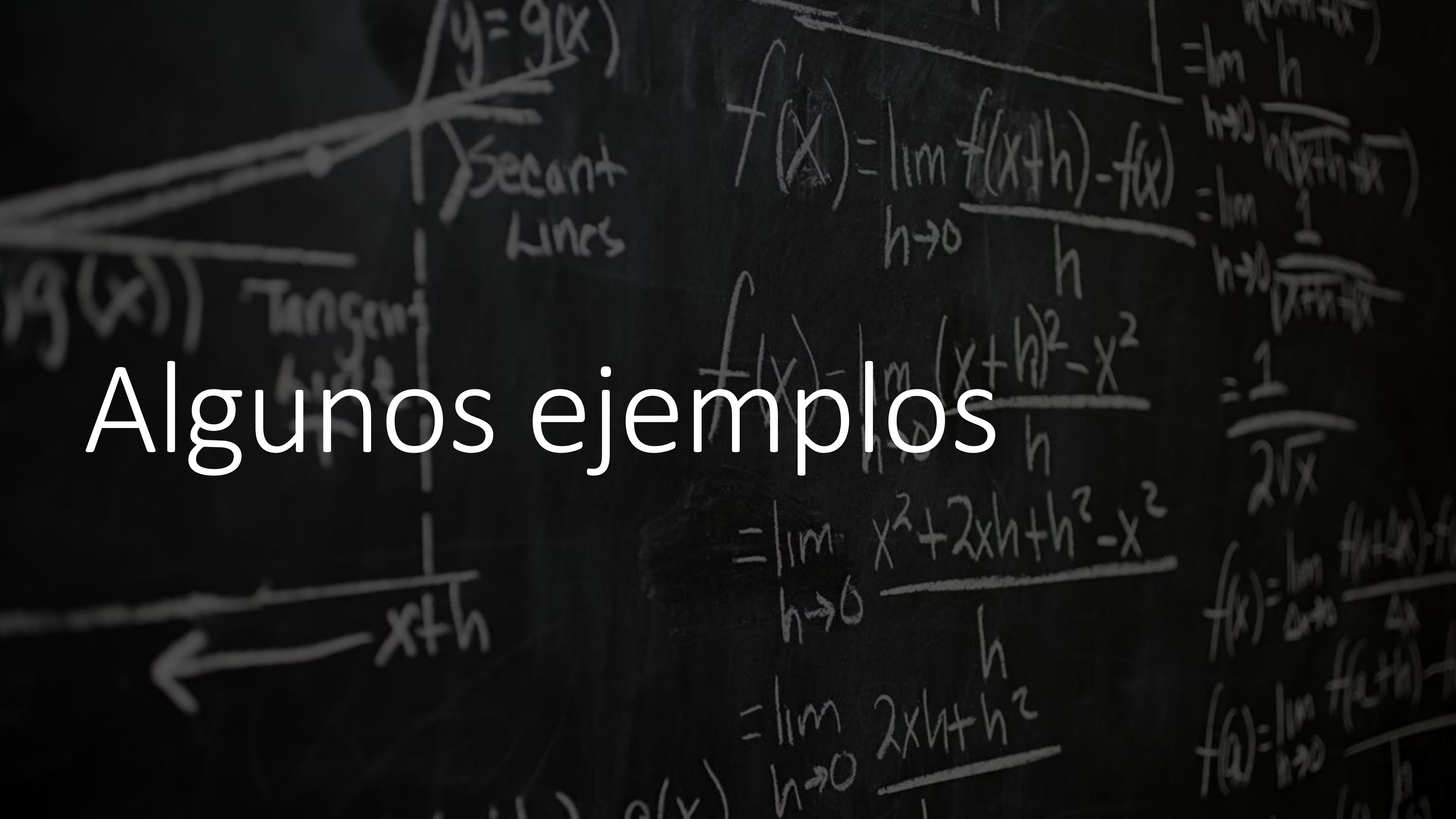
Suma de los pesos de las aristas(tiene en cuenta las aristas negativas)

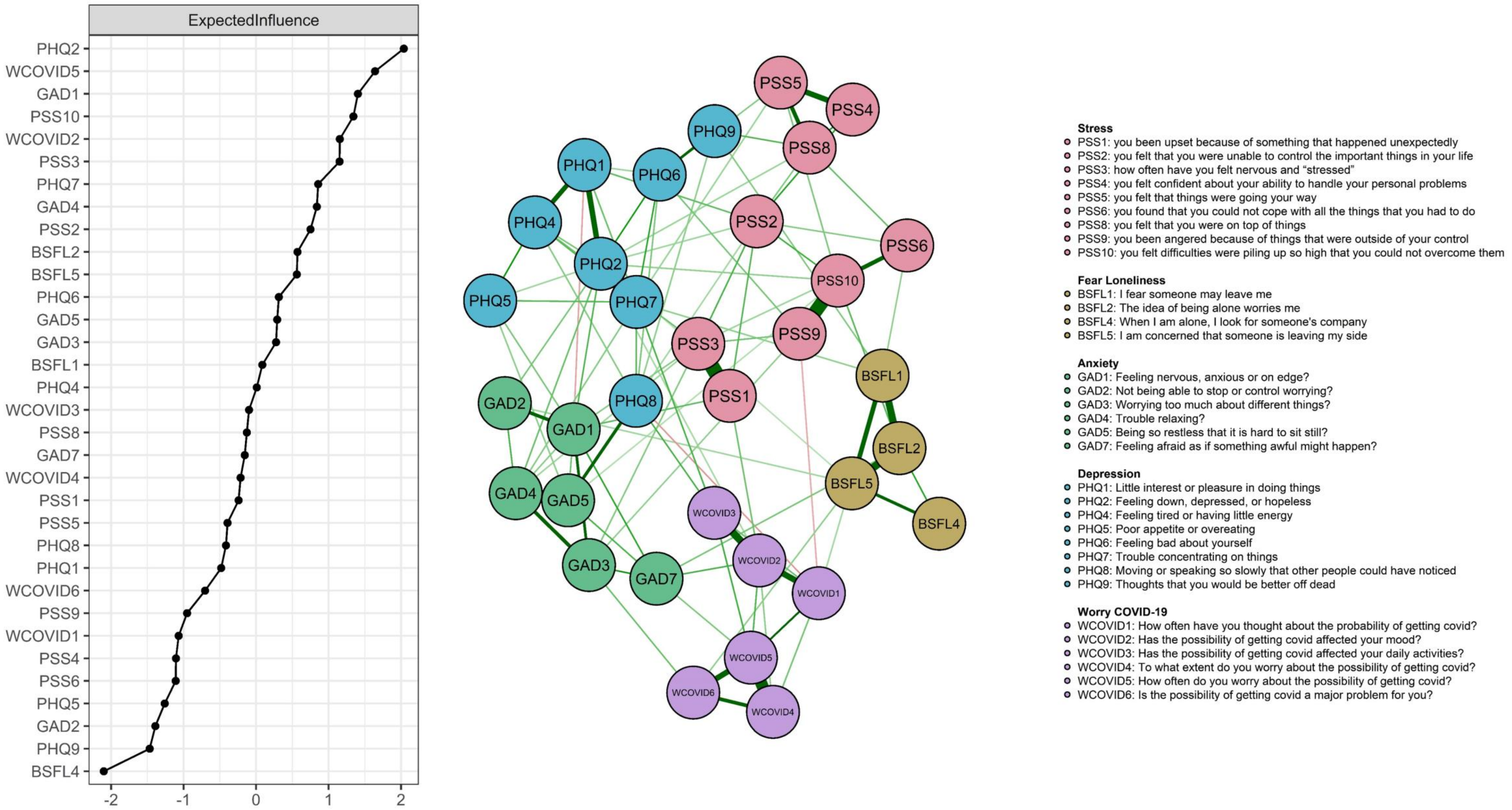
Expected influence = $r_1 + (-r_2) + r_3 + r_4 + r_5$



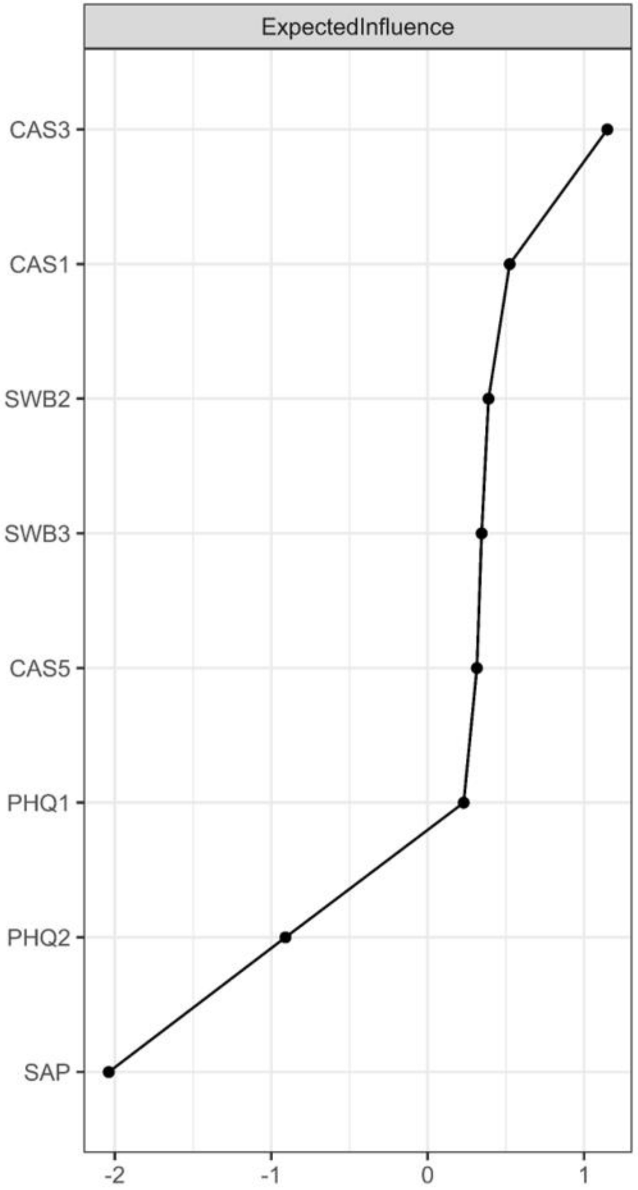


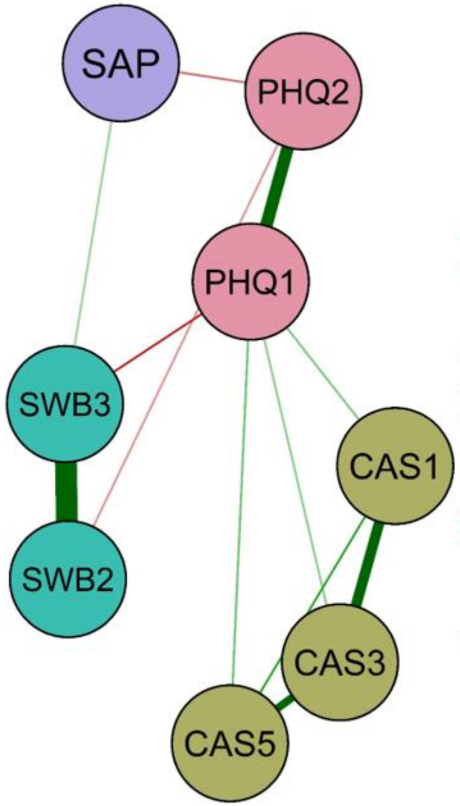
Algunos ejemplos





Ventura-León, J., López-Jurado, R., Porturas, E., León-Mostacero, I., & Canchanya-Balbin, S. E. (2022). Anxiety, depression, stress, worry about COVID-19 and fear of loneliness during COVID-19 lockdown in Peru: A network analysis approach. *Frontiers in Public Health*, *10*, 946697.





Depression
- PHQ1: Feeling discouraged, depressed or hopeless
- PHQ2: Little interest or pleasure in doing things

Anxiety COVID
- CAS1: Felt dizzy when reading or hearing news about COVID-19
- CAS3: I felt paralyzed when I thought about or was exposed to information about COVID-19
- CAS5: I felt nauseated or had stomach problems when I thought about or was exposed to COVID-19.

Wellbeing
- SWB2: Compared to most people my age, I consider myself to be the happiest
- SWB3: In general, I am very happy and enjoy life.

Self-reporting of Academic Performance
- SAP: How would you rate your academic performance during the pandemic?

Ventura-León, J., Caycho-Rodríguez, T., Talledo-Sánchez, K., & Casiano-Valdivieso, K. (2022). Depression, COVID-19 anxiety, subjective well-being, and academic performance in university students with COVID-19-infected relatives: a network analysis. *Frontiers in Psychology*, *13*, 837606.

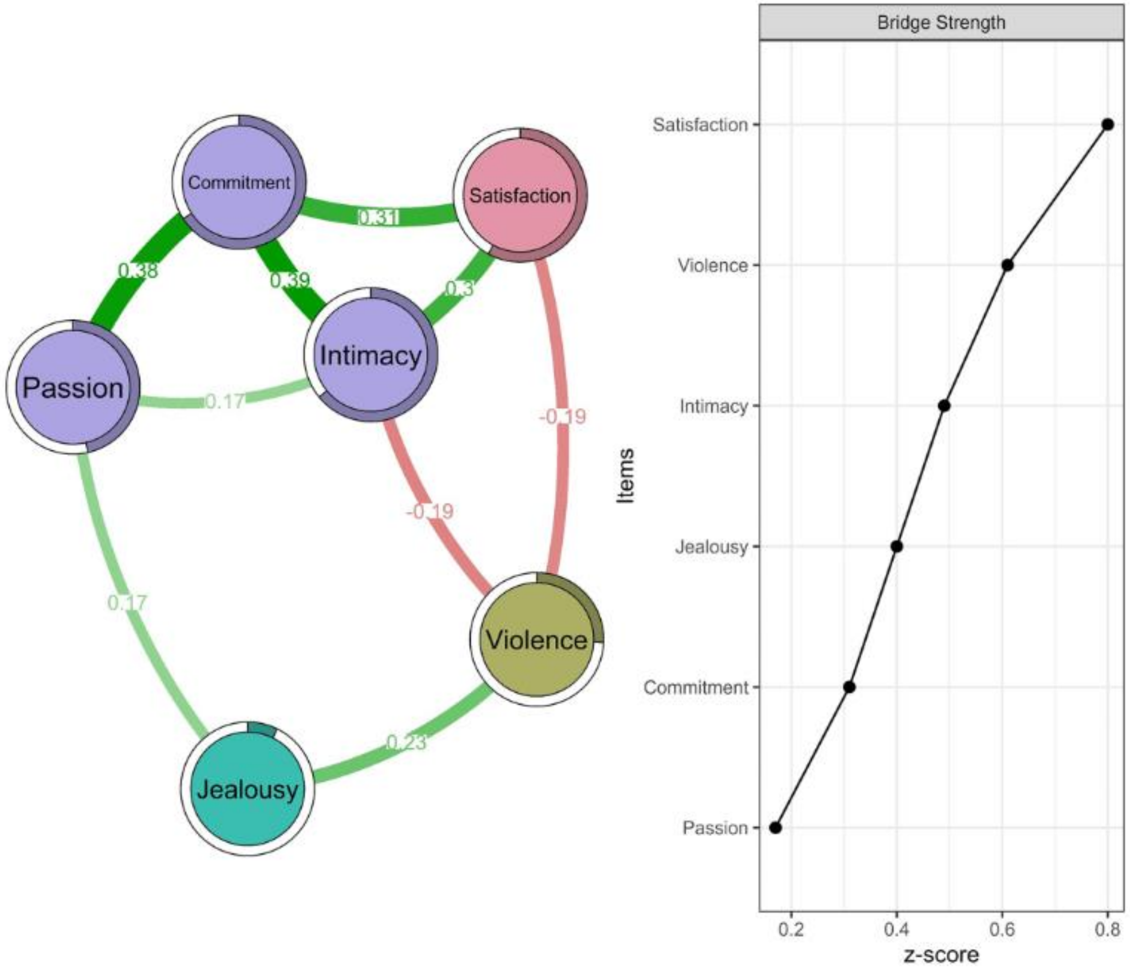
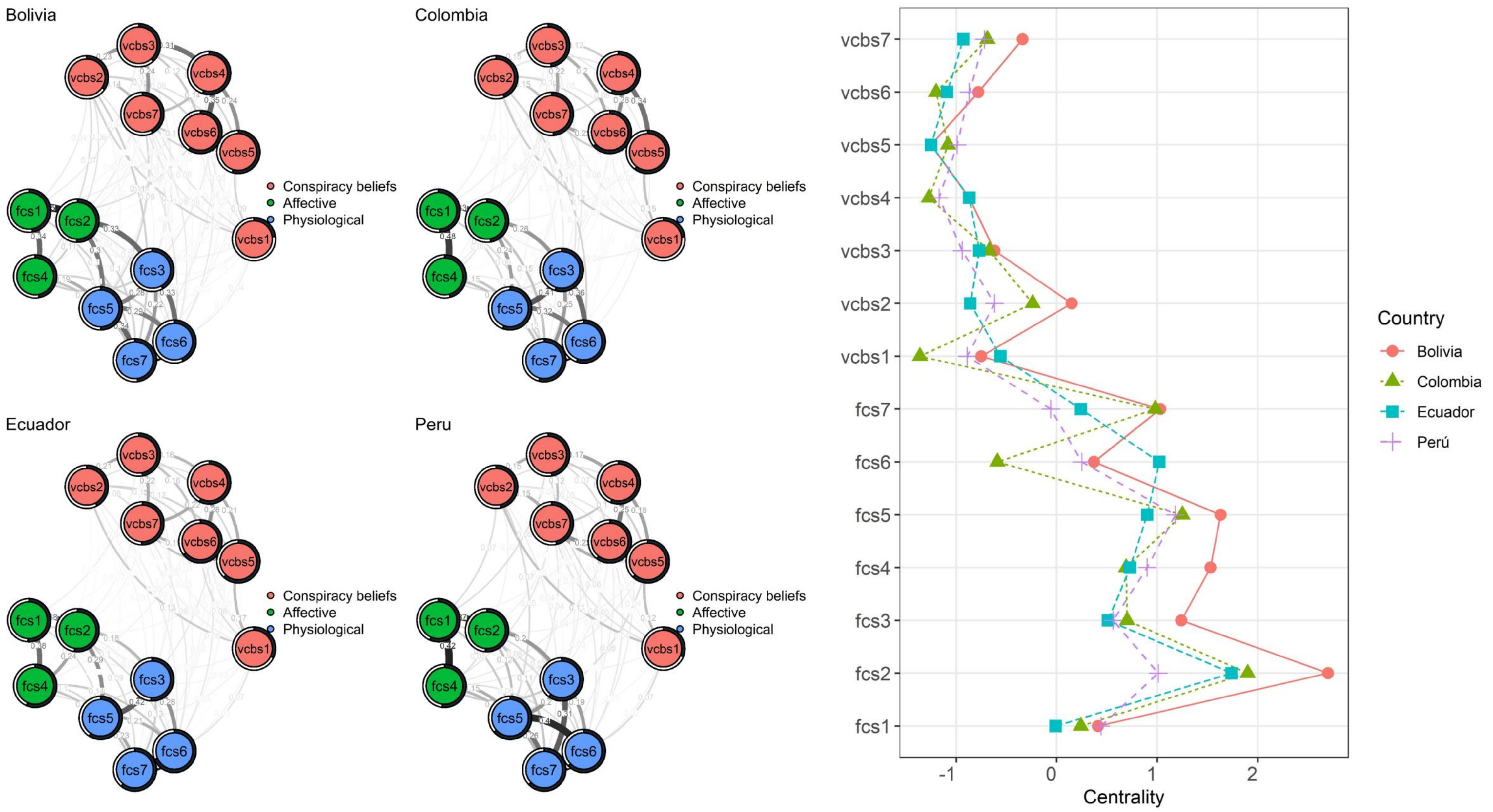


Fig 1.

Ventura-León, J., & Lino-Cruz, C. (2023). Love, jealousy, satisfaction and violence in young couples: A network analysis. *PLoS one*, *18*(5), e0285555.



Caycho-Rodríguez, T., **Ventura-León, J.,** Valencia, P. D., Vilca, L. W., Carbajal-León, C., Reyes-Bossio, M., ... & Petzold, O. (2022). Network analysis of the relationships between conspiracy beliefs towards COVID-19 vaccine and symptoms of fear of COVID-19 in a sample of latin american countries. *Current Psychology*, 1-16.

Estimación de una red en bootnet

```
# Load bootnet:
library("bootnet")

# Estimate network (see ?estimateNetwork):
Results <- estimateNetwork(Data, default =      )

# Obtain weights matrix:
Results$graph

# Plot network (same arguments as qgraph):
plot(Results, layout = "spring")

# Centrality:
library("qgraph")
centralityPlot(Results)
```

"pcor" for GGM
"IsingSampler"

Estimación de una red en bootnet

```
# Load bootnet:
library("bootnet")

# Estimate network (see ?estimateNetwork):
Results <- estimateNetwork(Data, default =      )

# Obtain weights matrix:
Results$graph

# Plot network (same arguments as qgraph):
plot(Results, layout = "spring")

# Centrality:
library("qgraph")
centralityPlot(Results)
```

"pcor" for GGM
"IsingSampler"

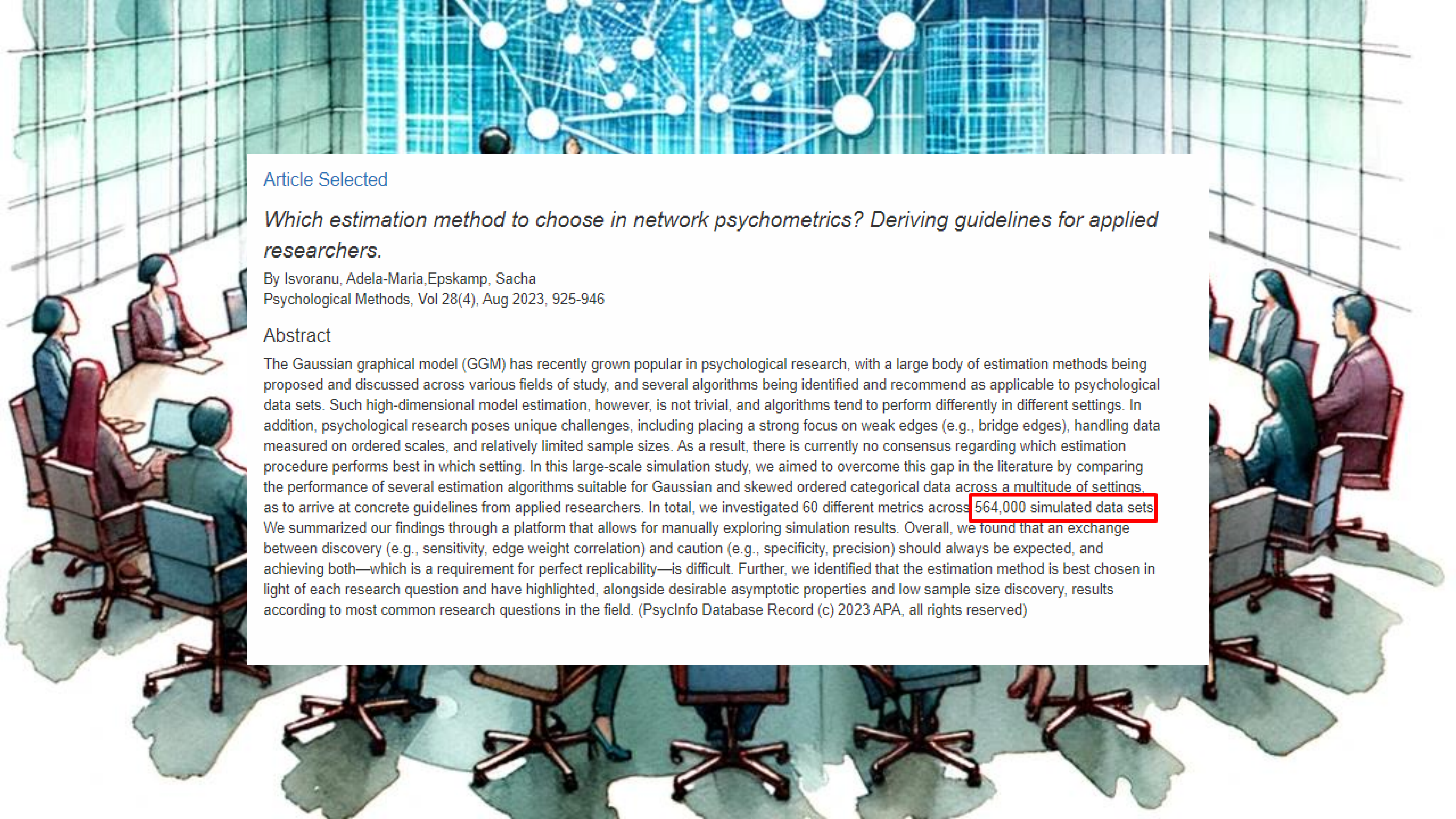
JASP
A Fresh Way to Do Statistics

R Studio

```
# Estimate a network:
library("bootnet")
Network <- estimateNetwork(Data, default = "...")
```

Default	Model	Data	Estimation	Penalty	Selection	Package
pcor	GGM	Continuous, ordinal	Inverse	None	None, sig, FDR	qgraph
EBICglasso	GGM	Continuous, ordinal	Inverse	glasso	EBIC	qgraph
ggmModSelect	GGM	Continuous, ordinal	Stepwise model fit	None	BIC	qgraph
IsingFit	Ising	Binary	Nodewise	LASSO	EBIC	IsingFit
IsingSampler	Ising	Binary	Nodewise, MLE	None	None	IsingSampler
adalasso	GGM	Continuous	Nodewise	Adaptive LASSO	CV	parcor
huge	GGM	Continuous	Inverse	glasso	EBIC	huge
mgm	MGM	Continuous, count, binary, categorical	Nodewise	LASSO	EBIC, CV	mgm
relimp	“GGM”	Continuous	Nodewise	None	Any other default	relimpo

CV = Cross validation; Inverse = Inverse covariance matrix; MLE = Maximum (pseudo) likelihood



Article Selected

Which estimation method to choose in network psychometrics? Deriving guidelines for applied researchers.

By Isvoranu, Adela-Maria,Epskamp, Sacha

Psychological Methods, Vol 28(4), Aug 2023, 925-946

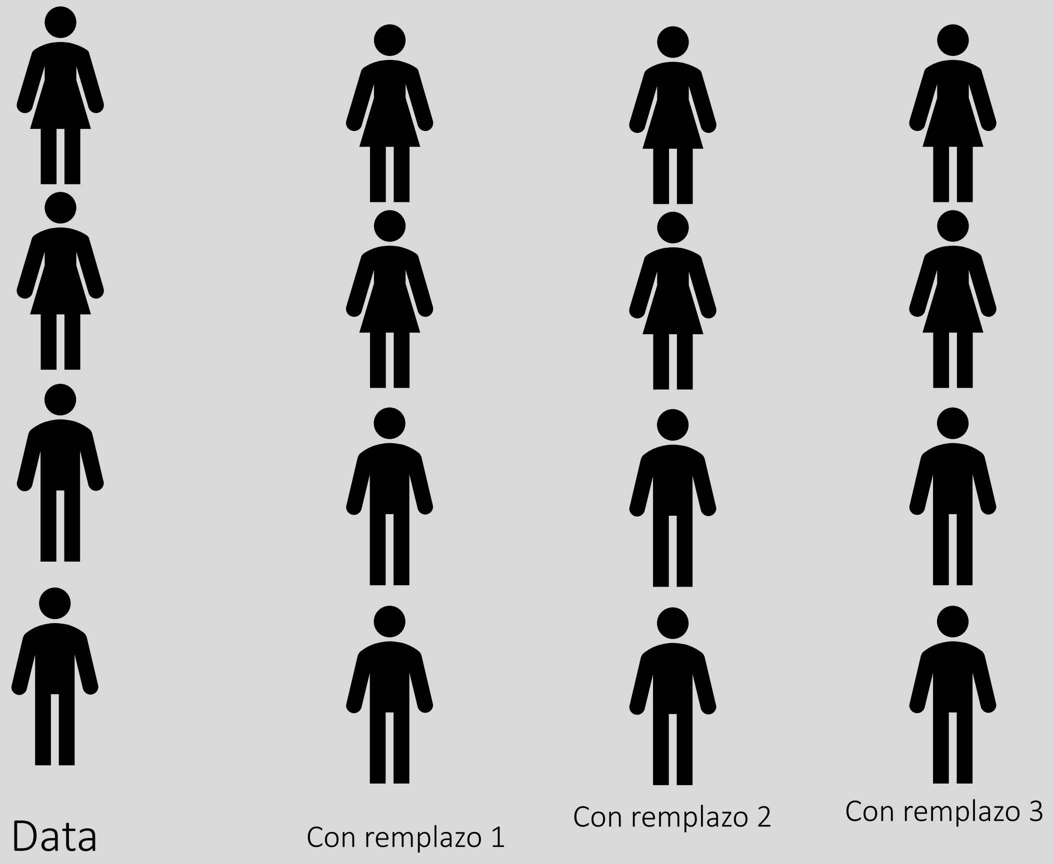
Abstract

The Gaussian graphical model (GGM) has recently grown popular in psychological research, with a large body of estimation methods being proposed and discussed across various fields of study, and several algorithms being identified and recommend as applicable to psychological data sets. Such high-dimensional model estimation, however, is not trivial, and algorithms tend to perform differently in different settings. In addition, psychological research poses unique challenges, including placing a strong focus on weak edges (e.g., bridge edges), handling data measured on ordered scales, and relatively limited sample sizes. As a result, there is currently no consensus regarding which estimation procedure performs best in which setting. In this large-scale simulation study, we aimed to overcome this gap in the literature by comparing the performance of several estimation algorithms suitable for Gaussian and skewed ordered categorical data across a multitude of settings, as to arrive at concrete guidelines from applied researchers. In total, we investigated 60 different metrics across 564,000 simulated data sets. We summarized our findings through a platform that allows for manually exploring simulation results. Overall, we found that an exchange between discovery (e.g., sensitivity, edge weight correlation) and caution (e.g., specificity, precision) should always be expected, and achieving both—which is a requirement for perfect replicability—is difficult. Further, we identified that the estimation method is best chosen in light of each research question and have highlighted, alongside desirable asymptotic properties and low sample size discovery, results according to most common research questions in the field.

Precisión, estabilidad y comparación de redes

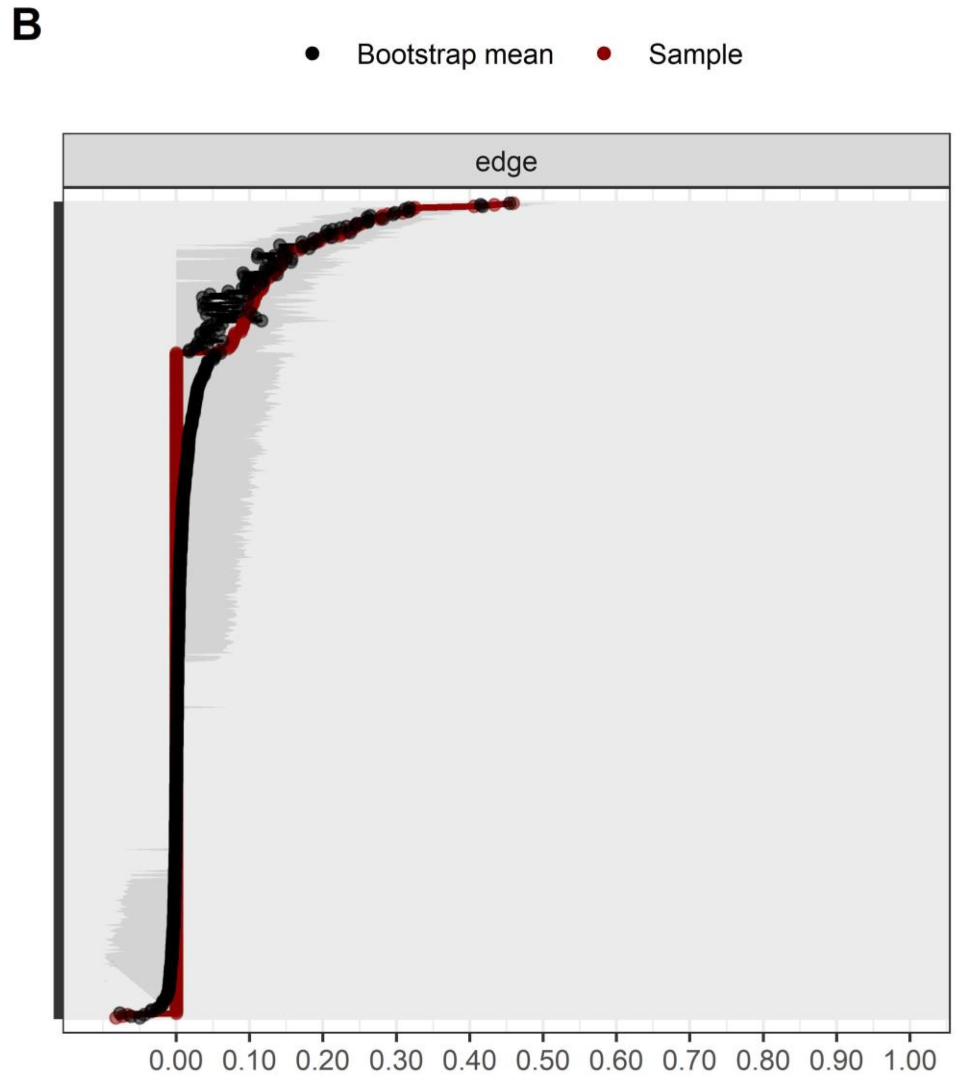
Bootstrap no paramétrico

- 1. Calcular la estadística (por ejemplo, el peso del borde) en la muestra original
- 2. Genere un nuevo conjunto de datos tomando muestras de los datos originales con reemplazo
- 3. Calcule la estadística (por ejemplo, el peso de las aristas) en el nuevo conjunto de datos.
- 4. Repita los pasos 2 y 3 y utilice los intervalos de la estadística calculada para establecer intervalos de confianza



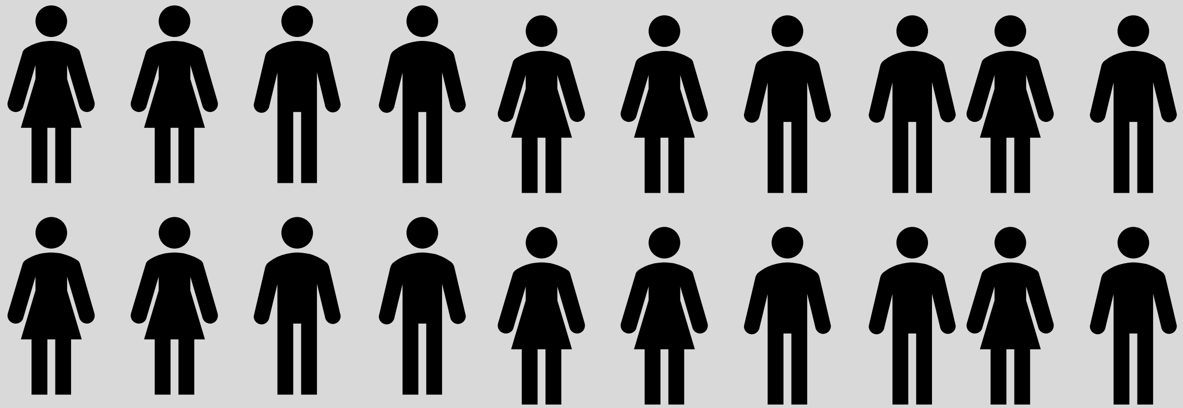
```
# Perform bootstrap:
boot_nonparametric<-bootnet(
net_glasso,
nBoots= 1000,
nCores= 8)


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



Case-dropping Bootstrap

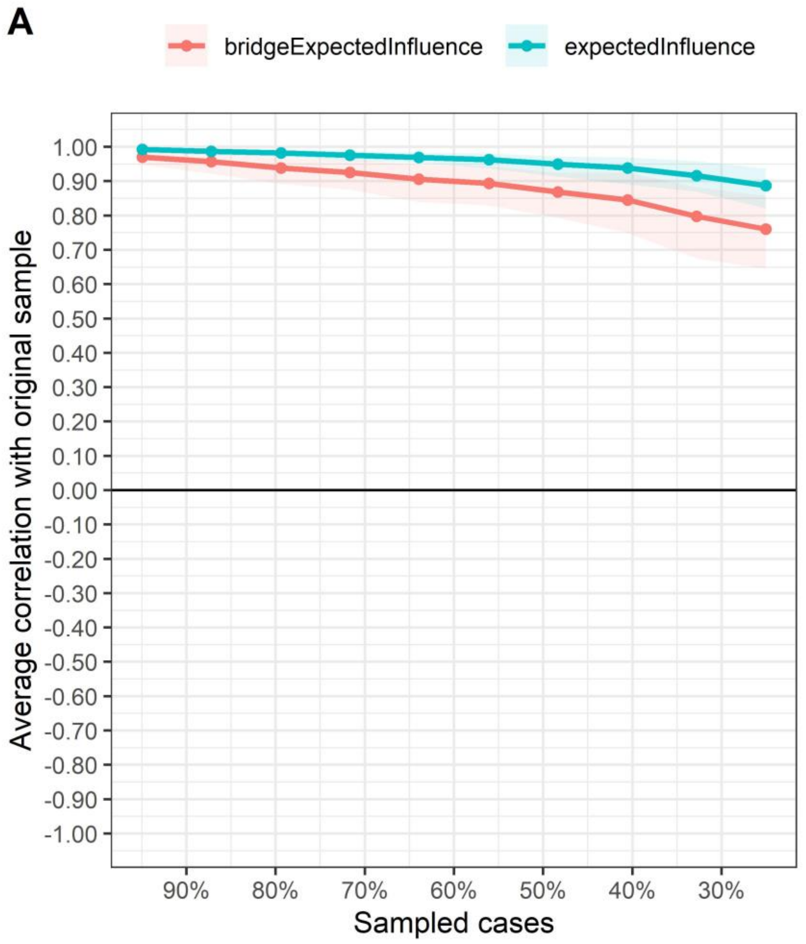
- 1. Obtener la centralidad para el conjunto de datos (dolor > mal humor > ... > psicosis)
- 2. Subconjunto de datos eliminando el 10% de las personas
- 3. Obtener la centralidad para el subconjunto del 10% de las personas
- 4. Repita los pasos 2 y 3 para el 20%, 30%, ..., 90%.
- 5. Correlación de los índices de centralidad de todas las redes de subconjuntos con la red de muestra original



```
# Run bootstrap:
boot_casedrop<-bootnet(net_glasso,
nBoots= 1000,
nCores= 8,
type = "case",
statistics = c('bridgeExpectedInfluence',
'expectedInfluence’))
```

```
# Plot stability:
plot(boot_casedrop, statistics =
c'bridgeExpectedInfluence', 'expectedInfluence’))
```

```
# CS-Coefficient (best if above 0.5):
corStability(boot_casedrop)
```



Referencias

Epskamp, S., Rhemtulla, M., & Borsboom, D. (2017). *Generalized Network Psychometrics: Combining Network and Latent Variable Models. Psychometrika, 82(4), 904–927.* doi:10.1007/s11336-017-9557-x

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

Cramer, A., Waldorp, L., Van der Maas, H., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences, 33*(2-3), 137-150. doi:10.1017/S0140525X09991567

Borsboom, D., & Cramer, A. O. (2013). Network analysis: an integrative approach to the structure of psychopathology. *Annual review of clinical psychology*, *9*, 91-121.

Borsboom, D., Cramer, A. O. J., Fried, E. I., Isvoranu, A. M., Robinaugh, D. J., Dalege, J., & van der Maas, H. L. J. (2022). Chapter 1. Network perspectives. In Isvoranu, A. M., Epskamp, S., Waldorp, L. J., & Borsboom, D. (Eds.). *Network psychometrics with R: guide for behavioral and social scientists*. Routledge, Taylor & Francis Group.

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., ... & Snippe, E. (2019). What do centrality measures measure in psychological networks?. *Journal of abnormal psychology*, *128*(8), 892.

Hallquist, M. N., Wright, A. G., & Molenaar, P. C. (2021). Problems with centrality measures in psychopathology symptom networks: Why network psychometrics cannot escape psychometric theory. *Multivariate behavioral research*, *56*(2), 199-223.

Starr, J., & Falk, C. F. (2023). Comparison of latent variable and psychological network models in PROMIS data: output metrics and factor structure. *Quality of Life Research*, 1-9.

Ventura-León, J., López-Jurado, R., Porturas, E., León-Mostacero, I., & Canchanya-Balbin, S. E. (2022). Anxiety, depression, stress, worry about COVID-19 and fear of loneliness during COVID-19 lockdown in Peru: A network analysis approach. *Frontiers in Public Health*, *10*, 946697.

Ventura-León, J., Caycho-Rodríguez, T., Talledo-Sánchez, K., & Casiano-Valdivieso, K. (2022). Depression, COVID-19 anxiety, subjective well-being, and academic performance in university students with COVID-19-infected relatives: a network analysis. *Frontiers in Psychology*, *13*, 837606.

Ventura-León, J., & Lino-Cruz, C. (2023). Love, jealousy, satisfaction and violence in young couples: A network analysis. *PLoS one*, *18*(5), e0285555.

Caycho-Rodríguez, T., **Ventura-León, J.,** Valencia, P. D., Vilca, L. W., Carbajal-León, C., Reyes-Bossio, M., ... & Petzold, O. (2022). Network analysis of the relationships between conspiracy beliefs towards COVID-19 vaccine and symptoms of fear of COVID-19 in a sample of latin american countries. *Current Psychology*, 1-16.

Isvoranu, A. M., & Epskamp, S. (2023). Which estimation method to choose in network psychometrics? Deriving guidelines for applied researchers. *Psychological methods*, *28*(4), 925.

Muchas gracias

Dr. José Ventura-León
Docente investigador

https://joseventuraleon.com/