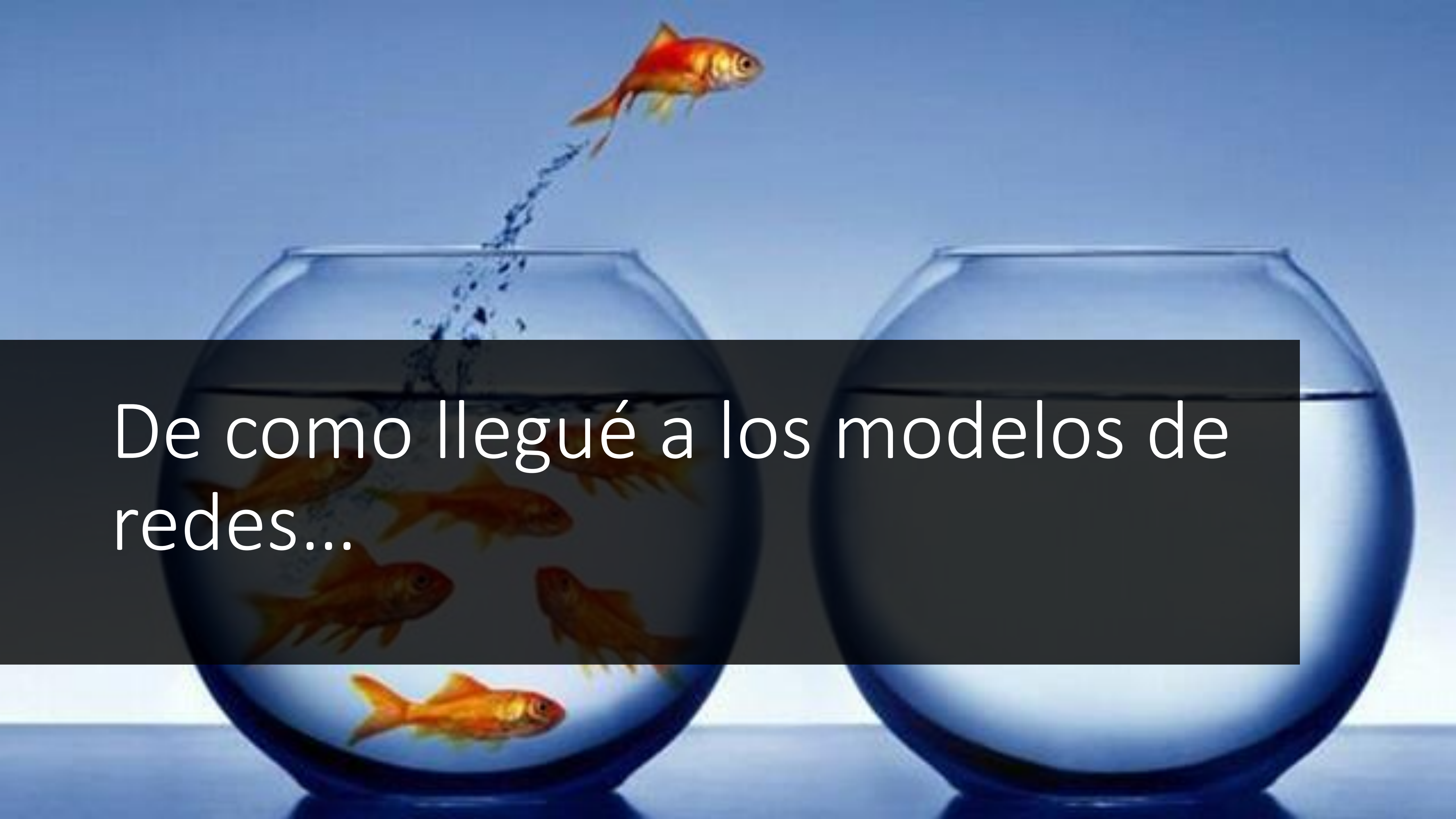
PSICONETRIA: OTRA FORMA DE MIRAR LA PSICOMETRÍA

Dr. José Ventura-León
Docente Investigador

Ventura-León, J. (2023). *Psiconetria: Otra forma de mirar la psicometría* [Diapositivas de PowerPoint]. Facultad de Salud, Universidad Privada del Norte.

De como llegué a los modelos de redes…

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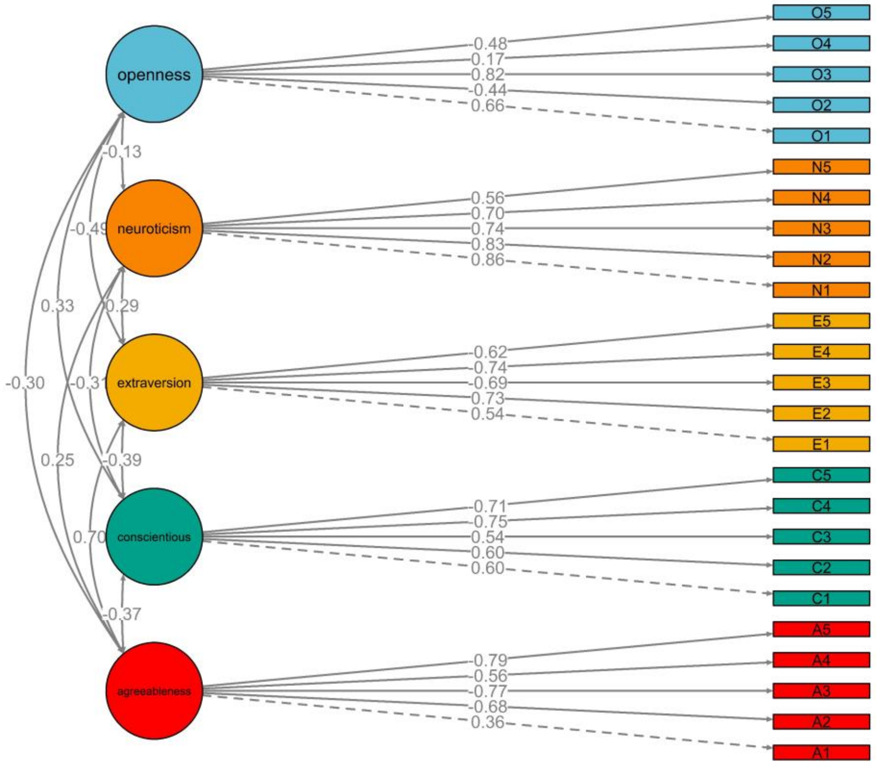


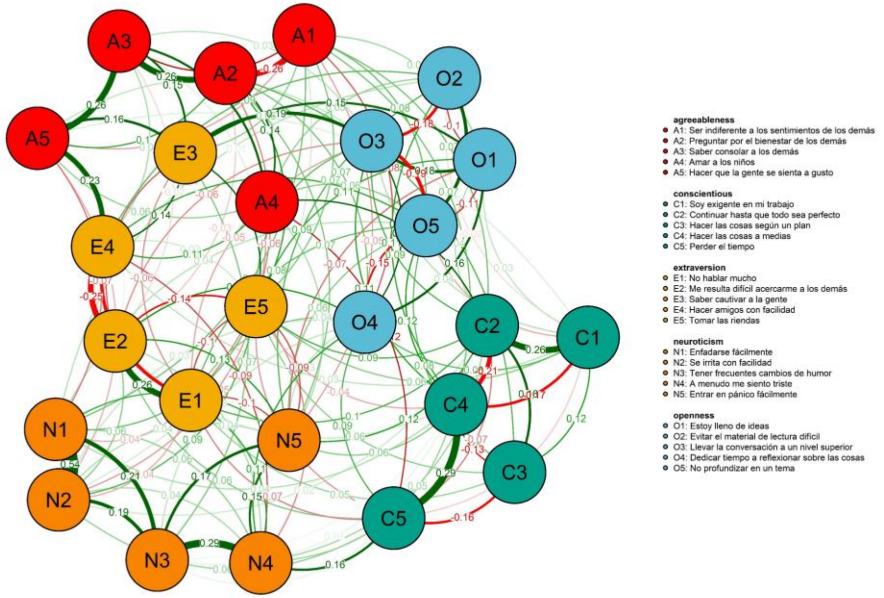
Carga varianza-covarianza

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

Carga Factorial

Residual varianza-covarianza

Network Analysis

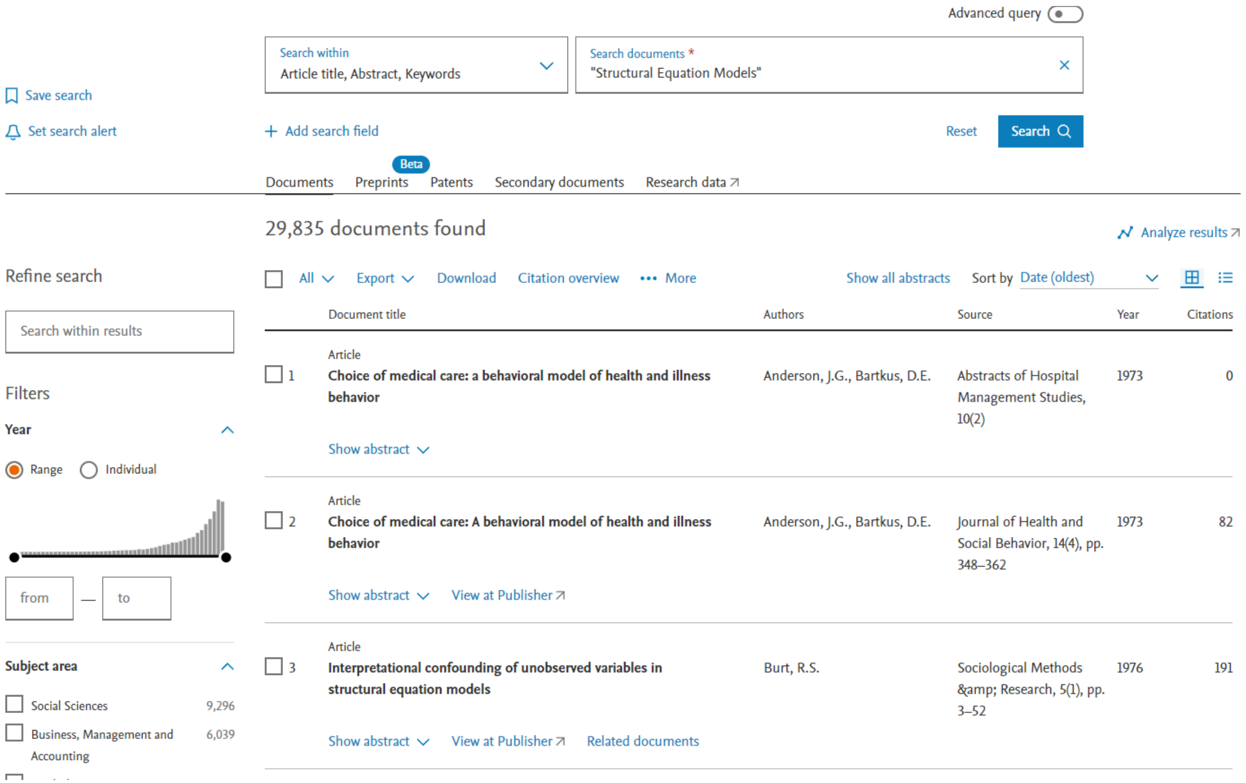


Matriz de escalado diagonal

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

Matriz de varianza-covarianza

Red de correlación parcial



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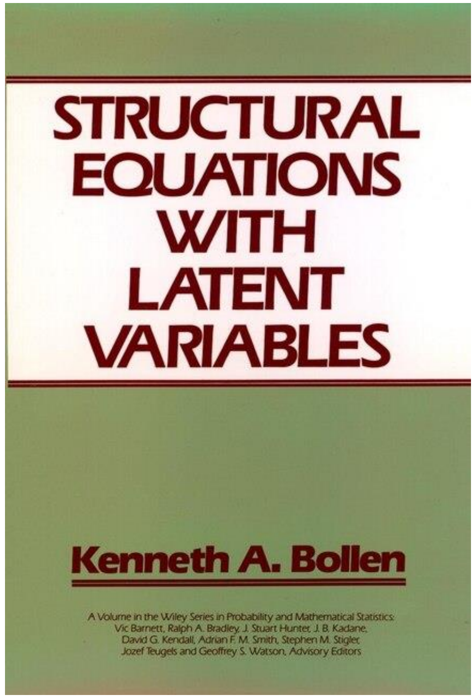

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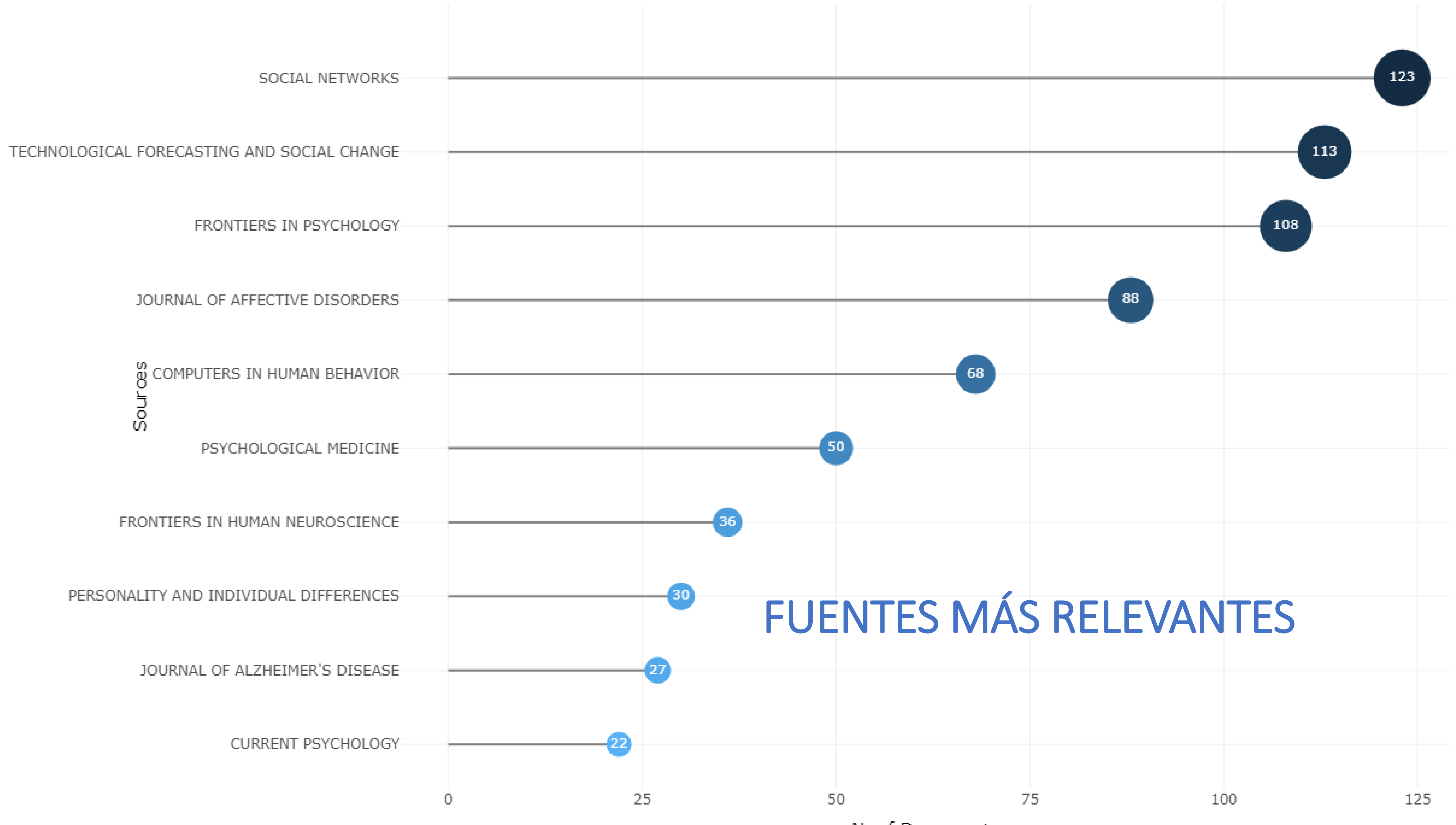

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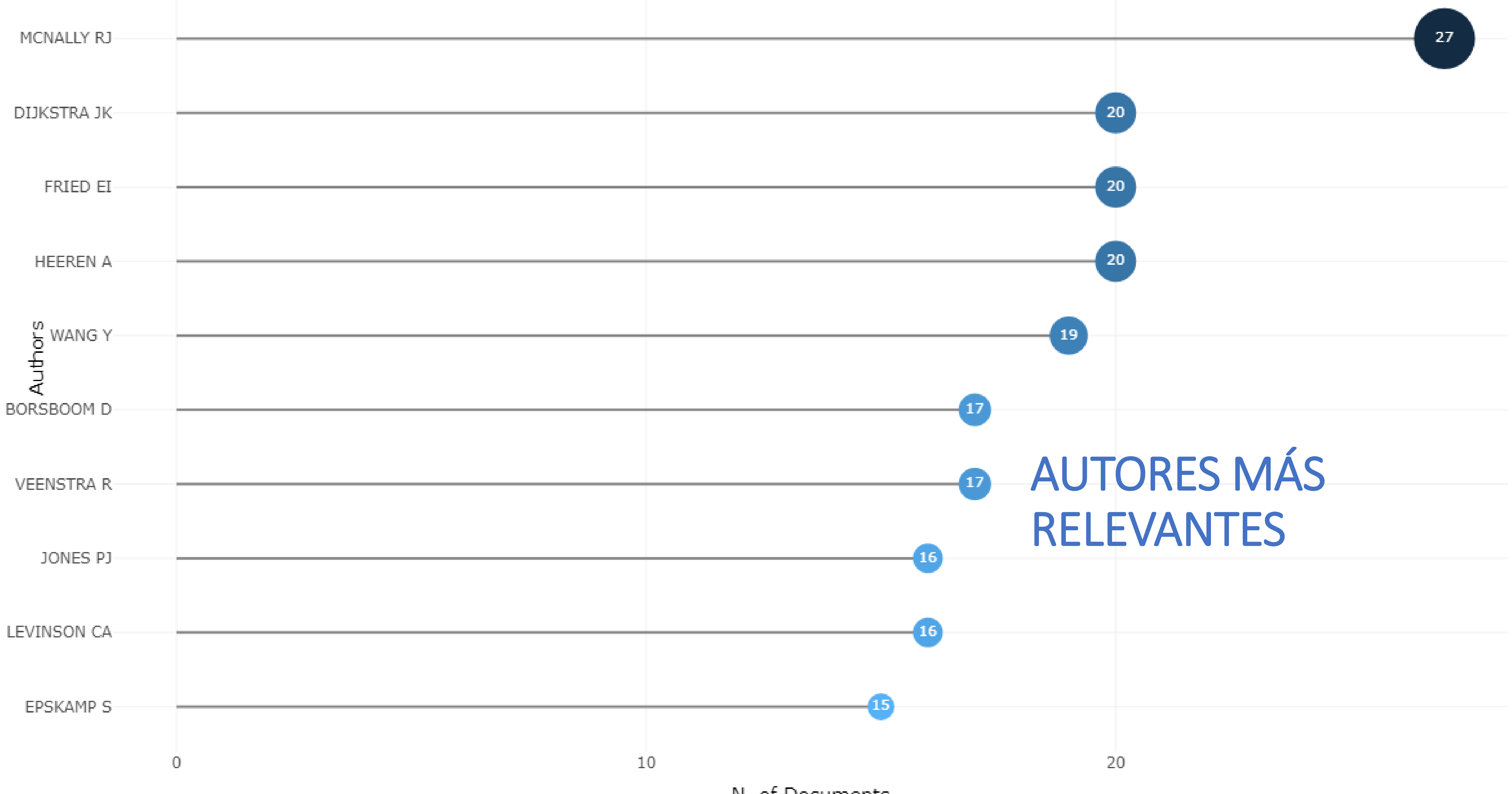

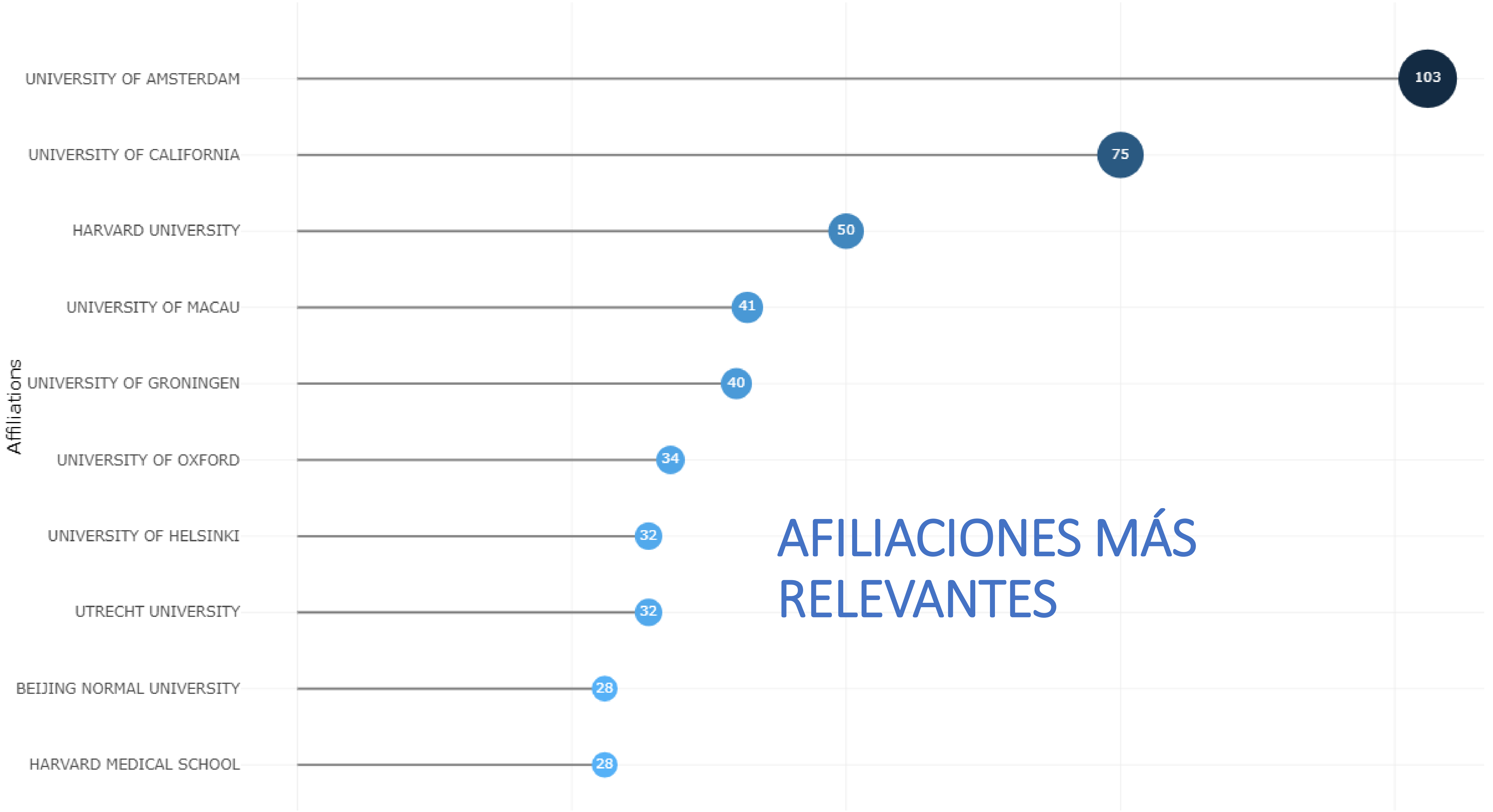

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BEARD C, 2016, PSYCHOL MED	10.1017/S0033291716002300	2016	261	Network analysis of depression and anxiety symptom relationships in a psychiatric sample
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HASLBECK JMB, 2018, BEHAV RES METHODS	10.3758/s13428-017-0910-x	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

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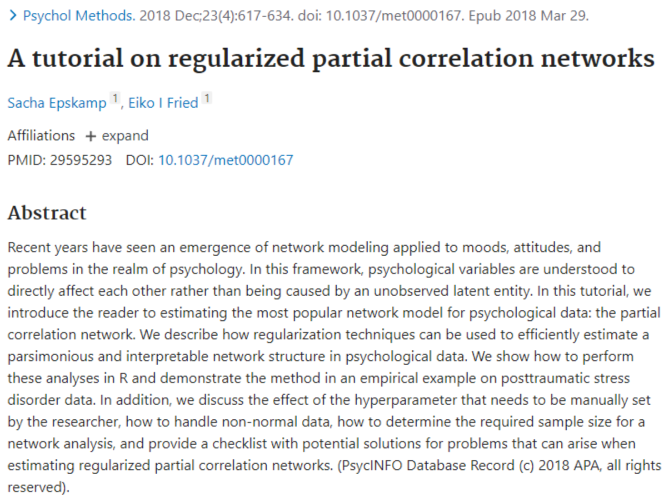


› Psychol Methods. 2018 Dec;23(4):617-634. doi: 10.1037/met0000167. Epub 2018 Mar 29.

A tutorial on regularized partial correlation networks

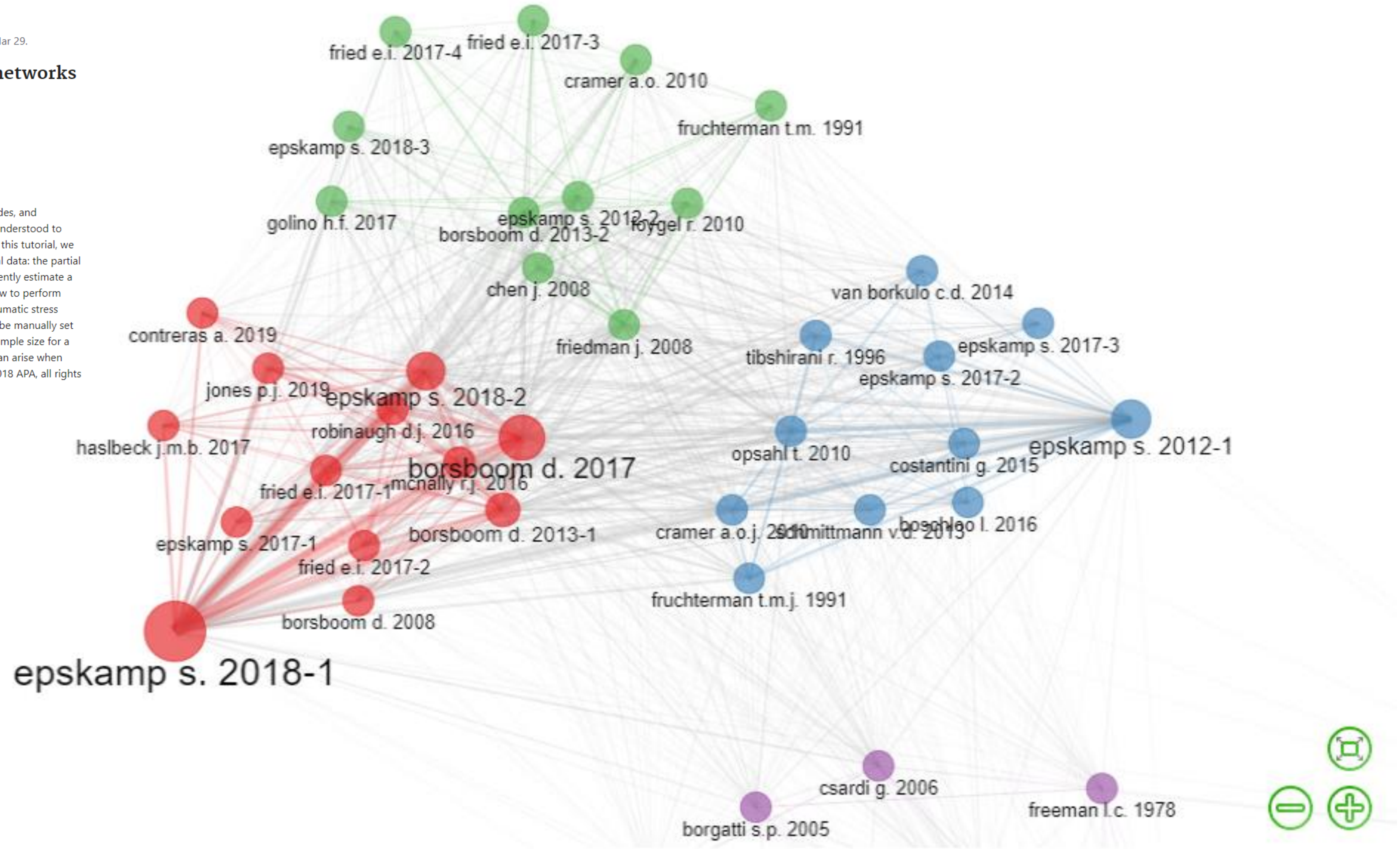
Sacha Epskamp [1], Eiko I Fried [1]

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).



Diseño de investigación en psicología y análisis de redes

Investigating the feasibility of idiographic network models.

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Mansueto, Alessandra C. Wiers, Reinout W. van Weert, Julia C. M. Schouten, Barbara C. Epskamp, Sacha

Citation

Mansueto, A. C., Wiers, R. W., van Weert, J. C. M., Schouten, B. C., & Epskamp, S. (2022). Investigating the feasibility of idiographic network models. *Psychological Methods*. Advance online publication. https://doi.org/10.1037/met0000466

Abstract

Recent times have seen a call for personalized psychotherapy and tailored communication during treatment, leading to the necessity to model the complex dynamics of mental disorders in a single subject. To this aim, time-series data in one patient can be collected through ecological momentary assessment and analyzed with the graphical vector autoregressive model, estimating temporal and contemporaneous idiographic networks. Idiographic networks graph interindividual processes that may be potentially used to tailor psy ng tool for clinical practice. However, the que e conducted a large-scale simulation study in the context of psychopathology, testing the performance of personalized networks with different numbers of

Diseños de caso único

Bayesian Analysis of Cross-sectional Networks: A Tutorial in R and JASP

Huth, K.B.S.[1,2,3], de Ron, J.[1], Goudriaan, A. E.[2,3,5], Luigjes, J.[2,3], Mohammadi, R.[4], van Holst, R. J.[2,3], Wagenmakers, E.-J.[1] & Marsman, M.[1,3]

1 Department of Psychology, University of Amsterdam;
2 Department of Psychiatry, Amsterdam UMC location University of Amsterdam;
3 Centre for Urban Mental Health, University of Amsterdam;
4 Department of Business Analytics, Amsterdam Business School, University of Amsterdam;
5 Arkin Mental Health Institute, the Netherlands;

This

Estimaciones bayesianas

An introduction to directed acyclic graphs in trauma research.

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Sonis, Jeffrey Jiang, Tammy

Citation

Sonis, J., & Jiang, T. (2023). An introduction to directed acyclic graphs in trauma research. *Psychological Trauma: Theory, Research, Practice, and Policy, 15*(6), 899–905. https://doi.org/10.1037/tra0001545

Abstract

Objective: Directed acyclic graphs (DAGs) are visual representations of the presumed causal structure of an empirical research data set. They are important tools for researchers but have been used rarely in the psychological trauma literature. The purpose of this article is to explain what DAGs are and why (and how) they are useful for trauma researchers. Method: We first describe the utility of DAGs for mak efinitions and rules

Diseños confirmatorios

Meta-analytic Gaussian Network Aggregation

Sacha Epskamp [1] [2], Adela-Maria Isvoranu [3], Mike W-L Cheung [4]

Affiliations + expand

PMID: 34264449 PMCID: PMC9021114 DOI: 10.1007/s11336-021-09764-3

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Erratum to: Meta-analytic Gaussian Network Aggregation.

Epskamp S, Isvoranu AM, Cheung MW.

Psychometrika. 2022 Mar;87(1):372. doi: 10.1007/s11336-021-09804-y.

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Metaanálisis de redes

Diseños para modelos relacionales

Estimating psychological networks and their accuracy: A tutorial paper

Sacha Epskamp[1] · Denny Borsboom[1] · Eiko I. Fried[1]

Published online: 24 March 2017

Abstract The usage of *psychological networks* that conceptualize behavior as a complex interplay of psychological and other components has gained increasing popularity in various research fields. While prior publications have tackled the topics of estimating and interpreting such networks, little work has been conducted to check how *accurate* (i.e., prone to sampling variation) networks are estimated, and how *stable* (i.e., interpretation remains similar with less observations) inferences from the network structure (such as centrality indices) are. In this tutorial paper, we aim to introduce the reader to this field and tackle the problem of accuracy under sampling variation. We first introduce the current state-of-the-art of network estimation. Second, we provide a rationale why researchers should investigate the accuracy of psychological networks. Third, we describe how bootstrap routines can be used to (A) assess the accuracy of estimated network connections, (B) investigate the stability of centrality indices, and (C) test whether network connections and centrality estimates for different variables differ from each other. We introduce two novel statistical methods: for (B) the *correlation stability coefficient*, and for (C) the *bootstrapped difference test* for edge-weights and centrality indices. We conducted and present simulation studies to assess the performance of both methods. Finally, we developed the free R-package *bootnet* that allows for estimating psychological networks in a generalized framework in addition to the proposed bootstrap methods. We showcase *bootnet* in a tutorial, accompanied by R syntax, in which we analyze a dataset of 359 women with posttraumatic stress disorder available online.

Keywords Network psychometrics · Psychological networks · Replicability · Bootstrap · Tutorial

Introduction

In the last five years, network research has gained substantial attention in psychological sciences (Borsboom & Cramer, 2013; Cramer et al., 2010). In this field of research, psychological behavior is conceptualized as a complex interplay of psychological and other components. To portray a potential structure in which these components interact, researchers have made use of *psychological networks*. Psychological networks consist of nodes representing observed variables, connected by edges representing statistical relationships. This methodology has gained substantial footing and has

A Tutorial on Regularized Partial Correlation Networks

Sacha Epskamp and Eiko I. Fried
University of Amsterdam

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.

Translational Abstract
Recent years have seen an emergence in the use of networks models in psychological research to explore relationships of variables such as emotions, symptoms, or personality items. Networks have become particularly popular in analyzing mental illnesses, as they facilitate the investigation of how individual symptoms affect one-another. This article introduces a particular type of network model: the partial correlation network, and describes how this model can be estimated using regularization techniques from statistical learning. With these techniques, a researcher can gain insight in predictive and potential causal relationships between the measured variables. The article provides a tutorial for applied researchers on how to estimate these models, how to determine the sample size needed for performing such an analysis, and how to investigate the stability of results. We also discuss a list of potential pitfalls when using this methodology.

Keywords: Partial correlation networks, Regularization, Network modeling, Tutorial

Supplemental materials: http://dx.doi.org/10.1037/met0000167.supp

Psychonetric – Psicometría de redes

30

Network Psychometrics

Sacha Epskamp, Gunter Maris, Lourens J. Waldorp, and Denny Borsboom

Introduction

"In fact, statistical field theory may have even more to offer. It always struck me that there appears to be a close connection between the basic expressions underlying item-response theory and the solutions of elementary lattice fields in statistical physics. For instance, there is almost a one-to-one formal correspondence of the solution of the Ising model (a lattice with nearest neighbor interaction between binary-valued sites; e.g., Kindermann & Snell (1980), Chapter 1) and the Rasch model Fischer (1974). (Molenaar, 2003, p. 82)"

In recent years, network models have been proposed as an alternative way of looking at psychometric problems Van der Maas et al. (2006); Cramer, Waldorp, van der Maas& Borsboom (2010); Borsboom & Cramer (2013). In these models, psychometric item responses are conceived of as proxies for variables that directly interact with each other. For example, the symptoms of depression (such as loss of energy, sleep problems, and low self-esteem) are traditionally thought of as being determined by a common latent variable (depression, or the liability to become depressed; Aggen, Neale, and Kendler (2005)). In network models, these symptoms are instead hypothesized to form networks of mutually reinforcing variables (e.g., sleep problems may lead to loss of energy, which may lead to low self-esteem, which may cause rumination that in turn may reinforce sleep problems). On the face of it, such network models offer an entirely different

A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires

Alexander P. Christensen[1*], Hudson Golino[2], and Paul J. Silvia[1]

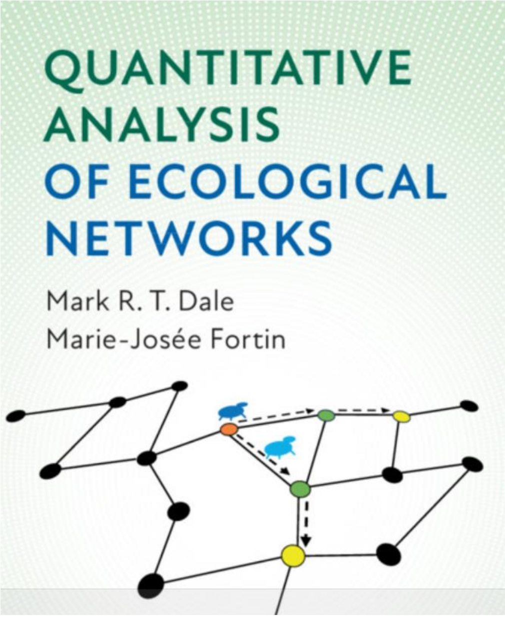
ABSTRACT

This article reviews the causal implications of latent variable and psychometric network models for the validation of personality trait questionnaires. These models imply different data generating mechanisms that have important consequences for the validity and validation of questionnaires. From this review, we formalize a framework for assessing the evidence for the validity of questionnaires from the psychometric network perspective. We focus specifically on the structural phase of validation where items are assessed for redundancy, dimensionality, and internal structure. In this discussion, we underline the importance of identifying unique *personality components* (i.e., an item or set of items that share a unique common cause) and representing the breadth of each trait's domain in personality networks. After, we argue that psychometric network models have measures that are statistically equivalent to factor models, but suggest that their substantive interpretations differ. Finally, we provide a novel measure of *structural consistency*, which provides complementary information to internal consistency measures. We close with future directions for how external validation can be executed using psychometric network models.

***Keywords*:** network analysis, personality, validity, measurement, assessment

Compiled: April 3rd 2020

Note: This is the pre-copyedit version of this article, which has been accepted as a part of the *European Journal of Personality*'s special issue on "New approaches towards conceptualizing and assessing personality."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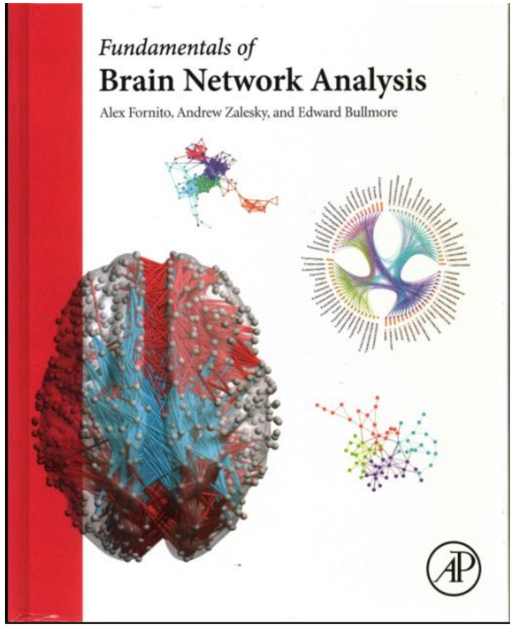
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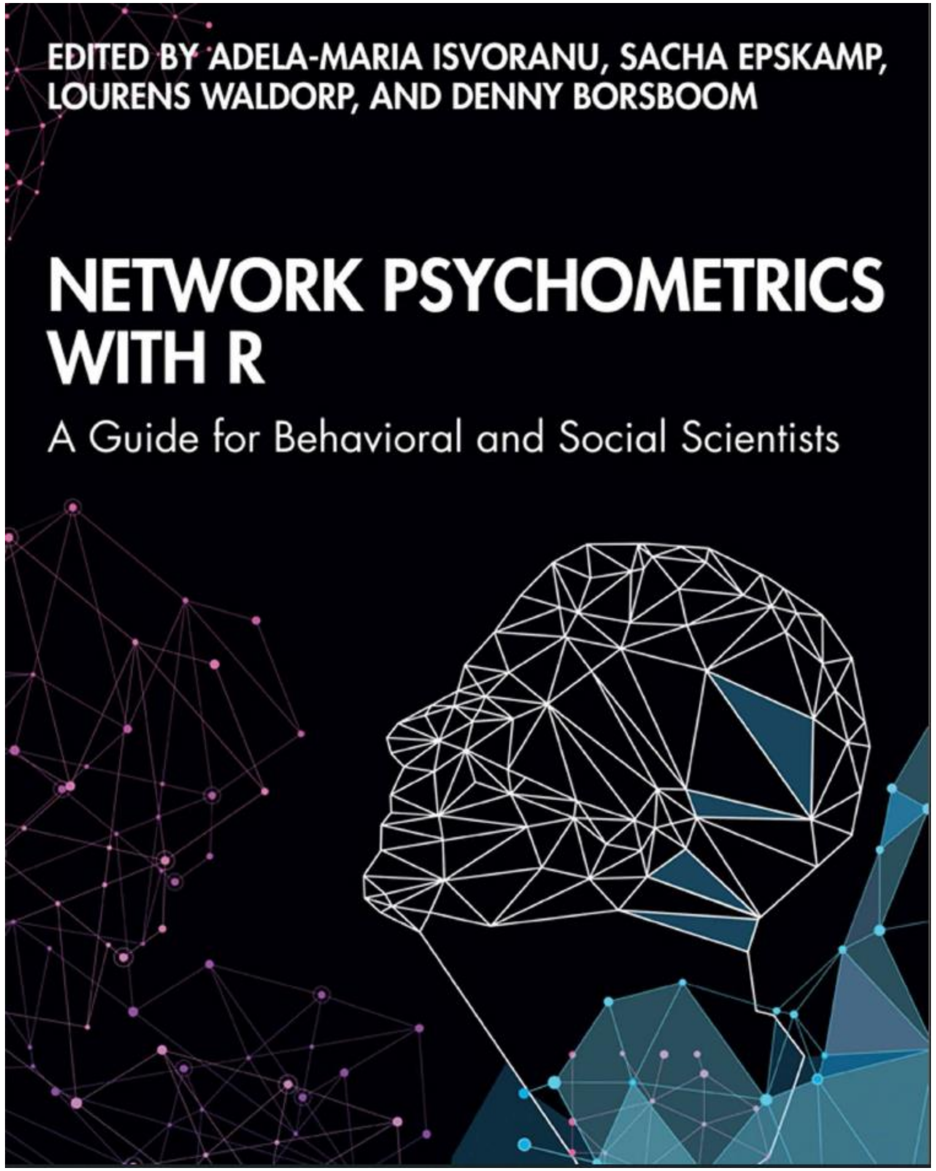
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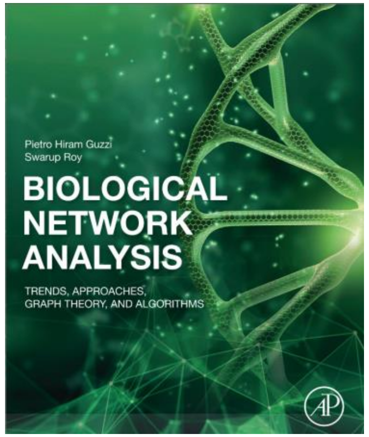
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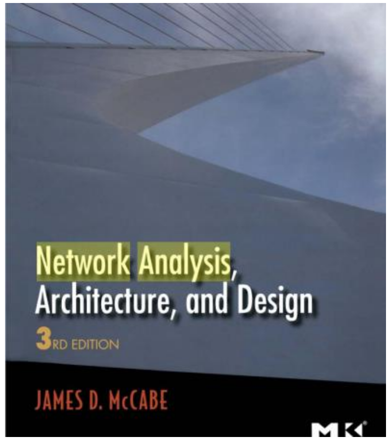
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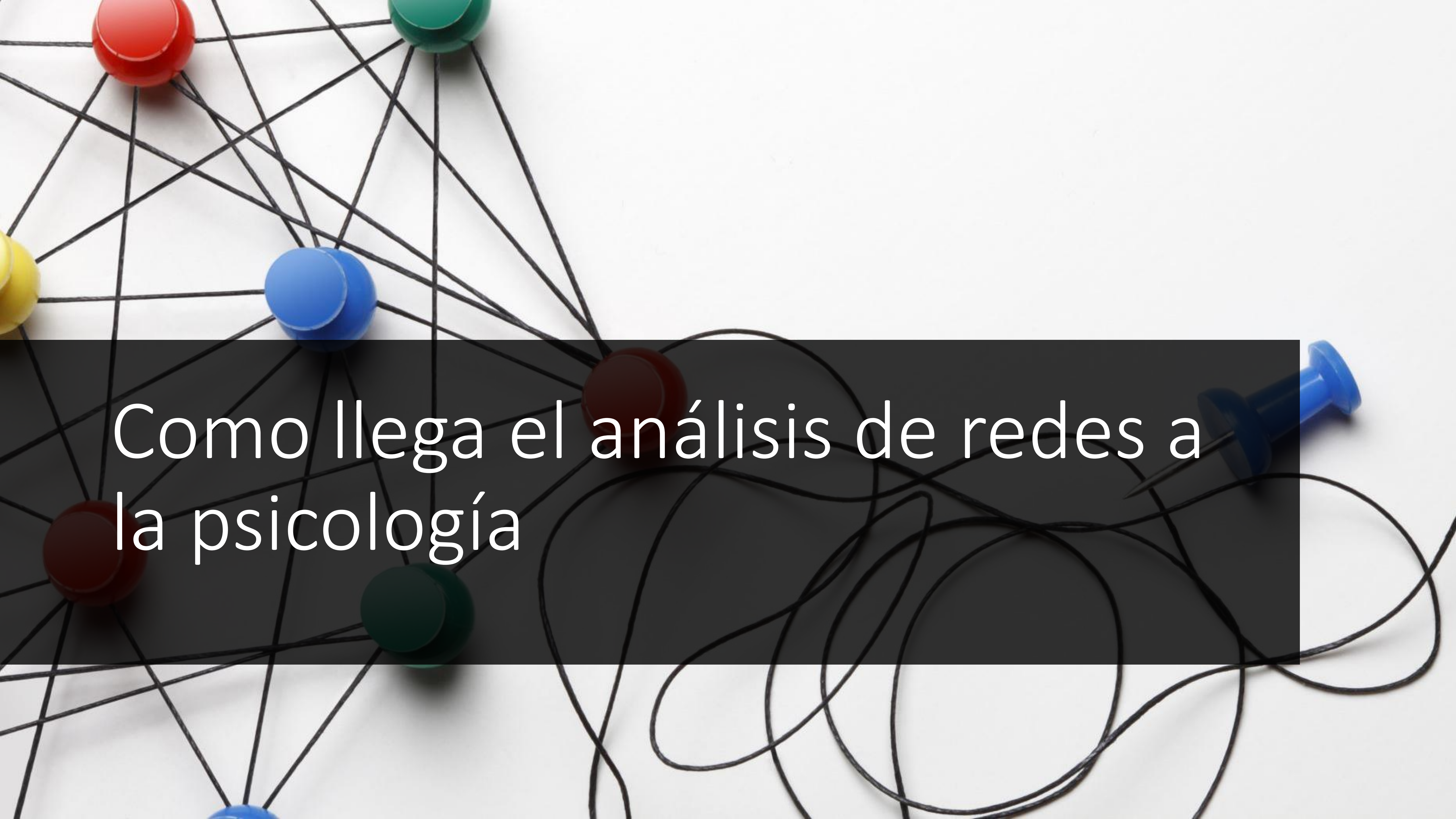


Como llega el análisis de redes a la psicología

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

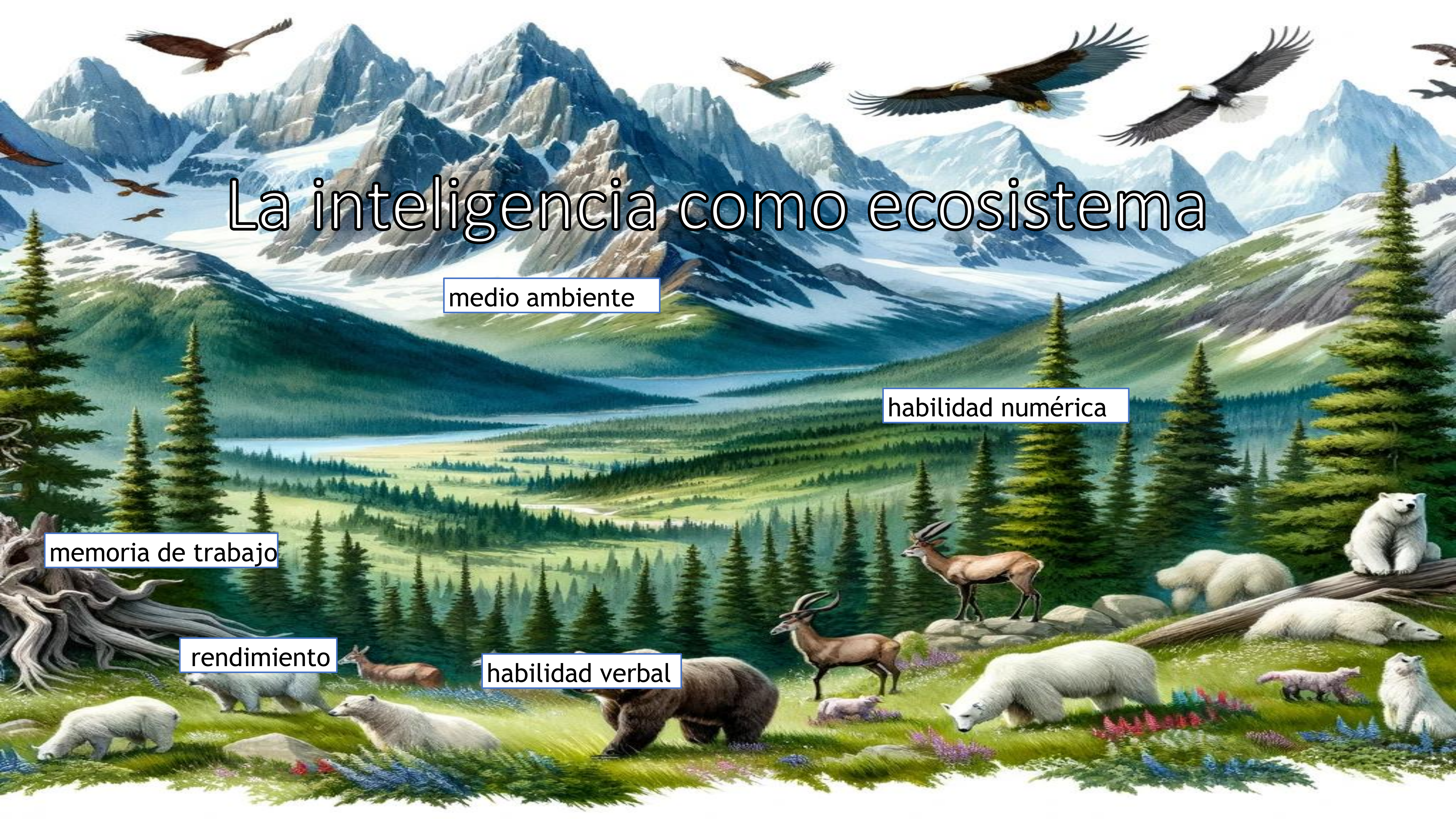
Scores on cognitive tasks used in intelligence tests correlate positively with each other, that is, they display a positive manifold of correlations. The positive manifold is often explained by positing a dominant latent variable, the *g* factor, associated with a single quantitative cognitive or biological 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

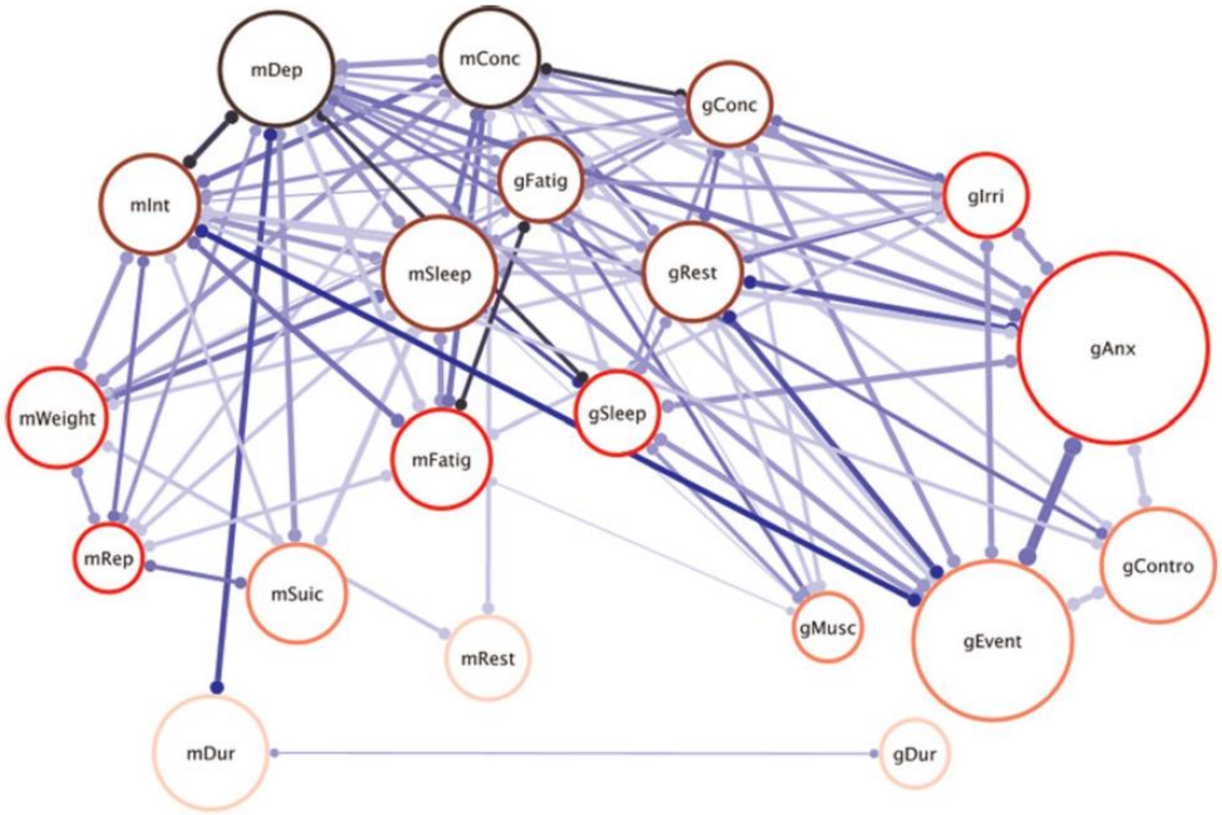


Figure 4. A comorbidity network for major depressive disorder (MDD) and general anxiety disorder (GAD). Larger nodes represent more frequent symptoms, darker circumference represents higher centrality, thicker edges represent higher frequency of co-occurrence, and darker edges represent stronger associations. 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

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

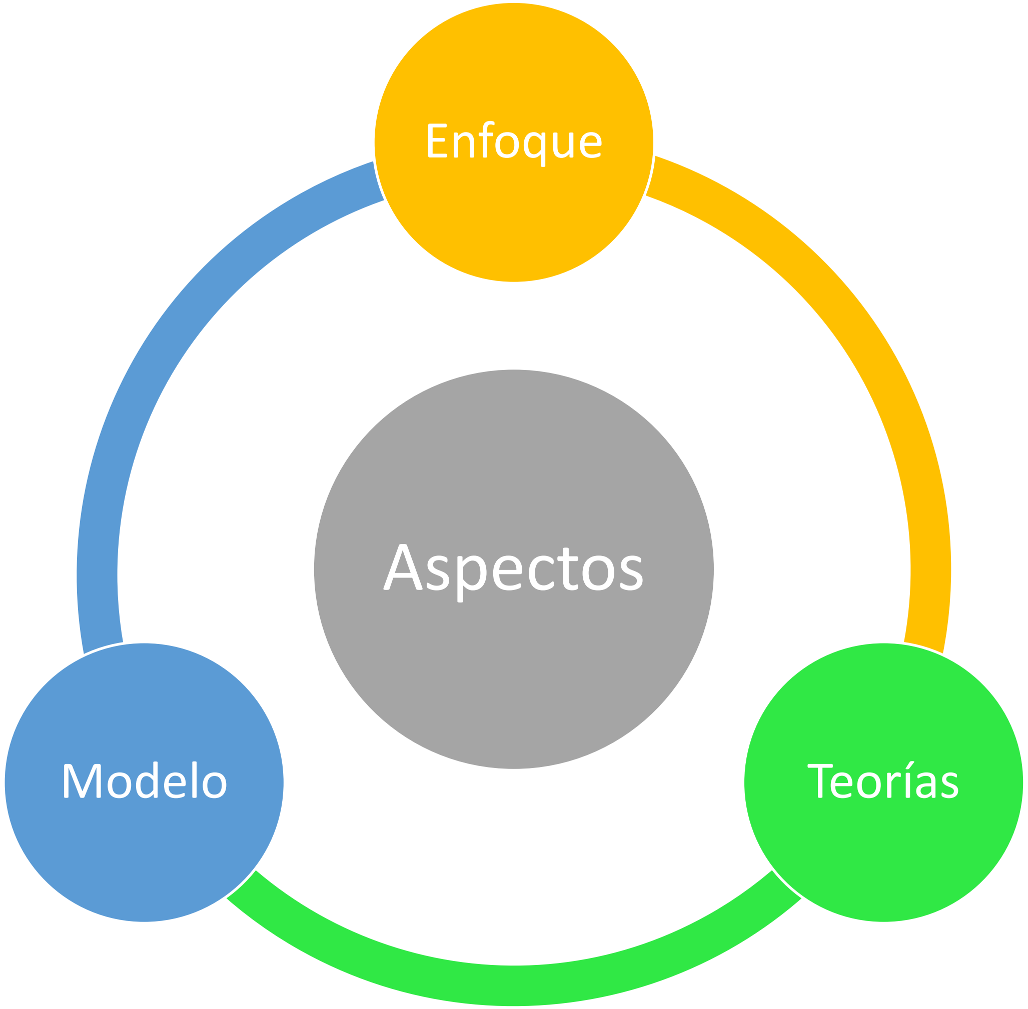
Abstract

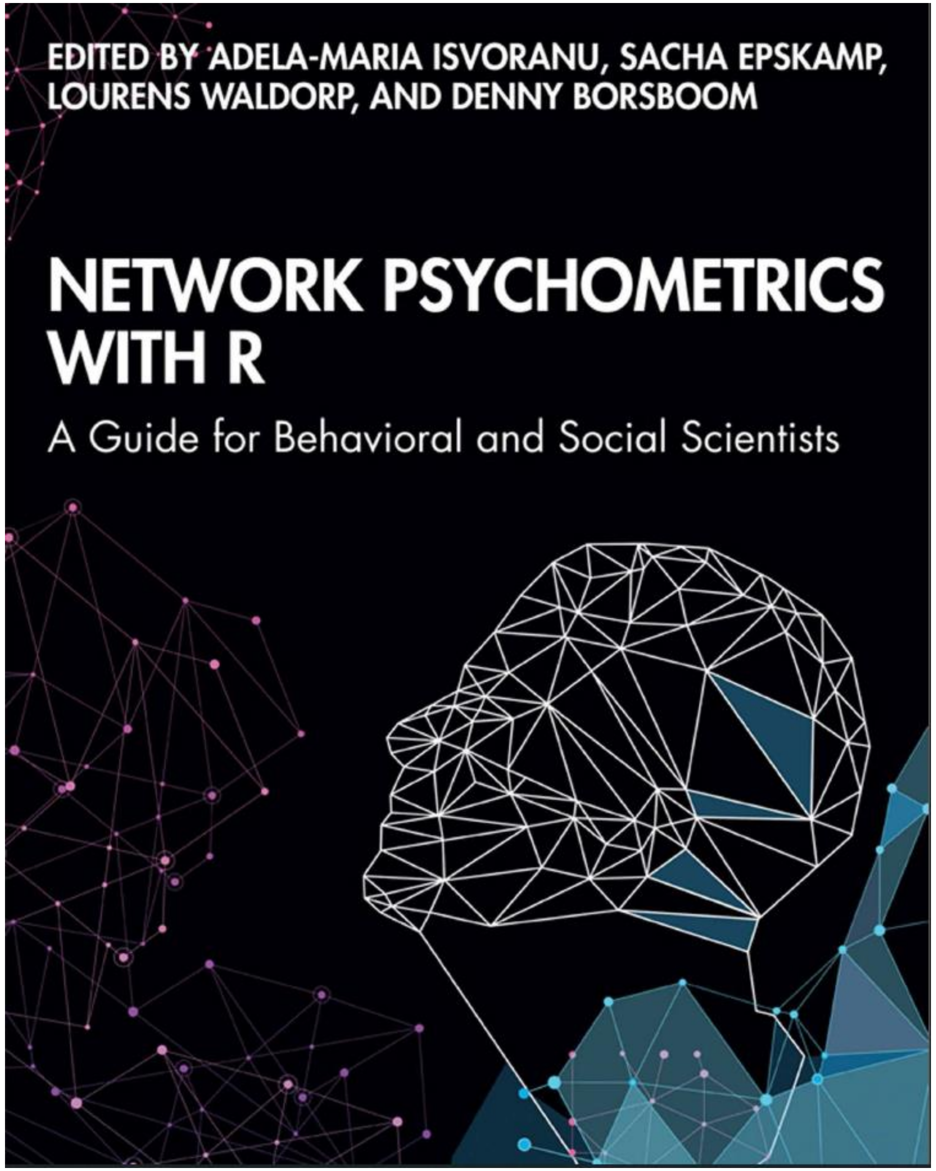
In network approaches to psychopathology, disorders result from the causal interplay between symptoms (e.g., worry → insomnia → fatigue), possibly involving feedback loops (e.g., a person may engage in substance abuse to forget the problems that arose due to substance abuse). The present review examines 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).

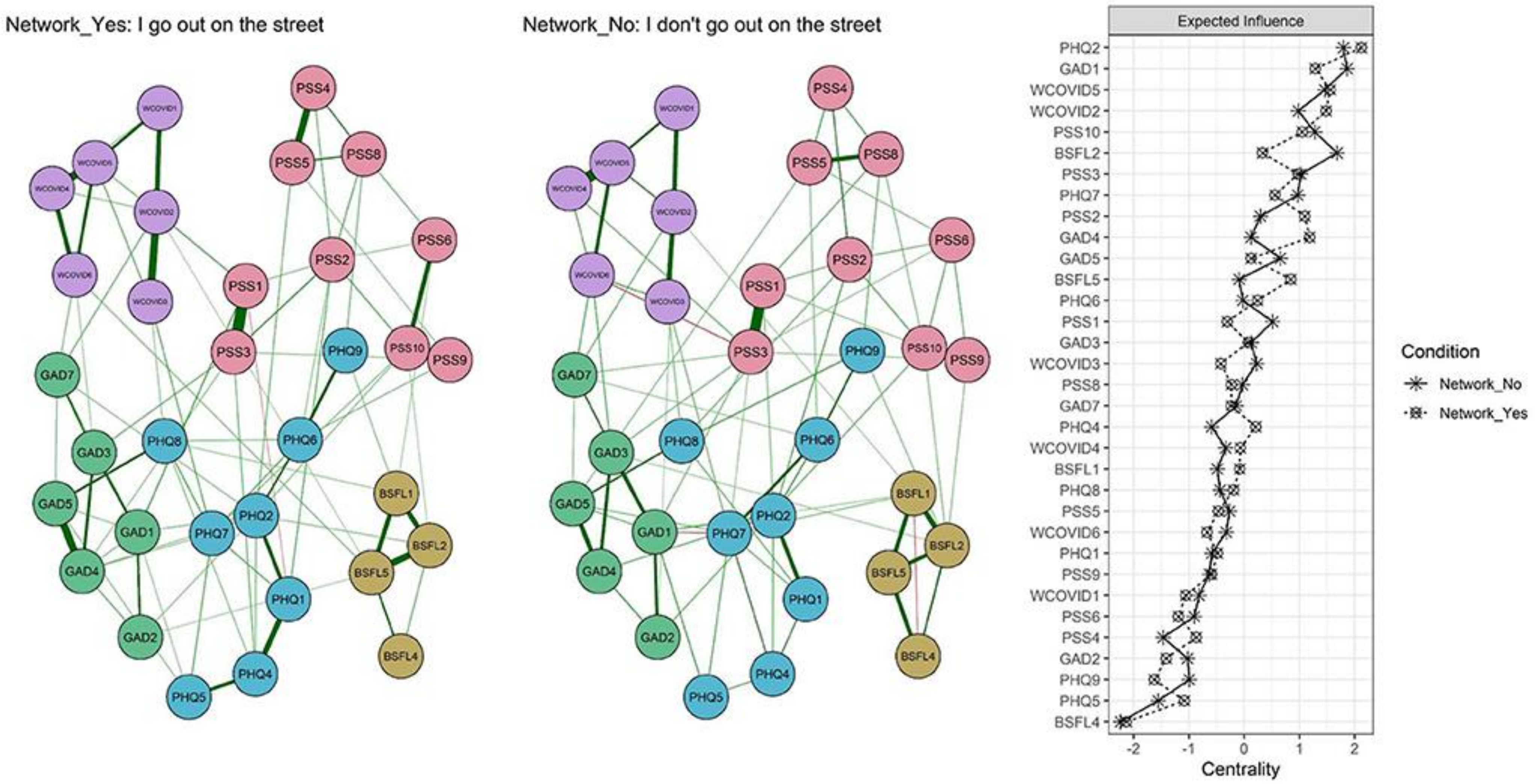
Borsboom, D., & Cramer, A. O. (2013). Network analysis: an integrative approach to the structure of psychopathology. *Annual review of clinical psychology*, *9*, 91-121.

Importante recordar…



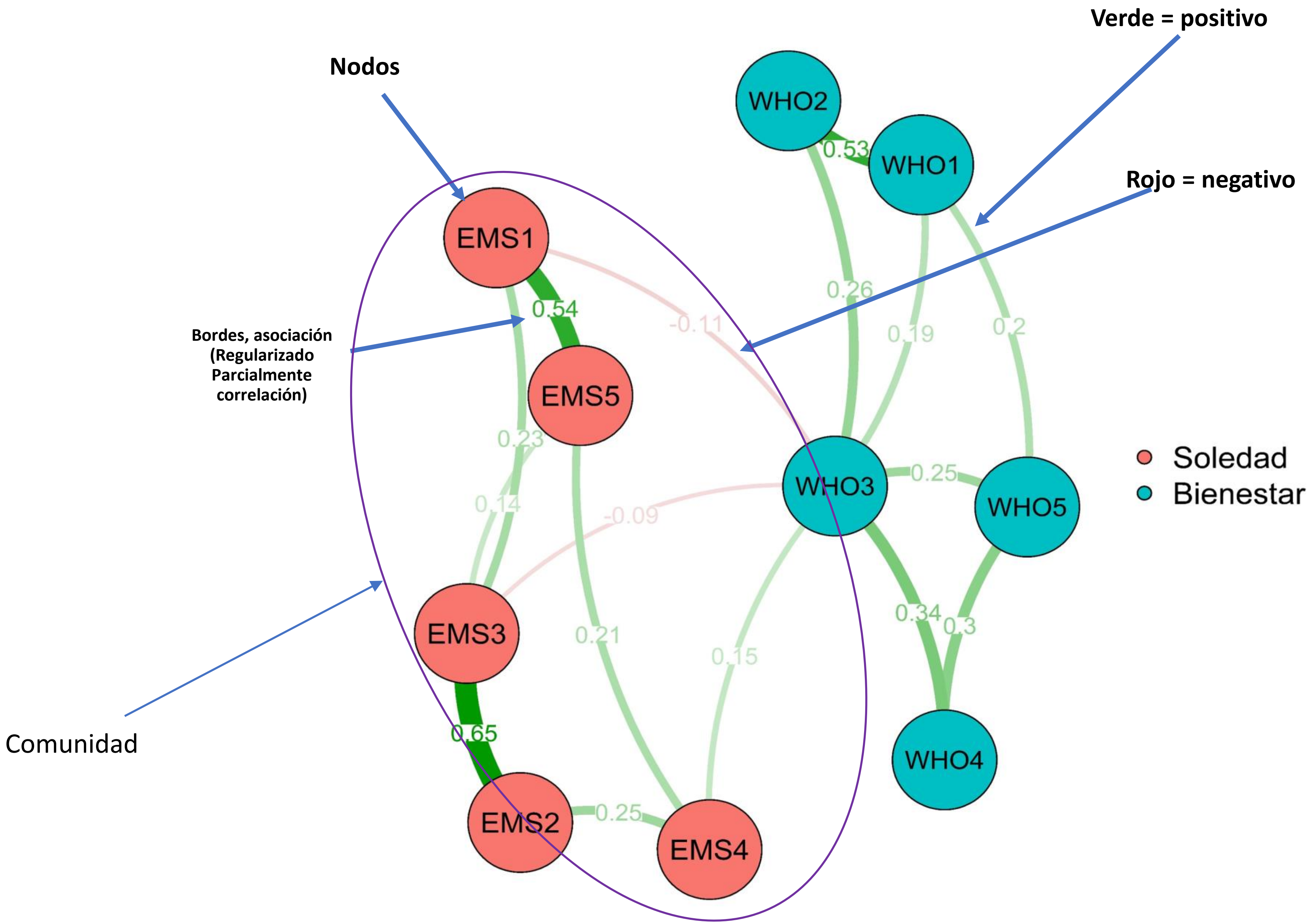


Borsboom, D., Cramer, A. O. J., Fried, E. I., Isvoranu, A. M., Robinaugh, D. J., Dalege, J., & van der Maas, H. L. J. (2022). Chapter 1. Network perspectives. In Isvoranu, A. M., Epskamp, S., Waldorp, L. J., & Borsboom, D. (Eds.). *Network psychometrics with R: guide for behavioral and social scientists*.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

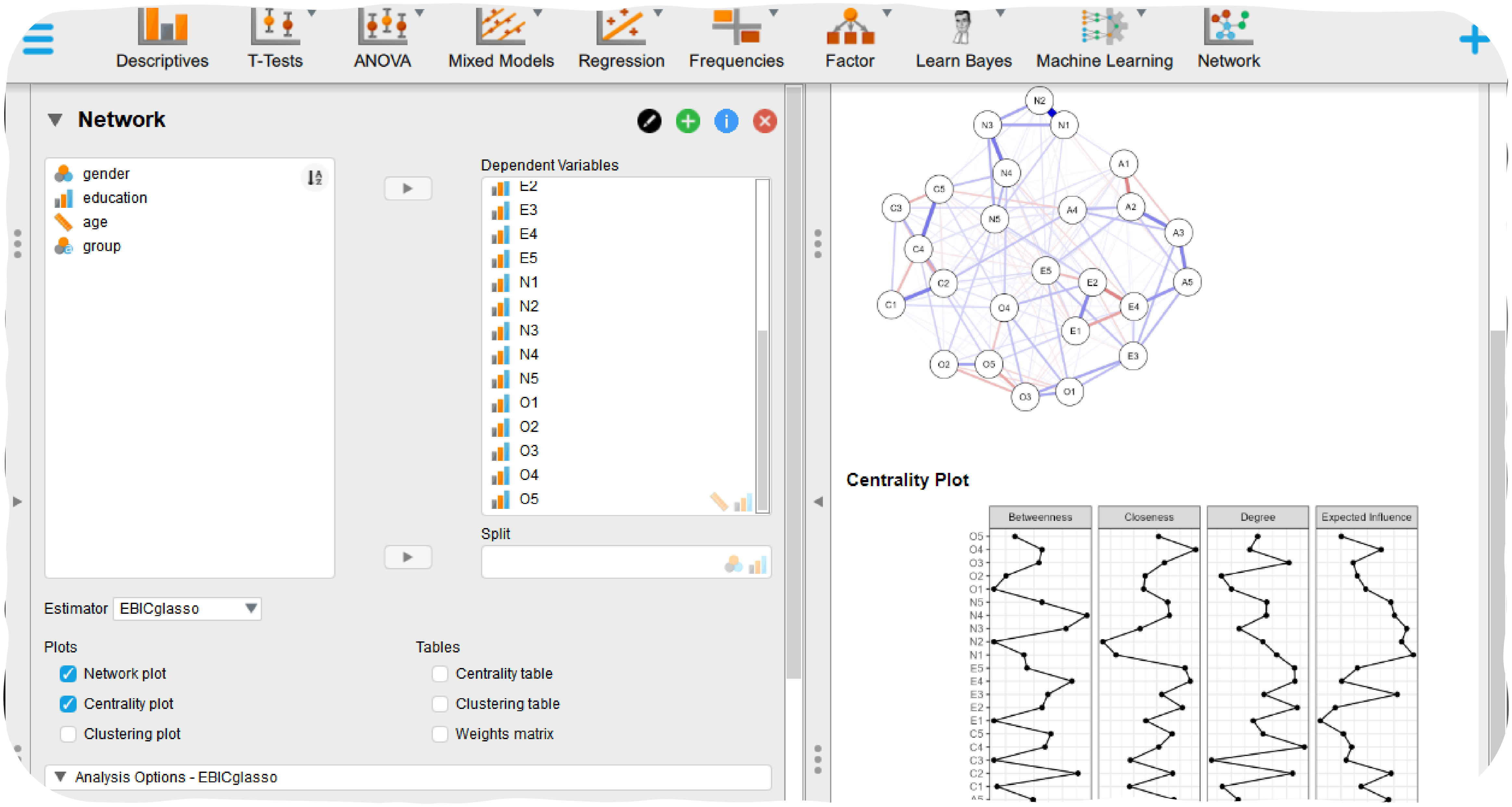


Ventura-León, J., López-Jurado, R., Porturas, E., León-Mostacero, I., & Canchanya-Balbin, S. E. (2022). Anxiety, depression, stress, worry about COVID-19 and fear of loneliness during COVID-19 lockdown in Peru: A network analysis approach. *Frontiers in Public Health*, *10*, 946697.

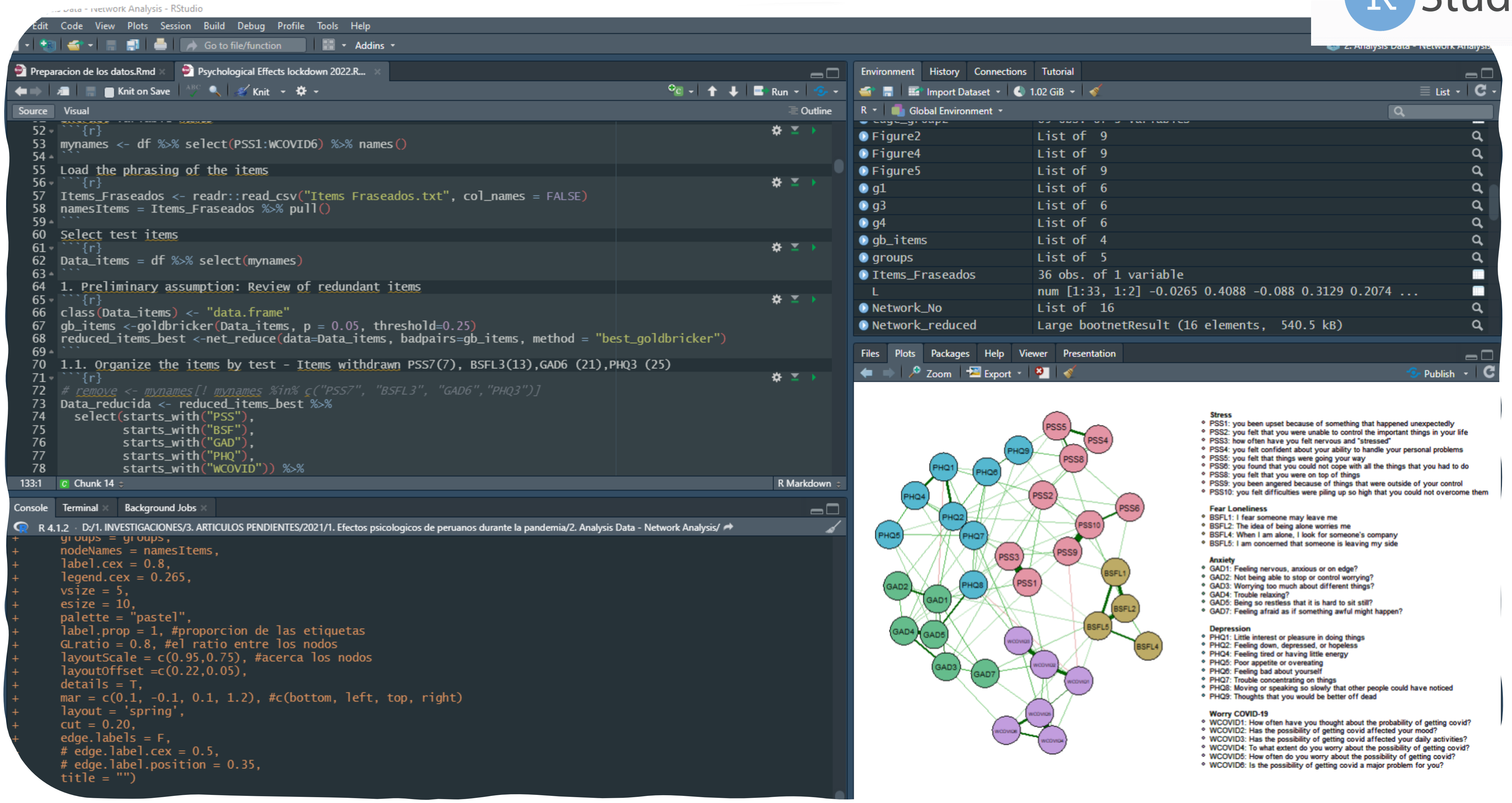
Elementos Básicos de las redes


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

Programas para su implementación



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
Centrality Plot
Betweenness
Closeness
Degree
Expected Influence



Network Analysis - RStudio
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
```{r}
mynames <- df %>% select(PSS1:WCOVID6) %>% names()
```
Load the phrasing of the items
```{r}
Items_Fraseados <- readr::read_csv("Items Fraseados.txt", col_names = FALSE)
namesItems = Items_Fraseados %>% pull()
```
Select test items
```{r}
Data_items = df %>% select(mynames)
```
1. Preliminary assumption: Review of redundant items
```{r}
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)
```{r}
# 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
PSS5 PSS4 PHQ9 PSS8 PHQ1 PHQ6 PSS2 PSS6 PHQ4 PHQ2 PSS10 PHQ5 PHQ7 PSS9 PSS3 BSFL1 PHQ8 PSS1 GAD2 GAD1 BSFL2 BSFL5 GAD4 GAD5 BSFL4 GAD3 GAD7
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?
```


Alexander P. Christensen

Hudson F. Golino

Librería EGAnet

Análisis exploratorio de grafos

https://github.com/hfgolino/EGAnet/blob/master/Readme.md

```r
# Load packages:
library("bootnet")
library("psychTools")

# Load data:
data("bfi")

# First 25 items:
bfiData <- na.omit(bfi[,1:25])
```

```r
ega.wmt <- EGA(
  data = data,
  corr = c("cor_auto", "pearson", "spearman"),
  model = c("glasso", "TMFG"),
  algorithm = c("walktrap", "leiden", "louvain"),
  plot.EGA = TRUE,
  plot.args = list()
)
```

La base de datos

```r
# Load packages:
library("bootnet")
library("psychTools")

# Load data:
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# First 25 items:
bfiData <- na.omit(bfi[,1:25])
```

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. (PsycInfo Database Record (c) 2023 APA, all rights reserved)

```r
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  data = data,
  corr = c("cor_auto", "pearson", "spearman"),
  model = c("glasso", "TMFG"),
  algorithm = c("walktrap", "leiden", "louvain"),
  plot.EGA = TRUE,
  plot.args = list()
)
```

Vamos a preferir Spearman

Isvoranu, A.-M., & Epskamp, S. (2023). Which estimation method to choose in network psychometrics? Deriving guidelines for applied researchers. *Psychological Methods, 28*(4), 925–946. https://doi.org/10.1037/met0000439

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# Load data:
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```

Towards A Network Psychometrics Approach to Assessment:

Simulations for Redundancy, Dimensionality, and Loadings

Alexander P. Christensen

University of North Carolina at Greensboro

Doctoral Dissertation

2020

Algoritmos de detección de comunidades

```r
ega.wmt <- EGA(
  data = data,
  corr = c("cor_auto", "pearson", "spearman"),
  model = c("glasso", "TMFG"),
  algorithm = c("walktrap", "leiden", "louvain"),
  plot.EGA = TRUE,
  plot.args = list()
)
```

En cuanto al número de respuestas, los algoritmos Louvain, Fast-greedy y Walktrap del método GLASSO obtuvieron la mejor precisión (88,6%, 87,8% y 87,1%), seguidos del algoritmo PCA del método PA (86,7%; Tabla 3). En cuanto a los métodos de red, se observó una tendencia general a que el método GLASSO (79,9%) obtuviera mejores resultados que los dos métodos de correlación parcial no regularizados (AIC = 63,3% y BIC = 58,6%).

Christensen, A. P. (2020, March 14). Towards a Network Psychometrics Approach to Assessment: Simulations for Redundancy, Dimensionality, and Loadings. https://doi.org/10.31234/osf.io/84kgd

Table 3

Percent Correct for Each Independent Conditions.

Algorithm	Method	Sample Size 250	500	1000	5000	# of Factors 1	2	4	# of Variables 4	8	12	Factor Correlations 0.00	0.30	0.50	0.70	Factor Loadings 0.40	0.55	0.70	Number of Responses Continuous	Polytomous	Overall
Edge Betweenness (57.7%)	AIC	36.4	46.9	54.1	55.7	83.7	47.1	15.9	57.7	49.7	37.7	53.7	51.4	47.2	40.3	38.4	52.5	53.7	55.5	40.9	48.2
	BIC	31.7	53.7	68.8	73.1	77.8	53.2	41.5	65.4	58	48.4	65.7	61.8	55.3	45.2	37.4	64.2	68.4	67.6	46.2	57
	GLASSO	62.2	66.3	69.3	74.4	98	64.4	40.7	64.6	69.5	70.9	80.5	74.3	65.4	53.1	52.9	70.9	78.7	72.3	64.6	68.3
Fast-greedy (74.9%)	AIC	52.2	73.7	84.4	87.9	89.7	61.5	72.6	79.9	79.2	64.2	80.9	78.7	73.6	64	60.4	81.4	81.4	83	65.7	74.3
	BIC	30.9	55.1	73.7	89.8	76.3	54	58.2	75.4	63.1	50	69.6	66.8	61.6	51.9	42.6	69.7	74.2	73.3	51.5	62.5
	GLASSO	79.7	86.8	89.8	93.7	98.7	80	84.4	85.3	89.2	89	94.7	92.2	87.3	77	68.3	93	99.3	89.1	86.7	87.8
Infomap (58.1%)	AIC	38.2	43.6	49.7	49.6	99.3	18.2	21.4	41.7	48.8	44.9	52	48.6	43	37.2	34.2	41.9	59.9	48.1	42.3	45.2
	BIC	34.1	53.5	68.7	71.8	81.7	47.5	44.2	60.4	60.6	51.1	66.6	62.8	55.3	44.1	36.7	62.8	71.1	66.9	47.4	57.3
	GLASSO	67.1	71.7	74.3	75.4	99.3	51.5	65.1	60.9	75.3	80.9	87.1	80.7	68.3	53.1	50.3	72.8	90.4	76.6	68.4	72.3
Label Propagation (60.6%)	AIC	42.7	51.2	58.4	61.1	95.9	44.5	21.9	58.6	54.4	47.1	60.9	57.4	51.6	43.1	40.6	55.3	64	59.3	47.2	53.2
	BIC	27.4	48.5	65.1	68.9	73.1	50.4	36	63.2	52.5	43.3	59.8	56.8	51.2	42.9	34.6	58.6	63.9	64.5	40.7	52.7
	GLASSO	70.1	76	78.2	78.9	98.4	69.8	58.5	71.8	76.7	79.7	89.6	83.5	73	58	54.9	76.6	93.4	79.6	72.7	76
Leading Eigenvalue (69%)	AIC	58.3	71.1	76.1	75.8	93.2	68.6	50.3	71.7	73.7	65.4	75.8	73.8	69.8	61.4	61.5	76.4	73	78	62.5	70.2
	BIC	31.6	52.7	67.8	78.1	77.4	57.3	39.8	69.8	57.9	46.6	63.8	61.3	56.8	48.9	41.7	64.4	66.2	67.8	47.5	57.7
	GLASSO	74.6	78.4	79.6	82.4	98.8	83.9	52.6	77.2	79.2	80.4	85	82.4	78.4	69.8	65.5	82.4	86.7	79.6	78.3	78.9
Louvain (75.2%)	AIC	51.1	72.8	84.3	90.1	89.2	62.2	72.4	80.9	79.7	62.8	80.5	78.4	73.9	64.4	61.4	81.3	80.5	83.1	65.5	74.3
	BIC	31	55	73.4	91	76	54.4	58.8	76.1	63.5	49.9	69.6	66.9	61.9	52.6	43.7	70	73.7	73.8	51.5	62.8
	GLASSO	80.2	87.2	90.4	95.3	98.7	81.4	85.3	85.9	90	89.9	94.8	92.7	88.4	78.5	70.2	93.4	99.4	89.9	87.4	88.6
PFA (79.4%)	PA	59.1	78.8	88	91.5	75.1	82	81	69.2	85.2	83.6	81.2	81.6	79.9	74.9	64	87.5	86.6	89.5	69.3	79.4
PCA (86.7%)	PA	70.1	87.9	92.3	96.4	98.4	87.1	74.5	78.8	90.5	90.7	94.5	93.1	88.2	71	81.1	88.3	90.6	91.7	81.6	86.7
Spinglass (70.7%)	AIC	46.5	66.7	77.2	83.2	80.9	56.5	69	80.6	71.6	54.7	73.3	71.6	67.9	60.7	59.2	75.1	70.7	77.7	59	68.4
	BIC	30.1	48.9	62	80.2	56.7	38.8	60.5	84.6	56.9	42.4	56.2	54	51.4	46.6	53.2	56.9	48.1	65.4	37.2	52.4
	GLASSO	74.8	82	84.8	86.9	91.8	73.7	76	84.7	80.5	78.1	84.7	83.7	80.9	74.3	59.3	85.3	89.5	88.7	75.8	80.8
Walktrap (73.8%)	AIC	54.5	71.3	80.3	85.8	92	66.1	61.4	73.2	76.6	68.5	80.3	77.6	72.1	60.9	58.1	80.4	80	82	63.6	72.7
	BIC	31.1	54.5	72.1	87.9	76.8	56.2	52.8	72.6	62.6	50.4	69.2	66.1	60.5	50.4	41.5	68.8	73.3	72.6	50.4	61.6
	GLASSO	80.4	85.9	88	93	98.6	83.7	78.3	82.2	88.8	90.4	94.8	91.7	86.3	75.6	67.1	91.9	99.3	88.3	86	87.1

Note. Bolded values represent conditions where 80% or more of the replicated samples were estimated correctly. The algorithms are denoted with their percent correct across conditions in parentheses. PFA = principal factor analysis and PCA = principal component analysis.

Christensen, A. P. (2020, March 14). Towards a Network Psychometrics Approach to Assessment: Simulations for Redundancy, Dimensionality, and Loadings. https://doi.org/10.31234/osf.io/84kgd

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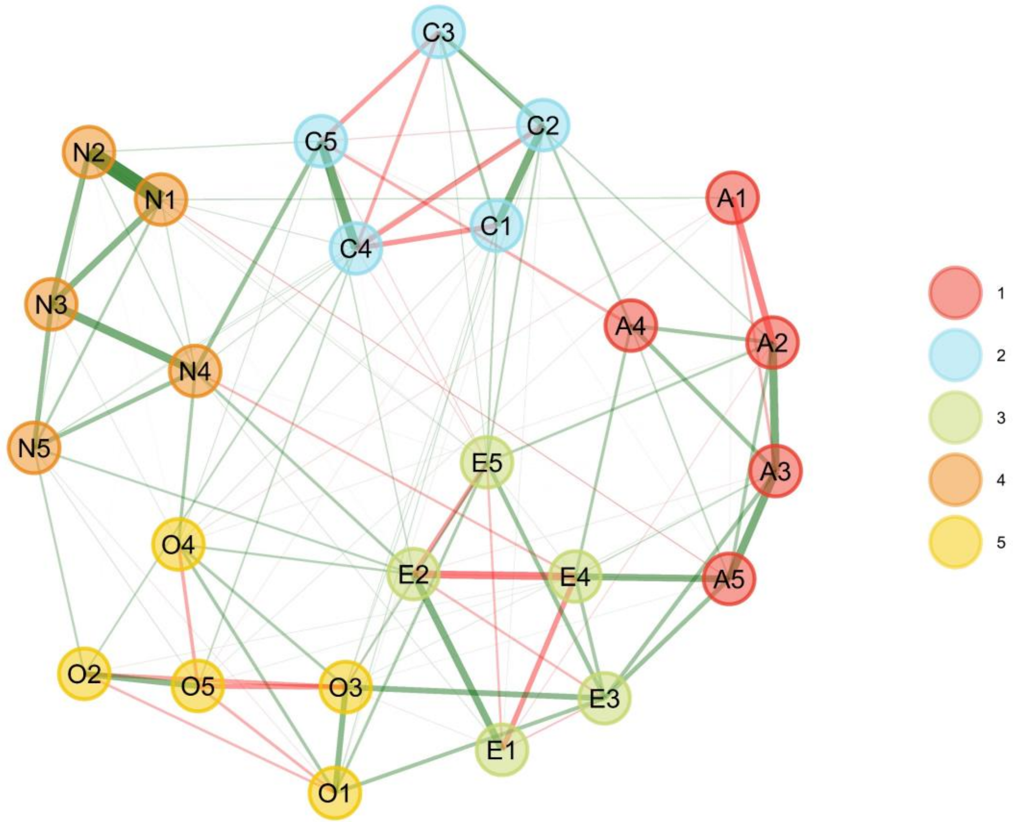

Christensen, A. P. (2020, March 14). Towards a Network Psychometrics Approach to Assessment: Simulations for Redundancy, Dimensionality, and Loadings. https://doi.org/10.31234/osf.io/84kgd

Cargas de red

E2	-0.03	0.03	0.32	0.09	0.
E1	-0.02	0.01	0.24	0.01	-0.
E5	0.05	0.12	-0.18	0.03	0.
E3	0.14	0.00	-0.18	0.00	0.
E4	0.19	0.00	-0.26	-0.04	0.
N1	0.04	0.02	0.01	0.41	0.
N3	0.00	0.00	0.00	0.39	0.

```r
# Calcular la fuerza estandarizada de los nodos
net.loads(ega.wmt)$std
```

Items	1	2	3	4	5
A3	0.38	0.00	0.10	0.00	0.01
A2	0.37	0.03	0.06	0.00	0.01
A5	0.22	0.00	0.18	-0.03	0.01
A4	0.17	-0.10	0.05	0.00	0.00
A1	-0.16	0.00	0.00	0.03	-0.02
C2	0.05	0.30	0.04	0.01	0.03
C1	0.00	0.26	0.03	0.00	0.06
C3	0.03	0.26	0.02	0.00	0.00
C5	-0.05	-0.24	0.04	0.09	0.02
C4	0.00	-0.37	-0.02	0.05	0.06
E2	-0.03	0.03	0.32	0.09	0.05
E1	-0.02	0.01	0.24	0.01	-0.01
E5	0.05	0.12	-0.18	0.03	0.09
E3	0.14	0.00	-0.18	0.00	0.16
E4	0.19	0.00	-0.26	-0.04	0.02
N1	0.04	0.02	0.01	0.41	0.00
N3	0.00	0.00	0.00	0.39	0.01
N2	-0.02	0.02	0.02	0.37	0.00
N4	0.00	0.09	0.10	0.24	0.06
N5	0.00	0.03	0.04	0.21	0.06
O3	0.02	0.03	0.14	0.00	0.30
O1	0.00	0.03	0.10	-0.01	0.25
O4	-0.02	0.03	0.04	0.06	0.17
O2	0.00	0.03	0.01	0.04	-0.21
O5	0.01	0.04	0.01	0.01	-0.30

Teniendo en cuenta estos resultados, sugerimos que las directrices generales sobre el tamaño del efecto para las cargas de red sean de
0,15 para las pequeñas,
0,25 para las moderadas y
0,35 para las grandes.

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On the equivalency of factor and network loadings

Alexander P. Christensen & Hudson Golino

Behavior Research Methods **53**, 1563–1580 (2021) | Cite this article

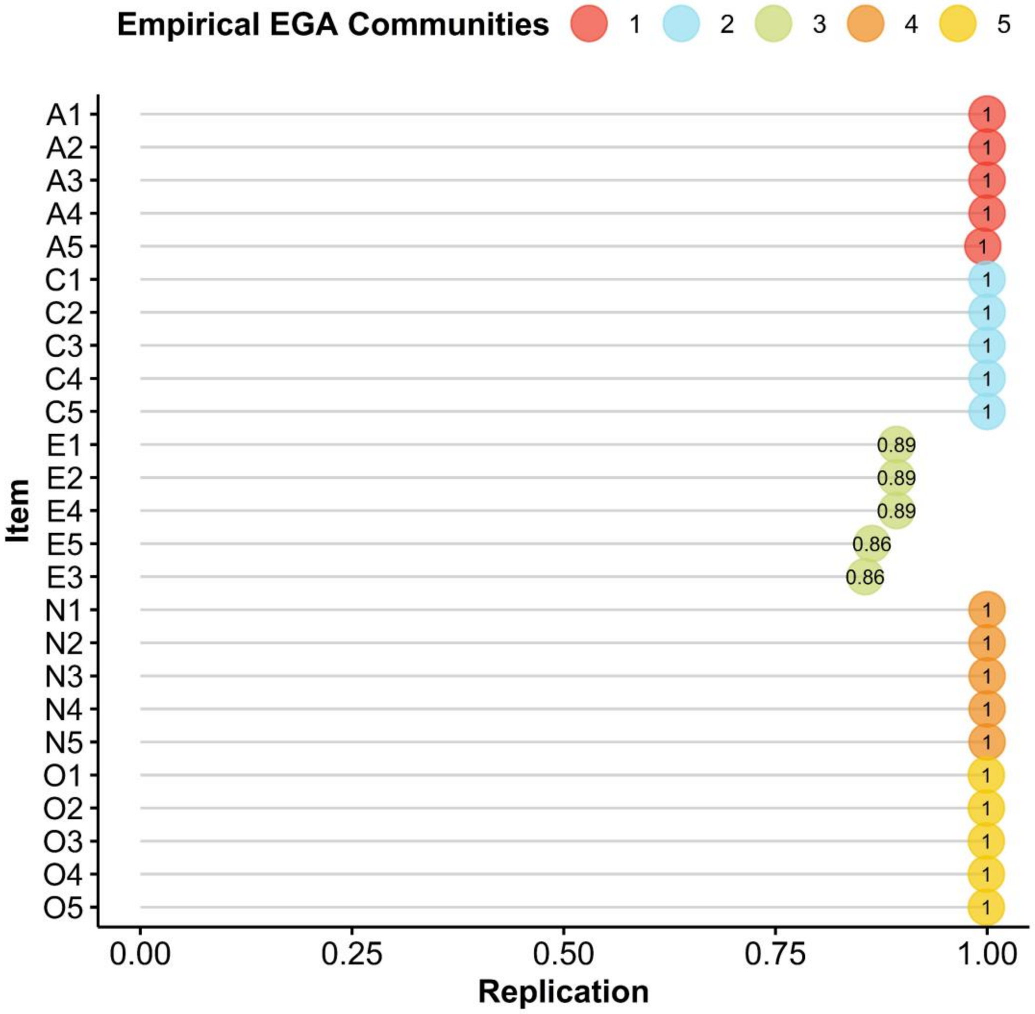
Abstract

Recent research has demonstrated that the network measure *node strength* or sum of a node's connections is roughly equivalent to confirmatory factor analysis (CFA) loadings. A key finding of this research is that node strength represents a combination of different latent causes. In the present research, we sought to circumvent this issue by formulating a network equivalent of factor loadings, which we call *network loadings*. In two simulations, we evaluated whether these network loadings could effectively (1) separate the effects of multiple latent causes and (2) estimate the simulated factor loading matrix of factor models. Our findings suggest that the network loadings can effectively do both. In addition, we leveraged the second simulation to derive effect size guidelines for network loadings. In a third simulation, we evaluated the similarities and differences between factor and network loadings when the data were generated from random, factor, and network models. We found sufficient differences between the loadings, which allowed us to develop an algorithm to predict the data generating model called the *Loadings Comparison Test* (LCT). The LCT had high sensitivity and specificity when predicting the data generating model. In sum, our results suggest that network loadings can provide similar information to factor loadings when the data are generated from a factor model and therefore can be used in a similar way (e.g., item selection, measurement invariance, factor scores).

Christensen, A.P., Golino, H. On the equivalency of factor and network loadings. *Behavior Research Methods, 53*, 1563–1580 (2021). https://doi.org/10.3758/s13428-020-01500-6

Estabilidad de los items

```
boot.wmt <- bootEGA(data = bfiData,
                    corr = "spearman",
                    model = "glasso",
                    algorithm = "louvain",
                    plot.type = "GGally",
                    #bootstrap
                    iter = 1000,
                    seed = "2023",
                    type = "resampling",
                    ncores = 12)
```



Un valor de 0.89 en el "item stability" indica que el ítem en cuestión ha sido identificado consistentemente en esa dimensión en aproximadamente el 89% de las muestras replicadas. Esto significa que ese ítem tiende a pertenecer predominantemente a esa dimensión en particular en el análisis de la red psicométrica. Sin embargo, también puede haber ocasiones en las que el ítem se haya replicado en otras dimensiones en menor medida

Christensen, A. P., Golino, H., and Silvia, P. J. (2020) A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires. *European Journal of Personality*, *34*, 1095–1108. https://doi.org/10.1002/per.2265.

Consistencia estructural

Métodos basados en la covariación de los ítems

Kuder & Richardson (1937)

$$KR_{20} = \frac{K}{K-1}\left[1-\frac{\sum pq}{S_X{}^2}\right]$$

Σpq: suma de varianzas de todos los ítems

$S_x{}^2$: Varianza del test

k= número de ítems

Ítems dicotómicos

Kuder, G. F., & Richardson, M. W. (1937). The theory of the estimation of test reliability. *Psychometrika*, *2*(3), 151-160.

Cronbach (1951)

$$\alpha = \frac{K}{K-1}\left[1-\frac{\sum S_i{}^2}{S_T{}^2}\right]$$

Dónde:

k= Número de Ítems

$\sum S_i^2$ =Suma de las varianza de cada Ítems

S_T^2 = Varianza Total

Ítems politómicos

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297-334.

McDonald (1999)

$$\omega = \frac{\left[\sum \lambda_j\right]^2}{\left[\sum \lambda_j\right]^2 + \left[\sum \psi_j^2\right]}$$

Dónde:
ω: es el símbolo de coeficiente omega
ʎj, es la carga factorial estandarizada de i.

McDonald, R.P. (1999). *Test theory. A unified treatment*. Mahwah, NJ, Lawrence Erlbaum Associates.

```r
# Estimación Consistencia estructural
res <- dimensionStability(boot.wmt)
res$dimension.stability$structural.consistency
```

Dim	value
1	0.995
2	1.000
3	0.856
4	1.000
5	0.999

La consistencia estructural se refiere a la medida en que los componentes de un cuestionario forman una subred coherente dentro de una red más amplia. Es un indicador de la homogeneidad y coherencia interna de los ítems en un contexto multidimensional. La consistencia estructural puede evaluarse utilizando una medida llamada "consistencia estructural" que proporciona información complementaria a las medidas de consistencia interna tradicionales

Estos valores indican la magnitud de la consistencia estructural en cada dimensión. Cuanto más cercano a 1 sea el valor, mayor será la consistencia estructural. En este caso, las dimensiones 1, 2 y 4 tienen una consistencia estructural muy alta, cercana a 1. La dimensión 5 también tiene una alta consistencia estructural, aunque ligeramente inferior a las dimensiones anteriores. Sin embargo, la dimensión 3 presenta una consistencia estructural algo más baja en comparación con las otras dimensiones. Esto puede indicar que los elementos dentro de esta dimensión pueden ser menos homogéneos o interrelacionados en comparación con las otras dimensiones.

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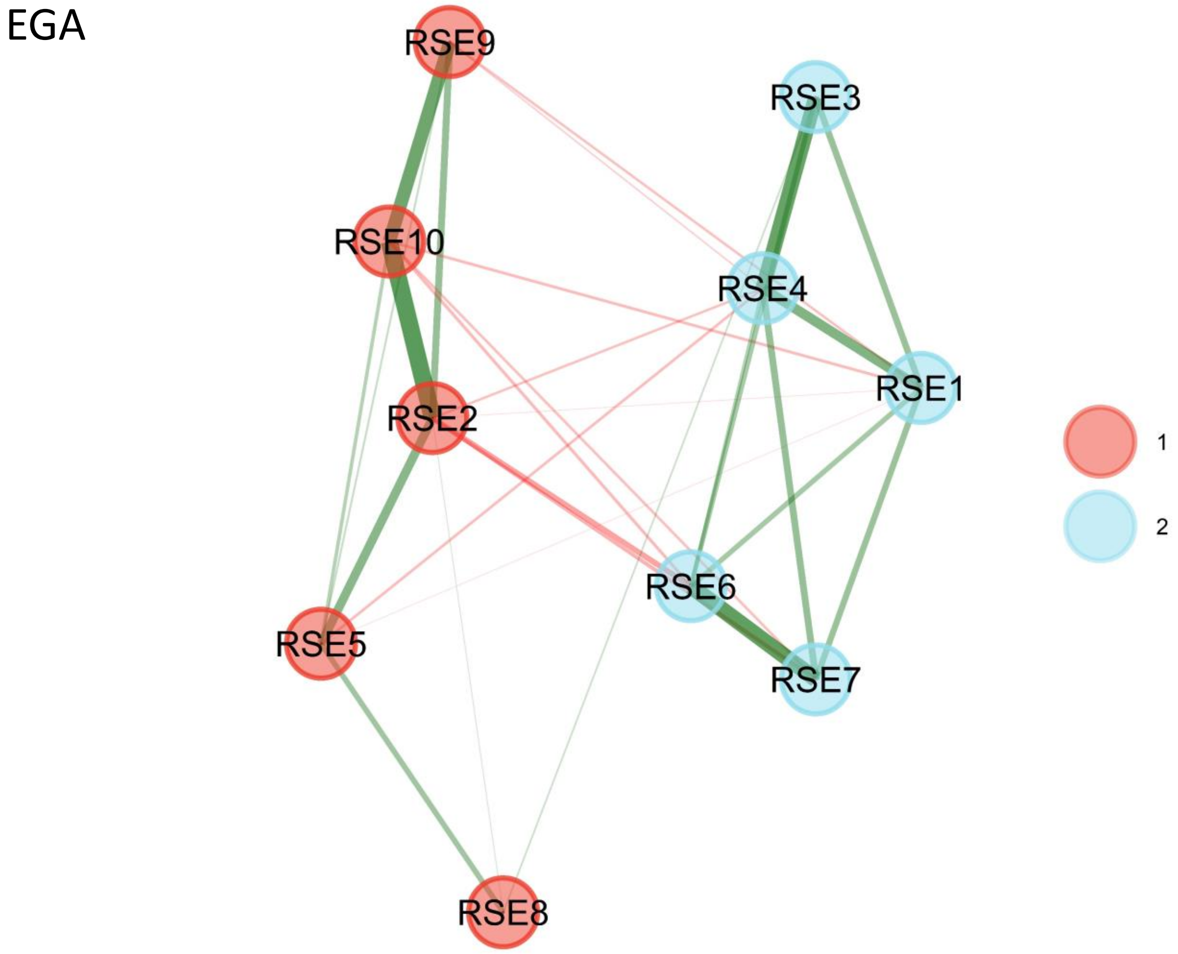
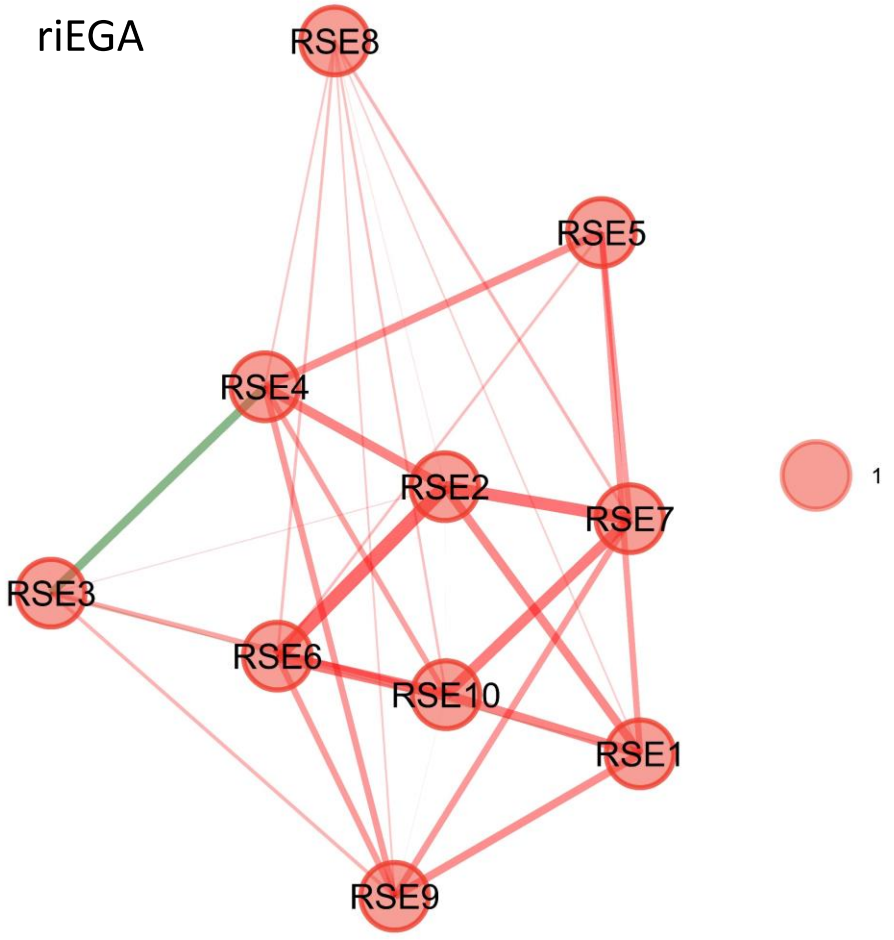
Wording Effect

```
EGAWT <- EGA(Autoestima_Data %>% select(RSE1:RSE10), algorithm="louvain")

## EGA with random-intercept model
riEGAWT <- riEGA(Autoestima_Data %>% select(RSE1:RSE10), algorithm="louvain")
```

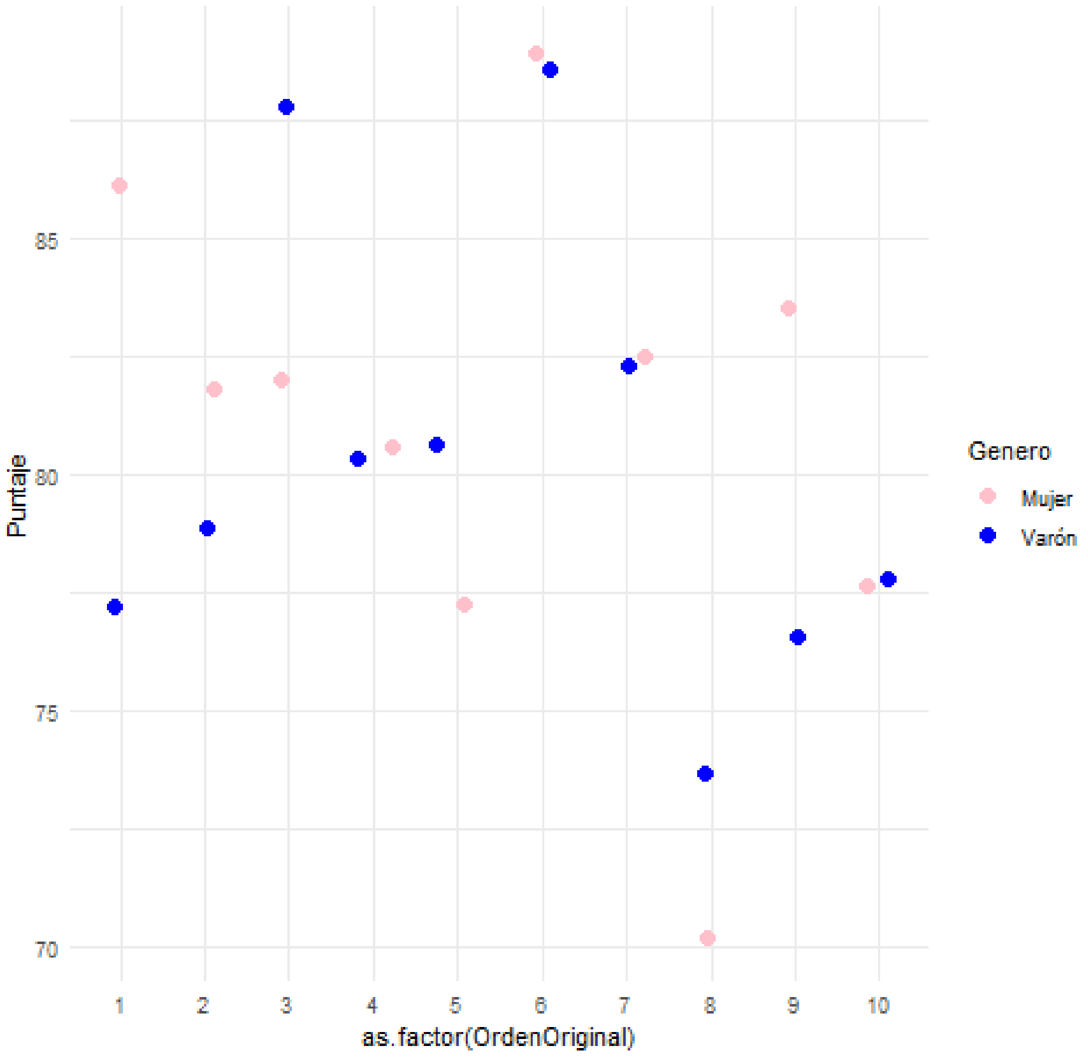


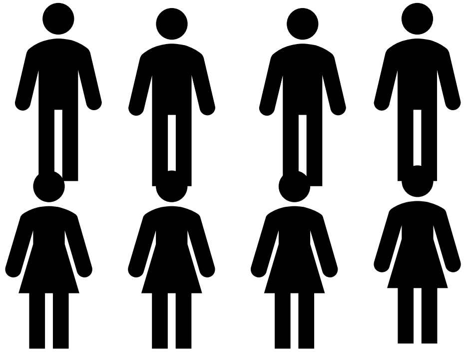


Garcia-Pardina, A., Abad, F. J., Christensen, A. P., Golino, H., & Garrido, L. E. (2022). *Dimensionality assessment in the presence of wording effects: A network psychometric and factorial approach*. PsyArXiv. doi:10.31234/osf.io/7yqau

Invarianza de medida de la estructura "EGA”

Permutación: 1





Node	Membership	Difference	p	sig
RSE2	1	-0.032	0.848	n.s.
RSE5	1	0.011	0.908	n.s.
RSE8	1	-0.112	0.214	n.s.
RSE9	1	0.083	0.358	n.s.
RSE10	1	0.007	0.952	n.s.
RSE1	2	0.199	0.098	.
RSE3	2	-0.030	0.766	n.s.
RSE4	2	-0.215	0.092	.
RSE6	2	-0.039	0.738	n.s.
RSE7	2	0.141	0.188	n.s.

El procedimiento Benjamini-Hochberg es una potente herramienta que reduce la tasa de falsos descubrimientos.

El ajuste de la tasa ayuda a controlar el hecho de que a veces los valores p pequeños (menos del 5%) se producen por casualidad, lo que podría llevarle a rechazar incorrectamente las hipótesis nulas verdaderas. En otras palabras, el procedimiento B-H le ayuda a evitar errores de tipo I (falsos positivos).

```
# Plot with BH-corrected alpha = 0.10
plot(results, p_type = "p_BH", p_value = 0.10)
```

Jamison, L., Golino, H., & Christensen, A. P. (2023). *Metric invariance in exploratory graph analysis via permutation testing*. PsyArXiv. doi:10.31234/osf.io/j4rx9

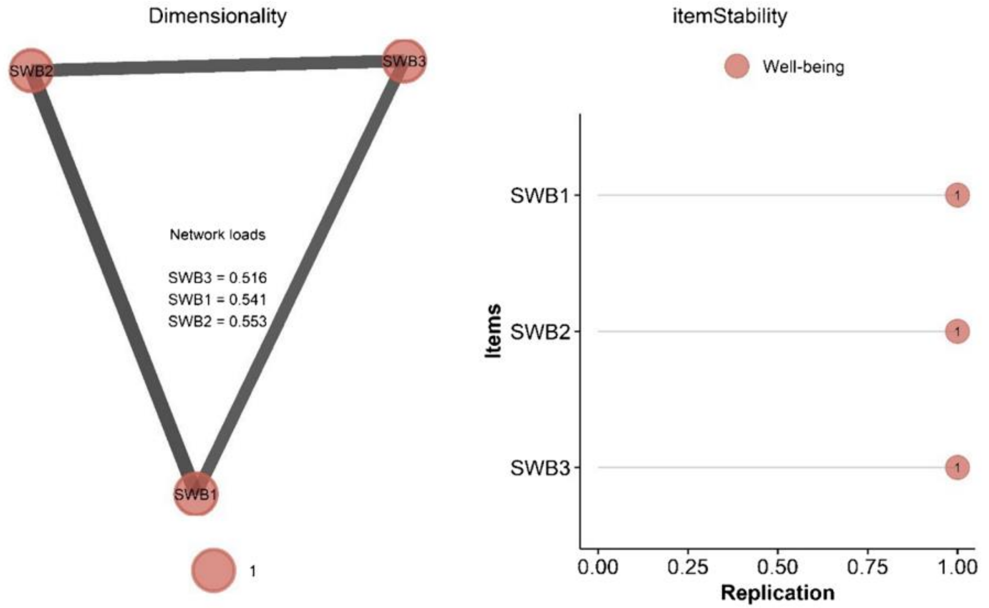


Fig. 2 Dimensionality and stability of items

Trends in Psychology
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ORIGINAL ARTICLE

Validity Evidence and Reliability of a Subjective Well-Being Scale: A Psychometric Network Analysis

José Ventura-León[1] · Andy Rick Sánchez-Villena[1] · Tomás Caycho-Rodríguez[1]

Accepted: 10 November 2022

Abstract
The objective of the present research was to analyze the psychometric properties of a short scale of subjective well-being based on the metrics corresponding to the network models. A total of 3196 young people and adults between 18 and 56 years of age (mean = 25.88; *SD* = 8.81) from three cities in Peru were selected by non-probabilistic purposive sampling and divided into two phases: exploratory ($n = 642$) and confirmatory ($n = 2527$). The methodology used was network analysis to determine internal structure and reliability. Evidence in relation to another variable was explored by latent network modeling using *Patient Health Questionnaire* (PHQ-2) and *Generalized Anxiety Disorder Scale* (GAD-2) as convergence measures. The results reveal that the SWB is a unidimensional measure both in its exploratory phase by *Exploratory Graphical Analysis* (EGA) and confirmatory (CFI = 1.00; RMSEA = 0.00). The reliability obtained through structural consistency identified that 100% of the time only one dimension was obtained; in addition, the items were stable because they replicated within the empirical dimension in all cases. The relationship with the PHQ-2 ($r = -.44$) and GAD-2 ($r = -.34$) maintained the expected direction and strength. The current data lays the groundwork for future research on subjective well-being in Peru, particularly because we now have a quick, valid, and reliable measure that can contribute to the scientific literature on subjective well-being, which is an intriguing construct to investigate due to its association with basic human needs and the prevention of mental health problems in a community.

Keywords Subjective well-being · Validation · Network approach · Psychometric

Referencias

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.

Christensen, A. P. (2020, March 14). Towards a Network Psychometrics Approach to Assessment: Simulations for Redundancy, Dimensionality, and Loadings. https://doi.org/10.31234/osf.io/84kgd

Christensen, A. P., Golino, H., and Silvia, P. J. (2020) A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires. *European Journal of Personality*, *34*, 1095–1108. https://doi.org/10.1002/per.2265.

Christensen, A.P., Golino, H. On the equivalency of factor and network loadings. *Behavior Research Methods*, *53*, 1563–1580 (2021). https://doi.org/10.3758/s13428-020-01500-6

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

Garcia-Pardina, A., Abad, F. J., Christensen, A. P., Golino, H., & Garrido, L. E. (2022). *Dimensionality assessment in the presence of wording effects: A network psychometric and factorial approach*. PsyArXiv. doi:10.31234/osf.io/7yqau

Isvoranu, A.-M., & Epskamp, S. (2023). Which estimation method to choose in network psychometrics? Deriving guidelines for applied researchers. *Psychological Methods*, *28*(4), 925–946. https://doi.org/10.1037/met0000439

Jamison, L., Golino, H., & Christensen, A. P. (2023). *Metric invariance in exploratory graph analysis via permutation testing*. PsyArXiv. doi:10.31234/osf.io/j4rx9

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

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.