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UNIQUE VARIABLE ANALYSIS OF REDUNDANCY IN ADHD ITEMS FROM THE CONNERS TEACHER RATING SCALE – REVISED: SHORT

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SUMMARY

Attention deficit hyperactivity disorder (ADHD) is a neuropsychiatric disorder interfering with the normal development of the child. The disorder can be screened at school with the Conners Teacher Rating Scale Revised Short (CTRS-R:S). This scale goes beyond the disorder itself and covers a wider construct, that of abnormal child behavior. This can be understood as a complex system of mutually influencing entities. We analyzed a data set of 525 children in French-speaking primary schools from Belgium, and estimated a network structure, as well as to determine the local dependence of items through Unique Variable Analysis. A reduced network was computed including 15 non-locally dependent items. The structural consistency of the network was not affected by redundant items and was structurally sound. The reduction of the number of variables in network studies is important to improve the investigation of network structures as well as better interpret results from inference measures.

Key words: *network analysis – ADHD - CTRS-R:S - psychometric scale - redundancy*

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INTRODUCTION

Attention deficit hyperactivity disorder (ADHD) is a neuropsychiatric disorder that interferes with the normal development of the child, according to the Diagnostic and Statistical Manual of Mental Disorders 5 (DSM 5). This disorder has two main features: inattention and hyperactivity and/or impulsive behavior. Prevalence for ADHD has been estimated to be around 6% in recent studies (Willcutt 2012), but it may vary depending on the country and whether children receive a diagnosis; 4 to 12% of children may be undiagnosed (Green et al. 1999). Screening ADHD is essential to prevent impacts and complications (Shaw et al. 2012).

ADHD symptoms can be exacerbated in schools, making screening for ADHD in school settings useful (Conners et al. 1998). The *Conners Teacher Rating Scale-revised: short* (CTRS-R :S) is known as a specific psychometric tool completed by teachers, containing items adapted to school environment and offering clinicians an overview on the behavior child at school (Conners et al. 1998). CTRS-R :S is psychometric test composed by 28 items, subdivided into four sub scales, namely *oppositional* (items 2, 6, 10, 15, 20), *hyperactivity* (3, 7, 11, 17, 21, 24, 27), *cognitive problems/inattention* (4, 8, 13, 18, 22) and *ADHD index* (1, 5, 9, 12, 14, 16, 19, 23, 25, 26, 28) previously known as hyperactivity index in old version (Conners et al. 1998). However, CTRS-R :S items do not include only ADHD symptoms mentioned in the DSM 5, but the scale goes beyond ADHD diagnosis and contains characteristics of abnormal child behavior such as emotional and behavioural problems (Parry 2005, Till et al. 2022).

The network approach is a recently developed framework to investigate psychiatric constructs as complex systems (Borsboom 2017). In child psychiatry, this concept has already been used for autistic traits (Briganti et al. 2020), ADHD (Preszler et Burns 2019, Silk et al. 2019), or recently to assess interaction between different trouble as ADHD and autism (Farhat et al. 2022).

The network theory considers symptoms as active components causally influencing each other: the mental disorder is a network that arises from both symptoms and the set of their interactions (Borsboom 2017). In network structures, items or symptoms are represented by nodes (circles) which are interconnected by edges (lines); therefore networks allow to investigate interactions among symptoms (Borsboom 2017).

Network theory is accompanied by a set of statistical tools called network analysis (Borsboom et al. 2021). Network measures are used to quantify the relationships between nodes in a network. The most commonly used measures in psychology are called centrality. These measures quantify the relative position of nodes in the network (e.g., the number and magnitude of connections to a node). Researchers interpret network structures by identifying high-centrality (highly connected) nodes and detecting items that are strongly connected, which represent communities (statistically similar to factors in factor models)(Golino & Epskamp 2017).

Semantically similar items are common feature of psychological scales (Leising et al. 2020). These items will often have greater connectivity in networks and hence contribute significatively in network centrality measures (Golino et al. 2022). In psychometric terms, these items are said to be locally dependent - they do not contribute any unique information over and above the other (Edwards et al. 2018). Local dependence is problematic for all of psychometric measurement and especially for network models (Hallquist et al. 2021).

Moreover, removing locally dependent variables may help to reduce the number of items of the network and simplify the teachers scale (e.g., CTRS-R: S). Local dependence can be evaluated using Unique Variable Analysis (UVA). UVA identifies locally dependent variables in a psychometric tool and presents them to the researcher as to facilitate the process of reducing the numbers of variables while retaining the important information (Christensen et al. 2020). With UVA, as variables are removed, the centrality of items is also likely to be modified: the impact of variable removal from the network therefore requires additional investigation (Christensen et al. 2020).

The question that arises is that once UVA is performed and locally dependent items are excluded, how will the CTRS-R: S network be modified. Therefore, by this statistical manipulation, how will the centrality be modified and how will the communities be affected?

This study is structured as follow: we will evaluate the local dependence in CTRS-R:S and its impact on network centrality. UVA will be used to identify locally dependent variables. A new “refined” network will be computed, containing unique variables only. We also re-evaluate the community structure of the network to determine whether it is logical and similar to previous studies.

METHOD

Dataset

Data from this study were retrieved from 525 French-speaking Belgian primary schools. Teachers completed the CTRS-R:S by filling in age, sex, the date of birth. Since the questionnaires were on paper, the data were encoded on Excel. Our study protocol was approved by the Ethical Committee of the Brugmann Teaching Hospital in Brussels (CHU Brugmann, protocol B0772020000052/I/*U Modeling of interactions between ADHD symptoms of the CTRS-R: S scale*).

Network estimation method

EGA

Exploratory Graph Analysis is a new approach in psychometric networks that focuses on estimating undirected network patterns to estimate the number of network dimensions with multivariate data (Golino et al. 2020, Golino & Epskamp 2017). The advantages of this method are providing the number of dimensions of the network but also the placement of items and their level of association. Moreover, symptoms can be represented as a network of interconnections within and between psychopathological dimensions (Peralta et al. 2020). It identifies the key role of items individually. EGA surpasses other data-reduction methods in estimating the number of dimensions inherent to the date set, and sample size correlations among factors, and the number of items and factors affect the accuracy of EGA less (Golino et al. 2020, Golino & Epskamp 2017).

Bootstrap Exploratory Graph Analysis

After estimating the dimensions of the network via EGA, the stability of dimensions will be evaluated using a new method, the Bootstrap Exploratory Graph Analysis, also called bootEGA (Christensen & Golino 2021). BootEGA algorithm uses parametric or non-parametric (resampling) procedures. If the distribution is non-normal or unknown, the resampling procedure should be preferred, and so used in this paper. Technically, EGA is performed for each test, to a pre-selected number of testing (Christensen & Golino 2021).

Unique Variable Analysis

UVA detects redundant variables in network psychometrics has several interests in network analysis (Christensen et al. 2020). On one hand, there is an overestimation number of factors (domains) in the data due to minor factors created by redundant variables (Christensen et al. 2020). On the other hand, the estimated network can be distorted due to redundant variables that are expected to have higher node strength values (Briganti et al. 2020, Hallquist et al. 2021), which gives a strength value falsely augmented estimation (counter to a network without redundancies).

It is first necessary to compute a network and estimate the weighted topological overlap with the partial correlation matrix which quantifies the amount to which pairs of nodes have imbricated (or “overlapping”) connections (Zhang & Horvath 2005). In other words, it determines the degree to which they have a similar number and the extent of connections and how they are connected to similar nodes.

We applied the recommended significance default of adaptive alpha (Pérez & Pericchi 2014), which adjusts alpha (e.g., α=0.05) based on sample size (here, the number of weights in the network).

If the variable X is redundant with the variable Y and variable Y is redundant with Z, then X and Z, which are not two redundant variables, will be so indirectly redundant. We consider that X, Y and Z are part of a *redundancy chain*. In R, it is possible to highlight different redundancies chains and to select a target variable. This target variable is a variable that shares the most directed and undirected connection (linked through only other variables) with the other redundant variables. Therefore, two variables can be indirectly redundant (Christensen et al. 2020).

Community detection

Community detection is performed using the Walktrap algorithm. It informs on the connectedness of subgraph and therefore highlights communities (Pons & Latapy 2005). See Golino et al. (2020) for a more detailed description.

Structural consistency

Structural consistency is a measure that evaluates the stability of dimensions by bootEGA. This concept is defined as the proportion of times that each empirically derived dimension (resulting from the initial EGA). Furthermore, it brings how dimensions are interrelated (internal consistency) and homogeneous (test homogeneity) in the presence of other related dimensions (Christensen et al. 2020). Structural consistency ranges can take is from 0 to 1. A dimension's structural consistency can only be 1 if the items in the empirically derived dimension conform to that dimension across all replicate samples (Christensen et al. 2020).

Centrality Stability and Difference Test

The centrality stability and difference tests were performed in the reduced network through bootstrapping to evaluate if centrality estimate are stable (Epskamp et al. 2018). *Centrality-stability* coefficient (CS-coefficient) was applied to quantify the stability of centrality indices using subset bootstraps (Epskamp et al. 2018). CS-coefficient should not be below 0.25, and preferably above 0.5 (Epskamp et al. 2018).

Data analysis

All analyses were performed in R (version 4.0.5; R Core Team, 2020). UVA, EGA, and bootEGA were applied using the EGAnet package (version 0.9.8) and were visualized using ggplot2 (version 3.3.5) packages in R. Centrality stability and different tests were performed using the bootnet (version 1.4.3) package in R.

RESULTS

Initial Bootstrap Exploratory Graph Analysis

BootEGA was executed to evaluate the stability of the network. We highlight only 4 clusters with the Walktrap algorithm, but there are logical compared to the first, as it will be explained in the discussion (Figure 1).

Each community were called according to their included items. Community 1 was called *Inattentive* contains items 1, 4, 8, 13, 14, 16, 18, 19, 22, 25, 26. Community 2 includes items 3, 7, 9, 12, 11, 21, 28 and was named *Agitated*. Community 3 involves items 5, 17, 23, 24, 27, and was entitled *Impulsive*. And finally, items 2, 6, 10, 15 and 20 are included in the fourth community 4 named *Oppositional*. The structural consistency was satisfying for community 1 (0.98), community 2 (0.83) and community 4 (0.89) but less comforting for community 3

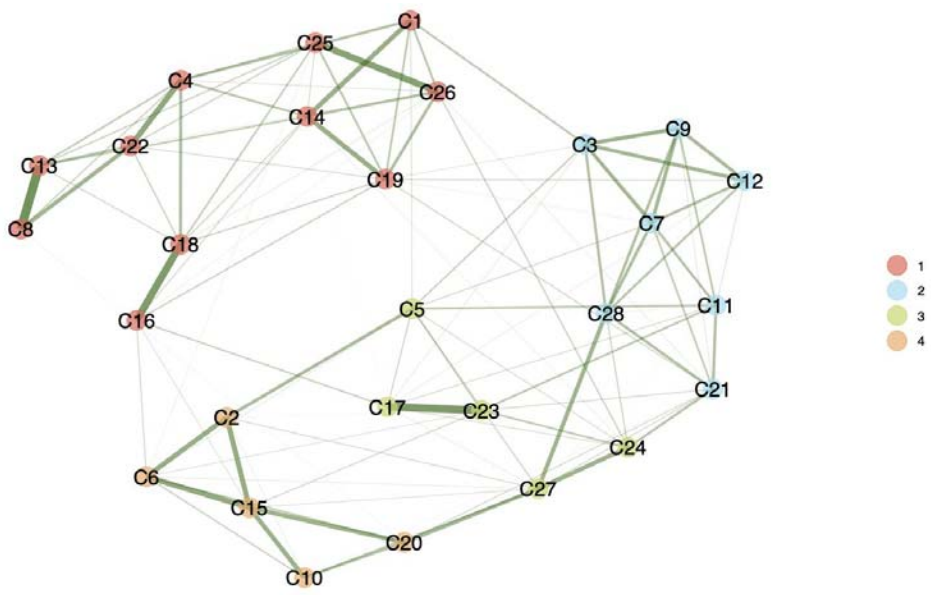

Figure 1. 28-items network of CTRS-R:S estimated with BootEGA

with a "mean stability" of 0.59. Item 28 has the lowest stability with 0.58. We did not remove items with the lowest stability as they were all included in the "hyper-activity" group: extracting them from the network would have deleted an important part of the abnormal child behavior construct.

Redundancy of CTRS-R:S network

UVA identified redundant variable from the 28 items CTRS-R:S and gives target variable from a cluster of redundant variables. For example, item C9 was identified as target in the group of 5 items (C9, C12, C28, C3, C7). 13 items out of 28 were identified as redundant, the final network being composed of 15 items, following state-of-the-art recommendations on the technique (Christensen et al. 2020). Figure 2 was produced after applied BootEGA.

Items 8, 12, 14, 15, 17, 18, 26, 27 were all selected as target variables (variables to be kept). Other items were preserved as well in the reduced network (items 4, 5, 10, 11, 21, 22). The reduced network community stability is overall higher than the stability of the full network, where community 1 stability equal= 0.99 and community 2 stability equal to = 0.90.

Network inference and stability

The CS-coefficient of the reduced network was equal to 0.672, that signifies that the centrality order was overall stable: up until 67.2 % of the sample can be dropped, and the centrality order would correlate at least 67.2 with 95% of bootstrapped samples. For the 28 items network, the CS coefficent was equal to 0.75.

DISCUSSION

This study evaluates local dependence in the CTRS-R:S and its effect on the network structure. It is the first paper to our knowledge studying local dependences in CTRS-R:S. Certainly, previous ADHD network studies evaluate the nodes with local dependence, even with other trouble like autism (Farhat et al. 2022). Our purpose is different than anterior publications and aim to find local dependences of variables in the CTRS-R:S thanks to UVA. Henceforward, this method should be considered as a supplementary tool in network studies, as psychometric scales contain items with local dependence or with Synthetic Aperture Personality Assessment, SAPA (Christensen et al. 2020). Still local dependence in items from psychometric test have impact on network structure because they falsely improve the stability of a network.

Items locally dependent, and sometimes which are semantically similar, impact the network and its connectivity. As previously stated, non-reduced networks have "optimistic" results. Just as in this study, the network reduced from variables with local dependence is different than the initial network, and the stability too. We obtained an overall accurate network. Networks estimated from the complete scale will usually be more stable than the reduced networks because locally dependent items will have more consistent (partial) correlations with one another, making node strength more stable. Two new subgroups were determined, with a satisfactory stability.

The 28 items network were analyzed through bootEGA, and four communities were identified. This result differs from previous study treating about CTRS-R:S

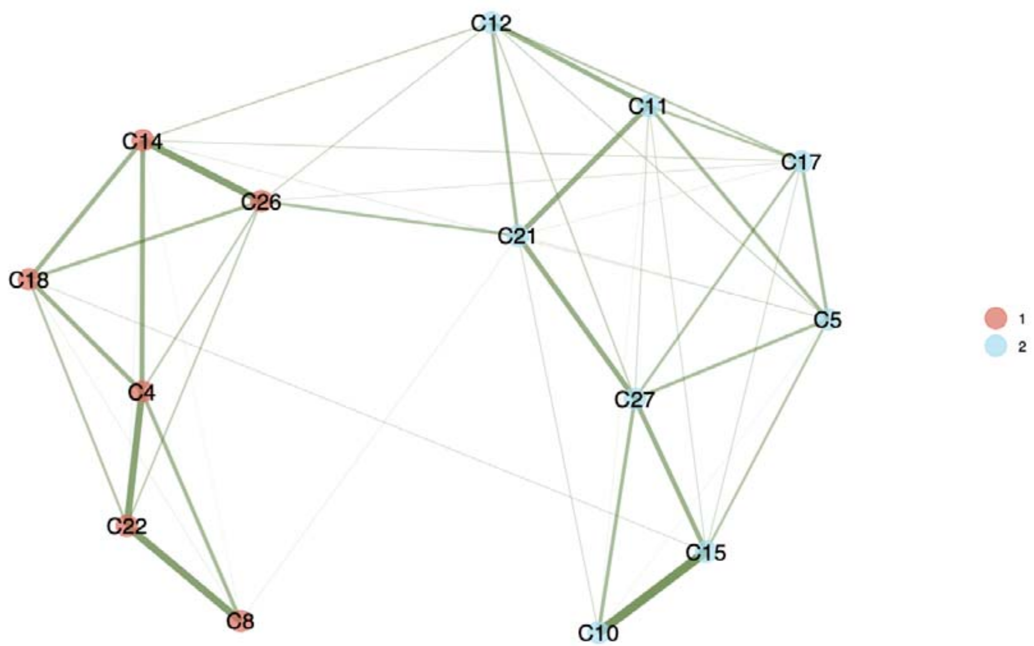

Figure 2. Reduced network of CTRS-R:S. The variables in the reduced network were retrieved with Unique Variable Analysis

network and the estimated network is somewhat different from the original Bayesian estimation (Till et al. 2022). The number of communities was different but communities are similar. That is relatively expected and a comforting result compared to the previous network CTRS-R:S study (Till et al. 2022). Bayesian GGMs, based on the value of the Bayes Factor used to select the model can be sparser than traditional GGMs selected with EBICglasso.

Some items appearing semantically comparable were not excluded or proposed during the UVA procedure. For example, items 11 "*Leaves seat in classroom or in other situations where remaining seated is expected*" and 21 "*Runs about or climbs excessively in situations where it is inappropriate*" are very similar, but are kept in the reduced network. Indeed, redundancy do not necessarily mean semantic similarity.

All items selected by UVA with local dependences arise from their respective community. Each domains contains locally dependent items, and the selection off target variable may be executed on the full community, as is the case for community 3 (where the conserved variable was item 12) and community 4 (excepted for item 10) where the chosen variable was item 15. In regard of this study (Till et al. 2022), most of locally dependent items were from this communities to, for example items 25 "*Poor in spelling*" and 26 "*Does not follow through on instructions and fails to finish schoolwork (not due to oppositional behavior or failure to understand instruction)*" from community 1 *Ineffectiveness*, and the more relevant item (with the highest strength centrality) from previous study was the target variable selected in this paper.

In the reduced network, four communities do not recur and only 2 communities are detected; community 1 reflects the inattention dimension with learning difficulties (item 8 "*Poor in spelling*" and 22 "*Poor in arithmetic*") and community 2 reflects the motor behavior (see item 12 "*Fidgets with hands or feet or squirms in seat*") and the relational behavior (for example items 5 "*Disturbs other children*" or 15 "*Argues with adults"*). Some items are related to DSM 5 criteria for ADHD diagnosis, and other items, although often associated to ADHD, are more common for other disorders, such as oppositional disorder or learning disorders like dyscalculia. That emphasizes CTRS-R:S is more than an ADHD tool, and ease to find comorbidities, and other troubles, and generally the children's classroom behavior (Conners et al. 1998). The four communities' stability (in 28 items network) were lowered because of the weak items stability of community 3, but in our assessment and in view of clinical interest to this items, we did not exclude them.

The results of this study should be interpreted in light of several limitations. First, the data from this study was collected in a sample of French-speaking Belgian primary school students and this study aimed to study a network structure estimated from a non-clinical sample. We do not know whether within the observed group there are children diagnosed with and/or treated for ADHD. Moreover, the CTRS-R:S was obviously completed by the teacher themselves, so bias will betide; for instance, the subjects were evaluated depending on the teacher that did the evaluation.

CONCLUSION

The search and discovery of variables with local dependence will offer a scale that is easier to use for the teacher and to interpret for the clinician. Our findings should be reevaluated based on future studies using clinical samples in various settings to ensure their replicability and application in practice.

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Contribution of individual authors:

Apolline Till conceptualized the work, collected the data, performed the statistical analysis and wrote the first draft.

Rémi Florquin collected the data and reviewed the manuscript.

Alexander Christensen & Hudson Golino conceived the statistical methods used in the study and reviewed the manuscript.

Charles Kornreich & Marie Delhaye reviewed the manuscript.

Giovanni Briganti supervised the data collection and analysis and reviewed the manuscript.

References

1. *Borsboom D: A Network Theory of Mental Disorders. World Psychiatry: Official Journal of the World Psychiatric Association (WPA) 2017; 16:5-13. doi:10.1002/wps.20375*
2. *Borsboom D, Deserno MK, Rhemtulla M, Epskamp S, Fried EI & McNally RJ: Network Analysis of Multivariate Data in Psychological Science. Nature Reviews Methods Primers 2021; 1:1-18. doi:10.1038/s43586-021-00055-w*
3. *Briganti G, Zcutari M & Linkowski P: A Machine Learning Approach to Relationships Among Alexithymia Components. Psychiatr Danub 2020; 32(Suppl 1):180-87*
4. *Briganti G, Williams DR, Mulder J & Linkowski P: Bayesian network structure and predictability of autistic traits. Psychological Reports 2020; 20200033294120978159*
5. *Christensen AP, Garrido LE & Golino H: Unique Variable Analysis: A Novel Approach for Detecting Redundant Variables in Multivariate Data. preprint. PsyArXiv 2020. doi:10.31234/osf.io/4kra2*

6. Christensen AP & Golino H: Estimating the Stability of Psychological Dimensions via Bootstrap Exploratory Graph Analysis: A Monte Carlo Simulation and Tutorial. Psych 2021; 3:479-500. doi:10.3390/psych3030032
7. Christensen AP, Golino H & Silvia PJ: A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires. European Journal of Personality 2020; 34:1095-1108. doi:10.1002/per.2265
8. Conners CK, Sitarenios G, Parker JDA & Epstein JN: Revision and restandardization of the Conners Teacher Rating Scale (CTRS-R): factor structure, reliability, and criterion validity. Journal of abnormal child psychology 1998; 26:279-91
9. Edwards MC, Houts CR & Cai L: A diagnostic procedure to detect departures from local independence in item response theory models. Psychological Methods 2018; 23:138-49. doi:10.1037/met0000121
10. Epskamp S, Borsboom D & Fried EI: Estimating Psychological Networks and Their Accuracy: A Tutorial Paper. Behavior Research Methods 2018; 50:195-212. doi:10.3758/s13428-017-0862-1
11. Farhat LC, Brentani H, de Toledo VHC, Shephard E, Mattos P et al.: ADHD and Autism Symptoms in Youth: A Network Analysis. Journal of Child Psychology and Psychiatry 2022; 63:143-51. doi:10.1111/jcpp.13436
12. Golino H, Christensen AP & Garrido LE: Exploratory Graph Analysis in Context, 2022
13. Golino HF & Epskamp S: Exploratory Graph Analysis: A New Approach for Estimating the Number of Dimensions in Psychological Research. edited by M. Voracek. PLOS ONE 2017; 12:e0174035. doi:10.1371/journal.pone.0174035
14. Golino H, Shi D, Christensen AP & Garrido LE: Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. Psychological Methods 2020; 25:292-320. doi:10.1037/met0000255
15. Green M, Wong M, Atkins D, Taylor J & Feinleib M: Diagnosis of Attention-Deficit/Hyperactivity Disorder. Rockville (MD): Agency for Health Care Policy and Research (US), 1999
16. Hallquist MN, Wright AGC & Molenaar PCM: Problems with Centrality Measures in Psychopathology Symptom Networks: Why Network Psychometrics Cannot Escape Psychometric Theory. Multivariate Behavioral Research 2021; 56:199-223. doi:10.1080/00273171.2019.1640103
17. Leising D, Burger J, Zimmermann J, Bäckström M, Joshua R. et al.: Why Do Items Correlate with One Another? A Conceptual Analysis with Relevance for General Factors and Network Models, 2020
18. Parry TS: 12. Assessment of Developmental Learning and Behavioural Problems in Children and Young People. Medical Journal of Australia 2005; 183:43-48. doi:10.5694/j.1326-5377.2005.tb06892.x
19. Peralta V, Gil-Berrozpe GJ, Sánchez-Torres A & Cuesta MJ: The Network and Dimensionality Structure of Affective Psychoses: An Exploratory Graph Analysis Approach. Journal of Affective Disorders 2020; 277:182-91. doi:10.1016/j.jad.2020.08.008
20. Pérez M-E & Pericchi LR: Changing Statistical Significance with the Amount of Information: The Adaptive α Significance Level. Statistics & Probability Letters 2014; 85:20-24. doi:10.1016/j.spl.2013.10.018
21. Pons P & Latapy M: Computing communities in large networks using random walks. P. 284-93 in International symposium on computer and information sciences. Springer 2005
22. Preszler J & Burns GL: Network Analysis of ADHD and ODD Symptoms: Novel Insights or Redundant Findings with the Latent Variable Model? Journal of Abnormal Child Psychology 2019; 47:1599-1610. doi:10.1007/s10802-019-00549-y
23. Shaw M, Hodgkins P, Caci H, Young S, Kahle J et al.: A Systematic Review and Analysis of Long-Term Outcomes in Attention Deficit Hyperactivity Disorder: Effects of Treatment and Non-Treatment. BMC Medicine 2012; 10:99. doi:10.1186/1741-7015-10-99
24. Silk TJ, Malpas CB, Beare R, Efron D, Anderson V, et al.: A Network Analysis Approach to ADHD Symptoms: More than the Sum of Its Parts. edited by S. E. Medland. PLOS ONE 2019; 14:e0211053. doi:10.1371/journal.pone.0211053
25. Till AC, Florquin R, Delhaye M, Kornreich C, Williams DR & Briganti G: A network perspective on abnormal child behavior in primary school students. Psychological Reports 2022; 00332941221077907. doi:10.1177/00332941221077907
26. Willcutt EG: The Prevalence of DSM-IV Attention-Deficit/Hyperactivity Disorder: A Meta-Analytic Review. Neurotherapeutics 2012; 9:490-99. doi:10.1007/s13311-012-0135-8
27. Zhang B & Horvath S: A general framework for weighted gene coexpression network analysis. in Statistical Applications in Genetics and Molecular Biology 4: Article 17, 2005

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