Studying Statistics Anxiety Requires Sound Statistics: A Comment on Siew, McCartney, and Vitevitch (2019)

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Empirical scientists cannot do without statistics. This fact is reflected by the pervasiveness of statistics courses in the curricula of essentially all scientific disciplines. Unfortunately, many students exhibit *statistics anxiety*, that is, “feelings of anxiety [...] when taking a statistics course or doing statistical analyses” (Cruise, Cash, & Bolton, 1985, p. 92). In a recent publication in *Scholarship of Teaching and Learning in Psychology*, Siew et al. (2019) aim to shed new light on this highly relevant topic by using data analysis tools from the field of network science. Specifically, they analyzed a data set consisting of the responses of $n = 228$ psychology undergraduates to the Statistical Anxiety Rating Scale questionnaire (STARS; Cruise et al., 1985), which consists of 51 items rated on a 5-point Likert scale. To investigate differences in relations between items between students with low/high statistics anxiety, Siew et al. (2019) split the sample into two groups based on the median STARS sum score. For each group, the authors constructed a network in which questionnaire items constitute nodes and pairwise Pearson correlations constitute edges. If a correlation was lower than 0.3, the authors removed the connection between the two variables. The authors further computed node centrality measures *strength*, *closeness*, and *betweenness*. In addition, they applied a community detection analysis to both groups, respectively. They found that the network structure and the most central nodes differ between the “low” and “high” statistics anxiety groups, and suggested that their findings can help develop effective interventions that reduce statistics anxiety by targeting central nodes in the respective low/high anxiety groups.

Network models — marrying graph and probability theory to visualize, understand, and interpret variables and their relations as nodes and edges in a graph — have become popular across different empirical disciplines, allowing us to better understand multivariate systems (e.g., Bassett & Sporns, 2017; Borsboom, 2017; Van Der Maas, Kan, Marsman, & Stevenson, 2017). We welcome the increased application of network models across scientific disciplines and agree with Siew et al. (2019) that they are a promising tool to further the understanding of statistics anxiety. However, just as with any other statistical model, one has to carefully assess the adequacy and robustness of a network model. In this commentary, we point to a number of shortcomings in the article by Siew et al. (2019) with respect to this goal that question their main conclusions. We explain each problem and suggest ways to address it. We hope that these suggestions help to put future investigation of statistics anxiety using network models on a firm methodological basis.

Pearson correlation or Partial correlation? From a network perspective, instead of assuming latent common causes, one typically assumes that the variables are in direct causal relation to each other. To highlight possible pairwise causal relations, Siew et al. (2019) use Pearson correlations, while the majority of researchers uses partial correlations (see e.g., Haslbeck & Fried, 2017). The reasoning behind this choice is usually that partial correlations are better suited to uncover possible causal effects than correlations. To illustrate this, consider the three STARS items *enroll* (“Enrolling in a statistics class.”), *homework* (“Doing the homework for a statistics class.”), and *seven_grade* (“I can’t even understand seventh- and eighth-grade math; how can I possibly do statistics?”), which are all connected in the high anxiety correlation network provided by Siew et al. (2019). It is likely, however, that the item *seven_grade* interacts with the item *enroll* (students who feel they couldn’t understand high school math will likely not enroll in a statistics class), and the item *enroll* interacts with the item *homework* (students who enroll for more statistics classes will do more homework). Due to these interactions, it is very likely the items *seven_grade* and *homework* will correlate, but only due to their shared interactions with the item *enroll*. This leads

to the old adage that in psychology and the social and behavioural sciences more broadly, everything tends to correlate with everything (Meehl, 1990). Such *spurious* correlations, however, are not interesting from a network perspective. Estimating a partial correlation network, also known as Gaussian graphical model (Lauritzen, 1996; Epskamp, Waldorp, Möttus, & Borsboom, 2018), coupled with significance testing or regularization as discussed in the next paragraph would likely lead to this edge being removed from the network. Thus, from a network perspective, partial correlation networks are to be preferred over correlation networks. Of course, if a researcher is not willing to assume that the system consists of variables causing each other, but rather espouses a common cause perspective or wants to study concepts such as “conceptual overlap”, then Pearson correlations may be a better approach than Partial correlations. Not surprisingly, then, the answer to “Pearson correlation or Partial correlation?” depends on one’s background assumptions on how the data was generated. Based on those assumptions, one can select the appropriate method to answer the question at hand.

Estimation procedures. A large amount of literature focuses on how the parameters and the overall *structure* of such partial correlation networks can be adequately recovered (e.g., Meinshausen & Bühlmann, 2006; Foygel & Drton, 2010; Epskamp, Waldorp, et al., 2018; Epskamp & Fried, 2018; Williams, Rhemtulla, Wysocki, & Rast, 2019; Borsboom, Robinaugh, Group, Rhemtulla, & Cramer, 2018). The structure of a network indicates which variables are conditionally independent, that is, which edges are zero. This is important, because we would like to ensure that our model is close to the true population model (i.e., has low estimation error) and thereby also accurately describes the dependencies between variables in new samples drawn from the same population. The estimation procedures discussed in the literature have been studied methodologically; they thus provide more principled ways of selecting which edges are present compared to arbitrary thresholding rules such as the one used by Siew et al. (2019).

Inferential statistics and assessing stability and accuracy. Siew et al. (2019) argue based on community detection analyses that the networks, and based on centrality analyses that the central nodes of low and high anxiety students differ. However, they do not allow the reader to evaluate whether these differences are reliable. In fact, they do not actually use inferential statistics to infer a potential population difference, nor do they provide standard errors for their estimates. We suspect that any such assessment would indicate large uncertainty as to whether such a difference actually exists, given the low n/p ratio. In particular, with $n = 228$ participants, the sample size used by Siew et al. (2019) is rather small compared to the large number of variables ($p = 51$), which results in $\binom{51}{2} = 1275$ (partial) correlations that have to be estimated. It has been recognized in the literature that it is imperative to study whether parameters (e.g., edge-weights) and associated summary measures (e.g., centrality coefficients) derived from the network structure are *stable* (the same conclusions would be drawn with subsets of the data) and *accurate* (estimates are not highly influenced by sampling variation) (Epskamp, Borsboom, & Fried, 2018; Borsboom et al., 2018). While Siew et al. (2019) cite tutorial papers calling for such checks on accuracy and stability (Epskamp & Fried, 2018; Epskamp, Borsboom, & Fried, 2018), they did not perform such checks themselves, making it impossible to judge how reliable their results are.

Selecting participants on summary statistics biases results. Siew et al. (2019) estimate separate network models for participants whose STARS sum score is below or above the median. This practice, however, is known to produce biased network estimates (Epskamp & Fried, 2018; De Ron, Fried, & Epskamp, 2019). In particular, it is equivalent to conditioning on a common effect (Pearl, 2009; Muthén, 1989), which induces spurious correlations (see Figure 1 for an illustration). Specifically, because the individual items are positively related to the sum score, the resulting edges between items will be downward biased. This effect is also known as Berkson’s bias (Berkson, 1946). As such, it is not clear to what extent the results by Siew et al. (2019) are biased. The issue of Berkson’s bias has only recently been discussed in the literature on psychological network models (De Ron et al., 2019). Since the emergence of this bias is not trivial nor easy to overcome, we recommend to avoid conditioning on sum scores or to clearly mention the resulting bias in the limitations.

Figure 1: Left: The STARS sum score is a common effect of, among others, the items *enroll*, *home-work*, and *seven_grade*. Right: Conditioning on a common effect induces spurious or downward biased correlations between items *enroll*, *homework*, and *seven_grade*.

Interpretation of centrality indices. It has been recognized that the logical steps required to interpret central nodes in psychological networks in the same way as central nodes in social networks (e.g., influential people) are far from trivial (Bringmann et al., 2019; Borgatti, 2005). Siew et al. (2019) find that *seven_grade* has the highest betweenness centrality in the high anxiety network, and argue that effective interventions should thus target this item. However, it is unclear what betweenness centrality, which relies on the notion of a shortest path, actually captures in a psychological context (Bringmann et al., 2019). Similarly, highly central nodes need not be causally effective nodes (Dablander & Hinne, 2019). In addition to these theoretical issues, centrality measures can be highly unstable and, without checks for accuracy and stability, there is no certainty about whether differences in centrality are not simply due to chance (Epskamp, Borsboom, & Fried, 2018). To this end, the strong causal conclusions by Siew et al. (2019), such as “results suggest that the most effective interventions for students with very high level of statistics anxiety would need to address the (incorrect) perception that strong mathematical ability is a necessary prerequisite to excel in statistics” (p. 1), are not warranted. We recommend to carefully assess the stability of centrality measures, and avoid interpreting them causally without additional knowledge.

Conclusion. Network models are an extremely useful tool for understanding multivariate systems. Siew et al. (2019) have introduced these models to the study of statistics anxiety, an issue of great importance. However, in order to draw on the full potential of network models to the study of statistics anxiety, one has to apply them with the same care as any other statistical model. In this commentary, we have re-evaluated the application of network models by Siew et al. (2019), and pointed out a number of shortcomings that put their main conclusions into question. In particular, when studying statistics anxiety using network models, we recommend to (a) use partial correlation instead of Pearson correlation networks, and estimate them with non-arbitrary estimation methods; (b) when interested in differences between populations, statistically assess whether these differences are reliable, as well as assess the stability and accuracy of the parameters of network models; (c) be aware of the bias introduced by conditioning on sum scores; and (d) assess the reliability of centrality indices and avoid incautiously interpreting highly central nodes as highly causally effective nodes. For more detailed recommendations and considerations concerning network models, we refer the reader to Epskamp and Fried (2018). Statistics anxiety is a topic that is also dear to our hearts; by drawing attention to these issues, we hope that our commentary helps to put future investigation of statistics anxiety using network models on a firm methodological basis.

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