

CROSS-FERTILIZATION UPDATE

Using Network Science to Understand Statistics Anxiety Among College Students

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Many psychology students experience statistics anxiety, which negatively affects academic performance and necessitates the application of new methods to understand the underlying nature of statistics anxiety. In the present analysis we use the tools of network science, a set of mathematical techniques to examine the relationships between entities in a system, to create networks from the items in the Statistical Anxiety Rating Scale (STARS), a widely used instrument to measure statistics anxiety. Separate networks were constructed and analyzed for students who were high or low in statistics anxiety. The items in the STARS were the nodes in the network, with connections placed between nodes if responses to those 2 items in the STARS were correlated. The network analysis revealed differences in the overall structure of high- and low-anxiety networks and in which nodes were most “important” in the 2 groups, suggesting that different interventions might be required depending on the level of statistics anxiety experienced by the student. Furthermore, our results suggest that the most effective interventions for students with very high levels of statistics anxiety would need to specifically address the (incorrect) perception that strong mathematical ability is a necessary prerequisite for excelling in statistics. Centrally located nodes in the network may help instructors appropriately target classroom interventions to help all students succeed regardless of the level of statistical anxiety experienced by students.

Keywords: statistics anxiety, network science, higher education

Knowledge of statistics increases critical reasoning and conditional logic (Lehman & Nisbett, 1990; VanderStoep & Shaughnessy, 1997) and is essential in many academic and professional fields (Maat & Rosli, 2016). Within the psychological sciences, a strong grasp of statistics is essential for a successful career in academia or in practice. A survey of psychology

major requirements revealed that almost 77% of the course curricula included at least one statistics course (Messer, Griggs, & Jackson, 1999), and in the majority of these curricula psychology students were required to take at least two courses of statistics to not only gain a strong foundation in understanding a variety of statistical models and their assumptions but also ac-

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quire the skills to implement an array of statistical techniques to analyze behavioral data.

However, the importance of learning statistical interpretation and analysis is undermined by the high prevalence of statistics anxiety among students (Onwuegbuzie & Seaman, 1995; Onwuegbuzie & Wilson, 2003). *Statistics anxiety* is defined as “feelings of anxiety encountered when taking a statistics course or doing statistical analyses” (Cruise, Cash, & Bolton, 1985; p. 92) and is different from general anxiety (Benson, 1989) or mathematics anxiety (Baloglu, 2004; Onwuegbuzie & Wilson, 2003; Paechter, Macher, Martskvishvili, Wimmer, & Papousek, 2017). Indeed, Onwuegbuzie and Wilson (2003) found that up to 80% of students experience some form of statistics anxiety, which leads to delayed enrollment in statistics courses. Students find statistics to be the most anxiety-inducing course in their curriculum (Chew & Dillon, 2014).

Increased levels of statistics anxiety have a negative impact on academic achievement. These include failing a statistics course (Fitzgerald, Jurs, & Hudson, 1996), low exam performance (Macher, Paechter, Papousek, & Ruggeri, 2012), negative relationships between anxiety and academic performance (Bell, 2001, 2003; Feinberg & Halperin, 1978; Macher et al., 2012; Tremblay, Gardner, & Heipel, 2000), dropping out of courses (Macher et al., 2012), and struggling with completion of theses and dissertations (Rodarte-Luna & Sherry, 2008). Overall, these studies show that there is a strong negative relationship between performance and statistics anxiety. Because of statistics anxiety, students are more apt to avoid statistics-related tasks and increase levels of academic procrastination (Onwuegbuzie, 2004) and be unaware of the importance of statistics or regard it as unimportant (Conners, McCown, & Roskos-Ewoldsen, 1998; Keeley, Zayac, & Correia, 2008).

Given the negative influence of statistical anxiety on academic achievement and the importance of statistical competency to succeed in an increasingly data-driven world, it is imperative for instructors to address the high levels of statistics anxiety among college students. From the large literature on statistics anxiety, it is clear that high levels of statistics anxiety are associated with many negative academic out-

comes but considerably little has been learned about the nature of the statistics anxiety itself and about the underlying factors that lead to statistics anxiety. The application of network science techniques to this area could lead to new insights that help to better understand the nature of statistics anxiety experienced by students in ways that traditional analyses cannot and provide suggestions for effective interventions that minimize levels of statistics anxiety among psychology students.

Network science is an emerging discipline that uses mathematical and computational techniques to study complex systems in biological, social, and technological domains (Barabási, 2009). A network is a weblike structure that consists of nodes representing an individual entity in the system, as well as connections (also called links or edges) representing some type of relationship between entities. For example, in a network of a social system, a node would represent an individual person and links would connect individuals who are friends with each other.

Within the psychological sciences, network science has been used to study language processing (Vitevitch, 2008), how groups share information to solve a problem (Mason, Jones, & Goldstone, 2008), and the functional and structural connectivity of the brain (Sporns, 2014; for a review of how network science has been used in the psychological sciences see Vitevitch, 2016). The network approach has also been applied to examine how psychological disorders like major depressive disorder or posttraumatic stress disorder might arise from the relationships among various psychological and behavioral symptoms (Cramer, Waldorp, van der Maas, & Borsboom, 2010; McNally et al., 2015). In these “symptom” networks, nodes represent individual symptoms, and connections are placed between symptoms that tend to co-occur (for an application of network science to eating disorders see Forbush, Siew, & Vitevitch, 2016).

Before proceeding, it is worthwhile to closely examine the way in which these symptom networks are constructed and consider how network analysis differs from traditional statistical approaches. In psychopathological research, patients typically fill out a questionnaire with items that assess the frequency or intensity of symptoms experienced by the individual, such

as the Eating Pathology Symptoms Inventory analyzed in [Forbush et al. \(2016\)](#) and the PTSD Checklist analyzed in [McNally et al. \(2015\)](#), to list a few examples. Traditional approaches to analyzing such data involve conducting exploratory or confirmatory factor analysis to see which items load on specific latent factors. The network approach, however, treats each item as a single node in a network representation, and connections are placed between nodes that are significantly correlated with each other ([Cramer et al., 2010](#)).

Within the psychopathology literature, a key advantage of representing, and analyzing, questionnaire data as a network is that it shifts the dominant reductionist approach that views psychological disorders as stemming from a single underlying latent cause to an approach that conceptualizes psychological disorders as networks of causally interacting symptoms and emphasizes the interacting relationships between specific symptoms in the network ([Borsboom, Cramer, & Kalis, 2018](#)). This has led to several key insights into various psychological disorders that have important implications for treatment and therapy because the network approach provides clinicians with specific symptoms that could be targeted during therapy by employing centrality analyses to detect “important” nodes (i.e., symptoms) in the network.

Consider a recent application of the network science approach to analyze the experience of stuttering in speech pathology. [Siew, Pelczarski, Yaruss, and Vitevitch \(2017\)](#) analyzed the items on a scale that assessed a speaker’s experience of stuttering as a network and used network analysis to identify important experiences of stuttering that clinicians may want to prioritize during therapy. It is important to note that the network analysis revealed discrepancies between the experiences that were considered important by clinicians and those considered important by people who stutter, paving the way for clinicians to modify therapy so that it better focuses on treating the experiences of stuttering that are truly central to people who stutter. Such findings and recommendations are simply not possible if an approach such as confirmatory factor analysis were used instead.

In the present article, we applied the network science approach to analyze the Statistical Anxiety Rating Scale (STARS; [Cruise et al., 1985](#)), a widely used instrument to measure statistics

anxiety among students ([Chew & Dillon, 2014](#); [Onwuegbuzie & Wilson, 2003](#)). As demonstrated in the psychopathology literature, the application of network analysis could lead to new insights that help to better understand the statistics anxiety experienced by students in ways that traditional analyses cannot. A more nuanced understanding of the nature of statistics anxiety among students who have high-anxiety scores (as assessed by the STARS instrument), and how that might be different for students who have low-anxiety scores, could lead to targeted, specific instructional strategies for maximal impact in the classroom.

Method

Participants

Data were collected from 228 students (54 male, 155 female, and 19 choosing not to identify their gender) taking an introductory psychological statistics course offered at the sophomore level. Students were enrolled at a large comprehensive public university in the Midwest. A sample size of 228 participants is adequate for the present analysis because it is comparable to the sample sizes in prior literature that used network analysis to analyze the symptom networks of people with various clinical disorders ([Forbush et al., 2016](#); [McNally et al., 2015](#)). It is important to note that although techniques for conducting a power analysis for network analysis are still a work in progress (e.g., [Epskamp, Kruis, & Marsman, 2017](#)), it is a rapidly growing area of inquiry, and the current sample size is in line with that in preliminary simulation work suggesting that network analysis is robust using sample sizes typically used in psychological research ([Epskamp, Borsboom, & Fried, 2018](#); [Epskamp et al., 2017](#)). In addition, it is important to acknowledge that this is a convenience sample of enrolled students in a college class. The mean age of participants was 19.76 years ($SD = 3.89$), and 14 students were nontraditionally aged college students. The course is required in the psychology curriculum at the institution, but other majors enroll in it as well. The majors included psychology (43%), nursing (14.5%), and the behavioral sciences (8.3%), with the rest from other social and natural sciences. The sample included racial and ethnic minorities (26.3%) and first-

generation college students (35.1%). The STARS was completed during the first 2 weeks of the semester, and students gave their consent for their data to be used in this study. The instrument was completed online as part of a larger questionnaire that collected demographic and other types of information about the students. The results of this questionnaire were then anonymized and released to students in the course for analysis during the semester. Completion of the larger questionnaire was completed for course credit. The study was approved by the Institutional Review Board at the University of Kansas.

Description of the STARS Instrument

The STARS has 51 items in two parts, both of which are scored on a 5-point Likert scale (Cruise et al., 1985). The first part asks students to rate their level of anxiety in the situation described on a scale from 1 (*no anxiety*) to 5 (*a great deal of anxiety*), and the second part asks students to rate their level of agreement with statements related to statistics on a scale from 1 (*strong disagreement with statement*) to 5 (*strong agreement with statement*). The items on this scale load onto six factors: Worth of Statistics, Interpretation Anxiety, Test and Class Anxiety, Computation Self-Concept, Fear of Asking for Help, and Fear of Statistics Teachers. These factor loadings were obtained from the original article describing STARS by Cruise et al. (1985) and confirmed by others (e.g., Hanna, Shevlin, & Dempster, 2008). Table 1 shows the list of items from the STARS and their abbreviated labels (grouped by factors).

Network Analysis

An overall statistical anxiety score was computed for each participant by summing their scores on the STARS ($M = 120.74$, $SD = 33.63$). Participants were split into two groups (high anxiety; low anxiety) based on a median split ($Mdn = 120$). The high-anxiety group consisted of 115 participants with a mean score of 146.49 ($SD = 23.27$). The low-anxiety group consisted of 113 participants with a mean score of 94.53 ($SD = 19.18$). For the high-anxiety group, 82 were female and 26 male; for the low-anxiety group, 73 were female and 28 male, $\chi^2(df = 1, N = 228) < 1$, $p = .55$, indicating

that there were no gender differences between the high- and low-anxiety groups. Separate network representations were constructed for each group (high-anxiety network; low-anxiety network).

In each network, the 51 items in the STARS represented a node, and a connection was placed between nodes if responses to those items had a zero-order correlation coefficient of $\pm .3$ or greater. This cutoff is consistent with that in previous network analyses of psychological symptoms, which have excluded correlation coefficients less than $\pm .3$ (e.g., Forbush et al., 2016; McNally et al., 2015).

The R package *qgraph* (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) was used to visualize the network and compute the following measures of centrality: *strength*, *closeness*, and *betweenness*. These measures of centrality allowed us to identify nodes that reside in an *important* position in the network, with each centrality measure depicting a slightly different definition of importance and emphasizing different aspects of the network (Borgatti, 2005). *Strength* is the sum of weighted connections that are incident to a particular node, such that a node with many and high correlations is more important than a node with few and low correlations. *Closeness centrality* measures the distance from a particular node to all other nodes in the network, so an important node is one that is close to many other nodes in the network. *Betweenness centrality* measures the number of times a node appears on the shortest path between two other nodes, so an important node is one that acts as a “middleman” for many pairs of nodes in the network. For all centrality measures, higher values reflect a node’s greater importance to the network. Furthermore, each measure of centrality provides a slightly different measure of a node’s importance in the network that emphasizes different aspects of the network (Borgatti, 2005). For instance, strength quantifies the local structure of a node (i.e., the number of connections and how strong are these connections), whereas closeness and betweenness centralities quantify different aspects of the global connectivity patterns of a given node. Examining whether nodes converge on three distinct measures of centrality (as has been done in the literature; Forbush et al., 2016; McNally et al., 2015; Siew et al.,

Table 1
Items From the Statistical Anxiety Rating Scale and Their Abbreviated Labels Grouped by Factor

Abbreviated label	Item
Worth of Statistics	
subjective	24. Since I am by nature a subjective person, the objectivity of statistics is inappropriate for me.
actual_life	26. I wonder why I have to do all these things in statistics when in actual life I'll never use them.
philosophical	27. Statistics is worthless to me since it's empirical and my area of specialization is philosophical.
more_time	28. Statistics takes more time than it's worth.
waste	29. I feel statistics is a waste.
why_learn	33. I lived this long without knowing statistics, why should I learn it now?
dont_want	35. I don't want to learn to like statistics.
natural_ability	36. Statistics is for people who have a natural leaning toward math.
grind	37. Statistics is a grind, a pain I could do without.
remove_req	40. I wish the statistics requirement would be removed from my academic program.
why_needed	41. I don't understand why someone in my field needs statistics.
no_sig	42. I don't see why I have to clutter up my head with statistics. It has no significance to my life work.
dont_like	45. I can't tell you why, but I just don't like statistics.
not_fit	47. Statistical figures are not fit for human consumption.
cognitive	49. Affective skills are so important in my profession that I don't want to clutter my thinking with something as cognitive as statistics.
never_use	50. I am never going to use statistics so why should I have to take it?
Computation Self-Concept	
no_math	25. I haven't had math for a long time. I know I'll have problems getting through statistics.
seven_grade	31. I can't even understand seventh- and eighth-grade math; how can I possibly do statistics?
no_enjoy	34. Since I have never enjoyed math I don't see how I can enjoy statistics.
brains	38. I don't have enough brains to get through statistics.
mathematical	39. I could enjoy statistics if it weren't so mathematical.
mathematical2	48. Statistics isn't really bad. It's just too mathematical.
too_slow	51. I'm too slow in my thinking to get through statistics.
Fear of Statistics Teachers	
teacher_abstract	30. Statistics teachers are so abstract they seem inhuman.
teacher_not_human	32. Most statistics teachers are not human.
teacher_diff_lang	43. Statistics teachers talk a different language.
teacher_number	44. Statisticians are more number oriented than they are people oriented.
teacher_talk_fast	46. Statistics teachers talk so fast you cannot logically follow them.
Test and Class Anxiety	
study	1. Studying for an examination in a statistics course.
homework	4. Doing the homework for a statistics course.
final	8. Doing the final examination in a statistics course.
classroom	10. Walking into the classroom to take a statistics test.
diff_ans	13. Finding that another student in class got a different answer than you did to a statistical problem.
morning	15. Waking up in the morning on the day of a statistics test.
enroll	21. Enrolling in a statistics course.
final_after	22. Going over a final examination in statistics after it has been graded.
Interpretation Anxiety	
interpret	2. Interpreting the meaning of a table in a journal article.
decision	5. Making an objective decision based on empirical data.
read_article	6. Reading a journal article that includes some statistical analyses.

(table continues)

Table 1 (continued)

Abbreviated label	Item
analysis	7. Trying to decide which analysis is appropriate for your research project.
auto_ad	9. Reading an advertisement for an automobile which includes figures on gas mileage, compliance with population regulations, etc.
p_value	11. Interpreting the meaning of a probability value once I have found it.
data	12. Arranging to have a body of data put into the computer.
null_h	14. Figuring out whether to reject or retain the null hypothesis.
odds	17. Trying to understand the odds in a lottery.
printout	18. Seeing a student poring over the computer printouts related to his/her research.
understand	20. Trying to understand the statistical analyses described in the abstract of a journal article.
Fear of Asking for Help	
help_indiv	3. Going to ask my statistics teacher for individual help with material I am having difficulty understanding.
help_lecturer	16. Asking one of your lecturers for help in understanding a printout.
help_computer	19. Asking someone in the computer center for help in understanding a printout.
help_student	23. Asking a fellow student for help in understanding a printout.

2017) provides compelling support for a node's importance in the network.

Finally, a community detection analysis was conducted on each of the networks constructed to examine the smaller connected clusters (i.e., communities) embedded within a network. The Louvain modularity optimization method (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008) was used to quantify the network's community structure by computing the highest possible modularity value for each network. Modularity, Q , measures the density of links inside communities compared to links between communities (Fortunato, 2010). Larger Q values indicate a higher density of links within communities relative to the density of links between communities and suggest that the network exhibits robust patterns of clustering.

Results

Figure 1 shows the high-anxiety network, and Figure 2 shows the low-anxiety network. In both networks, each node represented an item on the STARS, and connections were placed between nodes if the responses to those items had a correlation coefficient of $\pm .3$ or greater. Thicker lines represent correlations that approach ± 1.0 , whereas thinner lines represent correlations closer to $\pm .3$.

Visual inspection of the networks in Figures 1 and 2 shows that the factor structure of STARS was more or less replicated. Items be-

longing to each of the six factors (Worth of Statistics, Computation Self-Concept, Fear of Statistics Teacher, Interpretation Anxiety, Test and Class Anxiety, Fear of Asking for Help) tended to be clustered together in both networks.

The high- and low-anxiety networks clearly have very different network structures. A community detection analysis was conducted to quantify this visual observation. In the high-anxiety network (see Figure 1), all items were connected to each other. The community detection analysis found $Q = .16$, which indicates that nodes within a community were likely to connect to other nodes in the community as well as to nodes in other communities. In other words, there was a weak community structure in the high-anxiety network.

However, in the low-anxiety network (see Figure 2), the network was split into two distinct components, with one component consisting of items related to Worth of Statistics, Computation Self-Concept, and Fear of Statistics Teacher and the other component consisting of items related to Interpretation Anxiety, Test and Class Anxiety, and Fear of Asking for Help. Furthermore, the community detection analysis found $Q = .55$, which indicates that nodes within a community were likely to connect to other nodes in the community and were less likely to connect to nodes in other communities. In other words, there was a stronger community structure in the low-anxiety network. The im-

High Anxiety STARS Network

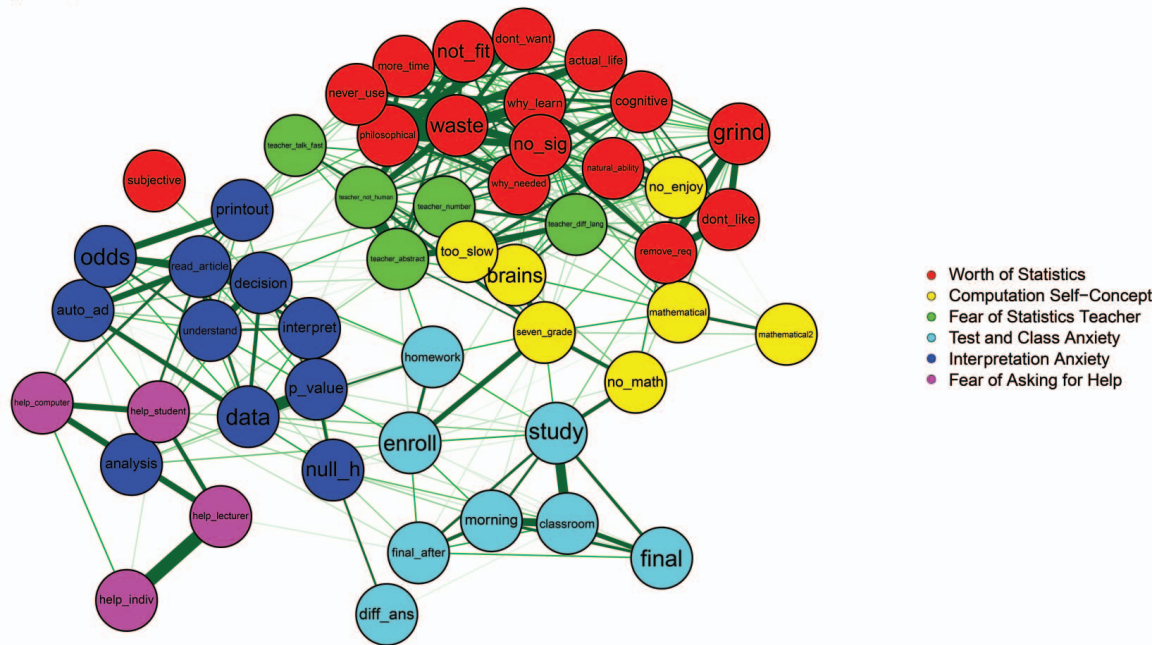


Figure 1. The high-anxiety network formed by pairwise correlations of the 51 items in the Statistical Anxiety Rating Scale based on the responses from students with high-anxiety scores. Each node in the network represented an item on the statistical anxiety scale, colored according to the each of the factors that each item loaded on in previous research. The connections between nodes represented the correlations between the items. Connections are shown only if the correlation coefficient was $\pm .3$ or greater. Thicker lines indicate that the correlation coefficient was closer to $+1.0$, and thinner lines indicate correlation coefficients closer to $+0.3$. All the lines are green (light or dark gray in the print version), indicating that all the correlations were positive. See the online article for the color version of this figure.

plications of these different network structures are explored further in the Discussion section.

Centrality Measures

Figures 3 and 4 show, for the high- and low-anxiety networks, respectively, three plots indicating the betweenness centrality values, closeness centrality values, and the strength values for each of the 51 nodes in the network. Table 1 shows the abbreviated labels used to represent each item in the STARS.

Betweenness centrality measures the number of times a node appears on the shortest path between two other nodes. The shortest path is defined as the fewest number of connections that need to be traversed to get from one node to another. A node is said to be high in betweenness centrality if it lies along many shortest paths between any two nodes in the network; a node is low in betweenness centrality if it lies along few shortest paths between any two nodes

in the network. For the high-anxiety network, the five nodes highest in betweenness centrality were (in decreasing order) 31, 30, 1, 18, and 6. For the low-anxiety network, the five nodes highest in betweenness centrality were (in decreasing order) 23, 2, 15, 38, and 46. Table 2 shows the top five items for betweenness centrality for the high and low statistical anxiety networks.

Closeness centrality is defined as the inverse of the sum of distances from a particular node to all other nodes in the network. High closeness indicates a short average distance between a given node and all other nodes in the network, whereas low closeness indicates a longer distance (i.e., more connections must be traversed) to get from a given node to all other nodes in the network. For the high-anxiety network, the five nodes highest in closeness centrality were (in decreasing order) 30, 38, 42, 31, and 44. For the low-anxiety network, the five nodes highest in

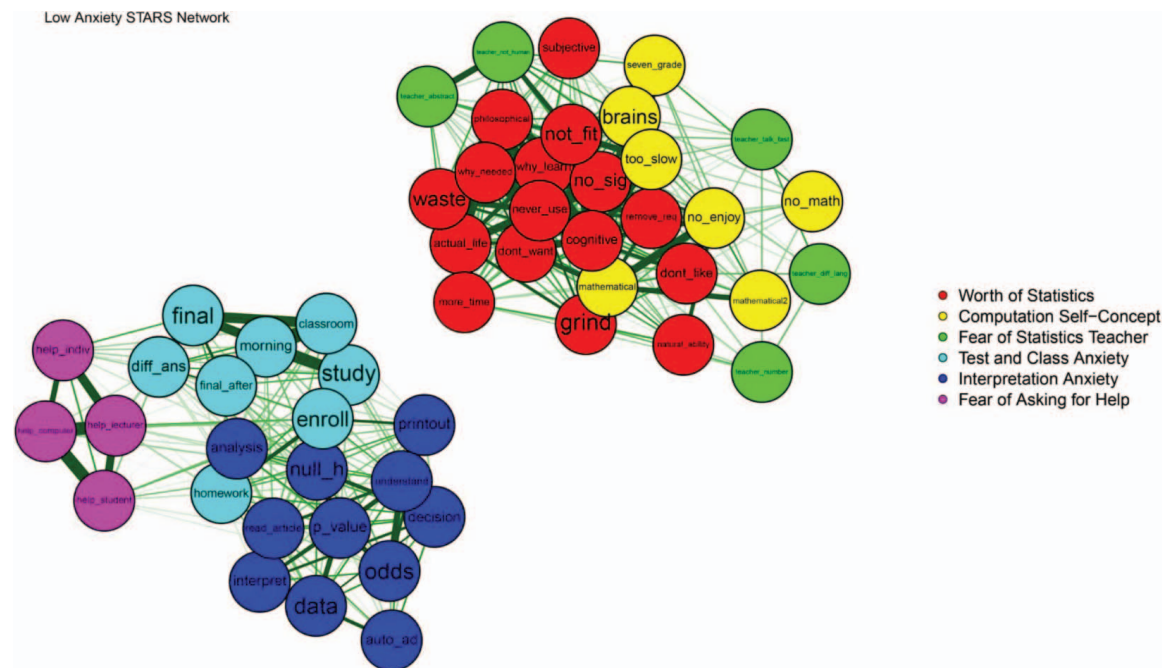


Figure 2. The low-anxiety network formed by pairwise correlations of the 51 items in the Statistical Anxiety Rating Scale based on the responses from students with low-anxiety scores. Each node in the network represented an item on the statistical anxiety scale, colored according to the each of the factors that each item loaded on in previous research. The connections between nodes represented the correlations between the items. Connections are shown only if the correlation coefficient was $\pm .3$ or greater. Thicker lines indicate that the correlation coefficient was closer to $+1.0$, and thinner lines indicate correlation coefficients closer to $+ .3$. All the lines are green (light and dark gray in the print version), indicating that all the correlations were positive. See the online article for the color version of this figure.

closeness centrality were (in decreasing order) 38, 50, 42, 49, and 27. Table 2 shows the top five items for closeness centrality for the high and low statistical anxiety networks.

Strength centrality is defined mathematically as the sum of weighted connections that are incident to a particular node. In the present case, strength is obtained by adding together the correlation coefficients on each of the connections of a given node. For the high-anxiety network, the five nodes highest in strength were (in decreasing order) 30, 42, 27, 29, and 38. For the low-anxiety network, the five nodes highest in strength were (in decreasing order) 50, 49, 42, 33, and 47. Table 2 shows the top five items for strength for the high and low statistical anxiety networks.

It is important to note that several of the same nodes had high values on the three different measures of centrality. A few of these nodes (brains and no_sig) were central in both high and low statistical anxiety networks, whereas

others were central in one network and not the other. As is discussed in the next section, the identification of central, or *important*, nodes in the anxiety networks may point instructors to aspects that could reduce statistical anxiety among students.

Discussion

In the present study we used network analyses to examine statistics anxiety in students with high or low levels of statistics anxiety as measured by the STARS instrument. It is important to note that the application of network analysis to analyze the relationships between items in the STARS has increased our understanding of the nature of statistics anxiety itself, in contrast to prior work that predominantly used the scale to measure levels of statistics anxiety among students and then correlated statistics anxiety with

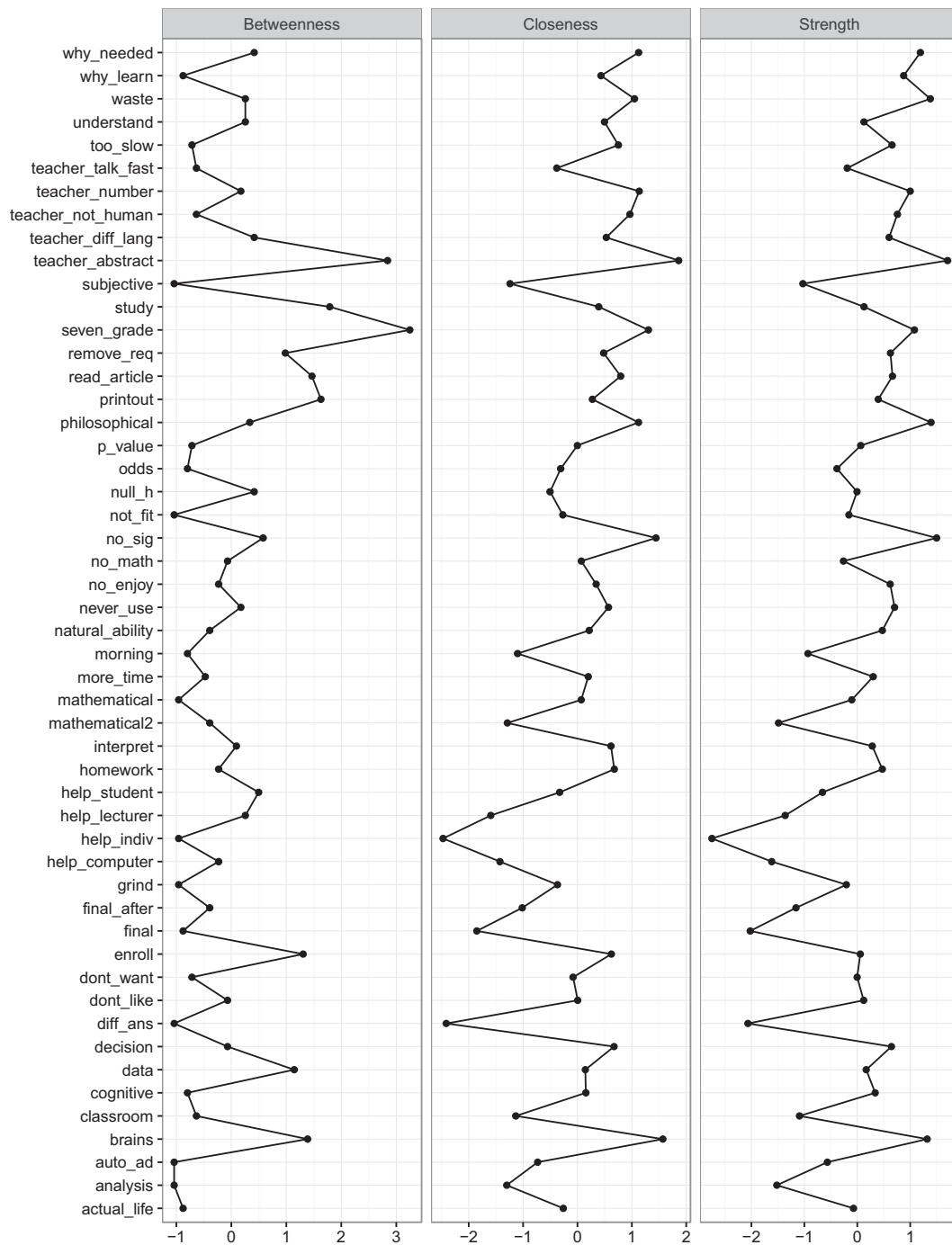


Figure 3. The values for betweenness centrality, closeness centrality, and strength for the 51 nodes in the high-anxiety Statistical Anxiety Rating Scale (STARS) network. The y-axis lists the abbreviated labels used to represent the 51 items from the STARS. The values in the x-axes represent the magnitude of the three different centrality measures noted at the top. These values were standardized and scaled relative to the largest value for each centrality measure.

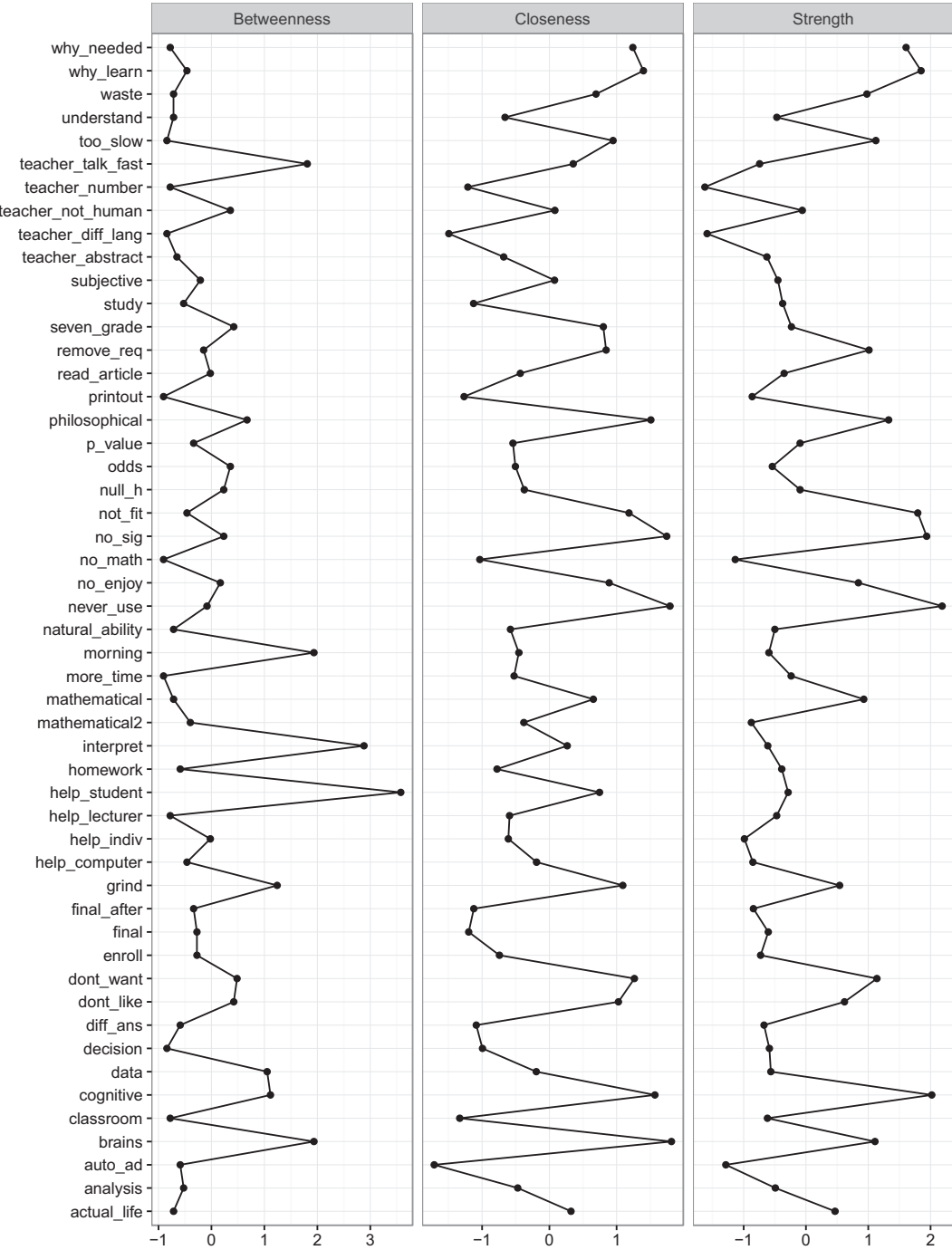


Figure 4. The values for betweenness centrality, closeness centrality, and strength for the 51 nodes in the low-anxiety Statistical Anxiety Rating Scale (STARS) network. The y-axis lists the abbreviated labels used to represent the 51 items from the STARS. The values in the x-axes represent the magnitude of the three different centrality measures noted at the top. These values were standardized and scaled relative to the largest value for each centrality measure.

Table 2
 “Top 5” Items for Each Centrality Measure for the High and Low Statistical Anxiety Networks

Item labels	Betweenness	Item	Closeness	Item	Strength
High-anxiety network					
31. seven_grade	3.25	30. teacher_abstract	1.86	30. teacher_abstract	1.71
30. teacher_abstract	2.84	38. brains	1.57	42. no_sig	1.50
1. study	1.79	42. no_sig	1.44	27. philosophical	1.39
18. printout	1.63	31. seven_grade	1.30	29. waste	1.38
6. read_article	1.47	44. teacher_number	1.14	38. brains	1.32
Low-anxiety network					
23. help_student	3.58	38. brains	1.81	50. never_use	2.18
2. interpret	2.88	50. never_use	1.79	49. cognitive	2.02
15. morning	1.94	42. no_sig	1.74	42. no_sig	1.94
38. brains	1.94	49. cognitive	1.57	33. why_learn	1.85
46. teacher_talk_fast	1.81	27. philosophical	1.51	47. not_fit	1.79

Note. Items are from the Statistical Anxiety Rating Scale, and those that have high values across different centrality measures are highlighted in bold. The values for betweenness centrality, closeness centrality, and strength centrality are z-scored values (i.e., standardized and scaled relative to the largest value for each centrality measure).

academic performance (Bell, 2001, 2003; Feinberg & Halperin, 1978; Macher et al., 2012; Tremblay et al., 2000) or levels of motivation to complete courses and dissertations (Macher et al., 2012; Rodarte-Luna & Sherry, 2008). A key strength of the network approach is that it allowed us to analyze the overall (macro-) and individual (micro-) levels of the system in question. The network analyses conducted at each level provide different but complementary insights into the nature of statistics anxiety experienced by students. In this section, we first explore the implications of the differences in overall network structure between students with high and low statistics anxiety before turning to the microlevel analysis of central nodes in the network.

Overall Network Structure

Clear differences in the overall network structure of the high and low statistics anxiety networks could have implications for understanding how the nature of statistical anxiety might differ across students. Consider the structure of the low-anxiety network (see Figure 2). The presence of two disconnected components indicate that the activation of certain items would not “spread” to, and hence would not activate, other areas of the network. For instance, low-anxiety students may experience anxiety related to a lack of competency in mathematics; however, this anxiety is not likely to

activate the other areas of the network (e.g., those associated with test-taking anxiety). It seems plausible that these students are using various strategies to understand that there are different areas within statistics where they will excel or be challenged.

For students with high anxiety, all 51 nodes in the anxiety network were connected to each other within a single network component (see Figure 1), suggesting that the activation of one area of the network is likely to spread to and activate the rest of the network. For instance, high-anxiety students may experience anxiety specifically related to a lack of competency in mathematics; however, the structure of the high-anxiety network suggests that this would ultimately spread to the rest of the network and lead to additional anxiety related to test taking and interpretation of statistics. These students might experience more of a “global” statistics anxiety because they believe they will struggle with every aspect of their statistics experience in college.

Centrality Analyses

Recall that centrality analyses allow for identifying nodes that reside in an *important* (i.e., central) position in the network (Borgatti, 2005). In the present study, the centrality analyses identified important items in the STARS networks of high and low statistics anxiety students and could provide instructors with some

insight about specific areas to focus on to reduce statistical anxiety among students. Furthermore, our results suggest that, for maximal impact, different aspects of the STARS network may need to be addressed depending on whether the student has high or low statistical anxiety.

Consider the two items *brains* (“38. I don’t have enough brains to get through statistics”) and *no_sig* (“42. I don’t see why I have to clutter up my head with statistics. It has no significance to my life work”), which were identified as important nodes in both high- and low-anxiety networks. This appears to be consistent with many students’ experiences with statistics classes where they find the material difficult and cognitively overwhelming (i.e., statistics requires a lot of “brain power”). This suggests that addressing students’ misconceptions of statistics’ being a subject that requires a lot of brain power with little to no significance to the real world would be helpful to students with either high or low levels of statistical anxiety.

In addition, somewhat different aspects of the STARS network emerged as central or important depending on students’ level of statistical anxiety. The following items were identified as important nodes in the high-anxiety network but not the low-anxiety network: *teacher_abstract* (“30. Statistics teachers are so abstract they seem inhuman”) and *seven_grade* (“31. I can’t even understand seventh- and eighth-grade math; how can I possibly do statistics?”). For high-anxiety students, it might be especially worthwhile to address the perception that they do not have the mathematical ability to do well in statistics (and that high levels of mathematical ability are a prerequisite for doing well in statistics) and the perception that statistics teachers are inaccessible and unapproachable.

On the other hand, the following items were identified as important nodes in the low-anxiety network but not the high-anxiety network: *never_use* (“50. I am never going to use statistics so why should I have to take it?”) and *cognitive* (“49. Affective skills are so important in my profession that I don’t want to clutter my thinking with something as cognitive as statistics”). Low-anxiety students appear to harbor the view that statistics is “worthless” because it does not have much relevance to their lives and future careers. Overall, the analyses revealed that items relating to negative *internal* attributions

(i.e., not being smart or mathematically inclined to do well in statistics) appeared to be central for students with high statistical anxiety, whereas items relating to negative *external* attributions (i.e., statistics is not relevant or useful to me) appeared to be central for students with low statistical anxiety.

Implications for Instructors

There are several recommendations to reduce statistics anxiety that are supported by research (e.g., [Conners et al., 1998](#); [Lalonde & Gardner, 1993](#); [Onwuegbuzie & Seaman, 1995](#)); however, the results of a study by [Keeley et al. \(2008\)](#) suggest that the goal of these interventions should not be to simply lower statistics anxiety uniformly across all students. Keeley et al. showed a curvilinear relationship between students’ level of statistics anxiety (as measured by STARS scores) and their performance on tests, such that students with a moderate level of anxiety outperformed students with very high or very low levels of statistics anxiety. This suggests that different interventions should be implemented for students with high or low levels of statistics anxiety.

As discussed earlier, various recommendations exist to reduce statistics anxiety among students. However, our results from the centrality analyses suggest that the most effective interventions (particularly for students with very high anxiety) would be ones that specifically address the perception that strong mathematical ability is required to do well in statistics, as well as the perception that statistics teachers are “abstract” and “inhuman” ([Chiou, Wang, & Lee, 2014](#); [Onwuegbuzie, 2004](#); [Waples, 2016](#)). In addition, results from the centrality analyses of the low-anxiety network suggest a different approach for students with low anxiety. Because these students appear to believe that statistics is “worthless” (presumably because it does not have much relevance to their lives and future careers; [Slootmaeckers, Kerremans, & Adriaensen, 2014](#)), it is possible that increasing their awareness of the importance of acquiring basic statistical literacy in the real world ([Gal, 2002, 2003](#)), and their awareness that statistical competency is in fact highly valued by employers in various industries ([Harraway & Barker, 2005](#); [Pefanis Schlee & Harich, 2010](#)), could serve to elevate their level of statistics anxiety to a mod-

erate range of statistic anxiety, leading to a higher level of performance on statistics tests, as observed by Keeley et al. (2008).

Before concluding, we note a few limitations of the current work and suggest how future work could address these limitations. First, although past work has shown that statistical anxiety is distinct, and separate from, generalized anxiety (Benson, 1989), it is important to consider how generalized anxiety might interact with statistics anxiety, given the high prevalence of students who experience very high levels of general anxiety, as measured by clinical inventories such as the Beck Anxiety Inventory (Beck & Steer, 1990). Second, the current analysis focuses on a single snapshot of students' representation of statistics anxiety in time. Future work could explore how the structure of students' statistics anxiety network changes over time, as they learn more about statistics, and in response to classroom interventions on statistics anxiety as an alternative way to evaluate the success of such interventions. Finally, the present analysis was exploratory in nature. We encourage future researchers to use network analyses to test well-defined, a priori hypotheses related to statistics anxiety, such as how to most effectively reduce, or increase, statistics anxiety in students to achieve optimal performance, as suggested by Keeley et al. (2008), which we merely speculate on in the present analyses.

The present analyses illustrate how the network approach might be applied to better understand the nature of statistical anxiety that is experienced by a majority of students in statistics classes (Onwuegbuzie & Wilson, 2003). Given the increasing need for statistical and numerical literacy in the contemporary job market (Harraway & Barker, 2005; Pefanis Schlee & Harich, 2010) and the increasing need for consumers of information to be statistically literate (Gal, 2002, 2003), it is imperative to address statistical anxiety to help students more successfully learn about these important quantitative tools. Furthermore, the results of the network analysis has provided deeper insights (that would not have been possible if traditional approaches had been used) into the interventions that should be prioritized by instructors and that research in applied disciplines (such as educational psychology) may begin to address in a future intervention study. By appropriately

targeting interventions for students who are high or low in statistics anxiety, better learning outcomes could be obtained for all students.

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