Closeness in a physics faculty online learning community predicts impacts in self-efficacy and teaching

Chase Hatcher  
Department of Physics, Drexel University, 3141 Chestnut Street, Philadelphia, PA 19104

Edward Price  
Department of Physics, California State University San Marcos, 333 South Twin Oaks Valley Road, San Marcos, CA 92096, USA

P Sean Smith  
Horizon Research, Inc., 326 Cloister Court, Chapel Hill, NC 27514

Chandra Turpen  
Department of Physics, University of Maryland–College Park, College Park, Maryland 20782, USA

Eric Brewe  
Department of Physics, Drexel University, 3141 Chestnut Street, Philadelphia, PA 19104, USA

Community-based professional development initiatives have been shown to support physics faculty in their adoption of research-based instructional strategies. Hoping to better understand these initiatives’ mechanisms of success, we analyze the results of two surveys administered to a faculty online learning community teaching a common physics curriculum designed primarily for pre-service elementary teachers. We use social network analysis to represent the faculty network and compare members’ centrality, a family of measures that capture the prominence of individuals within a network, to their reported experience in the community. We use a principal component analysis of different centrality measures to show that closeness, a measure of how closely connected a person is with every other person in their network, is the most appropriate centrality measure for our network. We then compare regression models according to Bayes factors to find relationships between participants’ closeness and their survey responses. We find that participants’ self-efficacy, as well as their sense of improvement to their teaching and sense of benefitting from the community, are predictors of their closeness with other participants and thus their breadth and depth of participation in the community. Our results are consistent with other studies that have highlighted interactions among faculty as key components of successful professional development initiatives. They may also be useful for designers of similar communities as they decide how to prioritize time and resources to meet specific goals.
I. INTRODUCTION

An emphasis on improving undergraduate STEM education has led to a focus on faculty professional development and supporting the implementation of research-based instructional strategies (RBISs). Faculty communities of practice are one mode of facilitating professional development and promoting the adoption of RBISs [1–4].

A community of practice is a group of people with a common interest that comes together to fulfill both individual and group goals in a spirit of learning, knowledge generation and sharing, and collaboration [5]. Participation takes place at different levels, often beginning with legitimate peripheral participation, and learning is thought to take place as members move toward core participation in the community [6]. By design, communities of practice attend to the social aspects of learning. Though such communities exist for all kinds of practices, this study will focus on a group of physics educators participating in a type of faculty learning community (FLC), called a faculty online learning community (FOLC).

There is growing interest in FLCs and FOLCs as ways to encourage faculty adoption of RBISs in the fields of physics education research (PER) and STEM education research. As such, there is a need for greater understanding of the way FLCs and FOLCs function. This study aims to reveal the mechanisms underlying the desirable outcomes associated with FOLC participation, thereby strengthening the foundational framework that future FOLC designers might build upon. We believe that our results will help the designers of future FOLCs decide how to use time and resources to prioritize certain impacts for participants, which will hopefully lead to more of these initiatives for physics and STEM faculty.

In this study, we use social network analysis (SNA), which is a set of tools and approaches for quantitatively analyzing communities, to represent and characterize the network that exists between members of a FOLC based on how they describe their connections with other members in response to a survey. By considering this network along with self-described impacts resulting from participation in the FOLC, we hope to answer the following research question: What relationships, if any, exist between participants’ place in the network and the impacts they report from participating in the community? In answering this question, we found that we needed to answer another question related to our methodology: How can we determine the most appropriate measure of centrality for this network and study? Answering this question requires a statistical approach that is relatively new to the field of network analysis and which may be of interest to researchers using SNA in their studies.

We begin by providing background and theory on FLCs and FOLCs, the specific FOLC we are analyzing, social network analysis, and the use of Bayes factors. Then, we describe the methods used, including the data collection and analysis, and present our results. Finally, we discuss our results and their implications and conclude by addressing limitations of our study and directions for future work.

II. BACKGROUND & THEORY

A. Faculty Learning Communities

Faculty learning communities arose after the reported success of student learning communities (SLCs) as a way to improve students’ retention of course material, deepen students’ learning, and encourage collaborative participation in both curricular and extracurricular activities, to name a few impacts [7]. SLCs were first proposed as an educational structure in the 1930s as cohorts of students that were taking the same classes across disciplines [8, 9]. They were more firmly established in the second half of the 20th century, and later shown to have the aforementioned impacts [7, 10–12].

FLCs function similarly to SLCs and can achieve analogous results for faculty. In an SLC or FLC, all participants are learners that work together to facilitate learning, which stands in contrast to the more typical classroom learning environment wherein students are independent learners that only come together in the same space for practical purposes of there being only one teacher [13]. FLCs may be seen as an attempt to help a faculty population that was often isolated and stagnant in their professional development by re-framing learning and teaching as a cooperative and communal experience [14].

According to Milton D. Cox, who designed and studied one of the first FLCs at Miami University in the late 1990s, an FLC is typically a group of about ten faculty from various disciplines that meets regularly to discuss their work and learn from each other with the goal of professional development [7]. Ideally, they are engaged in an active and collaborative year-long program that features seminars and activities that aim to improve teaching and learning and build community among the faculty. According to Cox, FLCs aim to increase faculty interest in teaching and learning, nourish the scholarship of teaching, increase interdisciplinary collaboration among faculty, and increase the financial support for teaching and learning initiatives, among other things.

More recently, faculty online learning communities (FOLCs) have been used as geographically distributed, discipline-specific FLCs that serve to support and provide resources for faculty implementing RBISs to enhance student learning. FOLCs have been shown to provide benefits similar to those provided by FLCs while offering the distinct advantage of including faculty from different institutions, which means they can draw from a larger pool of faculty and which may lead to greater diversity in ideas and perspectives. This also means that the communities may be more specific, like focusing on first-year instructors or the instructors of specific courses [1]. Now that remote videoconferencing has become more commonplace, we may expect that FOLCs become more and more normalized and easier to facilitate.

FLCs and FOLCs have been the subject of recent research in both the PER and broader STEM education research fields. In PER, research on FLCs has come after research on faculty adoption of RBISs has shown that professional development initiatives based on interaction among faculty and
community-based learning are needed [15–18]. More studies provided evidence of the effectiveness of FLCs and FOLCs in faculty adoption of RBISs [1, 2, 4], and some studies sought to identify the mechanisms underlying these desirable outcomes through case studies of participants [3] and facilitators [19]. These studies have identified facilitators’ attentiveness to logistical issues and the changing needs of the community as well as ample opportunities for participants to reflect on their teaching practice as key characteristics of successful FOLCs [3, 19].

B. The Next Gen PET FOLC

The Next Generation Physics and Everyday Thinking (Next Gen PET) FOLC is a community of practice for university and two-year college physics faculty using a common curriculum (Next Gen PET) to teach physics and physical science to pre-service elementary teachers [2].

Next Gen PET is a guided-inquiry, physical science curriculum where students use data to explore phenomena and develop scientific concepts [20]. The curriculum can be adopted in lecture, lab, or hybrid settings. Next Gen PET was designed according to evidence-based science instruction techniques and has been linked to positive changes in students’ science identities [21]. In a typical class setting, the instructor acts as a facilitator, which requires a significant shift if they are used to instructor-centered, lecture-based practice; it is expected that adopters will need considerable pedagogical skill at facilitating guided-inquiry learning. The Next Gen PET FOLC was designed to support faculty in implementing the curriculum [22].

The FOLC began in 2017 and initially consisted of about 40 physics faculty that taught physics or physical science courses for pre-service elementary teachers. It was led by 10 physics faculty that were recruited and trained for leadership because they had experience using Next Gen PET or one of its predecessors. Participants were grouped in clusters of about 5-13 people and would convene one or two times a month online via videoconference for at least an hour, with two to three leaders facilitating each cluster meeting. The FOLC operated for four academic years, which sets it apart from other similar FOLCs [1], and with about 50 active participants (including participants and cluster facilitators) at any time. Most participants stayed for all four years, but some left due to changes in institution or teaching assignment and some joined the FOLC after it began in 2017.

Participants were in different clusters over the course of their participation in the FOLC. For the first two years, they were grouped based on their classroom structure (studio or lecture), and in the last two years the clusters were formed based on schedule availability. In either case, participants were assigned to groups rather than selecting them. They were also able to participate in programming beyond the cluster meetings, like a FOLC-wide virtual conference and a Slack space with channels for clusters, cluster facilitators, and the entire FOLC. Because of this, the average FOLC member would have had many opportunities to interact with most, if not all, other FOLC members over a few years.

Data collected from participants and observations of FOLC activities reveal how the FOLC accomplishes the goals of supporting instructors in their adoption of RBISs. Cluster meetings provide opportunities for dynamic social interactions that often center around research-based components of the NG-PET curriculum. The FOLC functions as a sounding board for participants’ ideas and a venue for troubleshooting their teaching. It provides the opportunity to share resources, ideas, and experiences, and is a source of support for participants [2]. The facilitators have adapted to the needs of the participants and the participants have found opportunities to reflect on their practice in meaningful ways [3, 19]. Since these outcomes are linked to participation in cluster meetings, we expect that analysis of the FOLC social network will tell us even more about the social mechanisms underlying certain outcomes.

C. Social Network Analysis and Centrality

Social network analysis (SNA) was developed from elements of network theory, primarily by social scientists, for use in social science research [23]. It includes using quantitative methods to characterize a group of people by analyzing the connections between the people, certain qualities of the people, and sometimes by the qualities of the connections themselves. With it, we can describe characteristics of individuals by examining their place within the larger network structure, and we can describe characteristics of the network itself [24].

SNA incorporates elements of graph theory, particularly in representing networks visually. Graphical representations of social networks, often referred to as simply graphs, feature nodes (or people) as solid shapes, and edges (or connections) as lines connecting them [24]. By representing networks using different methods and algorithms, we can highlight different features of the networks, like tight-knit groups of people, particularly well-connected people, or particularly isolated people.

Network theory has been applied in education research contexts in many ways, with different agents serving as nodes in a network [25]. In educational applications, students in a classroom or other designed learning space usually act as nodes, though some studies have considered faculty [26] and even responses to multiple choice questions [27] as nodes as well. Since social influence has been shown to affect many parts of the educational experience, like GPA, cheating, and career choice [28], a research tool that quantifies connections, or opportunities for influence, clearly has potential to be informative. As such, SNA has already been used in education research and physics education research [25] to investigate gender and ethnicity as they relate to students’ positions in a network [29], students’ social interactions in laboratory contexts [30], and students’ persistence in physics as it relates to their positions in a network [31], to name but a few examples.

We can use SNA to characterize a person’s place within a network by measuring centrality, which will be critical in an-
swering our research question. Centrality is a family of measures that capture the prominence of individual nodes within a network. It can signify connectedness, importance, influence, or other qualities about a person depending on the measure being used and the nature of the network. There are many ways to measure centrality (we will consider as many as 50), though some are more common than others, like degree, betweenness, and closeness [32].

One may be able to choose, based on the nature of their network and the nature of their research questions, which is the most appropriate measure of centrality based on the subtle differences in what each measure of centrality purports to represent. For example, degree is the total number of connections a node has, so we may think of it as a way of measuring the extent of a person’s immediate connectedness within a network. Betweenness is the number of shortest paths between a pair of other nodes that pass through the node in question, so it considers the importance of being an intermediary between other people in a network. Closeness is related to a node’s average distance to other nodes in the network as measured by the smallest number of edges connecting them, so it may be seen as a measure of how closely connected a person is with every other person in their network [32].

But there are still more types of centrality to consider, many of which are variations of these three primary measures. For example, one may simply consider the number of connections in determining degree, or they may consider the degree of the nodes which one is connected to and attach weights to those connections accordingly. That is, a node may have many connections with other nodes that are not so well connected with the rest of the network, or they may have many connections with nodes that are more well connected in the network. Bonacich’s influence and power measures consider these differences important and go so far as to say that being well connected to others that are not so well connected gives one power, whereas being well connected with others that are also well connected gives one influence [32].

Choosing an appropriate centrality measure for a network is important because they measure different qualities, albeit in subtle ways. With a growing number of ways to measure centrality, we see a need for a method to choose the most appropriate measure(s) of centrality for a given network when theoretical assumptions alone do not make for an obvious choice. In Section III, we describe a method for doing so.

D. Bayes Factors

Social networks violate the most basic assumption of frequentist statistics, which is that the data are independent [35]. Since any analysis of a network considers connections between nodes, the data that comprise a network are, by definition, interdependent, so statistical methods that do not assume independence of data are useful, like Bayesian methods [35].

By using Bayesian methods, we seek to establish a degree of belief in the validity of a given hypothesis. More specifically, we revise our beliefs about the validity of a particular hypothesis (or multiple hypotheses) according to data [36]. We do this using Bayes’ theorem and an application of Bayes’ theorem called Bayes factors.

Bayes’ theorem says that, for two events $A$ and $B$, the probability that $A$ occurs if $B$ has occurred (the posterior probability) is equal to the probability of $B$ occurring if $A$ has occurred, multiplied by the probability of $A$ occurring with no other conditions, divided by the probability of $B$ occurring with no other conditions, both of which are referred to as prior probabilities or simply priors. That is,

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}.$$  \hfill (1)

In many applications of Bayes’ theorem, the events considered are hypothesis and data. That is, in many applications Bayes’ theorem reads

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)},$$  \hfill (2)

where $H$ represents the hypothesis being considered and $D$ represents the data collected. If we wish to consider two hypotheses and compare their likelihood given the data, we may use Bayes factors [37]. First, consider

$$P(H_1|D) = \frac{P(D|H_1)P(H_1)}{P(D|H_1)P(H_1) + P(D|H_2)P(H_2)},$$  \hfill (3)

where $H_1$ and $H_2$ represent the two different hypotheses. Note that, in this case we assume only two hypotheses, so $P(H_1|D) + P(H_2|D) = 1$, and that we have made use of Bayes’ theorem to express the denominator in Eq. 2 in a convenient way. We may then say

$$P(H_1|D) P(H_2|D) = \frac{P(D|H_1)P(H_1)}{P(D|H_2)P(H_2)},$$  \hfill (4)

Then, the Bayes factor,

$$\beta_{12} = \frac{P(D|H_1)}{P(D|H_2)},$$  \hfill (5)

represents the ratio of the posterior probability of $H_1$ to its prior probability, which, in our case, means the likelihood of $H_1$ over $H_2$ given the data. Thus, a Bayes factor can be calculated to quantify the degree of belief in any model in comparison to any other model, much like an odds ratio. We will describe our use of Bayes factors in this analysis in Section III.

III. METHODS

A. Data Collection

The data for this analysis come from two surveys: an “SNA survey” and a “final survey.” The surveys were administered
to current and former members of the FOLC by the project’s evaluation team in May 2021 and June 2021, respectively. Both surveys were sent to all 61 current and former FOLC members, and of these, 42 (69 percent) and 44 (72 percent) completed the SNA and final surveys, respectively.

The purpose of the SNA survey was to record self-reported connections between FOLC members after joining the FOLC. The survey asked respondents whether they “had a conversation with” or “collaborated with” every other current and former FOLC member after joining the FOLC. Respondents saw a list of names of every other FOLC participant and were able to check boxes describing their connections.

The final survey asked respondents to reflect on their experience in the FOLC in the previous year and on their entire experience in the FOLC, since it was coming at the end of the project. The survey included 10 Likert-scale questions that sought to measure the extent and types of impacts the respondents experienced. For example, participants were asked:

To what extent has each of the following happened as a result of participating in the Next Gen PET FOLC? [not at all, minimally, moderately, to a great extent]

- I have gained confidence in my teaching.
- I have gained knowledge about pedagogical techniques.
- I have saved time in preparing and implementing my course.

B. Data Preparation & Network Development

We administered the SNA survey electronically and organized the raw data into an edgelist, with columns representing the first node (the survey respondent), the second node (the person with whom they are indicating a connection), and a variable representing whether that connection was a conversation or collaboration. Since the survey asked respondents about two different types of social connections, we split the data into a conversation network and a collaboration network. The networks are undirected, meaning that a connection is represented and treated the same regardless of which node(s) indicated the connection.

We cleaned the connection data so that only people that completed both the SNA survey and the final survey would be included in the networks. This means that the networks do not include any connections where at least one member did not complete either survey, so our networks are limited representations of the actual networks that exist among FOLC members. We removed 413 of the original 1202 connections, leaving 66 percent of the connections from the raw data.

By cleaning the data such that only members that completed both surveys were included in the networks, we can ensure that every node being analyzed had equal opportunity to be included in the network, both as a reporter and as someone that could be reported in a connection. We were also able to ensure that it would be possible to compare all nodes according to their survey responses.

We also removed data from respondents that completed very different versions of the final survey than most other respondents. Since the survey went to all members past and present, some former participants skipped all questions related to their experience in the FOLC in the past year, which comprised many of the responses we examined. In total, we removed 7 nodes in the conversation network and 6 nodes in the collaboration network, leaving 37 and 34 nodes in these networks, respectively.

C. Attribute and Composite Definitions

After cleaning and splitting the connection data, we used an R [33] package called igraph [34] to turn the edgelists into graph objects, allowing us to generate lists of nodes in the networks and add attributes for those nodes. In this case, the attributes include the answers to each question on the final survey that could be captured numerically.

The final survey consisted of nearly 20 questions. Some were free-response, and thus not included as attributes for the network, and many had multiple parts, sometimes over 10. Treating each numerical (Likert scale) response as a separate attribute would mean nearly 70 attributes per person, so we developed composite variables of question parts to make the attributes more manageable.

The composites, which we will also refer to as impact composites (ICs) were developed concurrently with the final survey and aim to group together items that address similar topics, most of which concern impacts from FOLC participation. For example, one question contained 10 sub-questions that asked respondents to rate their agreement with various statements about impacts on their teaching after participating in the FOLC. These sub-questions form the “Teaching impacts” composite, so a respondent’s average numerical response to these sub-questions is recorded as a single attribute for their “Teaching impacts” composite score.

We measured the reliability of the ICs by calculating Cronbach’s alpha for the related items of each IC. Cronbach’s alpha is a coefficient ranging from 0 to 1 that indicates the degree to which different variables seem to be measuring the same thing [38]. Thus, a higher coefficient indicates more reliable ICs. The coefficients associated with all of our ICs were near or exceeding 0.8, so we conclude that the designed composites are reliable and reasonable ways to group the items.

Descriptions of the ICs and some examples of their related questions can be found in Table I. All survey items related to the ICs can be found in the Appendix.

D. Statistical Methods

1. Principal Component Analysis of Centrality

A primary goal of this analysis is to look for relationships between FOLC participants’ centrality and the way they responded to questions on the final survey. As we discussed in Section II, centrality is a family of measures that capture the prominence of individual nodes within a network. There are many ways of calculating centrality, and we can consider the differences between centrality measures to decide which is most appropriate for our network and our research question.
TABLE I: Descriptions, examples, and reliability measures of the ICs. Participants rated agreement with each item unless otherwise noted.

| Composite name                        | Example item                                                                 | Alpha |
|---------------------------------------|-----------------------------------------------------------------------------|-------|
| Attitude toward participating in cluster meetings (AP) | The member-led cluster meetings were valuable to me.                      | 0.81  |
| Teaching impacts (TI)                  | I have gained confidence in my teaching.                                     | 0.89  |
| Community benefits (CB)                | I have gained a community which supports my teaching practice               | 0.83  |
| Sense of community (SC)                | I can trust people in the Next Gen PET FOLC                                 | 0.89  |
| Preparedness to teach                  | Structure your course using the Next Gen PET curriculum [rate preparedness] | 0.86  |
| Next Gen PET (PT)                      |                                                                           |       |
| Self-efficacy for instructional leadership (SE) | Mentor a faculty member who is new to teaching Next Gen PET [rate confidence] | 0.87  |
| Ability-related concerns (ARC)         | I am concerned about how to organize my course using the Next Gen PET curriculum | 0.87  |
| Student-related concerns (SRC)         | I am concerned about students’ attitudes toward the Next Gen PET curriculum. | 0.77  |
| Collaboration-related concerns (CRC)   | I would like to help other faculty in their use of the Next Gen PET curriculum. | 0.90  |
| Refocusing-related concerns (RRC)      | I would like to revise Next Gen PET’s instructional approach.               | 0.86  |

However, we wonder if the subtle differences in so many centrality measures will make them too difficult to distinguish based on their theoretical applicability alone, especially in a network as small as ours. So, we consider a way to analyze our network using many centrality measures as a means of determining which is (or are) most appropriate.

We used an R [33] package called CINNA (Deciphering Central Informative Nodes in Network Analysis) [39], developed by Ashtiani, Mirzaie, and Jafari to analyze the applicability of different centrality measures on a protein interaction network, to perform a principal component analysis (PCA) of different centrality measurements of our network. PCA is a method for extracting important information from a data table in which observations are described by many variables. In general, it is a dimensionality reduction technique that makes datasets with many dependent variables more informative by finding the most important variable or sets of variables among them [40]. To be exact, it finds the eigenvectors of a matrix with dimensionality of the observations and the dependent variables, and treats these as the “principal components” of whatever is being measured (in our case, centrality) [41].

We used CINNA to calculate centrality for all nodes in either network using 50 different methods that were built into the package—these serve as the dependent variables describing our observations, which are the nodes. We then used a PCA function built into the package to quantify the informativeness of each centrality measure, meaning we found which centrality measures most closely align with the principal components revealed by the PCA. The PCA function returns a contribution level for each centrality measure which is the proportion of contributions to the determination of the principal components for which that centrality measure is responsible [42]. If we take the principal components to represent the centrality of nodes in our network most accurately, since it considers many types of centrality, we would say that those measures of centrality which contribute more to the principal components are more informative measures of centrality for our network [39, 42].

We took the most informative centrality measures for each network and proceeded to measure their relationships with survey responses using linear regression.

2. Model Development and Selection

To answer our research question, we must look for relationships between FOLC participants’ centrality (position in the network) and their ICs (survey responses related to impacts). Since both of these qualities are represented numerically, we can develop linear regression models that relate centrality as a dependent variable to the ICs as independent variables. In Section II we introduced Bayes factors, which are a tool for comparing models (or hypotheses) based on data. In this case, our models are the results of linear regression using ICs as predictor variables for centrality, which is our response variable.

Using Bayes factors, we compared the intercept-only model, that is, the model that suggests that the centrality of one node is best predicted by the average centrality of all nodes, to models that suggest that a node’s centrality is best predicted by some combination of its ICs, where all possible combinations of anywhere from 1 to 10 of the 10 ICs can comprise a combination (there are 1023 such combinations).

We calculated a Bayes factor for each model which tells us how much more likely that model is than the intercept-only model. In other words, each Bayes factor tells us how much better a particular model using ICs as a predictor for centrality is than the model which uses average centrality as a predictor for centrality [36]. We used the same method of model selection for each of the most informative centrality measures revealed by the PCA.
IV. RESULTS

A. Networks

Representations of the conversation and collaboration networks can be found in Fig. 1. The nodes are arranged according to the Fruchterman-Reingold algorithm, which treats nodes as like charges with a repulsive force between them and edges as spring-like attractors. The algorithm finds an arrangement that minimizes the energy in the system, which usually means that nodes with more connections are closer to the center [43]. We note that, although facilitators and participants had different responsibilities, they engaged in the community in similar ways, as evidenced by similar average centralities between the two groups.

Perhaps most apparent from the graphs is that the conversation network is denser than the collaboration network. In network analysis, density measures the overall connectedness of a network—it is the total number of connections divided by the total number of possible connections. The densities of the conversation and collaboration networks are 0.29 and 0.08, respectively. This may not be surprising, as many people probably see a collaboration as a more effort-intensive sort of interaction than a conversation.

B. Principal Component Analysis

A PCA performed on 50 different centrality measures revealed which centrality measures contributed the most to the principal components of all centrality measures. Put another way, the PCA revealed which centrality measures seem to be most descriptive of centrality as measured by the group. Results are shown in Fig. 2.

As can be seen in Fig. 2, many centrality measures have similar levels of contribution to the principal components of centrality as discovered by the PCA, though others have significantly lower levels of contribution. Since our goal is to determine which centrality measures are most appropriate and descriptive for these networks, and since all centrality measures purport to measure similar things (different aspects of prominence in a network), we will look more closely only at a handful of those centrality measures with the highest PCA contributions. For the conversation network, we will consider the first 10, and for the collaboration network we will consider the first 9. In both cases we want a large enough group to ensure that we consider sufficiently different centrality measures, and we note a barely noticeable drop in contributions at those points.

We note, however, that some centrality measures, while contributing in the PCA, were not informative when we compared regression models, as they either returned numerical values for centrality that did not vary at all (Geodesic K-path, for example) or they returned values that were nearly exactly the same as other centrality measures (Residual closeness and Dangalchev closeness, for example). In the case of the former, we have removed those measures from the analysis, and in the case of the latter, we have removed all but the simplest model of centrality which returns the repeated results.

C. Model Selection

Since our model selection method involves calculating Bayes factors for over 1000 models of centrality, we decided it would be most informative to compare the three models with the highest Bayes factors for each of the most informative centrality measures to see if the results are similar. We note, however, that we only included models with Bayes factors greater than or equal to 3.0, since we are using this as a cutoff for evidence, as we discuss further at the end of this section. Results for the conversation and collaboration networks can be found in Tables II and III, respectively.
FIG. 2: Contributions of different centrality measures, as percent of total contributions, ranked in descending order for conversation network (a) and collaboration network (b). The red dotted line indicates an 80 percent threshold against the measure with the most contributions, which the program designers consider the threshold for meaningful contribution [42].

For each network, the best models according to their Bayes factors were the same for each of these most informative centrality measures, and they were nearly always in the same order. Therefore, our method of answering our research question—comparison of Bayes factors of models of centrality that use different combinations of ICs—gives similar results for any of the different centrality measures that a PCA revealed to be most appropriate for our networks.

Since all of the centrality measures in Tables II and III are almost equally appropriate for our dataset according to PCA, and since they all give almost identical results in our model comparison scheme, we believe that we should choose a single centrality measure from these for each network based on simplicity and theoretical appropriateness when applied to our research question and network.

As we discussed earlier, nearly all of the many measures of centrality that we considered here belong to a few families of centrality measures—degree, closeness, and betweenness. We consider these measures in their most basic form to be the most simple because all other centrality measures are based on or derived from them. Indeed, many of the repeated results removed from Tables II and III were measuring the same or almost the same thing in the case of these networks. We note that degree and closeness are the only simple centrality measures represented among the most informative centrality measures for both networks, so we will consider only these.
TABLE II: Models with the highest Bayes factors for the most informative measures of centrality for the conversation network. Only two models of degree had Bayes factors greater than 3.0. Geodesic K-path and entropy were removed because all nodes had exactly the same numerical value. Wiener index was removed because it repeated the results of radiality, Dangalchev closeness because it repeated residual closeness, and harmonic because it repeated closeness.

| Centrality Measure | 3 models with highest Bayes factors |
|--------------------|-----------------------------------|
|                    | Bayes factors                     |
| Degree             | SE                                | 4.78 |
|                    | TI + SE                           | 3.62 |
| Laplacian          | SE                                | 4.51 |
|                    | TI + SE                           | 4.01 |
|                    | TI + CB + SE                      | 3.18 |
| Radiality          | SE                                | 8.12 |
|                    | TI + SE                           | 5.08 |
|                    | TI + CB + SE                      | 4.88 |
| Residual Closeness | SE                                | 8.31 |
|                    | TI + CB + SE                      | 5.05 |
|                    | TI + SE                           | 4.95 |
| Closeness          | SE                                | 8.37 |
|                    | TI + CB + SE                      | 5.04 |
|                    | TI + SE                           | 4.97 |
| Semi-local         | SE                                | 13.01|
|                    | TI + SE                           | 7.92 |
|                    | TI + CB + SE                      | 7.01 |

Furthermore and as we discussed earlier, different centrality measures purport to measure slightly different things in the context of a network. Degree is the total number of connections a node has, so it may be seen as the breadth of a person’s connectedness within their network. Closeness is related to the average path length (as measured by edges or connections) of one node to every other node in their network, so it may measure how closely connected a person is with all other people in their network. Since closeness increases with more connections and with closer connections, it may be seen as a measure of the breadth and depth of a person’s connectedness within a network. Since it captures much of the same information as degree and adds to it a characterization of how closely connected a node is with other nodes, we believe closeness is the most comprehensive and thus appropriate measure of centrality for our networks.

A focus on closeness is also consistent with the nature and function of the community. As other studies have shown the importance of interactions and connectedness among faculty participating in professional development initiatives [44, 45], we believe that connectedness with greater breadth and depth is crucial if a participant wants to engage in cluster meetings in richer and more meaningful ways—sounding out ideas, sharing resources and experiences, and giving and receiving affective support. Since these modes of engagement were identified as key elements of the FOLC experience, we think closeness is the most appropriate measure of centrality for this network based on the nature of the community as well as its utility in the context of SNA.

D. Models of Closeness

Our primary result concerns the relationship between centrality and final survey responses. A model selection method that used closeness as the centrality measure with which to compare models revealed a Bayes factor of 8.37 for ‘Self-efficacy for instructional leadership,’ which suggests that a model of the Self-efficacy IC was over eight times more likely to predict a node’s closeness in the conversation network than a model of the average closeness only. It also suggested that the combination of ‘Teaching impacts’, ‘Community benefits’, and ‘Self-efficacy’ together was five times more likely to predict closeness than average closeness only. These results and others are summarized in Table IV. For the collaboration network, the same combination of ‘Teaching impacts’, ‘Community benefits’, and ‘Self-efficacy’ together was 20 times as likely to predict closeness as the average closeness model, though SE alone was not as significant a predictor as it was in the conversation network. Other models that were signifi-
TABLE IV: The five models for closeness in the conversation network with the highest Bayes factors.

| Model                      | Bayes factor |
|----------------------------|--------------|
| SE                         | 8.37         |
| TI + CB + SE               | 5.04         |
| TI + SE                    | 4.97         |
| PT + SE                    | 3.64         |
| TI + CB + PT + SE          | 3.50         |

cantly (at least 10 times) more likely to predict closeness included 4 or more ICs and are summarized in Table V.

TABLE V: The five models for closeness in the collaboration network with the highest Bayes factors.

*Because of the way it was worded, a lower value for this IC indicates more positive impacts, so its numerical value was included in the analysis as 100 - (IC).

| Model                      | Bayes factor |
|----------------------------|--------------|
| TI + CB + SE               | 20.0         |
| AP + TI + CB + SE          | 14.4         |
| AP + CB + SC + SE          | 12.9         |
| TI + CB + SE + SRC*        | 11.8         |
| AP + TI + CB + SC + SE     | 11.1         |

Other studies have suggested that a Bayes factor between 3 and 20 constitutes “positive evidence [37] [36].” Therefore, there is positive evidence that the above ICs, mainly ‘Self-efficacy,’ followed by ‘Teaching impacts’ and ‘Community benefits,’ are predictors of centrality as measured by closeness in both networks. In other words, we have evidence that a FOLC participant that is more closely connected with other FOLC participants is more likely to report higher impacts related to their self-efficacy, teaching, and valuation of their community after participating in the FOLC.

For ease of understanding, we have added a diagram in Fig. 3 that shows the steps taken between our data sources and results.

V. DISCUSSION & CONCLUSION

Results of a model selection method that involves comparing Bayes factors of regression models suggest that ‘Self-efficacy’ is the best predictor of closeness in the conversation network of the Next Gen PET FOLC among all ICs and combinations of ICs. ‘Teaching impacts’ and ‘Community benefits’ are also good predictors of closeness in this network. For the collaboration network, we see that the same ICs, as well as ‘Attitude toward participating in cluster meetings’ and ‘Sense of community’, in various combinations, are good predictors of closeness. In general, then, we suggest that ‘Self-efficacy,’ followed by ‘Teaching impacts’ and ‘Community benefits,’ are the ICs most related to closeness for the entire FOLC.

We note that the Bayes factors of the top models for closeness in the collaboration network are higher than those for the conversation network. This may suggest that collaborative connections like planning lessons together, engaging in original collaborative research, or developing course materials together are stronger ways to prioritize the aforementioned impacts than just providing opportunity to connect through conversation.

It is unclear from our evidence whether the increased impacts are the result of a person’s higher closeness or their higher closeness is the result of increased impacts, only that they are related. In other words, it may be that a person with higher self-efficacy becomes closer with others in the FOLC, or alternatively that a person with higher closeness perceives more benefits from the community—we cannot say one way or the other.

The technique we used to identify the centrality measures most appropriate for a given network has not been widely used in SNA research. With so many different measures of centrality available, choosing the one that is most appropriate, especially when researchers do not have a strong reason for choosing one over another based on the nature of their network or their research questions, can be a daunting task. We believe that this technique can be an informative and useful method for finding the most applicable centrality measures and comparing them, especially as SNA is being used more and more in PER and STEM education research.

We note that this analysis is limited by the size of our dataset. The community itself is a relatively small network, and as noted earlier, our dataset does not represent the full FOLC network. This limitation became apparent when we tried to perform a principal component analysis on the full attribute (final survey response) list—we had too few data points and so we used the designed composites to group the attributes instead.

Since closeness is a measure of how well connected a person is with other people in a group, in the case of this FOLC, a person’s closeness may relate to the depth and breadth with which they participated socially in the FOLC. Then, our results suggest that participants that are more socially active in the community see greater impacts from participation in their self-efficacy, teaching, and perhaps other areas. If we take increased self-efficacy for instructional leadership and positive changes in teaching to be goals of FLCs and FOLCs, then these results are consistent with the motivation for creating FLCs in the first place—that participation in community-based learning interventions is an effective means of professional development. Indeed, other studies have shown that interactions among faculty, especially when those interactions include conversations about teaching, are crucial for the success of a professional development initiative that aims to improve undergraduate STEM education [16, 17, 44, 46].

This work provides more evidence for the importance of personal connections and interactions among faculty in pro-
FIG. 3: Diagram of methodology. Data are rectangles, results are circles, and processes are diamonds. Connections from the SNA survey and IC scores from the final survey contribute to the construction of the FOLC network. We developed linear regression models using ICs as predictors of centrality for various centralities. We performed a PCA on centralities calculated from the network and selected the most informative ones (based on contribution to principal components). We compared the regression models of various combinations of ICs based on Bayes factors for each of these centralities, then selected degree and closeness as the two most appropriate centralities based on their simplicity and the consistency of results across all centralities examined. We selected closeness as the most appropriate centrality measure based on its definition in the context of SNA and its applicability to the way the FOLC functions. From the regression model comparison for closeness, it is clear that SE, TI, and CB are most related to closeness.

Professional development initiatives that aim to improve the state of undergraduate education. It also strengthens our understanding of how a FOLC accomplishes its goals—through closeness among participants. These results may be particularly useful to those organizing similar FLCs and FOLCs in physics or other STEM disciplines. With a more solid foundation of knowledge on which to construct an experience for faculty, they may choose to design interventions to increase and strengthen connections among participants if improved self-efficacy and teaching are primary goals. In general, with a better understanding of how community based professional development initiatives for faculty achieve their goals, those in the PER and STEM education research fields can better design such initiatives based on desired outcomes.
We plan to extend this study qualitatively by analyzing the experiences of a few participants that were especially central or peripheral in the network. In doing so, we hope to obtain a more illustrative picture of what a participant’s centrality might suggest about their experience in the FOLC.

ACKNOWLEDGMENTS

We would like to thank Laura Craven at Horizon Research, Inc. for her help with creating the surveys and compiling and organizing the raw data. We would also like to thank Fred Goldberg for his perspective and input as we designed the two surveys. This material is based upon work supported by the National Science Foundation grant NSF DUE-1626496. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

VI. APPENDIX

Reproduced below are all Final Survey items associated with the Impact Composites, arranged according to the order in which they appeared in the survey and grouped according to the associated IC.

1. Attitude toward participating in cluster meetings (AP)

   Please rate your agreement with each of the following statements about PARTICIPATING in member-led cluster meetings: [6-point scale from Strongly Disagree to Strongly Agree]

   - The member-led cluster meetings were valuable to me.
   - I enjoyed participating in the member-led cluster meetings.
   - I was more motivated to attend the member-led meetings than those led by the normal leaders.
   - I learned new pedagogical strategies during the member-led meetings.
   - Distributing the responsibility for leadership to others was good for the cluster.

2. Teaching impacts (TI)

   To what extent has each of the following happened as a result of participating in the Next Gen PET FOLC: [not at all, minimally, moderately, to a great extent]

   - I have become more reflective about my teaching.
   - I have gained confidence in my teaching.
   - I have gained knowledge about pedagogical techniques.
   - I have developed my skills as a teacher more efficiently than I would have without the Next Gen PET FOLC.
   - I have saved time in preparing and implementing my course.
   - I have seen increased student learning.
   - I have incorporated ideas from the Next Gen PET FOLC into my teaching.
   - I have become more excited about my teaching.
   - I am more motivated to try new teaching techniques in my other classes.
   - I have gained a deeper appreciation for the complex aspects to consider in diagnosing teaching challenges.

3. Community benefits (CB)

   Please rate your agreement with each of the following statements: [6-point scale from Strongly Disagree to Strongly Agree]

   Through the Next Gen PET FOLC:
   - I have gained a community which supports my teaching practices.
   - I have received encouragement and moral support regarding my teaching.
   - I have learned that others face similar teaching challenges.

4. Sense of community (SC)

   Please rate your agreement with each of the following statements: [6-point scale from Strongly Disagree to Strongly Agree]

   - I get important needs of mine met because I am part of the Next Gen PET FOLC.
   - Next Gen PET FOLC members and I value the same things.
   - When I have a problem, I can talk about it with members of the Next Gen PET FOLC.
   - People in the Next Gen PET FOLC have similar needs, priorities, and goals.
   - I can trust people in the Next Gen PET FOLC.
   - Most Next Gen PET FOLC members know me.
   - I put a lot of time and effort into being part of the Next Gen PET FOLC.
   - Being a member of the Next Gen PET FOLC is a part of my identity.
   - I have influence over what the Next Gen PET FOLC is like.
   - If there is a problem in the Next Gen PET FOLC, members can get it solved.
   - It is very important to me to be a part of Next Gen PET FOLC.
   - I feel hopeful about the future of the Next Gen PET FOLC.
   - Members of the Next Gen PET FOLC care about each other.
5. Preparedness to teach Next Gen PET (PT)

Please indicate your current level of preparedness to do each of the following: [Not At All Prepared, Somewhat Prepared, Fairly Well Prepared, Very Well Prepared].

- Structure your course using the Next Gen PET curriculum
- Manage the equipment/logistics associated with implementing the Next Gen PET curriculum
- Teach the Next Gen PET curriculum materials effectively
- Assess student learning formatively in the context of the Next Gen PET curriculum
- Assess student learning summatively in the context of the Next Gen PET curriculum

6. Self-efficacy for instructional leadership (SE)

Please rate your agreement with each of the following statements: [6-point scale from Strongly Disagree to Strongly Agree]

- I’m confident I could facilitate collaborative pedagogical discussions in the future.
- I’m confident I could mentor a faculty member who is new to teaching Next Gen PET.
- I’m confident I could mentor a faculty member who is new to another guided-inquiry curriculum or technique.
- I’m confident I could lead a session on active learning for my department or Teaching and Learning Center.
- I’m confident I could draw on my experiences with Next Gen PET to effectively implement a new pedagogical technique or curriculum.

7. Ability-related concerns (ARC)

Please respond to each of the following statements in terms of your present thinking about the Next Gen PET curriculum. [6-point scale from Not true of me now to Very true of me now, option for Irrelevant]

- I am concerned about how to organize my course using the Next Gen PET curriculum.
- I am concerned about not having enough time to organize myself each day to use the Next Gen PET curriculum.
- I am concerned about being able to acquire and manage the materials and equipment the Next Gen PET curriculum requires.
- I am concerned about my ability to implement the teaching strategies in the Next Gen PET curriculum.

8. Student-related concerns (SRC)

Please respond to each of the following statements in terms of your present thinking about the Next Gen PET curriculum. [6-point scale from Not true of me now to Very true of me now, option for Irrelevant]

- I am concerned about students’ attitudes towards the Next Gen PET curriculum.
- I am concerned about students’ abilities to engage in the inquiry-oriented activities included in the Next Gen PET curriculum.
- I am concerned about how the Next Gen PET curriculum affects students’ learning.

9. Collaboration-related concerns (CRC)

Please respond to each of the following statements in terms of your present thinking about the Next Gen PET curriculum. [6-point scale from Not true of me now to Very true of me now, option for Irrelevant]

- I would like to help other faculty in their use of the Next Gen PET curriculum.
- I would like to develop working relationships with other faculty using the Next Gen PET curriculum.
- I would like to coordinate my effort with others to maximize the effects of the Next Gen PET curriculum.
- I would like to know what other faculty are doing with the Next Gen PET curriculum.

10. Refocusing-related concerns (RRC)

Please respond to each of the following statements in terms of your present thinking about the Next Gen PET curriculum. [6-point scale from Not true of me now to Very true of me now, option for Irrelevant]

- I would like to revise Next Gen PET’s instructional approach.
- I would like to modify my use of Next Gen PET based on the experience of my students.
- I would like to determine how to supplement, enhance, or replace Next Gen PET.
[1] Melissa Dancy, Alexandra C. Lau, Andy Rundquist, and Charles Henderson, “Faculty Online Learning Communities: A Model for Sustained Teaching Transformation,” Phys. Rev. Phys. Educ. Res. 15, 2 (2019) https://doi.org/10.1103/PhysRevPhysEducRes.15.020147.

[2] Edward Price, Alexandra C. Lau, Fred Goldberg, Chandra Turpen, P. Sean Smith, Melissa Dancy, and Steve Robinson, “Analyzing a Faculty Online Learning Community as a Mechanism for Supporting Faculty Implementation of a Guided-Inquiry Curriculum,” Int. J. STEM Educ. 8, 17 (2021) https://doi.org/10.1186/s40594-020-00268-7.

[3] Adriana Corrales, Fred Goldberg, Edward Price, and Chandra Turpen, “Faculty Persistence with Research-Based Instructional Strategies: A Case Study of Participation in a Faculty Online Learning Community,” Int. J. STEM Educ. 7, 21 (2020) https://doi.org/10.1186/s40594-020-00221-8.

[4] Teresa L. Tinnell, Patricia A. S. Ralston, Thomas R. Tretter, Mary E. Mills, “Sustaining Pedagogical Change via Faculty Learning Community,” Int. J. STEM Educ. 6, 26 (2019) https://doi.org/10.1186/s40594-019-0180-5.

[5] Etienne Wenger, Richard Arnold McDermott, and William Snyder, Cultivating Communities of Practice: A Guide to Managing Knowledge (Harvard Business Press, 2002).

[6] Jean Lave and Etienne Wenger, Situated Learning: Legitimate Peripheral Participation (Cambridge University Press, 1991), https://doi.org/10.1017/CBO9780511815355.

[7] Milton D. Cox, “Introduction to Faculty Learning Communities,” New Dir. Teach. Learn. 97 (2004) https://doi.org/10.1002/ntl.129.

[8] Alexander Meiklejohn, “Wisconsin’s Experimental College,” High. Educ. 1, 9 (1930) https://doi.org/10.2307/1974761.

[9] John Dewey, How we think: A restatement of the relation of reflective thinking to the educative process (D C Heath, 1910), https://doi.org/10.1086/10903-000.

[10] Richard Matthew Jones, Experiment at Evergreen (Schenkman Publishing Company, 1981).

[11] Rebecca William Mlynarczyk and Marcia Babbitt, “The Power Experiment at Evergreen,” in W. M. McDonald and Associates (eds.) Creating Campus Community. (Jossey-Bass, 2002).

[12] Paul Baker, “Creating Learning Communities,” in The Social Worlds of Higher Education: Handbook for Teaching in A New Century by Bernice Pescosolido, Ronald Aminzade, and Ronald J. Aminzade. (Pine Forge Press, 1999).

[13] Charles Henderson and Melissa H. Dancy, “Barriers to the Use of Research-Based Instructional Strategies: The Influence of Both Individual and Situational Characteristics,” Physical Review Special Topics - Physics Education Research 3 2 (2007) https://doi.org/10.1103/PhysRevSTPER.3.020102.

[14] Melissa Dancy, Charles Henderson, and Chandra Turpen, “How Faculty Learn about and Implement Research-Based Instructional Strategies: The Case of Peer Instruction,” Physical Review Physics Education Research 12, 1 (2016) https://doi.org/10.1103/PhysRevPhysEducRes.12.010110.

[15] Shams El-Adawy, Tra Huynh, Mary Bridget Kustusch, and Eleanor C. Sayre, “Context Interactions and Physics Faculty’s Professional Development: Case Study,” Physical Review Physics Education Research 18, 2 (2022) https://doi.org/10.1103/PhysRevPhysEducRes.18.020104.

[16] Charles Henderson, Andrea Beach, and Noah Finkelstein, “Facilitating Change in Undergraduate STEM Instructional Practices: An Analytic Review of the Literature,” Journal of Research in Science Teaching 48, 8 (2011) https://doi.org/10.1002/tea.20439.

[17] Makenna M. Martin, Fred Goldberg, Michael McKean, Edward Price, and Chandra Turpen, “Understanding How Facilitators Adapt to Needs of STEM Faculty in Online Learning Communities: A Case Study,” Int. J. STEM Educ. 9, 56, (2022) https://doi.org/10.1186/s40594-022-00371-x.

[18] Fred Goldberg, Steve Robinson, Edward Price, D. Harlow, J. Andrew, and M. McKean (2018). Next generation physical science everyday thinking. Greenwich: Activate Learning.

[19] Robynne M. Lock, Ben Van Dusen, Steven Maier, and Liang Zeng, “Impact of the Next GEN PET Curriculum on Science Identity,” in 2019 Physics Education Research Conference Proceedings (2019 Physics Education Research Conference, Provo, UT: American Association of Physics Teachers, 2020), https://doi.org/10.1119/perc.2019.pr.Lock.

[20] Kathleen C. Freeman, The Development of Social Network Analysis: A Study in the Sociology of Science, (Empirical Press, 2004).

[21] P.J. Carrington and J. Scott, “Introduction,” in SAGE Handb. Soc. Netw. Anal., edited by J. Scott and P.J. Carrington (Sage Publications Inc., 2011), pp. 1–8.

[22] Eric Brewe, “The Roles of Engagement: Network Analysis in Physics Education Research,” in Getting Started in Physics Education Research, edited by Charles Henderson and Kathleen A. Harper, (American Association of Physics Teachers, 2018), Reviews in PER Vol. 2, http://www.per-central.org/items/detail.cfm?ID=14725.

[23] Kathleen Quardokus and Charles Henderson, “Promoting Instructional Change: Using Social Network Analysis to Understand the Informal Structure of Academic Departments,” High. Educ.: Int. J. High. Educ. Res. 70, 3 (2015) https://doi.org/10.1007/s10734-014-9831-0.

[24] Eric Brewe, Jesper Bruun, and Ian G. Bearden, “Using Module Analysis for Multiple Choice Responses: A New Method Applied to Force Concept Inventory Data,” Phys. Rev. Phys. Educ. Res. 12, 2 (2016) https://doi.org/10.1103/PhysRevPhysEducRes.12.020131.

[25] Daniel Z. Grunspan, Benjamin L. Wiggins, and Steven M. Goodreau, “Understanding Classrooms through Social Network Analysis: A Primer for Social Network Analysis in Education Research,” CBE Life Sciences Education 13, 2 (2014) https://doi.org/10.1187/cbe.13-08-0162.

[26] Eric Brewe, Laird Kramer, and Vashti Sawtelle, “Investigating Student Communities with Network Analysis of Interactions in a Physics Learning Center,” Phys. Rev. Spec. Top., Phys. Educ. Res. 8, 1 (2012) https://doi.org/10.1103/PhysRevSTPER.
[30] Aaron R. Warren, “Network Analysis of Social Interactions in Laboratories,” AIP Conference Proceedings 1064, no. 1 (October 20, 2008): 219–22, https://doi.org/10.1063/1.3021259.

[31] Justyna P. Zwolak, Remy Dou, Eric A. Williams, and Eric Brewe, “Students’ Network Integration as a Predictor of Persistence in Introductory Physics Courses,” Phys. Rev. Phys. Educ. Res. 13, 1 (2017) https://doi.org/10.1103/PhysRevPhysEducRes.13.010113.

[32] Martin G. Everett and Stephen P. Borgatti, “Extending Centrality” in Models and Methods in Social Network Analysis, edited by Peter J Carrington, John Scott, and Stanley Wasserman (Cambridge University Press, 2005) pp 57-76.

[33] R Core Team (2021). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

[34] Csardi G, Nepusz T (2006). “The igraph software package for complex network research.” InterJournal, Complex Systems, 1695. https://igraph.org.

[35] Edoardo Airoldi, David M. Blei, Stephen E. Fienberg, and Eric P. Xing, “Combining Stochastic Block Models and Mixed Membership for Statistical Network Analysis” in Statistical Network Analysis: Models, Issues, and New Directions: ICML 2006 Workshop on Statistical Network Analysis, Pittsburgh, PA, USA, June 29, 2006. Revised Selected Papers, edited by Edoardo Airoldi, David M. Blei, Stephen E. Fienberg, Anna Goldenberg, Eric P. Xing, and Alice X. Zheng (Berlin Heidelberg, 2007) pp. 65-82 https://doi.org/10.1007/978-3-540-73133-7.

[36] DJ Navarro, “Bayesian Statistics” in Learning Statistics with R - A Tutorial for Psychology Students and Other Beginners, Open Educational Resource (OER), Accessed April 29, 2022 http://oer.iain-padangsidimpuan.ac.id/items/show/2381.

[37] Robert E. Kass and Adrian E. Raftery, “Bayes Factors,” Journal of the American Statistical Association 90, 430 (1995) https://doi.org/10.2307/2291091.

[38] L. J. Cronbach, “Coefficient alpha and the internal structure of tests,” Psychometrika, 16, 297-334 (1951) https://doi.org/10.1007/BF02310555.

[39] Minoo Ashtiani, Mehdi Mirzaie, and Mohieddin Jafari, “CINNA: An R/CRAN Package to Decipher Central Informative Nodes in Network Analysis,” Bioinformatics 35, 8 (2019): https://doi.org/10.1093/bioinformatics/bty819.

[40] Hervé Abdi and Lynne J. Williams, “Principal Component Analysis,” WIREs Computational Statistics 2, 4 (2010) https://doi.org/10.1002/wics.101.

[41] H. Hotelling, “Analysis of a Complex of Statistical Variables into Principal Components,” Journal of Educational Psychology 24, 6 (1933) https://doi.org/10.1037/h0071325.

[42] Minoo Ashtiani, Ali Salehzadeh-Yazdi, Zahra Razaghi-Moghadam, Holger Hennig, Olaf Wolkenhauer, Mehdi Mirzaie, and Mohieddin Jafari, “A Systematic Survey of Centrality Measures for Protein-Protein Interaction Networks,” BMC Systems Biology 12, 1 (2018) https://doi.org/10.1186/s12918-018-0598-2.

[43] Thomas M. J. Fruchterman and Edward M. Reingold, “Graph Drawing by Force-Directed Placement,” Softw. Pract. Exp. 21 11 (1991) https://doi.org/10.1002/spe.4380211102.

[44] Ellen Marie Aster, Jana Bouwma-Gearhart, and Kathleen Quardokus Fisher, “Contextualizing Communities in an Instructional Improvement Initiative: Exploring STEM Faculty Engagement in Teaching-Related Conversations,” Disciplinary and Interdisciplinary Science Education Research 3, 1 (2021) https://doi.org/10.1186/s43031-021-00038-7.

[45] Maha Bali and Autumm Caines, “A Call for Promoting Ownership, Equity, and Agency in Faculty Development via Connected Learning,” International Journal of Educational Technology in Higher Education 15 1 (2018) https://doi.org/10.1186/s41239-018-0128-8.

[46] Sreyasi Biswas, Rocio Benabentos, Eric Brewe, Geoff Potvin, Julian Edward, Marcy Kravec, and Laird Kramer, “Institutionalizing Evidence-Based STEM Reform through Faculty Professional Development and Support Structures,” International Journal of STEM Education 9 1 (2022) https://doi.org/10.1186/s40594-022-00353-z