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# Instructional Communities of Practice during COVID-19: Social Networks and Their Implications for Resilience†

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**In response to the COVID-19 pandemic, most spring 2020 university courses were abruptly transitioned mid-semester to remote learning. The current study was an exploratory investigation into the interactions among individuals within a single biology department during this transition. Our goal was to describe the patterns of interactions among members of this community, including with whom they gave advice on instruction, shared materials, co-constructed materials, and shared emotions, during the rapid online transition. We explored how instructional teams (i.e., the instructor of record and graduate teaching assistants, or GTAs, assigned to a single course) organized themselves, and what interactions exist outside of these instructional teams. Using social network analysis, we found that the flow of resources and support among instructional staff within this department suggest a collaborative and resilient community of practice. Most interactions took place between instructional staff teaching in the same course. While faculty members tended to have more connections than GTAs, GTAs remained highly interactive in this community. We consider how the observed networks might reflect a mobilization of social resources that are important for individual and departmental resilience in a time of crisis. Actively promoting supportive networks and network structures may be important as higher education continues to cope and adapt to the changing landscape brought on by COVID-19.**

## INTRODUCTION

In normal situations, instructors rely on experience, training, and colleagues to develop curriculum and implement instruction. However, many of these resources were not readily available following the abrupt wholesale transition of college courses to remote learning in spring 2020 in response to the COVID-19 pandemic. Studies investigating instructional transitions to online learning environments prior to 2020 suggest that faculty express numerous negative emotions, including anxiety, disconnection, frustration, and insecurity (1). The mantra to "plan ahead" to alleviate these types of stress in the online environment (2) simply did not apply in spring 2020, where many faculty had to pivot to host their curriculum entirely online in a matter of days.

Johnson et al. (3) reported that nearly all faculty modified at least one aspect of their teaching during the transition to remote instruction in spring 2020, and most reported making significant course-level decisions about delivery of content, class communications, and assessment. Work published during summer 2020 highlights the many innovations that contributed to shifting in-person science classes and labs to virtual activities (4–8). However, it is unclear whether these instructional decisions were made independently by the instructors of record or whether faculty relied on others to guide their decision-making in such curricular changes. This distinction might clarify the underlying value and role that instructional networks play and who the important actors may be.

Faculty rarely teach in isolation. Instead, they benefit from a community of experts within their department and across their institution. Using a sociocultural theory foundation, Wenger et al. (9) proposed that communities of practice (CoP) are groups of people who enrich their experiences and expertise through their interactions. In other contexts, participation in instructional CoPs can promote more active classrooms (10), provide reciprocal mentoring support to all instructors (11), facilitate the development of a pedagogical identity of all instructors (12), and foster collaboration that may lead to external funding (13). Wang and Lu (14) demonstrated that a virtual CoP may further provide pedagogical resources and improve instruction. In academic and industry settings, the CoP model has been used to explain effective team communication in crisis situations (15, 16).

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While faculty, including adjunct, tenured, or tenure-track professors, and instructors, represent part of these instructional CoPs, graduate teaching assistants (GTAs) often comprise another significant segment of these communities (17). Graduate teaching assistants serve as critical programmatic recruiters (18) and the primary educators in science laboratory settings (19), yet are commonly neglected in curricular planning and reform (20). Studying instructional networks that include GTAs may clarify the ways they are included and excluded within their community.

Spring 2020 provided a window to investigate patterns of interaction within instructional CoPs under duress. The networks of interactions that emerged between faculty and GTAs in spring 2020 can demonstrate the types of relationships and social resources that are mobilized in this departmental "stress test." These networks can illustrate the importance of a cohesive CoP and how it may affect the resilience of academic communities. Understanding how communities can better face adversity and effectively integrate members will be important as the instructional landscape continues to adapt amid the uncertainty brought on by the COVID-19 pandemic.

Here, we take an exploratory approach by studying the CoP of a single biology department during the spring 2020 transition to online instruction. We examined with whom instructors provided or received guidance on how to instruct their students, share or co-construct curricular materials, and discuss emotions about this unique pedagogical experience. In doing so, we had three general research goals. First, we sought to describe the patterns of interactions among members of this community during a rapid online transition. Second, we explored how instructional teams, i.e., the instructor of record and GTAs assigned to a single course, organized themselves. Third, we aimed to describe what interactions exist within the department, beyond instructional teams.

## METHODS

### Data collection

The study took place in a biology department at a comprehensive university in the Western United States. This department consists of 22 faculty and 30 GTAs. All these instructors, except two faculty members and one GTA, were teaching during this transition. Nine weeks into the 16-week spring 2020 semester, all courses were moved online as part of public health measures. Within days, the university closed its campus except for essential personnel, and within a week, statewide stay-at-home orders eliminated the possibility of physical interactions among members of this community. The university-wide decision was instituted at the start of Spring Break, giving the faculty nine days to transition their courses to an entirely remote format. In total, 31 courses were moved online. The composition of instructional teams for these courses varied (Fig. 1), ranging from courses with one instructor and no GTAs to the largest course, taught by a team of two faculty members and six GTAs.

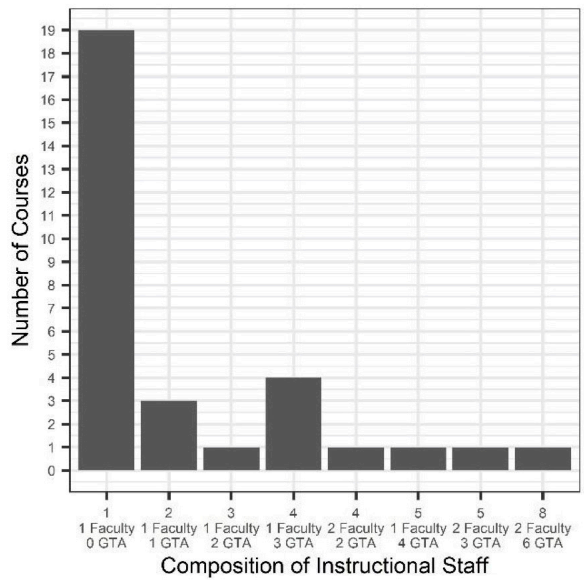


FIGURE 1. Frequency distribution of courses in the sampled department. Courses are denoted by their instructor composition (i.e., number of faculty and GTAs).

We sent a survey to all faculty and GTAs in the department three weeks after the first day of online instruction, approximately halfway through the period of post-transition instruction. Of the 52 instructional members in the department, 82.7% completed the survey. All 52 individuals are included in analyses because each was listed as part of other participants' responses. The survey, among other data collected during this effort but not analyzed here, asked each participant to rate the frequency and types of interactions in which they participated during and following the conversion of their course(s) from face-to-face to online in response to the COVID-19 pandemic (Appendix 1, Table S1). All depaprtmental faculty, GTAs, and administrative staff were included as options for collaborators. In the work presented here, we only analyzed data reflecting "active collaborations" between and among faculty and GTAs to focus on the most salient interactions. We asked about interactions with colleagues within the university, those outside the department, and those outside of the university itself; however, these latter data are not analyzed here. We also collected demographic data, including years of teaching experience, experience teaching online, gender, race and ethnicity, and generational status. To collect gender demographics, participants responded to an open response question. Gender is not a binary construct, and measuring it as a binary option is exclusionary and invalidates the experiences of nonbinary research participants (21, 22). The number of nonbinary responses in the survey was small (fewer than three). In order to include the experiences of nonbinary participants but also maintain confidentiality (23), nonbinary gender responses were analyzed collectively with women. Our approach attempts to reflect the impacts of bias and discrimination on STEM identity and belonging experienced, albeit differently, by non-dominant participants (22, 23). This study was approved by the Institutional Review Board of the University of Northern Colorado (Protocol #2004000109).

We focused on four different interactions that became urgent for all instructional staff during the rapid transition to online instruction: providing and receiving course materials, providing and receiving advice on instructional practices, co-constructing class materials, and discussing emotions related to the rapid instructional changes. The first two interactions were treated as directed ties; each tie between two individuals indicates the direction of the flow of materials or advice about instruction from one instructional staff member to another. The latter two interactions were treated as undirected; each tie between two individuals is assumed to be reciprocal.

### Analysis of global CoP networks

In describing the emergent CoP networks, we took an exploratory analytical approach. The first step in our analysis was to visualize the CoP networks as sociographs and make observations. Next, we investigated the degree distribution for the two undirected networks (co-construction and emotions). Degree is a network measure of the total number of connections (or "ties") each individual (or "node") has in a network. For the two directed networks (materials and instruction), we looked at the distribution of in-degree and out-degree, which measure the total number of ties that go into a node or away from a node, respectively. These degree distributions provide a sense of the number of connections individuals typically have, the range in the number of these connections, and whether any individuals were particularly well connected in these networks. We disaggregated these distributions by gender in order to investigate whether there were any trends in degree by gender.

We also measured each network's degree centralization. Degree centralization provides a standardized measure at the network level of how concentrated ties are to one or several focal individuals (24). A network is completely centralized when one node has ties to all other nodes, but these other nodes have no connections to one another. In this instance, the centralization score would equal one. In contrast, a completely decentralized network exists when ties are equally distributed across all nodes. One example of a decentralized network is a circular structure, where each node has two ties. In this instance, the centralization score would equal zero.

Exponential random graph models (ERGMs) were used to gain a better understanding of generative processes underlying the CoP networks. Exponential random graph models are a class of statistical approaches that can be used to test the importance of different social processes and structures to the formation of an observed network (25–27). Generally, these models work by modeling the presence of ties. Because the presence or absence of a tie between two nodes is a binary variable, ERGM results are interpreted similarly to logistic regression models. In fact, ERGMs reduce to a logistic regression model under certain parameterizations. However, unlike logistic regression models, ERGMs do not assume observations are independent from one another. Instead, ERGMs provide a means to incorporate dependent processes that are often of interest in social networks.

Exponential random graph models are advantageous when studying networks for several reasons. First, they can estimate the effect of individual and dyadic-level covariates on tie formation. For example, one could test whether faculty are more likely to be involved in an interaction than GTAs (individual level) or whether ties are more likely between two GTAs than between a GTA and a faculty (dyadic level). Second, ERGMs can simultaneously incorporate endogenous social processes and network structures into the model (26). For example, ERGMs can test whether there is a propensity for directed ties to be reciprocated, or whether two nodes become more likely to be connected to one another given that they share one or more mutual connections. These types of social processes are commonly observed and can have major implications for the overall structure of networks. Structural terms capture other network features like a tendency for individuals to only have one partner or to have no partners at all.

Exponential random graph models were specified for each network based on knowledge about the departmental organization, inspection of sociographs, and endogenous processes that are known to be prevalent in social networks. This included testing for the presence of homophily, a common social pattern where ties are more likely to occur between similar individuals (28). We tested for homophily by individual role (faculty or GTA) and gender (coded as man or woman/nonbinary). We also tested whether ties were more likely between individuals teaching in the same course. Homophily terms were parameterized using dummy variables, so coefficients are interpreted in comparison with a reference pairing (29).

Dyad-dependent terms were included in models to test for other important social processes in the CoP. Reciprocity was included in models for the two directed networks (materials and instruction) to test whether there was a tendency for individuals to give materials and instructional guidance to those from whom they received materials or instructional guidance, respectively. Additionally, we included a term for geometrically weighted edgewise shared partners (GWESP) in models for all four networks. These terms capture whether there is a propensity for a tie between two individuals given that they both have a tie to one or more shared partners (30).

Because our models included dyad-dependent terms, Markov chain Monte Carlo (MCMC) methods were used to estimate parameters. We examined MCMC diagnostics for each model to assess convergence (31, 32). We assessed goodness of fit of ERGM models by examining how well the estimated models were able to reproduce global network properties of the observed network (33). All analyses were performed in *R* using the *statnet* suite of packages (34), including *sna* (35), *network* (36), and *ergm* (30).

### Examining instructional team networks

An observation that members of the same instructional teams tended to cluster together led to the decision to more closely examine the networks of each instructional team. Individual sociographs for the nine courses with three or more instructional staff were plotted for each type of interaction. Inferences were drawn based on structural properties of these individual course staff networks.

### Analysis of informal CoP networks

Identification of clustering within instructional teams also led to the decision to examine interactions between individuals who were not on the same instructional staff (i.e., at the course-level). We refer to these ties as informal because they likely exist between individuals with prior informal relationships. This contrasts with ties within instructional teams that exist as a result of prescribed departmental organization.

In order to study these informal ties, we created informal networks by removing all ties between individuals teaching together as part of the same course. Using these informal networks, we followed similar procedures described above. We first investigated sociographs before specifying ERGMs to investigate the generative processes underlying the formation of informal ties. The ERGMs included the same variables described above and an additional term that captures a propensity for individuals to have zero ties.

## RESULTS

### Global CoP sociographs

The patterns of interactions among members of this community, representing a single biology department including its faculty and GTAs, are first described in four network sociographs (Fig. 2). Instructional role (faculty member or GTA) and gender (woman/nonbinary or man) are coded by the shape and color of the node, respectively. Whether an interaction takes place between two people who are part of the same instructional team or not is indicated by edge color. For the two directed networks, the direction of interactions is indicated by arrows (Fig. 2). Most department members are part of a single large connected group (i.e., component). This suggests that any transmission of resources that occurs through these interpersonal interactions can reach most CoP members.

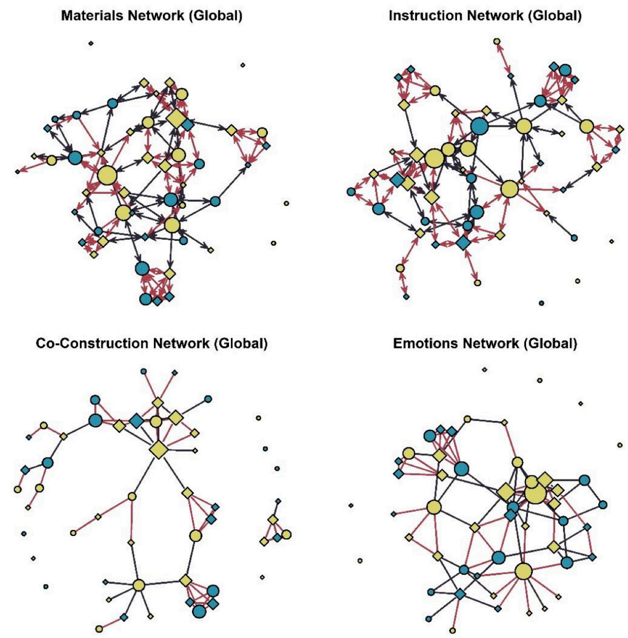


FIGURE 2. Global social networks depicting four different types of interactions within the entire instructional staff of a biology department. Each node ($n$ = 52) represents a member of the department (circles are faculty and diamonds are GTAs; yellow are women/nonbinary persons and teal are men). In the directed networks (Materials, Instruction), the size of the node correlates with their out-degree centrality: larger nodes are giving materials or instructional guidance to a greater number of colleagues than smaller nodes. In the undirected networks (Co-Construction, Emotions), the size of the node correlates with their degree centrality: larger nodes are co-constructing materials or discussing emotions with more of their colleagues than smaller nodes. Edges in these networks are color coded to indicate whether two individuals were instructional staff for the same course: red edges indicate interactions between individuals co-teaching the same course and dark gray edges indicate interactions between two individuals not co-teaching. Arrows in the two directed networks indicate the flow of materials or advice on instruction: tails indicate who is providing the materials or advice and heads indicate who is receiving those materials or advice. Edges with two heads indicate a reciprocal interaction where both individuals provided one another materials and/or advice on instruction. Node placement is based on a force-directed algorithm to minimize crossing edges and keep edge lengths similar in length.

Outside of the largest component, each network contains individuals disconnected from everyone else in the network (i.e., isolates), who did not actively participate in that function of the CoP. These isolates occurred most frequently in the co-construction network, where ties were most likely to exist between instructional team members. Most commonly, these isolates were faculty ($n$ = 2) or graduate students ($n$ = 1) who were not teaching at the time of the transition, or faculty who were teaching courses with no GTAs assigned ($n$ = 7).

All four global networks suggest clustering between individuals who were instructional staff for the same course (Fig. 2, red edges). Among all ties in the materials, instruction, co-construction, and emotions networks, 57.0%, 61.8%, 79.6%, and 63.1% existed between individuals on the same instructional team, respectively. This rate of course-dependent interactions is substantial considering that there are many more possible partners outside of one's instructional team than within. For example, each person in the largest instructional team ($n$ = 8) has seven potential partners within that team, but 44 possible partners outside of this instructional unit.

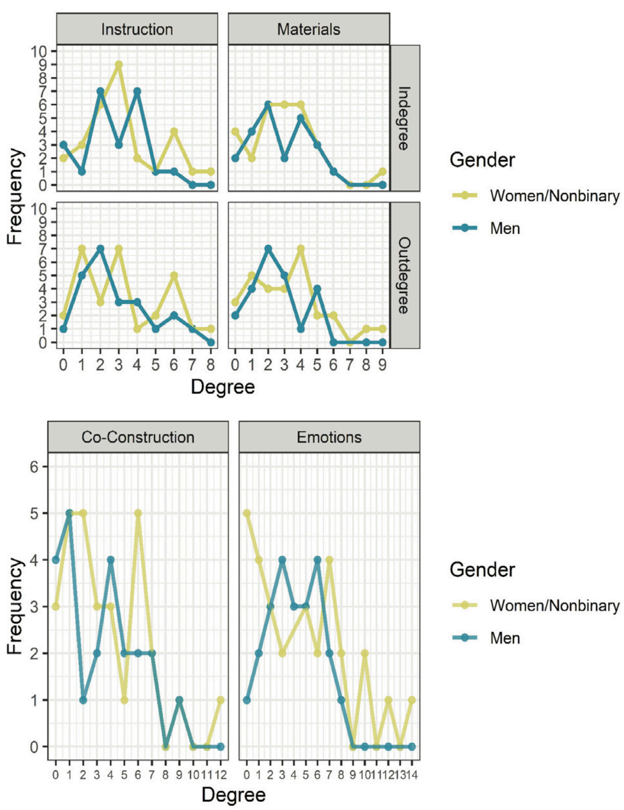


FIGURE 3. Distribution of in-degree and out-degree centrality scores for all 52 individuals in the four global networks. Women/nonbinary persons are coded in yellow and men in teal lines.

The degree distributions for each network are skewed right (Fig. 3), indicating that a small number of individuals are particularly well connected for each measured interaction. One reason for this disparity was variation in the number of co-instructors and GTAs in each course (Fig. 1). The size of instructional teams was significantly associated with greater degree centrality scores in every network (Appendix 1, Fig. S1). While individuals in larger instructional teams were connected to a greater number of colleagues (alters) on average, it is worth noting that the individuals with the highest degree centrality were women/nonbinary persons. The same woman/nonbinary GTA had the highest degree centrality in the co-construction network (12 alters), in-degree in the materials network (9 alters), and out-degree in the materials network (9 alters), likely because their teaching assignment necessitated that they interact with GTAs from more than one course. Likewise, the same woman/nonbinary faculty member had the highest degree centrality in the emotions network (14 alters), in-degree in the instruction network (8 alters), and out-degree in the instruction network (8 alters), and they were the only faculty member that taught two courses with GTAs during spring 2020. The department chair was also a central node in provisioning guidance on instruction but was by no means the most central person in any of the four networks.

The right skew in the degree distributions also suggests a level of centralization within these networks. Total degree centralization is a measure of how concentrated ties are to one or several central nodes. A centralization score of 1 occurs when all ties in a network connect to the same individual, while a score of 0 indicates that all nodes have the same number of ties. Total degree centralization scores across the four networks were in the range of observations from similar networks (37); the total degree centralization was 0.125 in the materials network, 0.102 in the instruction network, 0.174 in the co-construction network, and 0.197 in the emotions network.

### Modeling processes underlying global network formation

Exponential random graph models confirmed that interactions cluster between individuals who are part of the same instructional staff for the same course, demonstrated by the large effect size of the Teach in same course variable in models for all four networks (Tables 1 and 2: Global models). Further evidence of clustering is found through the positive and significant GWESP term across all networks and the large effect of Reciprocity in the two directed networks (Table 1). The GWESP term indicates a propensity for ties to exist between two individuals who are each linked to one or more shared colleagues. The Reciprocity term indicates that individuals are much more likely to receive materials or advice about instruction from colleagues to whom they provided materials or advice about instruction.

Controlling for these clustering effects, including whether or not two individuals were teaching in the same course team, there was a propensity for faculty to have more connections than GTAs across the four networks, as indicated by the Role homophily terms (Tables 1 and 2: Global models). The likelihood of a GTA providing a faculty member instructional guidance or materials did not differ from that of a transmission from a GTA to another GTA, but the likelihood of GTA to faculty ties in these networks were significantly lower than ties from faculty to faculty or faculty to GTAs (Table 1: Global models). Similarly, co-construction was more likely to occur between faculty members and GTAs than between two GTAs. These findings are likely driven by team dynamics in the nine courses where GTAs outnumber the faculty. Discussions about emotions were more likely to occur between two faculty than either of the two other possible pairings (Table 2).

Gender played a limited role in the global networks, especially when compared with the importance of course staff structure and roles of faculty and GTAs. No significant difference was found between the propensity for men or women/nonbinary persons to have ties in any of the four networks. However, gender homophily was significant in predicting the transmission of course materials and, while it wasn't significant at $\alpha = 0.05$, gender homophily greatly improved model fit for the emotions network.

### Within-course CoP sociographs

Given the importance of instructional teams to the formation of ties, we examined the network sociographs of nine courses with a minimum of three individuals on the course staff (Fig. 4). Instructional staff in four of these courses were either nearly or completely connected to one another (i.e., formed a clique) (Fig. 4A to D). Interactions in these courses were distributed across all staff, regardless of individual roles.

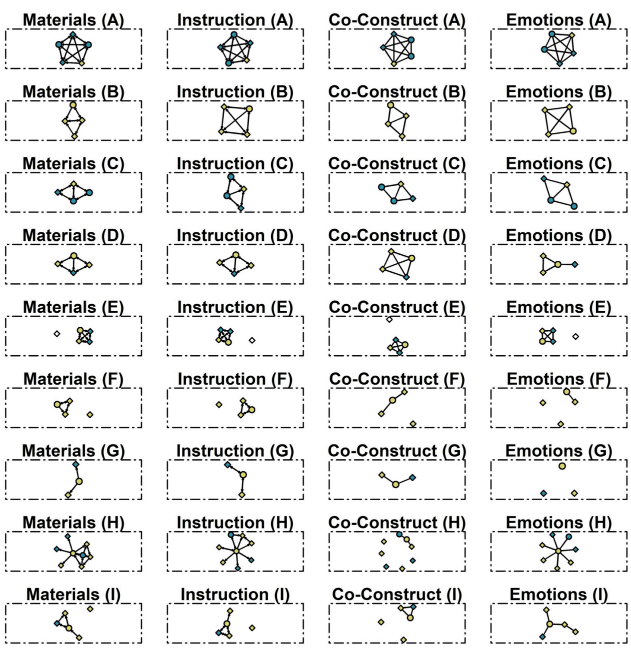


FIGURE 4. Connections between the 37 individuals in each of 9 courses with three or more instructional staff (labeled A-I). Circles are faculty and diamonds are GTAs. Yellow are women/nonbinary persons and teal are men.

Course E includes a four-person clique with one GTA isolated upon the transition to online instruction (Fig. 4E). This isolated GTA was solely responsible for lab preparation as part of this course. Traditional labs were cancelled in the course upon the transition to online instruction, and the emergent network suggests that this GTA was not involved in the course immediately following this transition. Similarly, the instructional duties of the isolate in three of the four networks in Course F was to support in-class instruction, a role that appears to have become less relevant after the transition to online instruction, at least in this class. Eight of the nine investigated courses had GTA positions where their duty was to support in-class instruction; however, those individuals were not isolated as they were in Course F.

Instructional staff in the other three courses (Fig. 4G, H, and I) did not form cliques. The network structures for these instructional teams tended to be more hierarchical, with a single instructor playing a central role in all interactions.

### Analysis of informal sociographs

While the organization of faculty and GTAs into instructional teams was a strong predictor of interactions, it represents an exogenous effect; this level of organization was out of the control of both faculty and GTAs. Thus, interactions outside of these instructional teams are more indicative of informal relationships between CoP members with previous rapport. Because these ties are not based on the delegation of tasks within the same course, studying them can provide a more distilled view of the department as a CoP.

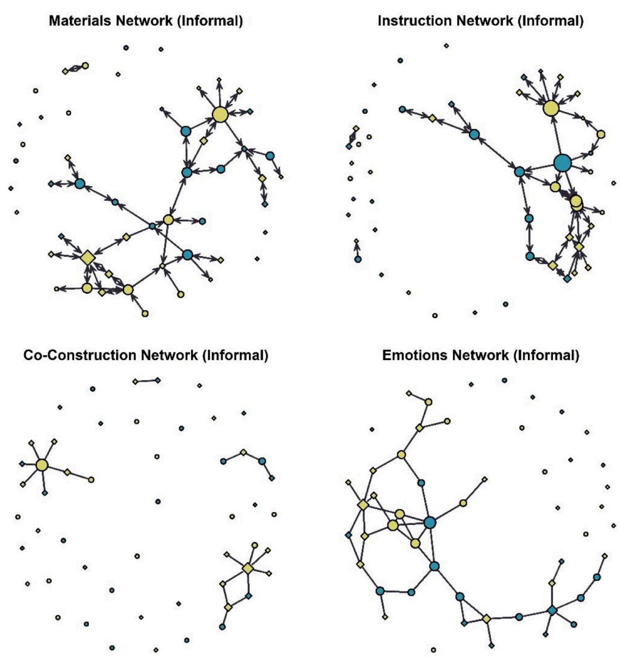


FIGURE 5. Informal social networks depicting only connections between 52 department members who were not co-teaching the same course. These networks are the same as in Fig. 2 but replotted to highlight interactions that are not dependent on teaching in the same course.

Networks of informal interactions show less clustering in the absence of ties between members of the same instructional team (Fig. 5). Overall, there appears to be less triadic closure, which occurs when three individuals are all mutually connected to one another (A is connected to B and C, B and C are also connected). Instead, there are more instances of intransitive triads, where one individual is connected to two or more individuals, but these alters are not connected to one another (A is connected to B and C, but B and C are not connected). Where clustering does occur, it seems to be gender homophilous, particularly in the instruction and emotions networks. In general, faculty seem to be more connected than GTAs. There are also more isolates, though these additional isolates simply represent individuals who do not have any informal ties outside of their course.

### Modeling processes underlying informal network formation

Exponential random graph model results for the informal networks find several structural properties to be generalizable across the different networks. First, the *Isolate co*efficient was positive and significant in the instruction and emotions networks and improved model fit in the co-construction network (Tables 1 and 2: Informal models). Given the context of these networks, this indicates a propensity for individuals to be disconnected from others with whom they are not on the same instructional team. The GWESP term was not significant for the instruction or emotions networks and failed to converge in models for the materials or co-construction networks (Tables 1 and 2: Informal models). The nonsignificance and failure to converge both indicate little tendency for triadic closure across all networks (most often, failed convergence in ERGMs suggests that the endogenous process being modeled is a poor representation of the observed network).

Similar to the global CoP networks, faculty had a greater tendency to be involved in informal interactions. In both the materials and instruction networks, the likelihood of a faculty-to-faculty tie was greater than the likelihood of a GTA-to-faculty or GTA-to-GTA tie, and not significantly different from the likelihood of a faculty-to-GTA tie (Table 1: Informal models). In the emotions network, conversations were more likely between two faculty than between two GTAs or between a faculty member and a GTA.

The role of gender was slightly less important in these informal networks than in the global CoP networks. In the instruction network, women/nonbinary persons were significantly more likely to provide guidance to other women/nonbinary persons than they were to men. Though neither coefficient was significant at $\alpha = 0.05$, gender homophily again improved model fit and suggests that discussions about emotions were more common between two men or two women/nonbinary persons than between a man and a woman/nonbinary person (Table 2, Informal models).

## DISCUSSION

This exploratory study examined the community structure of a single biology department during the abrupt transition to online instruction amidst the COVID-19 pandemic, paying attention to the interactions within and between course-specific instructional teams. We collected and analyzed network data regarding who provided course materials to whom, who provided advice on instructional practices to whom, who co-constructed class materials, and who discussed emotions related to the rapid instructional changes. The key findings of our analysis are summarized here and discussed throughout the sections that follow.

Across all four networks, we found that the structure of this department-wide CoP is best described as instructional team clusters that are connected to one another primarily by interactions between faculty (Figs. 2 and 5; Tables 1 and 2). Individuals with the highest degrees of centrality tended to be associated with larger instructional teams, suggesting that large classes with large instructional teams are hubs within the networks (Appendix 1, Fig. S1). Instructional team clusters were generally either highly connected cliques or had a hierarchical structure with a course instructor playing a central role (Fig. 4). Interactions were less common outside of instructional teams, with many individuals having no ties outside of their instructional teams. This was particularly the case for GTAs (Fig. 5), as faculty were more likely to be involved in informal interactions that bridged across different courses. While men and women/nonbinary persons did not differ in the number of interactions they had on average, there was limited evidence for gender homophily predicting ties (Tables 1 and 2).

As an exploratory study, our primary goal was to describe the CoP networks and understand the social mechanisms that drove their emergence. It is our impression that the level of interaction in these networks was strong, especially considering that our analyses only included relationships identified as an active collaboration that took place over a span of weeks. This timeframe is shorter than other studies on faculty networks, which often measure interactions over the course of a year or whole semester (37–40). Given our results, the intensity of interactions in these networks, and the stressful context under which these data were collected, we interpret and discuss our results in view of how they inform resilience in higher education. We want to emphasize that we did not directly measure resilience, but our findings suggest that this idea is important in explaining our findings. Understanding ways to manage human resources to maximize resilience will serve individuals and departments well as they continue to cope and adapt to the new educational landscapes brought on by COVID-19.

## Resilience and community structure

Despite disruptions introduced by COVID-19, academic departments are still expected to provide effective curriculum to undergraduates, train graduate students, and advance knowledge through research, among other institutional expectations. The ability to deliver on these expectations in the face of a crisis depends on the resilience of department members and the department as a whole. Resilience is a concept that has varying definitions across the numerous disciplines that study it (41, 42). We adopt a broad definition of resilience as "an ability to sustain a shock without completely deteriorating" (43). While this definition was written to describe resilience as an ability at the organizational level, we choose to apply it to our interpretation of both individual and group levels.

Social networks are commonly implicated in resilience research. This role of networks in supporting resilience has been demonstrated at different levels of social organization, including situations where crisis and stress affect individuals (44) and organizations (45). We consider below how the observed networks in our study may be reflective of the resilience of the individual department members, course teams, and the CoP as a whole. Lacking a direct measure of resilience or qualitative reflections from our participants, we use resilience as a conceptual frame to help understand our findings, not as direct correlations. In doing so, we review the ways social networks are operationalized in the resilience process in other related contexts.

## Individual resilience

For individuals, social support is critical for working through an unexpected crisis (44, 46). With just over a week to prepare to teach in a new mode, the resources, knowledge, and opinion of peers provided an efficient way to locate and evaluate new information. The majority of faculty and GTAs were well connected in each of the global networks. Individuals who did not have any network ties were rare (average five isolates per network) and frequently did not need support because they were not teaching at the time of the transition or were teaching courses without GTA

TABLE 1.
Coefficients from exponential random graph models for global and informal networks in the two directed networks, Materials and Instruction ($n$ = 52 nodes).

| Network | Materials (Global) | Materials (Informal) | Instruction (Global) | Instruction (Informal) |
|---|---|---|---|---|
| Edges | –5.949 (0.499)[a] | 4.319 (0.363)[a] | –5.739 (0.499)[a] | –3.990 (0.380)[a] |
| **Homophily terms** | | | | |
| Teach in same course | 1.928 (0.198)[a] | — | 2.128 (0.203)[a] | — |
| By Role | | | | |
| GTA to Faculty | 0 (baseline) | –1.061 (0.461)[b] | 0 (baseline) | –0.848 (0.474)[d] |
| Faculty to Faculty | 1.147 (0.35)[a] | 0 (baseline) | 1.483 (0.365)[a] | 0 (baseline) |
| Faculty to GTA | 1.763 (0.483)[a] | 0.611 (0.345) | 1.757 (0.522)[a] | –0.030 (0.400) |
| GTA to GTA | 0.384 (0.332) | –0.448 (0.270)[d] | 0.393 (0.351) | –0.575 (0.247)[c] |
| **By Gender** | | | | |
| Men to Women/Nonbinary | 0 (baseline) | –0.558 (0.426) | 0 (baseline) | 0.201 (0.414) |
| Women/Nonbinary to Men | 0.771 (0.463)[d] | –0.394 (0.425) | 0.009 (0.470) | –1.036 (0.487)[c] |
| Men to Men | 0.623 (0.314)[c] | –0.193 (0.250) | 0.077 (0.310) | –0.262 (0.262) |
| Women/Nonbinary to Women/Nonbinary | 0.710 (0.293)[b] | 0 (baseline) | 0.219 (0.279) | 0 (baseline) |
| **Dyad dependent terms** | | | | |
| GWESP | 0.297 (0.108)[b] | Does not converge | 0.324 (0.113)[b] | 0.247 (0.186) |
| Reciprocity | 4.534 (0.428)[a] | 5.699 (0.592)[a] | 4.701 (0.435)[a] | 5.391 (0.637)[a] |
| **Other structural terms** | | | | |
| Isolates | — | 0.473 (0.448) | — | 1.036 (0.450)[c] |

Significance levels: *$p \le 0.001$, [b]$p \le 0.01$, [c]$p \le 0.05$, [d]$p \le 0.1$

Standard errors are in parentheses. Coefficients represent the influence on the log-odds of a nomination for each predictor as described in the Methods. Positive coefficients indicate that ties are more likely to occur, while negative coefficients indicate that ties are less likely to occur. Reference groups for dummy coded variables are indicated in the columns as the baseline. GWESP = geometrically weighted edgewise shared partners.

TABLE 2.
Coefficients from exponential random graph models for global and informal networks in the two undirected networks, Co-Construction and Emotions networks ($n$ = 52 nodes).

| Network | Co-Construction (Global) | Co-Construction (Informal) | Emotions (Global) | Emotions (Informal) |
|---|---|---|---|---|
| Edges | –4.100 (0.309)[a] | –3.284 (0.552)[a] | –4.086 (0.277)[a] | –2.886 (0.357)[a] |
| Homophily terms | | | | |
| Teach in same course | 3.207 (0.318)[a] | — | 2.851 (0.272)[a] | — |
| By Role | | | 0 (baseline) | |
| GTA and Faculty | 0 (baseline) | Did not converge | 0 (baseline) | –0.742 (0.315)[c] |
| Both Faculty | –1.057 (0.684) | –0.173 (0.436) | 0.637 (0.313)[c] | 0 (baseline) |
| Both GTA | –0.825 (0.364)[b] | | –0.460 (0.293) | –0.567 (0.307)[d] |
| By Gender | | | | |
| Man and Woman/ Nonbinary | 0 (baseline) | 0 (baseline) | 0 (baseline) | 0 (baseline) |
| Both Men | –0.174 (0.428) | –0.879 (1.070) | 0.500 (0.289)[d] | 0.549 (0.360) |
| Both Women/ Nonbinary | 0.168 (0.314) | 0.550 (0.436) | 0.445 (0.247)[d] | 0.541 (0.315)[d] |
| Dyad dependent terms | | | | |
| GWESP | 0.818 (0.218)[a] | Did not converge | 0.688 (0.165)[a] | 0.380 (0.221)[d] |
| **Other structural terms** | | | | |
| Isolates | — | 0.933 (0.491)[d] | — | 1.001 (0.472)[c] |

Significance levels: *$p \leq 0.001$, [b]$p \leq 0.01$, [c]$p \leq 0.05$, [d]$p \leq 0.1$

Standard errors are in parentheses. Coefficients represent the influence on the log-odds of a nomination for each predictor as described in the Methods. Positive coefficients indicate that ties are more likely to occur, while negative coefficients indicate that ties are less likely to occur. Reference groups for dummy coded variables are indicated in the columns as the baseline.

support that were likely smaller in size. The instructional units were functionally important in maintaining structural social interactions, as indicated in the model results (Tables 1 and 2) and by the marked increase of isolates in the informal networks (average 19 isolates per system, Fig. 5). We suspect that, as the foundational aspect of a supportive and connected community, these units likely had a positive impact on each member's ability to handle the abrupt transition to online instruction.

### Course team resilience

At the level of individual course teams, we interpreted the different ways ties were distributed within courses as varying levels of resilience. In this context, resilience is likely higher when ties are more distributed across all members of the instructional team than when it is centralized around one main instructor. To illustrate, consider a hypothetical situation where the primary faculty instructor becomes sick with COVID-19. In a course where ties are distributed, a consensus knowledge and support amongst all instructional staff can help buffer against this shock (e.g., A in Figure 4). In this situation, all instructional staff equally share ownership of course curriculum and/or preparation, which provides more minds for troubleshooting and validates all members of the team. However, in a course where the primary instructor is completely centralized, it may be less clear how this situation might be handled (e.g., G or H in Fig. 4).

Resilience at the course level may reflect structuring within teams, which is dependent upon how instructors manage their GTAs (i.e., strict hierarchy or clique facilitation). In crisis situations, as experienced in spring 2020, GTA management style may have implications on how an instructional CoP can weather adversity. It is unclear whether our data indicate what happens under non-COVID-19 conditions (e.g., are GTAs part of curricular co-construction or emotional support system?); however, other research suggests that social networks before and during COVID-19 shift in the number of ties and isolates and the nature of those interactions changes to reflect different needs before and during COVID-19 (47).

### Organizational resilience

Resilience at the departmental level, which we equate to the overall CoP, partially depends on the social processes at the more granular levels discussed above. The fact that instructors were able to access relational resources within the department, and that these interactions were often reciprocated, bodes well for the CoP as a whole. The active transmission of resources and advice, alongside the co-construction of materials, suggests a situation where the whole is greater than the sum of its parts.

Importantly, the social capital realized in this CoP was both bonding and bridging. Bonding social capital refers to connections with others who share similar perspectives, resources, or information, while bridging social capital exists when ties connect individuals with different backgrounds, granting access to more diverse resources (48–50). Both types of social capital are useful in times of crisis (48, 51). While all ties within the departmental CoP could be considered an example of bonding social capital because everyone is part of the same larger network, some ties likely play a stronger bonding role while others play a more bridging role. For example, the finding that ties cluster within course teams indicates a presence of bonding ties, while bridging occurs through the tendency for co-construction to occur between faculty and GTAs or for materials and guidance to flow from faculty to GTAs. The generally small effect sizes for gender homophily in the ERGMs indicate similar likelihoods between all possible gendered pairings in the network. Thus, to the extent that perspectives, information, and resources vary by gender, there appears to be bonding and bridging. However, bonding capital is drawn on more frequently when it comes to discussing emotions and sharing materials.

We speculate that resilience for the CoP also depended on the ability to innovate and disseminate resources that helped cope with, and adapt to, the abrupt changes introduced by COVID-19. The processes of innovation and dissemination are simultaneously supported and hindered by networks. For example, by creating more unique opportunities to intersect previously distinct pieces of information, bridging ties are thought to increase the rate of innovation (52–54). In this context, discussions between instructors of different courses and those that integrate both faculty and GTA may represent important means for innovation. On the other hand, research suggests that greater levels of trust found in bonding ties may make them better suited for the actual transmission of innovations (55). The finding of gender homophily when it comes to providing course materials suggests that this may be the case in the observed networks.

The overall structure of the CoP networks, including how centralized they are, can also inform our application of resiliency in this context. However, the relationship between centralization and resiliency is neither linear nor well defined. In general, the observed networks were decentralized, with the instruction network most decentralized and the emotions network most centralized. Decentralized networks can be beneficial insofar as they represent a greater diversity of interactions, providing more opportunity for innovation and ensuring that everyone has some level of social support. However, this may not always reflect an optimal scenario. For example, decentralized networks may contain underutilized expertise (e.g., an instructor with expertise in online instruction being tapped for information as frequently as a particularly ineffective instructor). Decentralized networks are also less effective for coordination compared with more hierarchical communication structures. In these cases, a more centralized structure may be preferable. Indeed, this type of hierarchy was found within some of the instructional team networks, where faculty were central compared with GTAs. Further, resources tended to flow from faculty to GTAs, an expected finding given their organizational roles. The overall low centralization of other networks suggests that either this CoP does not contain individuals who are experts in online instruction or that those experts did not have the capacity or incentives to provide this level of support to other members of the CoP. This observation emphasizes the potential importance of instructional professionals during this time, including centers for teaching and learning, educational designers, and others in positions aimed at supporting teaching. Rupnow et al. (56) reported mixed reliance by faculty on similar types of institutional professional development amid the COVID-19 shift; however, these resources may become central in providing continuing support as academic institutions adapt in the future.

### Importance of CoPs

Mobilizing relational resources is part of an organization's repertoire for expressing resilience (57, 58). The department under study seemed to have expressed a robust social response. Few active instructors were isolated in their transition to online instruction. However, organizations vary in the level to which their members can depend on one another. What traits enable a department to mobilize social capital and activate other relevant social mechanisms when under duress?

In the current context, the department under study has an emphasis on its identity as a community, which may have played an important role. This community and its CoP is foundationally built around teaching as a departmental priority, which is true for both faculty and GTAs. A lower priority on teaching would likely be reflected in the network by more isolates and the presence of smaller disconnected groups or of greater centralization at the global level. These structures would suggest weaker social support around the task of teaching, and potentially less resilience.

### GTA roles

One motivation for this study was to better understand how GTAs were included and utilized in an instructional CoP at a time when curriculum had to be reimagined in only a few days' time. While GTAs are instrumental in teaching many of our science courses (17), rarely are they considered partners in instruction (59) or curriculum development. In our dataset, we noted that faculty were more connected in these instructional networks than GTAs; however, teaching was likely the faculty's central focus since COVID-19 shuttered the institution's research labs during the transition. In contrast, the GTAs' time was split between being lab instructors and being students themselves.

In the global CoP networks (Fig. 2), at most three GTAs were stranded as isolates outside of the larger community. However, this picture vastly shifts in the informal CoP network (Fig. 5), where many GTAs become isolated in the absence of course teams. The importance of socialization with their supervising instructor and GTA peers is noted by others as beneficial to graduate student professional development (60, 61). Yet the relationships that developed within these course teams, which appear critical for the transition to remote instruction that we observed in spring 2020, may only represent "convenient teaching interactions" that are not enduring (62). Instead, Wise (62) argues that it may be the informal relationships, established through common teaching experiences and developed through friendship, that are most influential. However, for graduate students being trained during a COVID-19–impacted system, teaching interactions may provide socialization opportunities that were previously provided by shared office space where friendships developed.

We noted high degrees of reciprocity between faculty and GTAs, excepting three of the courses that were centralized in dissemination of resources and support (G, H, and I in Fig. 4). This reciprocity signals both the faculty's perceived value of their GTAs and the GTAs' perception of inclusion in this CoP. We suggest that this reciprocity may foster resilience within course teams and for the community as a whole, but it undoubtedly also contributes to broader socialization of graduate students into academia.

### Gender roles

Neither the global nor informal networks observed for the department were strongly influenced by gender (Figs. 2 and 5). Academia is inherently a non–gender-neutral, patriarchal environment, and exclusion from male-dominant networks is detrimental to the development of women's careers (63–65). The flow of resources and decreased opportunities for interactions usually associated with reduced social capital (66–68) are generally not observed in this dataset of well-connected and integrated networks related to instructional practices and providing of and co-constructing course materials. Our results indicate some propensity for gender homophily in the sharing of course materials, instructional guidance, and discussion of emotions, though these effects were not strong or very consistent across networks. Social capital barriers often observed in academia are less apparent and possibly decreased in size and propensity within this department, which is perhaps indicative of a broadly collaborative departmental CoP.

### Limitations

Several elements of this study limit what can be concluded. First, it is unclear how these interaction networks compare with a baseline level of interaction. Data were only collected in the weeks following the transition to online instruction. While our impression is that the observed networks likely differ from the interaction patterns that typically exist in a "normal" semester, we did not have the appropriate background data to empirically test this supposition.

This study was restricted to a structural analysis of networks based on active collaborations. While much can be gleaned from network structures, more data and research would be needed to test the extent to which these structures helped or hindered faculty and GTAs amidst the pandemic. For example, we were able to identify that many pathways exist for innovations to spread in this department, but were unable to test the emergence or spread of any specific innovations.

The overall response rate in these data were high compared with networks collected from similar contexts, but data were missing from two faculty members and seven GTAs who declined to participate in the survey. While these missing data may alter results, their effect is limited by the way the data were collected. Participants were able to include these non-consenters in their own networks, including indicating whether they were givers or receivers in the directed networks. This method of data collection alongside a high response rate is likely to limit the number of missing edges in the network.

Lastly, interactions with individuals from outside the departmental CoP are not included in these analyses. These types of ties are likely to play an important role in bridging social capital, as connections to other departments or institutions are likely to bring in more diverse perspectives and resources that can help the department cope and adapt (51).

## CONCLUSION

Through an exploratory social network analysis of all instructional staff in a single biology department, we described the networks of four types of interactions that took place following the rapid transition to online instruction in spring 2020. The importance of the structure and composition of CoP networks to departmental resilience emerged as a key idea in this study. Here, expressing resilience was conceptualized as an ongoing process of anticipating, coping with, and adapting to shocks (57). As COVID-19 continues to disrupt higher education, individual instructors, departments, and institutions remain in the coping and adapting stages of resilience. We highlighted the strengths and weaknesses that different course- and department-level organizations may provide. While we propose that this CoP was resilient, we cannot attribute its resilience to a single trait. This department, within a regional university with a strong education mission, already had a focus on instruction as an organizational trait that may have contributed to its resilience. Or, potentially, the low incidence of illness amongst its instructional staff minimized the need to "adapt to shocks."

This work lends insight into the importance of social cohesion and community structure in academic departments, in the semesters following the outbreak of COVID-19 and in the years beyond. The COVID-19 pandemic compelled higher education into a stress test. Persistence through this stress test depends at least partially on the ability to mobilize relational resources. This mobilization may occur in a decentralized fashion, driven by both organizational structures and informal relationships, as seen in the current study. However, a more centralized response that makes use of educational specialists may also facilitate resilience. The inclusion of GTAs as equal reciprocators in instructional networks may not only help foster innovation but contribute to their long-term professional development. While the size and universality of disruption caused by COVID-19 is unique, smaller disruptions are commonly experienced by departments, and considering how faculty networks relate to resilience will continue to be important.

## SUPPLEMENTAL MATERIALS

Appendix 1: Supplemental tables and figures

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## REFERENCES

1. Regan K, Evmenova A, Baker P, Jerome MK, Spencer V, Lawson H, Werner T. 2012. Experiences of instructors in online learning environments: identifying and regulating emotions. Internet Higher Educ 15:204–212.
2. Cook JP. 2018. Online education and the emotional experience of the teacher. New Dir Teach Learn 2018:67–75.
3. Johnson N, Veletsianos G, Seaman J. 2020. U.S. faculty and administrators' experiences and approaches in the early weeks of the COVID-19 pandemic. Online Learn 24(2):6–21.
4. Allen TE, Barker SD. 2020. BME Labs in the era of COVID-19: transitioning a hands-on integrative lab experience to remote instruction using gamified lab simulations. Biomed Engineer Educ 1–6.
5. Holt EA, Heim AB, Tessens E, Walker R. 2020. Thanks for inviting me to the party: virtual poster sessions as a way to connect in a time of disconnection. Ecol Evol 10(22):12423–12430.
6. Howitz WJ, Guaglianone G, King SM. 2020. Converting an organic chemistry course to an online format in two weeks: design, implementation, and reflection. J Chemical Education 97:2581–2589.
7. Vergne MJ, Smith JD, Bowen RS. 2020. Escape the (remote) classroom: an online escape room for remote learning. J Chem Educ 97:2845–2848.
8. Youssef M, McKinstry EL, Dunne A, Bitton A, Brady AG, Jordan T. 2020. Developing engaging remote laboratory activities for a nonmajors chemistry course during COVID-19. J Chem Educ 97:3048–3054.
9. Wenger E, McDermott RA, Snyder W. 2002. Cultivating communities of practice: a guide to managing knowledge. Boston, MA: Harvard Business School Press.
10. Tomkin JH, Beilstein SO, Morphew JW, Herman GL. 2019. Evidence that communities of practice are associated with active learning in large STEM lectures. Int J STEM Educ 6:1.
11. Smith ER, Calderwood PE, Storms SB, Lopez PG, Colwell RP. 2016. Institutionalizing faculty mentoring within a community of practice model. Improve Acad 35:35–71.
12. Luguetti C, Aranda R, Enriquez ON, Oliver KL. 2019. Developing teachers' pedagogical identities through a community of practice: learning to sustain the use of a student-centered inquiry as curriculum approach. Sport Educ Soc 24:855–866.
13. Sack J, Quander J, Redl T, Leveille N. 2016. The community of practice among mathematics and mathematics education faculty members at an urban minority serving institution in the U.S. Innov Higher Educ 41:167–182.
14. Wang Q, Lu Z. 2012. A case study of using an online community of practice for teachers' professional development at a secondary school in China. Learn Media Technol 37:429–446.
15. Edwards AL, Sellnow TL, Sellnow DD, Iverson J, Parrish A, Dritz S. 2020. Communities of practice as purveyors of instructional communication during crises. Commun Educ 1–22.
16. Sellnow DD, Iverson J, Sellnow TL. 2017. The evolution of the operational earthquake forecasting community of practice: the L'Aquila communication crisis as a triggering event for organizational renewal. J Appl Commun Res 45:121–139.
17. Nicklow JW, Marikunte SS, Chevalier LR. 2007. Balancing pedagogical and professional practice skills in the training of graduate teaching assistants. J Profess Iss Engineer Educ Pract 133:89–93.
18. Bettinger EP, Long BT, Taylor ES. 2016. When inputs are outputs: the case of graduate student instructors. Econ Educ Rev 52:63–76.
19. Sundberg MD, Armstrong JE, Wischusen EW. 2005. A reappraisal of the status of introductory biology laboratory education in U.S. colleges & universities. Am Biol Teach 67:525–529.
20. Gardner GE, Jones MG. 2011. Pedagogical preparation of the science graduate teaching assistant: challenges and implications. Sci Educ 20:31–41.
21. Cameron JJ, Stinson DA. 2019. Gender (mis)measurement: guidelines for respecting gender diversity in psychological research. Soc Personal Psychol Compass 13:e12506.
22. Freeman JB. 2020. Measuring and resolving LGBTQ disparities in STEM. Pol Insights Behav Brain Sci 7:141–148.
23. Kennedy L, Khanna K, Simpson D, Gelman A. 2020. Using sex and gender in survey adjustment. arXiv preprint arXiv:200914401.
24. Freeman LC, Roeder D, Mulholland RR. 1979. Centrality in social networks: II. Experimental results. Soc Netw 2:119–141.

25. Robins G, Snijders T, Wang P, Handcock M, Pattison P. 2007. Recent developments in exponential random graph (*p**) models for social networks. Soc Netw 29:192–215.
26. Snijders TAB, Pattison PE, Robins GL, Handcock MS. 2006. New specifications for exponential random graph models. Sociol Methodol 36:99–153.
27. Wasserman S, Pattison P. 1996. Logit models and logistic regressions for social networks: I. An introduction to Markov graphs and *p**. Psychometrika 61:401–425.
28. McPherson M, Smith-Lovin L, Cook JM. 2001. Birds of a feather: homophily in social networks. Ann Rev Sociol 27:415–444.
29. Handcock MS, Hunter DR, Butts CT, Goodreau SM, Krivitsky PN, Morris M, Wang L, Li K, Bender-deMoll S, Krivitsky MPN. 2015. Package "ergm." https://cran.r-project.org/web/packages/ergm/index.html
30. Hunter DR, Handcock MS, Butts CT, Goodreau SM, Morris M. 2008. ergm: a package to fit, simulate and diagnose exponential-family models for networks. J Stat Software 24:nihpa54860.
31. Goodreau SM, Kitts JA, Morris M. 2009. Birds of a feather, or friend of a friend? Using exponential random graph models to investigate adolescent social networks. Demography 46:103–125.
32. Handcock, MS. 2003. Assessing degeneracy in statistical models of social networks. Center for Statistics and the Social Sciences, University of Washington, Tech. Rep. No. 39.
33. Hunter DR, Goodreau SM, Handcock MS. 2008. Goodness of fit of social network models. J Am Stat Assoc 103:248–258.
34. Handcock MS, Hunter DR, Butts CT, Goodreau SM, Morris M. 2008. Statnet: software tools for the representation, visualization, analysis and simulation of network data. J Stat Software 24:1548.
35. Butts CT. 2008. Social network analysis with sna. J statistical software 24:1–51.
36. Butts CT. 2008. Network: a package for managing relational data in R. J Stat Software 24:1–36.
37. Fisher KQ, Sitomer A, Bouwma-Gearhart J, Koretsky M. 2019. Using social network analysis to develop relational expertise for an instructional change initiative. Int J STEM Educ 6:17.
38. Lane AK, Skvoretz J, Ziker JP, Couch BA, Earl B, Lewis JE, McAlpin JD, Prevost LB, Shadle SE, Stains M. 2019. Investigating how faculty social networks and peer influence relate to knowledge and use of evidence-based teaching practices. Int J STEM Educ 6:28.
39. Ma S, Herman GL, West M, Tomkin J, Mestre J. 2019. Studying STEM faculty communities of practice through social network analysis. J Higher Educ 90:773–799.
40. Quardokus K, Henderson C. 2015. Promoting instructional change: using social network analysis to understand the informal structure of academic departments. Higher Educ 70:315–335.
41. Lake PS. 2013. Resistance, resilience and restoration. Ecol Manage Restor 14:20–24.
42. Tugade MM, Fredrickson BL. 2004. Resilient individuals use positive emotions to bounce back from negative emotional experiences. J Pers Soc Psychol 86:320–333.
43. Kendra JM, Wachtendorf T. 2003. Elements of resilience after the World Trade Center disaster: reconstituting New York City's emergency operations centre. Disasters 27:37–53.
44. Southwick SM, Sippel L, Krystal J, Charney D, Mayes L, Pietrzak R. 2016. Why are some individuals more resilient than others: the role of social support. World Psychiatry 15:77–79.
45. Barasa E, Mbau R, Gilson L. 2018. What is resilience and how can it be nurtured? A systematic review of empirical literature on organizational resilience. Int J Health Policy Manag 7:491–503.
46. Aldrich DP, Meyer MA. 2015. Social capital and community resilience. Am Behav Sci 59:254–269.
47. Elmer T, Mepham K, Stadtfeld C. 2020. Students under lockdown: assessing change in students' social networks and mental health during the COVID-19 crisis. PLOS One 15(7):e0236337.
48. Aldrich DP. 2012. Building resilience: social capital in post-disaster recovery. University of Chicago Press.
49. Gittell R, Vidal A. 1998. Community organizing: building social capital as a development strategy. Sage publications.
50. Putnam RD. 2000. Bowling alone: the collapse and revival of American community. Simon and Schuster.
51. Doerfel ML, Chewning LV, Lai C-H. 2013. The evolution of networks and the resilience of interorganizational relationships after disaster. Commun Monogr 80:533–559.
52. Burt RS. 2004. Structural holes and good ideas. Am J Sociol 110:349–399.
53. Gilsing VA, Duysters GM. 2008. Understanding novelty creation in exploration networks—structural and relational embeddedness jointly considered. Technovation 28:693–708.
54. Uzzi B. 2008. A social network's changing statistical properties and the quality of human innovation. J Phys A Math Theor 41:224023.
55. Mason WA, Jones A, Goldstone RL. 2008. Propagation of innovations in networked groups. J Exp Psychol Gen 137:422–433.
56. Rupnow RL, LaDue ND, James NM, Bergan-Roller HE. 2020. A perturbed system: how tenured faculty responded to the COVID-19 shift to remote instruction. J Chem Educ 97:2397–2407.
57. Duchek S. 2020. Organizational resilience: a capability-based conceptualization. Bus Res 13:215–246.
58. Sutcliffe K, Vogus TJ. 2003. Organizing for resilience, p 94–110. *In* Cameron KS, Dutton JE, Quinn RE (ed), Positive organizational scholarship. Berrett-Koehler, San Francisco, CA.
59. Sandi-Urena S, Gatlin T. 2013. Factors contributing to the development of graduate teaching assistant self-image. J Chem Educ 90:1303–1309.
60. Darling AL, Staton AQ. 1989. Socialization of graduate teaching assistants: a case study in an American university. Int J Qualitat Stud Educ 2:221–235.
61. Nasser-Abu Alhija F, Fresko B. 2020. Graduate teaching assistants: motives, difficulties and professional interactions and their relationship to perceived benefits. Higher Educ Res Dev 39:546–560.

62. Wise A. 2011. Supporting future faculty in developing their teaching practices: an exploration of communication networks among graduate teaching assistants. Int J Teach Learn Higher Educ 23:135–149.
63. Castilla EJ. 2008. Gender, race, and meritocracy in organizational careers. Am J Sociol 113:1479–1526.
64. Seibert SE, Kraimer ML, Liden RC. 2001. A Social capital theory of career success. Acad Manage J 44:219–237.
65. van den Brink M, Benschop Y. 2012. Gender practices in the construction of academic excellence: sheep with five legs. Organization 19:507–524.
66. Gilbert JA, Ones DS. 1998. Role of informal integration in career advancement: investigations in plural and multicultural organizations and implications for diversity valuation. Sex Roles 39:685–704.
67. Kegen NV. 2013. Science networks in cutting-edge research institutions: gender homophily and embeddedness in formal and informal networks. Proc Soc Behav Sci 79:62–81.
68. Scully MA. 2002. Confronting errors in the meritocracy. Organization 9:396–401.