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Resilience and fragmentation in healthcare coalitions: The link between resource contributions and centrality in health-related interorganizational networks

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ABSTRACT

Interorganizational coalitions or collaboratives in healthcare are essential to address the health challenges of local communities, particularly during crises such as the Covid-19 pandemic. However, few studies use large-scale data to systematically assess the network structure of these collaboratives and understand their potential to be resilient or fragment in the face of structural changes. This paper analyzes data collected in 2009–2017 about 817 organizations (nodes) in 42 healthcare collaboratives (networks) throughout Florida, the third-largest U.S. state by population, including information about interorganizational ties and organizations’ resource contributions to their coalitions. Social network methods are used to characterize the resilience of these collaboratives, including identification of key players through various centrality metrics, analyses of fragmentation centrality and core/periphery structure, and Exponential Random Graph Models to examine how resource contributions facilitate interorganizational ties. Results show that the most significant resource contributions are made by key players identified through fragmentation centrality and by members of the network core. Departure or removal of these organizations would both strongly disrupt network structure and sever essential resource contributions, undermining the overall resilience of a collaborative. Furthermore, one-third of collaboratives are highly susceptible to disruption if any fragmentation-central organization is removed. More fragmented networks are also associated with poorer health-system outcomes in domains such as education, health policy, and services. ERGMs reveal that two types of resource contributions – community connections and in-kind resource sharing – are especially important to facilitate the formation of interorganizational ties in these coalitions.

Introduction

Achieving health outcomes is thought to be the result of designing effective health strategies utilizing the right building blocks and the right actors, where multiple organizations work towards and share the responsibility for the health and well-being of a community or society. Healthcare systems are central for providing essential health services and facilitating key linkages that support resilient healthcare infrastructure (Wulff et al., 2015). Coalitions or collaboratives among organizations in healthcare systems have become crucial to implementing health policy and addressing health-related challenges in local communities (Provan et al., 2009; Varda et al., 2008). Interorganizational, goal-directed networks address common agendas between public, private, and nonprofit organizations that benefit from a cross-scale, coordinated effort surrounding a public health issue, such as alcohol abuse or child and family wellness (Agranoff, 2006; Chapman and Varda, 2017; Holder, 2002; Prilleltensky and Nelson, 2000). Overarching goals of healthcare collaboratives seek to address a wide variety of social determinants of health in the social fabric that underlies these community health-related challenges – such as equity, access to care, housing, and transportation (Provan and Milward, 1995, 2001; Healthy People, 2020). However, the positive gains from establishing healthcare collaboratives can be endangered by societal crises such as the Covid-19 pandemic, as global and local health support networks face new

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challenges, financial cuts, and increasing health inequalities (across ethnic, gender-based, socioeconomic, and geographic groups). Against this backdrop, understanding the strategic connections between organizations and resources becomes even more important to ensure that available assets are properly mobilized for public health policies and interventions.

The success of healthcare and public health for a community also lies in the extent to which cross-sectoral collaborations and synergies promote resilience for individuals and groups (Cantor and Haller, 2016; King et al., 2021). The adaptability of a community collaborative, and the ability of specific organizations to influence collaborative resilience, are related to how much agency an organization has to manage change in the social, political, and economic dimensions to which the collaborative is exposed (Folke et al., 2010). Although definitions of resilience encompass a vast and multidisciplinary conceptual terrain (Wang et al., 2020), recent studies of “community resilience” have evolved towards an integrated approach that borrows primarily from two strands of research (Berkes and Ross, 2013; Wang et al., 2020): the socio-ecological systems literature, which considers resilience as a collective capacity for response to changes or crises in an evolving environment (Hegney et al., 2008; Steiner and Markantonis, 2014); and the health and disaster response perspective, which understands resilience as a process of continual organization and development wherein a community can become more resilient over time as it faces adversities (Berkes and Ross, 2013).

Traditional resilience-building initiatives focused on preparedness and connecting people to essential infrastructures in times of emergency. Notions of resilience in public health settings have then expanded beyond preparedness towards a deeper integration of health systems, organizational resilience, social connectivity, psychological resilience and at-risk individuals (Wulf et al., 2015). In this context, the social network approach has presented opportunities to model and investigate how resilience can be better achieved for communities by maintaining stability and connectivity between individuals, communities, and systems in a time of crisis. In the health-related literature, however, few studies have used social network analysis to characterize healthcare resilience and investigate the degree to which healthcare collaboratives can withstand changes in structure or loss of resources, ensuring long-term durability.

The current study

Healthcare scorecards have ranked Florida as the third or fourth worst state in the United States according to overall rankings, access and affordability, prevention and treatment, avoidable hospital use and cost, and healthcare disparities, with a declining trend from previous years (McCarthy et al., 2018). In this study, healthcare collaboratives or coalitions are interorganizational, goal-directed networks seeking to address one or more aspects of community health. These collaboratives may be susceptible to fragmentation of communication and exchange channels, which then may impair the flow and employment of essential resources in the network. We analyze the resilience of healthcare collaboratives by examining their interorganizational connectivity, the factors that sustain the formation of ties in these coalitions, and how susceptible the coalitions are to fragmentation and departure of certain organizations. We consider, in particular, the following research questions:

1) Do central actors and key players in healthcare collaborative networks tend to contribute more resources to the coalitions than other organizations?

2) Which types of resource (e.g., funding, information, community relationships, etc.) do central actors contribute most?

3) Which aspects and measures of network centrality better detect the main contributors of resources to the coalitions?

4) What effect do resource contributions have on the probability of tie formation within coalitions? Which types of resources are more strongly associated with an organization’s inclination and ability to form collaborative ties?

Background on social network resilience

Social network analysis (SNA) has long been applied to questions and issues across the public health field (Luke and Harris, 2007; Valente, 2010; Valente and Pitts, 2017). Early insights on what constitutes a resilient social network arise from research on key players in social networks (Borgatti, 2006). Using this concept, Bakker et al. (2012) identified key players within dark or terrorist networks as nodes on which other actors depend for communication or flow of resources through the network. These analyses of resilience relied on replacing or eliminating nodes (social actors) or linkages (channels of resource exchange) and examining effects on the network’s ability to sustain communication or flow (Bakker et al., 2012). Similar methods have been applied to communication networks to understand the roles of personnel when large emergency management institutions face disruption of communication channels and have to reorganize to stay robust (Fitzhugh and Butts, 2021). Other studies have analyzed governance networks to determine what constitutes resilient or adaptive governance (Luhe et al., 2012; Sandstrom and Rova, 2009). Studies in the socio-ecological systems literature describe governance resilience through social network measures such as centralization and network density, showing positive relationships between density and adaptive capacity (Bodin et al., 2016; Luhe et al., 2012; Sandstrom and Carlsson, 2008).

Social network analyses of healthcare collaboratives have been employed to understand the mechanisms which may contribute to improved healthcare processes, for example, by assessing connectivity to determine the efficacy of interactions between partner organizations, or by determining which organizations are most crucial for producing proposed outcomes (Varda et al., 2008). A common mechanism that can contribute to resilience is the transmission of resources, such as funding or ideas, that flow along network paths and, as a result, influence overall network qualities or performance (Borgatti et al., 2009; Courtney et al., 2009). These flows can occur in different amounts and frequencies among organizations within a coalition, thus affecting the collaborative environment and the way it adapts to changes.

Methods

Data and study area

Healthcare collaboratives across the U.S. and Central America have contributed to a social network database – PARTNER (Program to Analyze, Record, and Track Networks to Enhance Relationships) – to assess and evaluate their interorganizational collaborations (Varda and Retrum, 2012; Varda and Spong, 2020). PARTNER is an online survey and analysis tool used to evaluate healthcare organizations’ connectivity, resource exchange, trust, and perceived values in connection with healthcare outcomes. It is one of the most extensive, most systematically collected network datasets for healthcare collaboratives, comprising many types of organizations with relevance to health-related interventions and policies, such as public health departments, schools, local businesses, community organizations, child advocacy groups, and universities.¹

¹ More information about PARTNER can be found on its website (https://visiblenetworklabs.com/partner-cprm/), including information about how to enroll a collaborative for research and evaluation and the origins of the PARTNER tool from initial funding in partnership with the RAND corporation.

This study evaluates a subset of the PARTNER dataset, focusing on
Florida collaboratives which were active between 2009 and 2017 (n = 99 collaboratives). These health-related coalitions self-select to use the PARTNER tool, resulting in a non-probability sample. The data were further subset to collaboratives which reached a minimum threshold of collaboration and communication, specifically a network density greater than 0.1, to only include data that could be subjected to the various analyses in this study. This subset resulted in 42 collaboratives, with 817 nodes (i.e., organizations), and a total of 5543 edges (i.e., collaborative ties). The average collaborative had approximately 20 member organizations (min 5, max 59). Approximately 48 % were public organizations, 46 % were nonprofit organizations, and the remainder were private organizations. Organizational sector types included schools (24 % of organizations, including preschools, k-12 schools, colleges), government (17 %, including local governments, local health departments, state health department, federal government agencies), healthcare (10 %, including private, public, and nonprofit hospitals, health clinics, primary care physicians, community health centers, providers of dental, hospice, or long term care), and a combination of nonprofit organizations, community advocacy organizations, faith-based groups, professional organizations, business groups, regional networks or alliances, and funders. Participating collaboratives were located in 23 counties out of 67 within the state of Florida (Fig. 1).

PARTNER surveys were prepared and sent to coalitions for review. Within our subset of 42 collaboratives, 68 % of member organizations responded, on average (min 37 %, max 100 %). More than two thirds of collaboratives had a response rate of 50% or higher among their members, and over one third of collaboratives had a response rate greater than 75 %. Existing SNA literature has found that some SNA measures are more susceptible to biases with missing data than others, mainly depending on network size, nature of missing data, network measurement, and whether the core actors are missing (Smith, 2017). However, generally, even with high levels of missing data, most network measures can be calculated accurately (Smith and Moody, 2013), and a response rate between 50 % and 70 % is acceptable for reliability of these measures, while a response rate greater than 75 % minimizes negative effects of missing data (Kossinets, 2006). Here, we also included a few collaboratives with a lower response rate, yet as in other studies, the collaboratives with lower than 50 % response rate were found to not significantly alter the results of the study (Retrum et al., 2013).

The questionnaire was proposed as a way to assist in understanding how effective a collaborative is by demonstrating how member organizations are connected, how resources are exchanged, and how outcomes are linked to processes. Collaboratives ranged in the health interventions or health outcomes they addressed (e.g., child obesity, tobacco prevention, mental health, aging population, etc.), so this study is a broad scale analysis of health-related collaboratives irrespective of specific focus area. The networks were constructed as undirected graphs based on a survey where respondents noted the frequency of contact (daily, weekly, monthly, yearly) between their organization and each other organization in the respective coalition. In addition, the survey (Varda and Sprong, 2020; Visible Network Labs, 2009) included the question “Please indicate what your organization/program/department contributes, or is willing to contribute, to the collaborative”. The organizations were offered to supply binary answers for whether the collaborative contributed (1) or did not contribute (0) resources in 11 categories: (1) Funding; (2) In-kind resources (e.g., meeting space); (3) Paid staff; (4) Volunteer staff; (5) Data resources including data sets, collection and analysis; (6) Information and feedback; (7) Specific health

![Fig. 1. Map of Florida counties and the number of collaboratives in each county out of the 42 collaboratives participating in the study.](image-url)
expertise; (8) Expertise other than in health; (9) Community connections; (10) Fiscal management (e.g., acting as fiscal agent); (11) Facilitation/leadership (Table 1).

OpenRefine software (Huynh, 2012) was used to clean the data by identifying similarities in organization name text in the dyads and node tables. This method aimed to identify most data entry errors or inconsistencies resulting from multiple groups and individuals filling out PARTNER surveys and spelling or representing the same organization differently. If any local department or agency stayed distinct—for example, if representatives from two distinct departments of the same organization participated in a collaborative—then their entries stayed separate.

**Identifying key players**

The position of an organization (node) within the collaborative (network) can be described using different centrality measures to quantify the structural significance of that organization to the rest of the coalition. Borgatti and Everett (2020) discuss different notions of centrality that have resulted in various metrics computed on a network. Several of these were used in the current study to understand how resources may be distributed according to these positions and how that may tie back into our definitions of resilience (Table 2).

Key player analyses seek to identify the set of network nodes that is most crucial to diffusion or cohesion in a network by calculating network-level measures of cohesion or fragmentation and then detecting the set of nodes that contributes the most to improvements in these measures (Borgatti, 2006). These methods have been incorporated into the keyplayer R package, which includes eight different measures to calculate centrality for identifying key players (An and Liu, 2016). We seek to apply these concepts to healthcare collaboratives within Florida to identify key players based on five centrality metrics: degree, betweenness, closeness, eigenvector, and fragmentation. The analysis was performed to identify key players within each collaborative.

From these results, the overall resilience of these collaborative networks can be assessed. Furthermore, information about the position of state-wide key players that are most involved at the local level can also be extracted. For regional analysis of key players within each collaborative, each of the 42 collaboratives was subjected to key player algorithms to identify two key players. These methods identify roughly 10% of all organizations or 84 key players (42 × 2) out of the 817 organizations involved.

**Fragmentation centrality and health outcomes**

To further characterize resilience, we calculated fragmentation centrality scores for each organization within each collaborative and reported the minimum and maximum fragmentation centrality scores for the collaborative. Since the key players are identified per collaborative, the key players detected by the fragmentation centrality metric are characterized by the maximum fragmentation centrality possible for each collaborative. We then used a linear model to determine if fragmentation centrality contributes to explaining the coalition’s number of systems-related policy and process outcomes. Organizational respondents chose outcomes from a list of 11 options (Health education services, health literacy, educational resources, Improved Services, Reduction of Health Disparities, Improved Resource Sharing, Increased Knowledge, Sharing New Sources of Data, Community Support Public Awareness Policy law and/or regulation, Improved Health Outcomes, Improved Communication), and each coalition’s mean outcome score was generated from the average responses from within the coalition.

**Core-periphery structure**

The intuitive concept of core/periphery structure is that some organizations are part of a central and cohesive subgroup of well-connected nodes (the core), which are closely connected to each other and more sparsely connected to all other, more marginal nodes (the periphery) (Borgatti and Everett, 2000). The core-periphery structure of each network was investigated to determine which resources the core was contributing and contrast those contributions with those of periphery organizations. The network core was identified as the subset of nodes that shared the maximum number of co-memberships in cliques (complete subgraphs of connected organizations) in each coalition’s network.

**Examining collaborative influence**

To investigate how resource contributions may influence collaborative relationships, we used Exponential Random Graph Models (ERGMs) to move beyond descriptive measures and identify generative processes behind relationship formation within the network (Borgatti et al., 2018; Goodreau et al., 2009). We used ERGMs mainly to understand the healthcare collaboratives observed network structure using a set of covariates: in our case, the node-level binary indicators for which resource contributions an organization made to the network, that we hypothesized as being conducive to formation of ties within the network.

Networks within the healthcare collaboratives have important structural differences from a simple random graph, and, in this study, social forces due to contributing specific resources, like information or funding, to the collaborative are hypothesized to facilitate the formation of ties. Our ERGM models included the 11 covariates using the node-factor term; additional terms were added for edges and geometrically weighted edgewise shared partners (GWESP) (Eq. 1).

\[
\text{Network} = \text{Edges} + \text{nodefactor(Funding)} + \text{nodefactor(In Kind Resources)} + \text{nodefactor(Paid Staff)} + \text{nodefactor(Volunteer and Volunteer Staff)} + \text{nodefactor(Data Resources)} + \text{nodefactor(Info Feedback)} + \text{nodefactor(Specific Health Expertise)} + \text{nodefactor(Community Connections)} + \text{nodefactor(Fiscal Management)} + \text{nodefactor(Facilitation Leadership)} + \text{GWESP}
\]

GWESP is a term to account for triadic closure among affiliated organizations in the collaborative that have ties in common to a third organization, forming a closed triad. The statistical model is interpreted similarly to a binary logistic regression where the connection between the organizations is the outcome, quantifying the extent to which the likelihood of having a tie is associated with contributing each resource; thus, measuring the propensity to establish ties for organizations that contribute each type of resource. All models were run using an MCMC sample size of 80,000 and a burnin of 20,000 in the statnet and ergm packages in R (Hunter et al., 2008).
models with low fragmentation (An and Liu, 2016; Borgatti, 2006). Then, the ERGM models from the collaboratives computing the geodesic distances between other nodes (An and Liu, 2016). According to the fragmentation centrality score, a metric used to describe convergence, mainly through checking the diagnostic trace plots and Geweke Diagnostic. All models were subjected to the goodness of fit diagnostics for model statistics and assessed to fit between the gray lines of diagnostic plots, and by checking p-values for the differences between the observed and simulated network (Supp Fig. 1), following guidelines by Hunter et al., 2008. If models failed to produce MCMC convergence or adequate fit, they were dropped from our results and discussion.

**Model result comparisons**

Finally, each collaborative healthcare network was analyzed according to the fragmentation centrality score; a metric used to describe the extent of fragmentation after a set of nodes are removed by computing the geodesic distances between other nodes (An and Liu, 2016; Borgatti, 2006). Then, the ERGM models from the collaboratives with medium or high fragmentation centrality (>0.8) were compared to models with low fragmentation (<0.8), seeking to find if there were disproportionate resource contributions within the networks of the fragmented vs. non-fragmented models. The final estimated coefficients for resource contributions that contributed to explain tie formation in the networks were compared via a chi-squared test.

**Results**

**Identifying key players within a collaborative**

A total of 84 key players per centrality metric were identified from 42 collaboratives. Key players were grouped, and the proportion of key players out of the 84 that made contributions to the collaboratives was calculated and reported (Table 2). Betweenness centrality was able to identify the maximum number of key players for the funding, fiscal management, and paid staff categories, which indicates that these key players, if removed, would significantly disrupt critical financial resource flows in the collaboratives. Eigenvector centrality did not perform as well as other metrics for identifying significant contributors of resources. Fragmentation centrality was the most influential measure for identifying key players who contributed resources in nearly every category, revealing the highest number of organizations contributing to a single category and the highest proportions of contributions for 9 out of the 11 resource types. Removal of key players identified by fragmentation centrality would disrupt the entire network’s communication capabilities and a significant proportion of resource exchange. For example, 16 key players out of 84 (25 %) identified by fragmentation and betweenness centrality metrics contributed financial resources to the collaborative. Comparatively, 39 organizations contributed funding out of the 817 (4 %) organizations within the entire system of collaboratives within this subset in the study. Overall, through running key players analysis on each of the collaboratives independently, the fragmentation and betweenness centrality measures were able to identify 41% of the financial contributors to healthcare collaboratives, or 16 fundraisers out of the entire statewide pool of 39 organizations who claimed to have contributed funding to the collaborative out of the 817 organizations that were part of the study. We can conclude that many funding contributors were identified through these centrality metrics.

The fragmentation centrality results indicate that nearly one third of our sampled collaboratives (16 out of 42) have a high fragmentation risk (0.90 fragmentation) by removing one or more members - not necessarily key players, but any organization within the collaborative (Table 3). These results show that most organizations have a high fragmentation centrality score, with ten collaboratives having all organizations with a fragmentation centrality score > 0.9, and ten more showing fragmentation centrality between 0.8 and 0.9. The coalitions with highest fragmentation centrality (>0.90) had 20 member organizations on average; the coalitions with fragmentation centrality between 0.80 and 0.9 had 22 organizations in membership; and the coalitions with a fragmentation centrality lower than 0.8 had 20 organizations in membership on average. This metric gives us a good idea of the high fragmentation risk that each of these coalitions faces and suggests a low level of network resilience to the removal or departure of one or more organizations from the collaborative. Since our previous results indicated that the key players identified through fragmentation centrality were often the organizations that contributed the most resources, we can further conclude that most networks in our sample have a high susceptibility to resource loss if fragmentation key players are removed. However, removing any organization within the collaborative will often completely fragment the network, strongly disrupting over one third of the collaboratives.

Furthermore, we attempted to link fragmentation centrality to outcomes by using a generalized linear model to describe the relationship.
between the mean number of outcomes and fragmentation centrality. The results found a significant coefficient of fragmentation to the mean outcomes score, finding a negative coefficient estimate (−0.9041) and a loosely fitting model (p-value = 0.0239, R² = 0.15). From these findings, we can understand that network fragmentation, likely combined with various unknown factors, is associated with achievement of other outcomes by a collaborative.

Identifying core-periphery

While investigating the core-periphery structure of each network, 27 out of 42 coalitions had a sufficient clique structure for core-periphery analysis, as some of the networks were too small to be considered. Within 27 networks, 213 member organizations out of 627 (roughly one third) participated in the maximum number of cliques. The results from core actors were paired with survey results about resource contributions (Table 4). This analysis shows that core organizations are 80% of all those which provide funding and fiscal management, ~70% of those offering paid staff and facilitation leadership, ~60% of members contributing in-kind resources, data resources, and volunteer staff, and ~50% of those transferring expertise other than health, specific health expertise, community connections, and info/feedback. Thus, the 213 core organizations provide a disproportionate amount of resources to the coalitions compared to organizations in the networks’ periphery.

Two conclusions can be drawn from this result. The first is that the resilience of the coalitions is strongly dependent on the core organizations staying within the coalition: where the collaborative were abandoned, it would lose a significant amount of resources. Second, the peripheral organizations are not contributing to the collaborative as much and may be either expendable organizationally or uninvolved compared to other more well-equipped organizations to participate.

Examining collaborative influence

Model selection by AIC identified the best model of 11 contribution categories, having selected models using forward selection and then adding the GWESP term to every model. The ERGM models were estimated on each of the 42 coalitions individually and assessed for GOE and MCMC convergence. Five coalitions were removed for insufficient goodness of fit diagnostics. Finally, 37 models were retained, which also had adequate MCMC convergence.

The community connections variable was significant in most models (67% of all coalitions). This result indicates that organizations within healthcare coalitions are more likely to be connected if they contribute to community connections or are connected to an organization that provides this type of resource. In-kind resources were significant in 62% of the cases. GWESP was significant in 9 (24%) of all models. This result indicates that transitivity affected some of the coalitions, and controlling for this factor yielded significant results in some models. Conversely, financial resources like paid staff (19% of models) and fiscal management (14% of models) were significant in a relatively low percentage of cases, revealing a relatively lower association with the probability of forming ties with other organizations than the other categories of resources.

This study also compared the significance of resource contribution categories for facilitating ties between fragmented (≥0.80 fragmentation centrality score) and non-fragmented networks (<0.80 fragmentation centrality score) (Table 5). The counts of models in which each resource type was significant (i.e., columns “Fragmented” and “Non-Fragmented” in Table 5) were compared between fragmented and non-fragmented coalitions using a Pearson’s chi-squared test and no significant association was found (p-value = 0.2162). In other words, there was no substantial difference in modeled significant resource contribution categories between fragmented and non-fragmented networks. This study could not identify significant drivers for fragmentation by these results, although we could identify the categories that produced the most ties for both fragmented and non-fragmented networks.

Table 3

| Collab | Min | Max | # orgs | Collab | Min | Max | # orgs |
|--------|-----|-----|--------|--------|-----|-----|--------|
| 97     | 0.794 | 0.838 | 25 | 2242  | 0.906 | 0.971 | 9 |
| 1806   | 0.854 | 0.913 | 19 | 2257  | 0.962 | 0.976 | 18 |
| 1807   | 0.671 | 0.728 | 23 | 2258  | 0.759 | 0.980 | 8 |
| 1809   | 0.859 | 0.889 | 56 | 2262  | 0.604 | 0.896 | 12 |
| 1810   | 0.581 | 0.683 | 14 | 2263  | 0.937 | 1.000 | 9 |
| 1811   | 0.900 | 0.943 | 17 | 2469  | 0.705 | 0.924 | 6 |
| 1831   | 0.630 | 0.695 | 17 | 2801  | 0.667 | 0.734 | 22 |
| 1926   | 0.731 | 0.877 | 15 | 2813  | 0.911 | 0.930 | 48 |
| 1927   | 0.600 | 0.667 | 20 | 2818  | 0.579 | 0.779 | 10 |
| 1928   | 0.765 | 0.815 | 23 | 3030  | 0.785 | 0.868 | 23 |
| 1929   | 0.681 | 0.713 | 31 | 3032  | 0.800 | 0.870 | 30 |
| 1930   | 0.404 | 0.581 | 9  | 3045  | 0.597 | 0.691 | 11 |
| 1931   | 0.167 | 0.500 | 5  | 3046  | 0.873 | 0.960 | 30 |
| 1932   | 0.716 | 0.797 | 20 | 3047  | 0.923 | 0.944 | 39 |
| 1934   | 0.711 | 0.795 | 17 | 3048  | 0.528 | 0.643 | 13 |
| 1935   | 0.726 | 0.806 | 18 | 3049  | 0.780 | 0.834 | 25 |
| 1936   | 0.702 | 0.768 | 21 | 3051  | 0.697 | 0.763 | 15 |
| 1937   | 0.749 | 0.837 | 15 | 3053  | 0.803 | 0.859 | 15 |
| 1938   | 0.731 | 0.781 | 26 | 3054  | 0.710 | 0.766 | 21 |
| 2166   | 0.690 | 0.718 | 27 | 3055  | 0.691 | 0.755 | 17 |
| 2240   | 0.881 | 1.000 | 10 | 3176  | 0.722 | 0.753 | 59 |

Table 4

| Question categories | Core orgs. | Total orgs. | Proportion |
|---------------------|------------|-------------|------------|
| 1 Funding           | 24         | 30          | 0.80       |
| 2 In Kind Resources | 101        | 171         | 0.59       |
| 3 Paid Staff         | 41         | 57          | 0.72       |
| 4 Volunteer and Volunteer Staff | 37 | 64 | 0.58 |
| 5 Data Resources    | 55         | 91          | 0.60       |
| 6 Info Feedback      | 126        | 273         | 0.46       |
| 7 Specific Health Expertize | 62 | 112 | 0.55 |
| 8 Expertize Other Than in Health | 66 | 120 | 0.55 |
| 9 Community Connections | 150 | 280 | 0.54 |
| 10 Fiscal Management | 20         | 25          | 0.80       |
| 11 Facilitation Leadership | 78 | 115 | 0.68 |

Table 5

| Variables          | Not fragmented | Fragmented | All models | Percentage of models |
|--------------------|----------------|------------|------------|---------------------|
| Funding            | 6              | 6          | 12         | 0.32                |
| Fiscal Management  | 2              | 3          | 5          | 0.14                |
| Facilitation       | 9              | 4          | 13         | 0.35                |
| Leadership         | 13             | 10         | 23         | 0.62                |
| In Kind Resources  | 13             | 10         | 23         | 0.62                |
| Paid Staff         | 3              | 4          | 7          | 0.19                |
| Volunteer Staff    | 5              | 4          | 9          | 0.24                |
| Data Resources     | 7              | 6          | 13         | 0.35                |
| Info Feedback      | 6              | 9          | 15         | 0.41                |
| Specific Health    | 9              | 7          | 16         | 0.43                |
| Expertize          | 4              | 5          | 9          | 0.24                |
| Expertize other    | 12             | 13         | 25         | 0.68                |
| than Health        |                |            |            |                     |
| Community Connections | 12         | 13         | 25         | 0.68                |
Discussion

The social network analysis approach presented in this paper sought to describe and analyze health-related collaborative networks in Florida in the context of resilience by analyzing key players, the core-periphery structure, and the association between resource contributions and collaborative ties. ERGM to determine susceptibility to fragmentation and loss of resources in these coalitions. Our research questions asked how key players detected from different centrality metrics would contribute to the coalitions. Since each centrality measure identifies key players differently, we can understand whether resource contributions are associated with an organization’s centrality. Our results showed that the loss of key players identified via fragmentation centrality would disrupt the networks’ communication channels and incapacitate significant resource contributions to the coalitions. Our results show that crucial players identified from fragmentation centrality - more than with any other centrality measure - are also significant resource contributors to healthcare coalitions. This result was unexpected, as other centrality measures may have a more meaningful interpretation in terms of resource flows through the network. For example, betweenness centrality refers to flows through shortest paths, and closeness centrality captures ability to reach organizations throughout the network. It appears from the results that the key players contributing the most resources are also the key players leaving the network most susceptible to fragmentation. Although other centrality metrics identified many organizations contributing resources, the key players identified through fragmentation centrality contributed the most resources compared to the other centrality metrics. Furthermore, the healthcare coalitions in this study showed high vulnerability to network fragmentation based on fragmentation centrality scores. Examining information about the most central key players, we sought to understand how substantial the losses would be for crucial resource contributions to the network. The coalitions appear to depend on these key player organizations, which do not necessarily coincide with the most accessible organizations or with key players through the least-cost paths or closeness channels in the network.

Similar to this study, research on collaborative governance in environmental management has discussed the consequences of removing key players and the impacts on idea exchange and decision-making processes on the complexity of the collaborative resulting in a loss of structural integrity. Key player analyses are crucial to understanding the sustainability of healthcare coalitions to be disbanded by removal or departure of certain organizations. Previous studies in the environmental governance literature have attempted to describe resilience through an in-depth discussion of fragmented vs. adaptive governance through policy analyses coupled with social network structural measurements such as density and centrality. Various problems can arise from having a fragmented system of governance. Individuals and outside organizations cannot identify who holds authority over a particular issue, such that regulatory responsibility becomes dispersed, shared, and potentially neglected due to collective mismanagement. Fragmented governance has been defined as allocating responsibility amongst multiple organizations with little to no coordination. It has been a term used in water resources governance literature for example, fragmentation across jurisdictions where multiple organizations share management and lack understanding for regulating a resource that can cause uncertainty. We have applied similar concepts to healthcare resilience to understand what characteristics of network structure produce resilient coalitions. Along with the concept that a fragmented and disjointed governance structure is dysfunctional, the converse, overly centralized governance structure is also shown to be inefficient for several reasons, such as homogeneity of ideas and a reduction in collective abilities for coordination. Similar to previous research about network performance under various network structures, the performance is seen as highest when group closure is high with a leader and dense network of connected people, and surrounded by more loosely connected network members with shared goals and objectives, thus creating bridging social capital. Currently, no guidelines for developing optimal public health collaborative networks exist, although research points to a balance of governance structures and mechanisms. However, evidence and experience suggest that well-connected multiorganizational partnerships are promising mechanisms for improving public health, and identifying and implementing key partnerships can improve the reach of interventions and policies.

In this study, we have also sought to understand the features of the most densely connected, core subgroup within each network. Core-periphery structural analysis was able to identify the most well-connected organizations within each collaborative, resulting in a subset of roughly 33% of all organizations considered to be the core within the coalitions. When combined with information about resource contribution types, the analysis found that these core organizations were responsible for most resource contributions in nearly every category, especially financial resources. The core-periphery results suggest broader regional generalizations about healthcare collaborative structures in Florida as easily fragmentable network arrangements with core players that hold most fiscal and operational resources. Core-periphery analyses can be useful diagnostics for healthcare coalitions to identify less connected members and assess how and which resources they may be able to contribute to the collaborative to better participate in the coalition. This descriptive analysis sought to understand the general structure of healthcare coalitions and how resources were distributed among the core and periphery, finding that core members were participating in the maximum number of cliques and contributing the most resources. Peripheral organizations were not contributing resources or participating to the same extent as core members, which highlights an interesting asymmetry. Future research may seek to further quantify the reach of healthcare coalitions in the broader community or how much effort they are making towards reaching the collaborative goals. These types of network analyses may be able to identify under-resourced organizations to prioritize network integration.

Additionally, questions about whether specific resource contributions facilitate the formation of network ties were addressed in this study. Community connections were the most frequently contributed type of resource, with 62% of all organizations contributing community connections. The majority of the coalitions’ structural weaknesses in this study lead to challenges in developing communication ties with more isolated organizations that are part of the network, as we have shown from the high levels of fragmentation potential within the coalitions. The results from ERGM models did not suggest that the players within the network that contributed financial or material resources were necessarily the most well connected, nor did those resources promote more ties to other organizations. We were also unable to identify significant differences between fragmented and non-fragmented coalitions in the significance of resource contributions for forming ties in the ERGM models. Organizations that contributed the most community connections and in-kind resources were driving the formation of ties within healthcare coalitions. This finding expands the state-society synergistic idea that government and mobilized communities can support relations to increase organizations’ social capital. These results add further complexity, revealing that the most networked organizations, with the probability of having many collaborations, were often contributing non-financial resources to their coalitions. They also highlight what more networked and involved organizations are contributing, which less integrated organizations may consider.

Aside from investigating resilience and network structure, there was an attempt at associating fragmentation centrality to the mean outcomes score of the coalitions, whereby the coalitions had indicated the
number of outcomes associated with the coalition. We found that reporting fewer outcomes was associated with higher fragmentation centrality in a coalition. Previous studies have attempted to link network effectiveness and outcomes, for example Provan and Milward (1995) assessed public health network effectiveness using surveys about the community perceptions towards the collaboratives paired with network structure and network context quantitative information. Provan et al. (2009) used longitudinal healthcare network data to demonstrate that network’s agency and well-established “embeddedness” is positively related to perceived key social outcomes like trustworthiness, reputation and influence within the community. Fujimoto et al. (2009) looked at coalition networks for substance abuse prevention to study how program adoption outcomes were associated with centralization or decentralization of advice networks. More research from specific case studies that tightly couple perceptions of health outcomes and improved policy changes from the collaborative with network structures would qualify these results further.

This study presents a comprehensive analysis of Florida healthcare collaborative networks and provides a comprehensive evaluation of what may be contributing to network resilience and where there is susceptibility to fragmentation. We were able to understand how key players contribute resources mainly from fragmentation centrality, indicating that the key players contributing the most resources are those making coalitions susceptible to fragmentation, and not the most well-connected or between-central organizations within collaboratives. Coalitions more susceptible to fragmentation were also those associated with fewer outcomes. Similarly, the core-periphery descriptive analysis identified organizations with high degree of clique membership as also contributing most of the resources. These results indicate that a small subset of the most well-connected organizations is mainly responsible for the functioning of collaboratives, while peripheral organizations appear to contribute resources in less than 20% of the cases. Furthermore, ERGM analysis concluded that the collaboratives mainly formed ties around organizations contributing community connections and kind resources such as skills and services, which are both social and non-monetary forms of contributions.

Conclusions

This analysis provided insights into the resilience of health-related interorganizational coalitions in Florida. Concepts of resilience and adaptive governance were addressed by analyzing network structure and performance. Overall, one third of coalitions were highly susceptible to fragmentation if any organization was removed from the collaborator, suggesting low levels of resilience in the face of structural changes. Not surprisingly, high levels of fragmentation were associated with achievement of fewer health system outcomes such as education, policy changes, and improved services. This study provides significant evidence that there is a high vulnerability to fragmentation of networks and resource flows within healthcare collaboratives, limiting attainment of health-related outcomes. The network structure that underlies communication and exchange in the collaboratives was based on exchange of human resources, information or services; however, the removal of one or more members of the network could result in high levels of fragmentation, and if key players were to be removed, the collaboratives would suffer substantial resource loss. Overall, this study was able to identify factors for relationship formation and examine the consequences of losing a key playerorganization from the collaborative, suggesting that Florida health coalitions are characterized by low resilience to structural changes.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2022.07.004.

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