

How Network Analysis Can Help Understand Relationships in a Resource Ecosystem

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Background

When we hear of social network analysis, we typically think of interwoven graphs that show us individuals connected through quantitative features of their relationships — who retweets whom, for example, how news articles spread online, or how many text messages are sent from person to person. Network theory¹ and social network analysis (SNA) are the concepts that undergird those web-like graphs — they are a strategy for investigating social structures, and they can be used for much more than online information patterns. SNA has been used in public health contexts, typically measuring how health information or behaviors can spread among individuals.^{2,3,4}

Increasingly, collaboratives, coalitions, and other groups of organizations are examining their relationships and communications and learning how to better work together.^{5,6,7,8} SNA can be a valuable tool to learn about how governance structures, communication channels, and trust between member organizations make it easier to work towards a shared goal, like improved community health or narrowing gaps in racial health inequities. Applying network theory encourages us to ask the big-picture questions: Does a network in which data flows freely between organizations foster trust, and thus willingness to share data and collaborate? Do participants rate their network as more efficient when it is managed by a backbone organization? SNA methods can help us conceptualize resource databases and community information exchanges not only as data collection and record-keeping tools, but also as living networks working towards a shared aim of improved community health and resilience.

Resource Referral Programs and SNAs

There have been applications of SNA methods applied to an essential needs referral platform.⁹ Within such a platform, a network of organizations or individuals — such as community health workers or promotoras — refers patients to resources within its central database. Resources aren't just places where patients can pick up food or clothing, for example. Community resources are carefully stewarded by people who make up organizations that specialize in direct services, resource distribution, and advocacy. By virtue of having information about a community resource in a database, there already exists a formal connection from a referring organization to a resource. However, based on our own analysis ([Best Practices: Using Social Determinants Of Health Resource And Referral Data To Increase Equitable Access And Connection Rates To Essential Resources](#)), we know that there is a large range in the strength of these relationships. Many resources never receive a referral, while a few resources receive a large number of referrals.

Though only one example of an essential needs referral platform, Health Leads' program model has already been evaluated for its impact on patient clinical outcomes.¹⁰ For seven years, Health Leads supported in-clinic and CBO workforces, including volunteers and staff, to support patients as they completed a standardized screening form. These forms created space for patients to self-identify unmet needs related to food, medications, transportation, utilities, employment, elder care services, and housing. Patients who choose to enroll in the program are referred to appropriate community resources and/or public benefits, with facilitation from the volunteer case manager.

Reach is a platform through which users (staff or volunteers) made referrals and recorded the outcomes of their referrals, as well as the database of resources to which they made referrals. Though it is specific in some of its features, it serves as a case study and proxy for similar platforms in the sector that provide the ability to track resource and referral activities as well as case management.

Our Social Network Analysis

The purpose of our analysis was to understand the state of the overall network of Reach referral hubs (referred to as desks) and resources, including the number and distribution of actors involved, the number of relationships formed through referrals, the strength of those relationships, and how the network changed over time.

DESIGNING A NEW PROXY FOR RELATIONSHIP STRENGTH

Measurement of referral networks tends to hinge on the assumption that overall success of a resource can be measured by: **1) how often it receives a referral**, and **2) the percent of successful connections it makes**. It follows then that these would be the typical proxies for the strength of relationships within a network.

However, people with firsthand knowledge administering resource referral programs have suggested that the trust and familiarity that exists between case managers and resource staff is the true strength of the network. While we are conceptualizing our program model as a network of organizations, it is the people at those organizations — the case managers, promotoras, and community health workers — who care for their patients and connect them to the resources they need.

With this consideration in mind, we hypothesized that a case manager who is familiar with a community resource and has personal connections to the staff there would be more inclined to refer their patients there. Thus, we set out to test a new proxy for strength of relationship — the degree to which resource fields (contact information, details on what to bring etc.) are completed by gathering and verifying information directly from resource staff.

With this new variable, we ask our first question: **does the degree to which a resource has completed information fields correspond to the typical measures of resource network strength (# of referrals and % successful referrals)?**



NETWORK STRUCTURE OVER TIME

As Reach has been in use from 2014 to 2021, the shape of the network it encapsulates has changed over the years not only in response to changes in Health Leads' strategies, but to the natural growth and contraction of the number of referring organizations, and to external events. The onset of the COVID-19 pandemic in 2020 strained an already-fragile system of essential needs as the United States continues to face soaring rates of illness, unemployment, and economic precarity. These overlapping crises have exacerbated existing inequities: Black, Indigenous, and Latinx people have been more likely to get sick and die of COVID,¹¹ and women in the US experienced heavy job loss and took on more caregiving duties.¹²

Because Reach has been in use throughout the pandemic and has continued to facilitate connections to community resources, examining the way the network has changed over the past year could aid in understanding how similar networks respond to crises, and how we might strengthen collaborative networks to better serve communities during the pandemic. This led us to our second research question: **has the overall shape and structure of the network changed pre and post COVID-19?**

Conceptual Diagrams

To better understand the resource network strength and network structure over time, we chose to analyze all Reach desks in Contra Costa County, CA. Only resources that received at least one referral between 2019 and 2021 were included in the statistical analysis, but for the time interval network animation, all resources were included. Visit the [Reach Network Analysis Visualizations](#) website for a visual representation of our analysis.

EDGE WEIGHTS

A referral from a Reach desk to a resource is represented by a grey line. The more referrals that have occurred, the greater the edge weight.

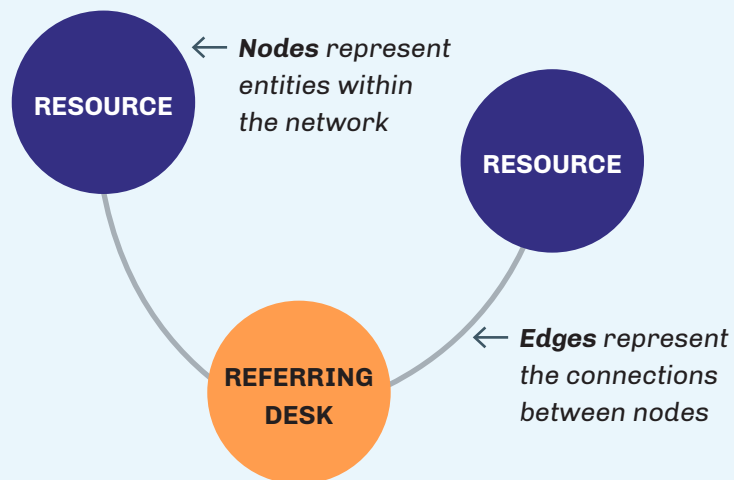
NODE COLOR

We selected what we believed to be the data fields that, if filled out, best represented how close a relationship we had with a given resource. These fields included phone number, website, materials to bring, eligibility

criteria, target population, and further instructions on how to access the service. Our "degree of contact information completeness" variable is the percent of these fields which were not missing. Resources are colored in a blue gradient, with the darkest blue reflecting a resource that has all the information completely filled.

NODE SIZE

The in-degree of each resource is represented by its size. In-degree describes the number of *different* resources that have made referrals to that resource. For example, a resource that has only ever received referrals from one Reach desk has an in-degree of one, while a resource that has received referrals from six different desks has an in-degree of six.





We first created the open order network layout, as its algorithm is designed to distinguish clusters,¹³ which by nature our network has. It was difficult to observe any clear relationship between contact information completeness and in-degree or strength of referrals with this layout. In fact, we noticed that some of the resources with the highest in-degree and that have received the most referrals had rather low contact completeness scores. For example, the Transportation Service at Contra Costa Health Plan resource has both an in-degree and a contact completeness score of four (both variables have maximums of six). To be able to better visualize these variables as they might relate to each other, we then produced a bipartite network, separating desks (orange nodes) from resources (blue nodes), and ordering resources from left to right by their degree of contact information completeness. Again, there did not appear to be a strong correlation between completeness of contact information and number of referrals. Upon further inspection, resources with the highest number of referrals are nearly all MediCal enrollment services.

In conversation with people closer to program design, these results which might seem surprising at first actually make perfect sense. If a patient screens positive for an unmet food need, there are many different food pantries that their advocate could potentially refer them to; conversely, if a patient needs assistance enrolling in MediCal, there is only one referral option. It does not matter if we know a particular staff person at the MediCal office or what hours they tend to be in office — every patient that needs MediCal is referred to MediCal. Furthermore, we often don't have personal relationships with the large government agencies in the way that we do with smaller, local CBOs.

Our observations from viewing the networks are supported by the numbers. **Contact information completeness is significantly, but weakly, negatively correlated with the number of referrals a resource receives. However there is no significant correlation between contact information completeness and rate of successful referrals** (the number of referrals closed as 'success' divided by the total number of referrals). While this contradicts our initial hypothesis that the two measures would be correlated, it makes sense. According to our Reach administrators, many of the community health workers in Contra Costa County used Reach for its case management functions, but did not rely on it as a primary source of information on community resources — they already had deep knowledge of the resources and services in their communities. The familiarity and trust among local organizations was there, but not necessarily reflected in the amount of contact information we stored in Reach for those resources.

TABLE 1 – CORRELATION CROSS-TABULATION OF NODE ATTRIBUTES

Pearson Correlation Coefficients, N = 275

Prob > |r| under H0: Rho=0

	# Successful referrals	Rate of successful referrals	Contact completeness score	In-degree
# Referrals	0.89	0.32	-0.13	0.57
# Successful referrals		0.45	-0.15	0.53
Rate of successful referrals			-0.06	0.25
Contact completeness score				-0.12

Correlations with $p \leq 0.05$ are bolded

To examine the change of the network over time, we created a network visualization animation. There is no notable, visible change in network structure or density pre and post 2020. Again, upon discussion with people closer to program design and implementation, this makes sense. Through this process of co-interpretation, we found that programmatic decisions and internal changes at Health Leads were better explanatory factors for network changes than any external event. The network expanded over time, in accordance with expanding use of our Reach platform, then plateaued as we slowed down adding new desks or resources. As we approach the present day, the velocity and number of referrals slows down, which corresponds to our gradual sunseting of the Reach application. Thus both of our research questions are answered similarly — network characteristics are better explained by asking someone with firsthand knowledge of running Reach why it looks the way it looks, than they are by outside influences.

Conclusion

Degree of contact information completeness may not be a useful variable with which to measure network strength, but we know that having personal relationships between staff of organizations within a resource referral network is valuable for building trust among network participants. Though rates of successful resource referrals were also independent of contact information completeness in our analysis, it is likely that familiarity between a case manager and resource staff would result in smoother referrals, and thus better patient experiences.



This analysis is just the beginning of a series of analyses, but beginnings are perhaps the best time to share openly with others who are attempting to set the course for public health collaborative design and learn from emerging practices. In that vein, we hope this study highlights how network analyses and other methodologies could help us understand racial health equity work among resource ecosystems, in both content and process.

Here are a few key principles for what diversity, equity, and inclusion (DEI) can look like in the world of analytics:

1 ANCHOR THE ANALYSIS WITH PEOPLE WHO HAVE FIRST-HAND EXPERIENCE OF THE PROGRAM OR ISSUE AT HAND.

If we hadn't shared our initial results with our resource database administrators, we could have mistaken a resource with low edge weights or in-degrees as "underperforming." With misinterpretations like that, important CBO's are at risk of losing funding. To further root network analysis into DEI principles, an even more inclusive process, with a wider range of represented perspectives, is necessary. Discussions with patients who have received referrals they found meaningful, as well as patients who did not, could reveal a much more nuanced understanding of why referrals do and don't work.

2 CONSIDER INNOVATIVE MEASURES

Without input from our program staff, we would not have honed in on the importance of personal relationships between community health workers and may have charged forward using only traditional key performance indicators (KPIs) to measure network strength. It's tempting to stick with variables that are easily quantifiable and familiar, like number of referrals or percent of successful referrals. Testing out a different approach sparked discussions of the value of community health workers' labor, the depth of their knowledge, and the limitations of tech-enabled data-sharing solutions.

3 DON'T INTERPRET RESULTS IN A VACUUM

For an extreme example of data interpreted in a vacuum — imagine that we share the results of our time-interval analysis with decision-makers who conclude that our community resources have been doing just fine during the pandemic, and as a result, decide that funding levels will remain the same. We embrace the trend towards data-driven decision making, but will continue to stress that inclusivity during scoping and interpretation phases are essential to conducting thoughtful, meaningful data analysis. A next step towards understanding the experiences of network organizations during 2020 and beyond might involve analysis of a referral program that continued at full capacity throughout the pandemic.

Future Directions

Network visualizations, even without an accompanying statistical analysis, can be useful for understanding governance structures and information flow between organizations. Community information exchanges (CIEs), health information exchanges (HIEs), and other similar types of networks are cropping up around the United States and are often proposed as ways to foster cross-sector collaboration. They typically involve data-sharing agreements between partners, sometimes facilitated by a shared technology platform. Does willingness to adopt such a platform and share health information with network members hinge upon personal familiarity among staff members? Does one organization's participation in the network dissuade patients from sharing their personal data? Answers to these questions would necessitate the combination of qualitative and quantitative data, but the analyses could teach us valuable lessons on how we can work better together.

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ABOUT HEALTH LEADS

Health Leads is a national non-profit organization working toward a vision of health, well-being and dignity for every person in every community. For over two decades, we've worked closely with hospitals and clinics to connect people to essentials like food, housing and transportation alongside medical care.

Today, we're partnering with local organizations and communities to address systemic causes of inequity and disease — removing the barriers that keep people from identifying, accessing and choosing the resources everyone needs to be healthy.

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