Healthcare Network Analysis of Patients With Diabetes and Their Physicians

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ABSTRACT

OBJECTIVES: To illustrate methods using administrative data on patients with diabetes that can offer a foundation for using network analyses in managed care.

STUDY DESIGN: The study used an administrative claims database to analyze patients with diabetes in a large health plan in Hawaii in 2010.

METHODS: The networks were explored graphically and analyzed at several levels of complexity. Levels ranged from major components comprising the majority in the networks to smaller, highly connected cliques to communities of patients and physicians grouped by a network algorithm. The attributes of patients linked by seeing the same primary physicians were evaluated using an exponential random graph model that predicted links in the network.

RESULTS: The study included 41,941 patients with diabetes of Native Hawaiian (16.3%), Filipino (14.2%), Japanese (46.7%), white (11.2%), and other (11.6%) ethnicity. About half were 65 years or older. When examined by Hawaiian island of residence, at least 95% of patients and at least 78% of physicians belonged to loosely connected major components within a network. Smaller communities of patients, identified by being closely linked together, averaged 150 to 177 patients; communities of physicians averaged 3 to 8 physicians. The average numbers of patients sharing physicians and physicians sharing patients were greater on the island of Oahu than on the rural neighboring islands. Patients of the same ethnicity were significantly more likely to share the same primary physician.

CONCLUSIONS: Network analyses reveal structures and links that health plans could leverage to strengthen quality improvement and disease management programs.

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Network analyses examine the structure of human connections, such as those between friends at school, workers in jobs, and individuals on the internet, as well as inanimate connections, such as proteins at the cellular level. Healthcare networks have also attracted network analysts. Researchers have studied physicians sharing patients, patient satisfaction, healthcare teams, and networks of physicians providing hospital care.[1-5] Network analysis offers a method to understand and manage healthcare. The analyses can reveal hidden structures that are distinct from formal structures, such as physician groups. The analyses can identify patients who might be best managed together and physicians who might lead in healthcare interventions. The results of network analyses can complement and extend more traditional healthcare analyses.

Administrative claims are a ready source of network analysis data. Patient links to physicians they share, as well as links between physicians caring for the same patients, define the networks. Physicians acknowledge that they share the patients found in administrative data, although recognition is higher among primary care physicians than among specialists.[6] A national study of Medicare patients compared physician sharing across the networks of 528 hospitals[7] and found that the higher the median number of links a physician had with other physicians, the higher the total costs and the number of hospital days. By contrast, the more centralized the network of primary care physicians, the fewer the specialist visits and the lower the spending on imaging and tests. A more recent study of physicians sharing patients for distinct episodes of care confirmed the findings.[8] These studies revealed that healthcare networks can influence health outcomes in both positive and negative ways.

A network analysis of 85 hospitals caring for patients having hip replacement placed the physicians into distinct groups called communities based on strong interconnections.[9] Hospitals averaged 4.25 communities in each physician collaboration network, and hospitals with more communities had lower readmission rates. Another study compared 2 hospital referral regions varying in the evidence-based use of cardioverter defibrillators (86% and 66%).[10]

Differences in network structure helped explain the differences in adherence to the clinical guidelines between the referral regions.

Other studies have analyzed claims data from private insurers or using electronic health records. A study of patients with congestive heart failure and diabetes developed a metric called "care density" that measures how often providers share patients with one another.[11] For both chronic conditions, patients in the highest tertile of care density had significantly lower costs and reduced rates of hospitalizations compared with patients in the lowest tertile. A second study created a criterion called the "shared positive outcome ratio"[12] and found that the patients of pairs of providers with greater ratios reported higher satisfaction with their care. A third study, however, provides a cautionary note: The study reported that among providers sharing patients, 54% shared only a single patient and just 19% shared 2.[13] Patient sharing in healthcare may often not occur.

In this paper, we illustrate methods of network analysis by examining connections among patients with diabetes in Hawaii, the physicians they shared, and the physicians caring for the same patients. We describe how identifying structures of differing complexity can help a health plan understand the networks it manages. The analyses investigate direct links and broader communities, as well as examine demographic and other influences that help explain the connections. This article illustrates methods using administrative data on patients with diabetes that can offer a foundation for using network analyses in managed care.

TAKEAWAY POINTS

Network analysis of administrative data can reveal hidden structures—clusters of patients and physicians—that offer targets for interventions. Our study of patients with diabetes in Hawaii highlights the strengths and flexibility of network analysis for managed care. Analyzing the structure of local networks can lead to enhanced strategies for disease management to improve health quality and outcomes.

- Network analyses can identify patients sharing doctors and doctors sharing patients, and they can uncover factors associated with network ties.
- Network analysis can be done with free, open-source software.
- Understanding patient links in administrative data could lead to more patient-centered care.

METHODS

Study Population

The study population was 41,941 patients with diabetes who belonged to a large insurer in Hawaii in 2010.[14] The diagnosis was based on criteria from the Healthcare Effectiveness Data and Information Set.

Study Variables

Patient characteristics included demographic variables, chronic diseases, and island of residence. Age was categorized as being either younger than 65 years or aged at least 65 years, and sex as male or female. Ethnicities were Native Hawaiian, Filipino, Japanese, white, and other ethnicity as self-reported on member satisfaction surveys.[14] Residence was examined by island of residence (Oahu, Kauai, Maui, or Hawaii) and by comparing the most populous island of Oahu with the other, more rural neighboring islands. The major chronic diseases comorbid with diabetes were coronary artery disease (CAD), congestive heart failure (CHF), and chronic kidney disease (CKD). Physician visits were defined as visits to primary care providers (ie, internal medicine, general practice, family practice physicians) and to specialists (ie, cardiologists, endocrinologists).

Network Analysis

The network of patients and providers is bipartite, meaning that it consists of 2 separate sets of connections: patients who see the same physicians and physicians who care for the same patients. There are no connections between individuals within a set (patients to other patients or physicians to other physicians). This paper analyzes both sets of relationships. The network structures are summarized using 5 metrics: components, degree, cliques, communities, and betweenness centrality.

Components are fully connected structures; everyone in a component has 1 or more direct or indirect paths to everyone else. Components are often large. Components are not connected to one another.

An individual's degree is their number of direct connections to others in the network. As an example, for a physician, degree is the number of patients they treat. Patients have 2 sets of degrees: 1 from their connections to all other patients seeing the same physicians and 1 based on connections to patients having the same primary physician.

Cliques are based on direct links between individuals; they are maximal subgraphs in the sense that a clique is not a subset of a larger clique and every pair in a clique is connected. Cliques are typically smaller than components because they require direct connections within the clique. A person can belong to multiple cliques. For the analyses, we selected the largest clique to which a person belonged.

Communities are identified by algorithms that divide a network into groups that are more densely connected internally than to other groups. Communities can range widely in size but are mutually exclusive: A person belongs to a single community. We used an algorithm called "fast greedy" to find patient and physician communities.[15] The fast greedy algorithm maximizes a measure called modularity that assesses the strength of the community networks. Modularity ranges from –0.5 to 1; if positive, connections within communities exceed that expected by chance.

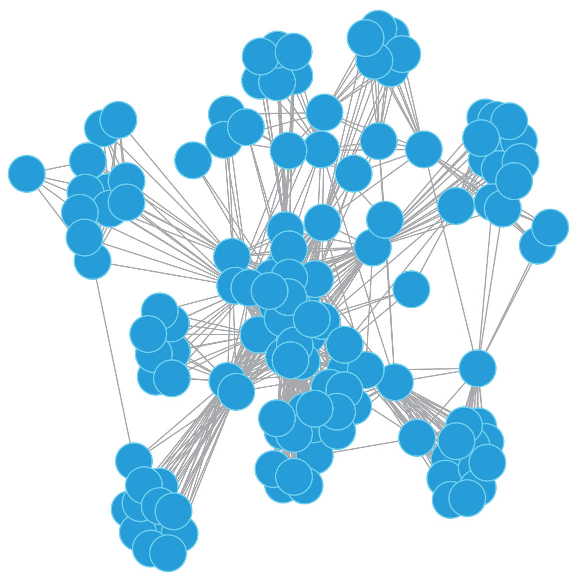
Betweenness centrality is a measure of how central an individual is in a network, or to what extent the shortest connections between others in a network pass through them.

Network analyses were performed with the igraph and statnet packages within R version 3.4.2.[16,17]

TABLE 1. Characteristics of the Study Participants

Characteristic	n (%)
Aged ≥65 years	20,077 (47.9)
Female	20,608 (49.1)
Ethnicity	
Filipino	2542 (14.2)
Native Hawaiian	2919 (16.3)
Japanese	8350 (46.7)
White	2009 (11.2)
Other	2070 (11.6)
Residence on Oahu	29,931 (71.4)
Coronary artery disease	9324 (22.2)
Congestive heart failure	3846 (9.2)
Chronic kidney disease	2378 (5.7)

FIGURE 1. Network of Patients in the Major Component of the Island of Kauai Who Were Connected by Sharing Physicians[a]



[a]The circles represent patients and the lines connect patients sharing physicians.

Statistical Analysis

Characteristics of the patients were summarized by descriptive statistics. The distributions of the network metrics were skewed and so are summarized by medians with 25th and 75th percentiles. Differences between Oahu and its neighboring islands were compared using the Wilcoxon rank sum test. Regression analyses employed an exponential random graph model (ERGM).[18] The outcome for the ERGMs was patients seeing the same primary physician, defined as the physician seen the most often or, in case of ties, most recently. ERGMs offer flexibility in incorporating regression predictors. Terms can be entered as comparisons (eg, are patients with CAD connected more often than those without CAD?) or as homophily, meaning comparisons based on similarities (eg, are Japanese patients more often linked to other Japanese patients?). Results are presented as odds ratios (ORs) with 95% CIs.

The University of Hawaii Institutional Review Board granted the study exempt status.

RESULTS

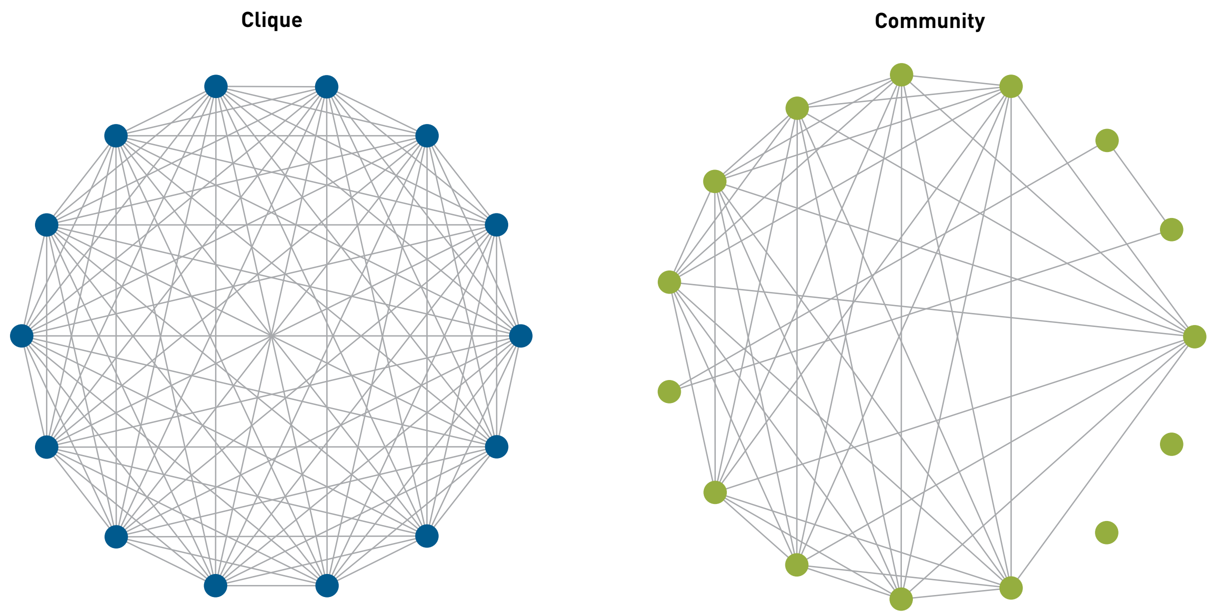
The study includes 41,941 patients with diabetes and the 1003 doctors who treated them. A little less than half of patients were 65 years or older, and 71.4% resided on Oahu, the most urban island in Hawaii (**Table 1**). The percentages of men and women were about equal. The most common ethnicity was Japanese (46.7%), followed by Native Hawaiian (16.3%), Filipino (14.2%), other ethnicities (11.6%), and white (11.2%). In terms of comorbidities, 22.2% of the patients had CAD, 9.2% had CHF, and 5.7% had CKD. The mean (SD) numbers of visits to primary care physicians and specialists were 1.27 (0.87) and 0.27 (0.76), respectively.

A primary aim of our study was to illustrate structures that can be identified in healthcare networks by examining networks in Hawaii; several network structures are illustrated in **Figures 1** and **2**. Both patient and physician networks were highly interconnected on the major Hawaiian islands, forming "giant" components with more than 95% of the respective populations. Figure 1 presents the component of patients living on the island of Kauai. The percentages of patients in the largest components were 99.8%, 98.9%, 98.7%, and 98.2% for the islands of Oahu, Maui, Kauai, and Hawaii, respectively. For physicians, the percentages in the largest components were 94.2%, 80.8%, 78.2%, and 77.7%, respectively.

Figure 2 provides examples of a clique and a community, which are smaller structures based on links between patients. The left panel illustrates that a clique is a maximally connected subgraph. The people in the clique are all linked to one another. The community on the right provides a contrast to the clique. Communities are identified based on the similarity of connections; not everyone in a community is necessarily connected to all the others. Modularity offers a measure of the extent to which the populations form communities on the Hawaii islands. Modularity was 0.61, 0.46, 0.59, and 0.56 for patients on the islands of Oahu, Maui, Kauai, and Hawaii, respectively. For physicians, modularity was 0.47, 0.34, 0.36, and 0.48, respectively.

Oahu and the neighboring islands were also compared on network measures based on individual patient and physician connections (**Table 2**). Communities of patients included a median of 150 to 177 patients, and communities of physicians included 3 to 8 physicians. Communities of patients and physicians were larger, on average, than the respective cliques. The median degree (ie, the number of links) between patients seeing the same physicians was greater on Oahu than on neighboring islands (195 vs 175), as was the median number of patients seeing the same primary physician (143 vs 126). The centrality of physicians was highly skewed toward high values and substantially greater on Oahu than on neighboring islands.

FIGURE 2. Examples of a Clique and a Community From the Network of Hawaii Patients With Diabetes[a]



[a]The circles represent patients and the lines connect patients sharing physicians.

Patients seeing the same primary physicians were analyzed in greater detail using an ERGM (**Table 3**). Patients of the same ethnicity were more likely to share primary physicians. The ORs for sharing a primary physician with patients of the same ethnicity versus patients of other ethnicities ranged from 1.26 for Native Hawaiians to 1.82 for Japanese. Other tests for network links based on having similar characteristics were statistically significant, but the ORs were smaller. Patients 65 years or older were more likely to see the same primary physicians, and men and women tended to share physicians with others of the same sex. The more physicians the patients saw, the less often they shared the same primary physician. Patients with CAD and CKD were more likely to see the same physicians than those without the conditions. Residents of neighboring islands less often shared the same primary care physicians than residents of Oahu.

DISCUSSION

Our results show that network analysis can uncover the underlying structures of healthcare networks, which are often invisible to those managing care. In Hawaii, the healthcare plan consists of highly connected networks both of patients seeing the same doctors and of doctors caring for the same patients. Network algorithms uncover subgroups that potentially could be managed together, ranging from clusters of directly connected patients or doctors to larger communities that include indirect connections. Healthcare interventions might be stratified based on the composition and quality of network structures.

Links between patients can result from sharing the same physicians, as we demonstrated for the patients sharing the physicians they saw most often. The strongest associations were by ethnicity: Native Hawaiian, Filipino, Japanese, and white patients all tended to share physicians with other patients of the same ethnicity. Similarities in older age, sex, and having CAD or CKD also helped identify patients seeing the same primary physicians. Patients seeing a higher number of primary care physicians were less likely to be connected. Health plans might use such information to understand how to best coordinate care or deliver culturally appropriate interventions.

Another study examined the similarity of patients among physician panels using national Medicare data.[19] Physician panels were similar by race/ethnicity for white, black, and Hispanic patients and alike in the mean health status of the patients treated. Physician sharing was greater when the distance between offices was shorter.

We observed in Hawaii that the structure of healthcare networks varied geographically. On the more rural neighboring islands, communities of patients and physicians were smaller and the degree (ie, the number of links) in the networks was fewer. For the physician networks, centrality was appreciably greater on Oahu than on neighboring islands. Leveraging the central individuals in networks by using them as opinion leaders to promote behaviors to change social norms has proven success for healthcare interventions.[20,21] Physicians with the highest centrality can be prominent in their networks and might be recruited to spearhead physician interventions.

TABLE 2. Characteristics of the Networks of Patients Seeing the Same Physicians and Physicians Caring for the Same Patients[a]

Network	Characteristic	Median (25th, 75th Percentile)		P
		Oahu	Neighboring Islands	
Patient	Patients in communities	177 (76, 835)	150 (102, 401)	.70
	Degree (all physicians)	195 (124, 370)	175 (100, 293)	<.001
	Degree (primary physician)	143 (85, 224)	126 (64, 187)	<.001
	Size of largest clique	85 (9, 165)	127 (49, 188)	<.001
Physician	Physicians in communities	8 (2, 42)	3 (2, 9)	.11
	Degree (all shared patients)	15 (4, 32)	3 (1, 10)	<.001
	Betweenness centrality	132 (5, 579)	5 (0, 175)	<.001
	Size of largest clique	6 (4, 7)	4 (2, 6)	<.001

[a]Communities are groups of patients or physicians more similar to others in the community than to those outside. Degrees give the number of direct connections, such as the number of patients a physician treats. Cliques are fully connected subgroups; every pair in a clique is connected. Betweenness centrality measures the tendency to be on the paths between others in the network.

TABLE 3. ORs (95% CIs) of Seeing the Same Primary Physician by Patient Characteristics[a,b]

Patient Characteristic	OR (95% CI)
Link to similar others (homophily)	
Aged <65 years	1.03 (1.02-1.04)
Aged ≥65 years	1.12 (1.11-1.12)
Female	1.02 (1.02-1.03)
Male	1.02 (1.02-1.03)
Filipino	1.80 (1.77-1.82)
Native Hawaiian	1.26 (1.24-1.28)
Japanese	1.82 (1.81-1.83)
White	1.51 (1.48-1.54)
Other	1.15 (1.13-1.18)
Difference per physician seen	
Primary care physician	0.91 (0.91-0.91)
Specialist	1.04 (1.04-1.04)
Comparison with reference category	
Residence on neighboring island	0.89 (0.88-0.89)
Coronary artery disease	1.14 (1.14-1.14)
Congestive heart failure	0.93 (0.92-0.93)
Chronic kidney disease	1.13 (1.13-1.14)

OR indicates odds ratio.

[a]The results summarize 3 types of relations: being connected in the network to similar others (eg, others of the same ethnicity), differences in the odds of being connected per unit difference (eg, per additional physician seen), and odds of being connected based on group differences (eg, living on Oahu vs on a neighboring island).

[b]All the ORs were highly statistically significant (*P* <.001).

The methods we applied for network analysis have been used in other healthcare studies. The most frequent approach, as we employed, analyzes the networks of patients sharing physicians and physicians sharing patients as separate networks.[6,7,9,10,19,22-24] This approach simplifies the analyses and interpretation of results and provides insight into both patient and physician relationships. Other healthcare studies have also employed ERGMs, the regression method used here.[10] ERGMs are like other regression models in that they can include multiple predictors of an outcome; however, with ERGMs, the outcome is being connected in network rather than incurring an outcome such as having an adverse event. The goal of ERGMs is to explain the network structure.

Limitations

Our study should be interpreted with respect to its limitations. The results are for the members of 1 large insurer in a single state that has a distinct, multiethnic population. The study is exploratory in nature; the cross-sectional design limits the breadth of the conclusions. Information on ethnicity is limited to members who returned member satisfaction surveys. The study methods, however, are applicable to the investigation of other populations and other geographic regions. The results illustrate the potential value to health plans of conducting network analyses.

CONCLUSIONS

The results have implications for managed care. Health plans might take advantage of the pre-existing structures to plan programs and encourage collaboration. Patients missing quality indicators might be reached through the multiple providers identified in networks, especially patients without a regular primary physician. Structures identified by network algorithms find patients and doctors with a high density of connections. These structures offer natural targets for interventions to show clinical or cost benefit. High-cost clusters, as an example, might be identified to provide coordinated or enhanced care. In these various ways, results of network analysis might aid health plans to reduce costs and improve clinical outcomes.

Health plans have detailed network information in their administrative claims data. The analysis software is free and open source, easily available to health plan analysts. Network analyses offer a distinct approach to understand the structure of healthcare and the relationships that are critical to managed care. Analyzing the structure of local networks can lead to enhanced strategies for disease management to improve health quality and outcomes and offer more patient-centered care. Network analyses reveal structures and links that healthcare plans might leverage to strengthen quality improvement and disease management programs. ■

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