TBM

SYSTEMATIC REVIEW

A scoping review of patient-sharing network studies using administrative data

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Abstract

There is a robust literature examining social networks and health, which draws on the network traditions in sociology and statistics. However, the application of social network approaches to understand the organization of health care is less well understood. The objective of this work was to examine approaches to conceptualizing, measuring, and analyzing provider patient-sharing networks. These networks are constructed using administrative data in which pairs of physicians are considered connected if they both deliver care to the same patient. A scoping review of English language peer-reviewed articles in PubMed and Embase was conducted from inception to June 2017. Two reviewers evaluated article eligibility based upon inclusion criteria and abstracted relevant data into a database. The literature search identified 10,855 titles, of which 63 full-text articles were examined. Nine additional papers identified by reviewing article references and authors were examined. Of the 49 papers that met criteria for study inclusion, 39 used a cross-sectional study design, 6 used a cohort design, and 4 were longitudinal. We found that studies most commonly theorized that networks reflected aspects of collaboration or coordination. Less commonly, studies drew on the strength of weak ties or diffusion of innovation frameworks. A total of 180 social network measures were used to describe the networks of individual providers, provider pairs and triads, the network as a whole, and patients. The literature on patient-sharing relationships between providers is marked by a diversity of measures and approaches. We highlight key considerations in network identification including the definition of network ties, setting geographic boundaries, and identifying clusters of providers, and discuss gaps for future study.

Keywords

Social networks, Patient-sharing, Care coordination, Social contagion, Diffusion of innovation, Scoping review

Implications

Practice: Social network tools can provide measures of health care provider relationships and the organizational context that affects health care delivery.

Policy: Policymakers should consider using social network tools to monitor health care organizational context and changes.

Research: A growing number of studies use patient-sharing relationships to construct physician networks, which offers opportunities to build on prior studies and harmonize methods.

INTRODUCTION

Social network studies seek to understand the connections between individuals and groups and how those connections affect subsequent outcomes. The use of social network tools to understand health care delivery is an emerging area of health services research spurred by recent delivery system reforms, including accountable care organizations and patient-centered medical homes. These models of care depend on fundamentally changing provider relationships to improve care coordination. Given the growing interconnectedness of care, social network tools provide a novel way of understanding the organizational context of health care delivery, and how relationships between providers affect patient outcomes.

At the same time, improved data storage and computational capacity have advanced researchers' ability to perform large-scale social network analysis in ways that were until recently, not feasible. Historically, surveys have been used to measure providers' social networks, yet this method is time intensive, costly, and prone to nonresponse and other biases. In contrast, administrative data—insurance claims, all-payer datasets, and electronic medical records—are often readily available, efficient to use, and more comprehensive. Social network studies of administrative data use "patient-sharing" relationships. In these studies, two providers are considered to be connected to one another if they both deliver care to the same patient; these studies are increasing in popularity.

A robust literature in sociology, public health, and other disciplines suggests that the structure and size of interpersonal networks can be both barriers and facilitators to the diffusion of information and norms that impact behavior [1, 2]. In public health, we know that these differences can then lead to different levels of knowledge with real implications on health such as whether to evacuate before a hurricane or access to free mammography screenings [1, 3].

The importance of physician peer networks in the delivery of care and patient health is an emerging literature, and may provide unique insights into the organization of care and patterns of care, which can be leveraged to develop interventions and broader policy changes to reduce health care spending and improve patient outcomes. Previous reviews have examined the application of social network methods in health services research have provided an overview of methodological approaches [4–6] and examined how social network analysis has been applied to the social transmission of health [5], interventions [7], dynamics of infectious disease spread [8], and health professional relationships [9–11]. These existing reviews do not address how provider patient-sharing networks have been studied using administrative data sets.

To assess current practice, we conducted a systematic scoping review of the peer-reviewed literature to identify studies which use social network analysis to characterize patient-sharing networks derived from administrative data. We summarize the literature with respect to three questions:

1) What theoretical frameworks have guided social network studies using patient-sharing relationships?
2) How have researchers constructed patient-sharing networks, measured the relationships between providers, and defined the characteristics of networks?
3) What relationships are observed between provider patient-sharing network measures and patient outcomes?

METHODS

Search strategy

We developed a search strategy in consultation with a research librarian based on key words and phrases identified from key review articles identified a priori to identify studies that used social network analysis or network science approaches to measure the structure of provider patient-sharing networks (Appendix 1). Studies were eligible if they (i) used patient-sharing data such as electronic medical record (EMR) or administrative claims data to construct measures to define the network relationships; (ii) published in a peer-reviewed publication; (iii) in English; (iv) reported on an original research study; and (v) if the actors in their networks were individual providers, hospitals, or other health care organizations.

We searched PubMed and Embase from database inception through June 29, 2015 for relevant studies, and then updated our search on June 6, 2017. We identified a total of 10,855 citations (Fig. 1). Two reviewers independently conducted title scans and abstract reviews, followed by full article reviews to assess eligibility for study inclusion. After eliminating duplicates, 6,677 records underwent a title screen eliminating any study that was clearly not related to health care delivery. After reviewing abstracts from 269 studies, 63 were selected for a full-text review after applying the study inclusion criteria. After full-text review, 40 met our criteria for inclusion.

We reviewed the reference list of the 40 articles as well as relevant review articles and other papers written by included authors to identify articles that the database searches may have missed. An additional nine papers after full-text review met our criteria for inclusion. A total of 49 articles were included in our study.

Data extraction and synthesis

We used a standardized data extraction form for the full-text review. Reviewers extracted information on study characteristics, data sources, social network measures, measure definitions, level of analysis, outcome measures, and effect sizes. Differences were reconciled by discussion or a third reviewer as appropriate. Consistent with the methods of a scoping review, we did not exclude studies or articles on the basis of their methodological quality [12]. Due to the diversity of methods and outcomes used, we were unable to perform a meta-analysis.

RESULTS

Search results

The characteristics of 49 included studies are reported in Table 1. Nearly two-thirds of included studies were published after 2013. The most common study design was cross-sectional (N = 39), followed by cohort (N = 6) and longitudinal (N = 4). Most studies used administrative databases collected from government sources, such as U.S. Medicare claims, Italian National Health System, and Dutch Medical Register (N = 40, 81%). Fewer studies leveraged private insurer claims data sets through IMS Health and HealthCore Integrated Research Database or health system EMR data. Thirty-seven studies utilized data from USA; six studies used data from Australia, three from Italy, two from the Netherlands, one from Canada, and one from UK.

What theoretical frameworks have guided social network studies using patient-sharing relationships?

We found that while most studies did not explicitly identify or reference a framework, they tended to draw on at least one or more overlapping theoretical concepts. These frameworks fall into four main areas. First, and most frequently, studies of patient-sharing networks hypothesized that networks reflect aspects of collaboration, continuity, and care coordination [13, 14]. Generally, these studies stipulated the expectation that providers who share patients will come into contact with one another and will be more likely to provide an integrated and organized health care experience.

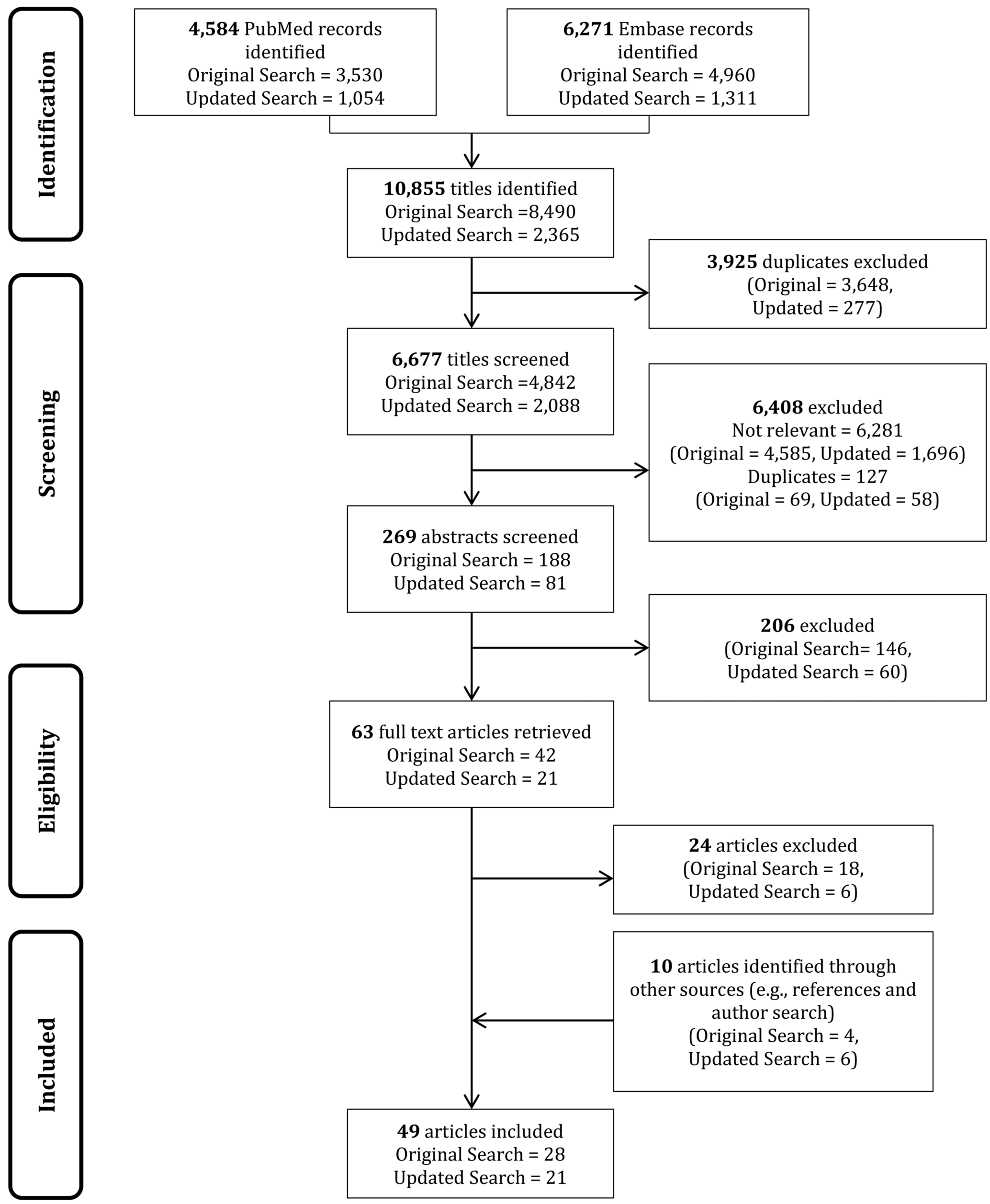

Fig 1 | PRISMA flowchart of study selection process.

Less commonly, studies were motivated by Mark Granovetter's strength of weak ties [15]. While many studies focus on the strongest connections, Granovetter suggested that an individual's weak ties—those relationships that are casual or infrequent—are actually quite powerful. Weak ties can speed the diffusion of information, serve as bridges to other networks, and increase an individual's mobility. For example, Iwashyna used this theoretical framework to develop a theory for how historical patient transfers between hospitals could inform future patient transfers [16].

Drawing on the work of Everett Rogers, other studies examined how networks influence the adoption of medical technology into clinical practice [17]. For example, Pollack and colleagues used the diffusion of innovation framework to examine whether surgeons who were connected to an early adopter of adjuvant radiotherapy (brachytherapy) for the treatment of women with early-stage breast cancer would be more likely to adopt this treatment for his or her own patients [18].

Finally, from an epidemiological perspective, several papers examined whether patient-sharing relationships serve as a vector for the spread of infectious diseases. While it is to be expected that some diseases are endemic to health care facilities such as *Methicillin-Resistant Staphylococcus Aureus* (MRSA) or *Clostridium difficile* (*C. diff*), these studies investigate whether the transfer of patients directly from one facility to another or whether patient use of multiple facilities increases the incidence rate of these diseases. For example, Simmering and colleagues examined the relationship between interhospital patient-sharing and *C. diff* infections in California hospitals [19]. Other studies examined MRSA [20] and *Carbapenem-Resistent Enterobacteriaceae* [21].

How have researchers constructed patient-sharing networks, measured the relationships between providers, and defined the characteristics of networks?

Network construction

Patient-sharing networks are by definition two-mode or affiliation networks [22]. That is, networks include two classes of actors: the patients and providers/organizations (Fig. 2A). In practice, we found that these modes are collapsed into a single one, such that patients form the ties between providers/organizations (Fig. 2B). In 36 of the articles, the nodes were physicians or other providers, and in 13 studies the nodes were hospitals and/or long-term care facilities.

Table 1 | Characteristics of included studies

	N (%)
No. of included studies	49 (100)
Study year	
≤2013	18 (36.7)
2014	5 (10.2)
2015	10 (20.4)
2016	10 (20.4)
2017	6 (12.2)
Study design	
Cross-sectional	39 (79.6)
Cohort	6 (12.2)
Longitudinal	4 (8.2)
Study data	
U.S. medicare claims data	20 (40.8)
Other government claims data	10 (20.4)
Private insurance claims data	12 (24.5)
Electronic medical record	4 (8.2)
Other	3 (6.1)

With regards to the connections between providers, a single-site validity study at an academic health system compared Medicare patient-sharing relationships to physician-reported professional relationships [14]. The authors found through claims data that as physicians shared more patients, they were more likely to report having a professional relationship (peaking at nine shared patients, with physicians reporting a relationship 82% of the time).

We identified two approaches to defining how many shared patients "counted" as a connection between two providers. One approach used a fixed threshold of shared patients (e.g., 1, 2, 5 shared patients) [23–27]. A second approach used relative thresholds. For example, Landon and colleagues retained the top 20% of the strongest ties for each physician [28]. Often, researchers varied their thresholds (either fixed or relative) to test the stability of their findings.

Among the studies focusing on physicians, there was some variation as to which specialties were included, depending on the particular data and study question. Nonpatient facing physicians such as anesthesiologists, emergency medicine, radiologists, and pathologists were excluded in 11 studies [14, 28–37]. Studies also varied in geographic scope, ranging from constructing networks by country [20, 38, 39], hospital referral region [26, 28, 30, 34, 40], state [16, 21, 31, 41], city [42, 43], or within a hospital or health system [24, 25, 29, 44–49]. The geographic boundaries of a network are important to consider because networks are subject to the boundary specification problem in which excluding

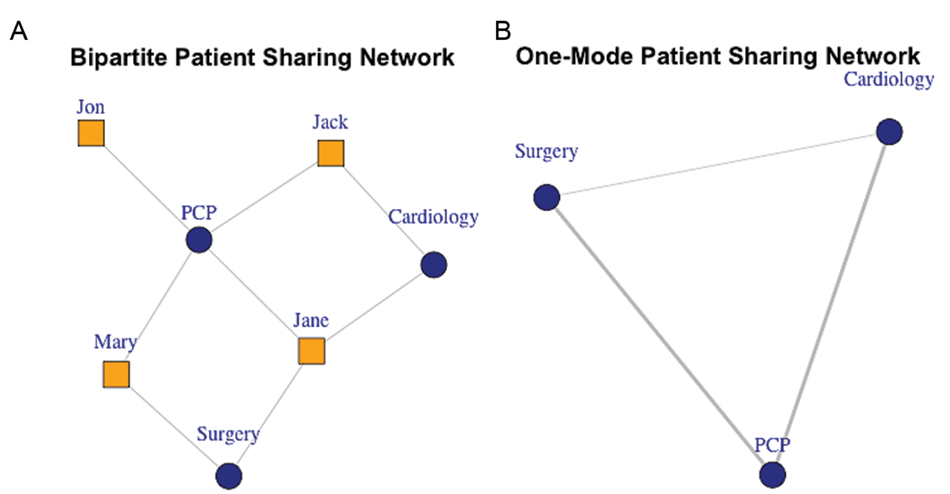

Fig 2 | Example of bipartite patient sharing network and one-mode network. (A) Bipartite patient sharing network. Squares represent patients. Circles represent physicians. (B) One-mode patient sharing network. Circles represent physicians.

certain patients and/or providers may alter the network structure [50].

Several studies used community detection algorithms to identify discrete groups of providers within the broader network (Appendix 2). The most common algorithm was that of Girvan and Newman, which uses a betweenness score (a measurement of the number of times a given node falls between two other nodes) to create community boundaries that maximize the number of ties within a subgroup and minimize the number of out-going ties [28, 42, 43, 48, 51]. Less commonly used were community detection algorithms developed by Armiri [45], Blondel [19, 31], and Clauset [20, 52], which use optimization strategies to identify communities based on within-group ties, and multidimensional scaling with Ward clustering [31, 45, 53], which assigns nodes to coordinates in a distance matrix based on their similarity to one another and then identifies clusters based on an objective function such as the error sum of squares. Two papers used a fixed rule to assign physicians to hospitals, which was originally developed to identify likely accountable care organization groupings [26, 28].

Social network measures

We identified a total of 180 social network measures across all studies as either an independent or dependent variable or characteristic of interest. Similar measures were grouped into 13 distinct categories. To provide a meaningful summary, we organized categories by their focus on providers (nodes), pairs (dyads) or triads of providers, or patients (Table 2). For each of these levels, we also noted related network-level measures that focus on groupings of more than three providers. These frequently were defined for the entire network within a given area or for subgroups of that network.

Provider-level measures

Provider-level measures described an individual provider's (the node's) relationships to others. These measures are derived by assessing a single provider's network (also called an ego network). As discussed under network measures, these provider-level measures are often aggregated to assess broader network characteristics.

Centrality measures a node's ability to send, receive, or interrupt information flow [54]. Lee and colleagues used *betweeness centrality*, which is measured as the proportion of pathways in the network where the provider of interest is on the shortest path [23, 55]. Mascia used Bonaich's centrality measure, which measures an actor's centrality as a function of his connections' degree [56].

While betweenness centrality is thought to measure a node's influence, *betweenness centralization* assesses the extent to which a network is hierarchical. Researchers also examined the relative ratio of primary care physician (PCP) centrality to other physicians' centrality to quantify the average centrality of PCPs compared to other physicians in a network [29, 31].

Degree is another measure of centrality. It indicates the number of other providers connected to a focal provider. Mandl and colleagues compared the median degree of providers across four geographic regions [32]. Some researchers preferred to use adjusted degree, a standardized measure, which is the total number of ties divided by the total number of patients shared with other nodes [28, 30, 31]. *In-degree* and *out-degree* account for the direction of the patient's movement—that is going from A to B or B to A [20, 23, 38, 55]. Degree has also been used to describe, in aggregate, the number of other providers that are connected to each node. Studies have also further classified degree by provider specialty (e.g., *average urologist degree*) [42].

Density is a measure of a network's cohesiveness—the level of connectivity among a given network. It is calculated as a ratio of the number of edges within a network to the number of edges that could potentially exist if every provider were connected to each other. Density was used to measure the cohesion of a given provider's network [32, 55, 56], as well a general network-level measure [23, 37, 40, 45, 55, 57].

Dyad- and triad-level measures

Dyads and triads are the building blocks of a network, which make them of particular interest to researchers. Dyad-level measures focus on understanding the relationship between a pair of providers, and triad-level measures focus on three providers.

Assortativity measures examine whether actors connect preferentially to other nodes that are popular (i.e., those who have many ties). For example, Lomi and colleagues examined assortativity with respect to the number of patients (intensity) and the number of hospitals sending patients (degree) [58].

As opposed to geographic distance (i.e., the physical distance between two providers), *distance* measures the level of connection or closeness between a pair of providers. Distance may be calculated as the shortest path (*geodesic distance*) between two nodes or longest path (*diameter*) of a network [23, 27, 57].

An *edge* or relationship between two providers is defined by a patient-sharing relationship. The number of shared patients, *ties* or *edge weight*, is a measure of the strength of the relationship between providers. Lee and colleagues used ties to examine the relationships between acute care facilities and long term care facilities in Orange County, California [55]. At a network level, Hollingsworth and colleagues examined the *repeat-tie fraction*, the proportion of provider pairs in a network who shared at least two patients [36]. Researchers also used Exponential-family Random Graph Models (ERGMs), a probability model that

Table 2 | Typology of social network measures used to study health care organization and delivery

Measure name	Related measures	Definition	Related network-level measure(s)
Node			
Centrality	Betweenness, Closeness, Eigenvector, Bonacich	A measure that describes the importance of a node	Betweenness Centralization, Specialty-specific relative centrality
Degree	Adjusted degree, In-degree, Out-degree	Quantifies the number of other connected nodes.	Degree Centralization, External Ties, Node strength
Density		The number of ties in an ego's network divided by the number of possible ties among the other actors in the ego network	Density, Cohesiveness
Dyadic and Triadic			
Assortativity		The extent patients are shared preferentially with providers who receive many patients	
Distance		Shortest or longest geodesic distance between two nodes	Average Distance, Diameter
Edge	Edge weight, Ties, shared patients	A tie (e.g., a shared patient) between two nodes).	Two-star, three-star, Triangle, Alt-K-Stars, Alt-K-Triangles, Alt-K-2-Paths, Repeat-Tie Fraction
Jaccard Similarity	Shared positive outcome ratio	The ratio of the number of shared patients between two providers divided by the total number of patients seen by both providers.	
Reciprocity		Whether patients are shared in both directions	Reciprocity
Recurrence	Persistence, Recency	Whether a node is likely to share patients with other nodes with whom the node he or she has shared patients in the past	
Transitivity	Transitive Closure, Clustering coefficient, Cyclic Closure	The probability that two providers who are connected to a common provider are also connected	Global Triadic Closure, Clustering, Bipartite Clustering Coefficient, Network modularity
Patient			
Care Density		The ratio between the total number of patients shared by provider pairs within a patient's care team, and the total number of provider pairs within the patient's care team	
Degree Centrality	Team Size	Numbers of providers connected to a particular patient	
Provider Constellation with Provider Type of Interest		The number of patients with provider teams that include a particular provider type such as a primary care physician or obstetrician	Community Structure

accounts for the complex dependencies within networks, to characterize a network's building blocks or subnetworks with respect to 2-star (dyads), triangles, and other configurations [26, 46].

Jaccard similarity examines the overlap between the connections (termed alters in the social network analysis literature) of two providers relative to the total connections of both providers. High similarity may reflect a stronger relationship between the two providers. Ong and colleagues used Jaccard similarity to examine the similarity in provider's professional networks in the context of benzodiazepine prescribing patterns [33]. Modeled on Jaccard similarity, Carson and colleagues developed the *shared positive outcome ratio,* which measures the relative occurrence of a positive outcome (e.g., patient satisfaction) between two providers relative to the positive outcomes shared between any other set of their alters [24, 25].

Reciprocity measures to what extent patients are shared in both directions (from Provider A to Provider B and from Provider B to Provider A). Lomi and colleagues (2014) used reciprocity to study how hospitals in Southern Italy share patients [58]. The principal of mutuality suggests that providers may be more likely to share patients with those who share patients with them.

Recurrence measures whether a provider is likely to again share patients with another provider in the future. Lomi and colleagues use the weighted history of past transfers between hospitals to assess event recurrence and the time between events (*recency*) [58]. DuGoff and colleagues examined the *persistence* of ties over time, which measures the proportion of providers sharing patients in a baseline year who also share patients in a subsequent year [34].

Transitivity is a triadic measure. It suggests that if Provider A is connected to Provider B and Provider C, then it is likely that Provider B and Provider C are also connected. Landon and colleagues measured transitivity using the *clustering coefficient* to quantify the proportion of a provider's colleagues who also shared patients with each other [30]. Lomi and colleagues used *transitive closure* to quantify the probability that two providers who were connected to a common provider were also connected [58]. Leveraging the direction of connections, *cyclic closure* quantified the extent to which a provider is likely to receive patients from providers connected to its partners [58].

Patient-level measures

The providers that a patient sees are used to construct the ties in a network. In turn, these networks have been used to reflect on the connections between a patient's providers. *Care density* defines, for each patient, the number of other patients shared by a patient's providers, normalized by the total number of providers seen [59]. Higher care densities have been posited to reflect greater connections among a patient's care team.

The size (e.g., *Team Size*) and composition of patient care teams were less frequently examined, but could provide useful information about variation in care delivery. One study used commercial administrative data to quantify the number of physicians who were connected to a particular patient, *Provider Constellation*, as well as whether a PCP or obstetrician/gynecologist was a member of a patient's care team [32].

What relationships are observed between provider patient-sharing network measures and patient outcomes?

A total of 32 papers examined the relationship between network characteristics and patient outcomes including health care costs, health care utilization, patient-reported outcomes, quality of care, and outcomes. Health care costs were examined in nine studies [29, 44–48, 59, 60]. Eight studies examined health care utilization including hospital use [59, 61], length of stay [29, 45, 49], and surgical procedures [18, 26, 43]. Seventeen papers examined quality of care such as appropriate prescribing [33, 37, 52], chronic care delivery [13, 51, 61], emergency department use or wait time [34, 35, 62], outpatient physician visits [29], hospital readmissions [34, 35, 44, 46–48, 56, 58], and preventable hospitalizations [13, 31]. Two papers examined patient experiences: patient satisfaction [24, 25]. Eight papers examined health outcomes: the spread of infectious diseases [19–21, 38, 39], surgical outcomes [42], and mortality [35, 60]. Key findings for all included studies are summarized in Appendix 3.

Included studies used a range of different statistical approaches from correlation coefficients to multilevel regression modeling to assess relationships of interest. Even studies that report on the same outcome frequently used different data sources and methods, precluding direct comparisons. While many papers used hierarchical models to account for clustering of, for example, patients within physicians, few papers formally accounted for the inter-dependent nature of network data. As an exception, three papers used ERGMS to account for the dependency of network structures [40, 46, 49]. ERGMs allow researchers interested in the structural properties of single or multiple networks to calculate maximum likelihood estimates for parameters of interest [63]. Another paper used a Multiple Membership Multiple Classification model, an extension of multilevel regression modeling that accounts for network and group dependencies [58]. Other studies used bivariate analyses such as correlation coefficients and *t*-tests.

Measures of coordination

We found 12 papers that examined the relationship between coordination and health care costs, health care utilization, quality of care, and outcomes. Studies examining indicators of coordination such as PCP centrality, Bipartite Clustering, and Care Density were statistically significantly associated with lower spending [29, 59, 61] and lower health care utilization as measured by shorter length of stay [29]. Coordination was also associated with better quality care including fewer inappropriate medications [33, 37, 52], fewer hospital readmissions [13, 35, 56], and less emergency department use [34, 35]. Two studies found coordination was associated with better patient outcomes measured using lower mortality rates [35, 60].

Studies also reported negative and non-significant results: Casalino and colleagues found that the percent of PCPs in a network was associated with more ambulatory care sensitive condition hospitalizations, and betweenness centrality was not significantly associated with ambulatory care sensitive condition hospitalizations. DuGoff and colleagues did not find that area-level tie persistence (i.e., multiyear patient-sharing relationships) between PCPs and other physicians were statistically associated with hospital readmissions rates [31, 34].

Measures of fragmentation

Several studies examined whether health care organizations or provider networks that are more diffuse and disconnected had worse patient outcomes such as higher spending and more hospitalizations. For example, degree for physicians in a network (representing the average number of other doctors that physicians in the network were connected to via shared patients) at the physician network level was significantly associated with higher spending [29] and higher preventable hospitalization rates [31]. In addition, using Medicaid claims data, Stein and colleagues found the likelihood that patients with an opioid use disorder would receive a prescription for an opioid or benzodiazepine increased with the number of physician communities seen [52]. In a study of prostate cancer care, Pollack and colleagues found the relationship between urologist degree and prostatectomy complications to vary by city [42].

Social contagion

The study of peer-group effects on physician practice is an emerging area of study using social network tools. Using descriptive analyses, Stein and colleagues found that rates of opioid analgesic and benzodiazepine prescribing rate varied between 2.5 and 3.3 times among Medicaid provider communities in 12 states. Using longitudinal data to identify the effect of early-adopting physician peers on physician behavior in a later period, Pollack and colleagues found that a surgeon's peer group use of brachytherapy—an adjuvant radiotherapy—and imaging studies influenced surgeons' use in a later time period [18, 51].

Network characteristics

Studies examining network substructures suggest that there is a relationship between the organization of provider patient-sharing networks and patient outcomes. Uddin and colleagues examined the structures of physician communities among hospitals with high and low readmission rates using ERGMs [46]. Two-star configurations, defined as three nodes connected by only two edges, were associated with hospital spending, and triangle, a three nodes connected on all three edges, and alternative k-star configurations, defined as configurations where a series of nodes from i to j are connected to the same node, were associated with hospital readmission rates [44] (see Fig. A1 for illustrations of these structures). Uddin and colleagues also found that the presence of multiple physician communities within a hospital's physician network was indicative of lower readmission rates [45].

Hospital acquired infections

Several papers focused on describing hospital patient-sharing network structures and variations therein to understand how patient transfers can influence to spread of infectious disease. These studies found that patient transfers contribute to the spread of infectious diseases including MRSA, *Carbapenem-Resistent Enterobacteriaceae*, and *C. diff* [19, 20, 38, 39].

DISCUSSION

In this scoping review, we identified 49 papers that used patient-sharing data derived from administrative data sets. Included papers were largely cross-sectional and focused on physician relationships. We identified 13 different measures calculated using patient-sharing data at the level of the provider, dyad or triad, patient, and network.

Studies often did not draw on a specific theoretical framework, but many studies made reference to the concepts of collaboration and coordination. Less commonly, studies referenced the importance of weak ties, diffusion of innovation, and epidemiological models of disease transmission. Depending on their focus, authors suggested a wide range of possible applications from identifying high-performing networks of providers to redesigning hospital patient transfer processes [16, 31]. Studies of provider patient-sharing networks could also be used to inform other important policy issues with respect to the ideal composition of provider networks, the appropriate size of networks (e.g., when is a narrow network too narrow?), and how to most efficiently refer patients to specialty care.

Studies frequently examined the association between network characteristics and aspects of health care utilization. Researchers employed a range of different statistical approaches that varied widely in the number and types of included covariates that may confound the associations, which may explain why studies examining the same measure sometimes disagreed. The heterogeneity in approaches indicate a continuing and significant uncertainty in how to best measure patient-sharing networks. Based on the current literature, we have developed a set of recommendations to inform future research in this area.

Recommendations

We identified four key decision points for researchers and recommendations on how to construct patient-sharing networks (Table 3).

First, researchers should determine how many shared patients are necessary to form a tie between two nodes. In our reviewed papers, researchers used a variety of thresholds, from any observed patient-sharing relationship counting as a tie, to a minimum of one shared patient, or the top 20th percentile. While strict cut-offs can be determined a priori, thresholds based on the observed distribution necessarily reflect exploratory data analyses. The definition of a tie can have dramatic ramifications for an analysis, so we recommend that researchers clearly state their choice, discuss the limitations and potential biases of their approach, and consider

Table 3 | Practical considerations in identifying networks

Question	Key consideration	Approaches
How many shared patients are necessary to form a tie between providers?	Validation work using 100% Medicare claims has found that reported relationships between providers increase as the number of shared patients increase, up to a certain point.	Studies required physicians to share a minimum number of patients. Frequently, this threshold is varied in sensitivity analyses. Researchers have also used a relative threshold in which they maintain the strongest proportion of ties for each physician.
Which providers should be included or excluded?	Certain physicians may or may not be relevant to the network construction or study question.	Physicians who are not directly involved in patient care or who are not directly referred to are often excluded.
What is the appropriate geographic scope for identifying networks?	Networks are subject to the boundary specification problem—excluding certain patients and/or providers may alter the network structure.	Studies vary as to the scope of geography, including hospitals, hospital referral regions, and metropolitan statistical areas.
What is the appropriate approach to identifying 'communities' or clusters of providers?	Multiple different approaches have been used to physicians who share many ties with one another (within group ties) but comparatively fewer ties with people outside the group (Appendix 2).	Six studies used the Girvan-Newman algorithm; 2 studies used the Blondel model. See Casalino (2015) appendix for discussion of the potential tradeoffs between these approaches

sensitivity analyses to test the robustness of their findings.

Second, researchers must determine which providers should be included or excluded. We recommend that researchers determine the list of included providers prior to the study. Often, health services researchers exclude physician specialties that are not directly patient facing or intentionally selected by a patient. It is important that the list of included providers is guided by the study question.

Third, appropriate geographic boundaries need to be set for determining a provider network, which may influence the network's structure. Hospital affiliation, political boundaries or hospital referral regions provide convenient units of analysis. However, health care delivery may transcend these boundaries, and adopting these units may oversimplify or mischaracterize how patients receive care. For example, accountable care organizations (ACO) experience a large amount of patient turnover due to patterns of care seeking outside of ACO-affiliated providers [64]. Researchers may consider examining the influence of different border definitions on their analysis. We also encourage researchers to consider using community detection algorithms to identify the actual health care community without regard to established geographic units.

Fourth, selecting an approach for identifying communities or clusters of providers may be challenging. We found Girvan-Newman's algorithm to be the most popular, but other approaches are likely valid. Researchers may benefit from exploring algorithms that have not yet employed in patient-sharing studies such as spectral clustering for identifying communities [65]. In addition, researchers should proactively address issues of how their approach may introduce selection bias into their study design [66].

Along with the considerations involved in creating networks, researchers must grapple with the problem of interpreting their social network measures so that the work is relevant for other researchers, health care organizations, and health policy audiences. For example, centrality is a commonly used measure in social network studies and is generally interpreted as a measure of a node's influence of the network. However, network researchers have yet to validate these measures within health care organizations or communities to understand the implications for a specific health care organization's or region's approach, strategy, or policies. In addition, researchers should explicitly specify their theoretical framework to improve our understanding of which aspects of patient-sharing networks are important.

Gap analysis

In our review, we identified several gaps in the literature. One gap centers on the actors used to construct the networks. Studies of providers focused on physicians and hospitals; only two studies included allied health professionals such as nurses and pharmacists [24, 25]. Depending on the research question, the inclusion of these providers may be important for the flow of information and activities within the network. With regard to organizational analyses, the role and influence of post-acute care facilities were only examined in two studies of hospital patient-sharing [20, 55]. Given the importance of post-acute care in geographic variations in health care utilization, further work is needed to understand the interplay between post-acute care facilities and community-based physicians [67].

Another area for further research is how patient-sharing networks change over time or in response to different incentives. Longitudinal studies may provide insight into the impact of policy reforms that seek to alter the ways in which patients receive care. This approach could be used to assess whether physicians in ACOs shift referral patterns towards other physicians within their organization.

Finally, social network approaches are increasingly being deployed in public health initiatives [6, 68]. However, we did not identify studies that used patient-sharing networks to develop or evaluate an intervention. Testing whether interventions may be built from a patient-sharing foundation—that is targeting particular types of organizational structures—or evaluated using patient-sharing data to see if physician networks change is an important step and will likely increase the perceived relevance of these studies. Social network approaches—and patient-sharing data in particular—can provide unique insights into the interdependency of organizational (and individual) relationships, which can be used to design and target interventions. For example, we found that evidence that patient-sharing connections are important pathways that can spread of information as well as disease. Health care systems and policymakers could consider developing interventions to address these issues using observed provider networks to identify key opinion leaders to seed the spread of innovation or to design regional hospital transfer networks.

Study limitations

These findings should be considered in light of the study's limitations. While we worked with a research librarian to develop our search strategy, we may have missed studies. As this is an emerging area of research, new studies are frequently being published. Heterogeneity in the level of analyses, threshold of shared patients, included provider types, and range of health care utilization outcomes considered precluded a formal meta-analysis. Data abstraction was independently conducted by two reviewers, but this does not preclude the possibility for errors in data collection. Lastly, all papers reviewed reported at least one statistically significant finding suggesting publication bias.

CONCLUSIONS

Patient-sharing studies utilize a variety of measures and methods to characterize provider networks. Researchers have documented wide variation in the characteristics of provider patient-sharing networks. More work is needed to understand how federal, state, and health system policy changes influence patient-sharing relationships, and how these changes affect patient care.

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Compliance with Ethical Standards: This study reviewed published papers and is exempt from IRB review.

Conflicts of Interest: The authors report no conflict of interests.

Informed Consent: For this type of study, informed consent is not required.

APPENDIX 1. SEARCH STRINGS USED

PubMed

("network analysis"[tiab] OR "reciprocity"[tiab] OR "clustering"[tiab] OR "care density"[tiab] OR "centrality"[tiab] OR "algorithm"[tiab] OR "algorithms"[tiab] OR (("patient"[tiab] or "patients"[tiab]) AND ("share"[tiab] OR "sharing"[tiab] OR "shared"[tiab] OR "constellation"[tiab]))) AND ((("physician"[tiab] OR "physicians"[tiab] OR "provider"[tiab] OR "providers"[tiab] OR "referral"[tiab] OR "referred"[tiab] OR "transfer"[tiab] OR "transferred"[tiab]) AND ("network"[tiab] OR "networks"[tiab] OR "dyad"[tiab] OR "connected"[tiab] OR "connection"[tiab] OR "connections"[tiab] OR "relationship"[tiab] OR "collaborate"[tiab] OR "collaboration"[tiab])) OR "coordinated care"[tiab] OR "coordinate care"[tiab] OR "Care coordination"[tiab])

Embase

("network analysis":ab,ti OR "reciprocity":ab,ti OR "clustering":ab,ti OR "care density":ab,ti OR "centrality":ab,ti OR "algorithm":ab,ti OR "algorithms":ab,ti OR (("patient":ab,ti or "patients":ab,ti) AND ("share":ab,ti OR "sharing":ab,ti OR "shared":ab,ti OR "constellation":ab,ti))) AND ((("physician":ab,ti OR "physicians":ab,ti OR "provider":ab,ti OR "providers":ab,ti OR "referral":ab,ti OR "referred":ab,ti OR "transfer":ab,ti OR "transferred":ab,ti) AND ("network":ab,ti OR "networks":ab,ti OR "dyad":ab,ti OR "connected":ab,ti OR "connection":ab,ti OR "connections":ab,ti OR "relationship":ab,ti OR "collaborate":ab,ti OR "collaboration":ab,ti)) OR "coordinated care":ab,ti OR "coordinate care":ab,ti OR "Care coordination":ab,ti)

Appendix 2. Clustering algorithms used to identify provider community structures

Measure	Description	Relevant studies
Extended Hospital Medical Staff	Assigns physicians to a hospital based on the plurality of where his/her patients receive inpatient care.	Landon et al. 2013; Moen et al. 2016
Girvan-Newman	Girvan-Newman's modularity maximization algorithm assigns each physician to a single community, and communities are comprised of distinct, non-overlapping groups of physicians.	Landon et al. 2013; Pollack et al. 2017; Pollack et al. 2014; Pollack et al. 2012; Uddin et al. 2015; Zand et al. 2017
Blondel	Blondel uses a "fast and greedy" style algorithm to identify communities.	Casalino et al. 2015; Simmering et al. 2015
Multi-Dimensional Scaling and Ward Clustering	Multi-dimensional Scaling is a data reduction technique used to identify the principal coordinates (or dimensions) of a dissimilarity matrix. Ward clustering is a type of hierarchical clustering.	Yaraghi et al. 2014
Amiri's firefly algorithm	A multi-objective optimization approach to identify community structures in complex networks.	Uddin, 2016
Hierarchical Agglomerative Algorithm	A bottom-up algorithm that treats every node as its own cluster, then iteratively groups together similar clusters.	Kunz et al. 2017
Modularity Maximization Community Detection	Systematically groups providers into different communities, calculating the modularity score for each proposed set of communities, and identifying the set of proposed communities with the highest modularity score.	Donker et al. 2012; Stein et al. 2017

Appendix 3 | Characteristics of included studies and key findings

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Barnett, Landon, O'Malley, Keating, and Christakis (2011)	USA	Cross-sectional	Medicare claims	Shared patients	What is the correspondence between physician-reported relationships and observed patient sharing relationships?	☐ At an academic medical center in Boston, the probability of a physician reporting a relationship with another physician (defined as advice, referral, sharing patients, or sharing a practice) increased with each additional Medicare patient shared up to nine. ☐ 51% and 37% of relationships observed with at least eight shared Medicare patients were defined as referral or advice relationships, respectively ☐ Primary care physicians (PCPs) recognized 55% of all observed patient-sharing relationships compared to 38% of medical specialists and 39% of surgeons.
Barnett, Christakis, O'Malley, Onnela, Keating, and Landon (2012)	USA	Cross-sectional	Medicare claims	Degree, PCP centrality	How does the structure of patient-sharing networks contribute to the variation in the cost and intensity of care delivered in U.S. hospitals?	☐ Across 51 hospital referral regions (HRRs), the structure of hospital physician patient-sharing relationships were associated with hospital-level outcomes. ☐ Median physician adjusted degree ranged from 155 in small hospitals to 281 in large hospitals. Mean PCP relative centrality to other physicians ranged from 1.11 in small hospitals to 0.80 in large hospitals. ☐ After adjustment, a one standard deviation increase in adjusted degree was positively associated with total Medicare spending, hospital days, and physician visits in the last two years of life. ☐ After adjustment, a one standard deviation in PCP relative centrality was negatively associated with total Medicare spending, Medicare spending on imaging and tests, physician visits, and medical specialist visits.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Bridewell and Das (2011)	USA	Cross-sectional	OncoShare	Density, Strength of networks, Cohesiveness	Do formal health system affiliations influence patient-sharing relationships between physicians in breast cancer care?	☐ The patient sharing relationships of medical oncologists, radiation therapists, and surgeons who care for breast cancer patients largely reflected formal health system affiliations at two health care organizations. ☐ The authors observed low densities across both networks suggesting physicians have few connections relative to all possible connections ☐ Subgroup cohesion measures were greater than 1 suggesting more connections within each organization than external organizations. ☐ Surgery patients seen at an academic medical center were more likely to receive care following surgery from external providers. ☐ Across both organizations, there was some evidence that the probability of seeking care from external providers increased with tumor stage.
Carson, Scholtens, Frailey, Gravenor, Powell, Wang, Kricke, Ahmad, Mutharasan, and Soulakis (2016)	USA	Cross-sectional	Northwestern Memorial Hospital EHR	Shared Provider Outcome Ratio (SPOR)	Do rates of satisfaction vary across provider teams and pairs of providers?	☐ Satisfaction rates varied across provider teams in a cardiology unit. ☐ After multivariate adjustment, SPOR identified physician pairs with higher and lower than expected patient self-reported likelihood to recommend the health system.
Carson, Scholtens, Frailey, Gravenor, Kricke, and Soulakis (2016)	USA	Cross-sectional	Northwestern Memorial Hospital EHR	SPOR, Clustering coefficient, Density, In-degree, Out-degree, Network modularity, Network diameter	Is it possible to identify pairs of providers with high and low rates of satisfaction?	☐ Among providers who saw patients in the Emergency Department, the authors found that it is possible to identify pairs of providers with extreme high scoring and low scoring patient satisfaction rates using the Shared Provider Outcome Ratio.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Casalino, Pesko, Ryan, Nyweide, Iwashyna, Sun, Mendelsohn, and Moody (2015)	USA	Cross-sectional	Medicare claims	Mean adjusted value, PCP centrality, Percentage of PCP providers, Size	Is there a relationship between ambulatory care sensitive hospitalizations and physician patient-sharing network characteristics?	☐ Across 5 states, the authors identified 417 physician communities with a median of 98 to 153 physicians depending on the state using the Blondel model. ☐ Using a multi-level model the authors report that at the physician-level, a one standard deviation increase in a physician's adjusted value degree (the number of connections to other physicians standardized by a physician's number of patients seen in that network) and betweenness centrality was positively associated with ambulatory care sensitive hospital admissions (ACSA). ☐ At the network level, a one standard deviation increase in the proportion of PCPs and average adjusted value degree was positively associated with ACSAs.
Donker, Wallinga, and Grundmann (2010)	Netherlands	Cross-sectional	Dutch national medical register	In-degree, Out-degree, Connectedness	Is the prevalence of hospital-acquired infections affected by patient-sharing between hospitals?	☐ A simulation study found that higher rates of methicillin-resistant *staphylococcus aureus* (MRSA) at university medical centers is due to their higher rate of in-degree (receipt of patients) compared to other hospitals.
Donker, Wallinga, Slack, and Grundmann (2012)	UK and Netherlands	Longitudinal	NHS Hospital Episode Statistics and Dutch National Medical Registry	Infectious relative indegree, Network modularity	Does hospital connectedness influence the spread of hospital-acquired infections?	☐ In England, hospital patient-sharing relationships were correlated with hospital Methicillin-resistant *Staphylococcus aureus* (MRSA) rates. Using an agent-based model, the authors compare the spread of MRSA in England and the Netherlands.
DuGoff, Cho, Si, and Pollack (2017)	USA	Cohort	Medicare Physician Referral Data Set	Reciprocity, Degree, Edge weights, Tie persistence	How stable are primary care physician patient sharing relationships across regions?	☐ Over a two-year period, the majority of primary care physician patient sharing relationships (70%) were persisted over time. ☐ At an area-level (hospital referral regions), greater tie persistence was associated with decreased ER utilization, while more connections were associated with more ER visits. ☐ There was no relationship between tie persistence and hospital readmission rates.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Fernandez-Garcia, Onnela, Barnett, Eguiluz, and Christakis (2017)	USA	Cross-sectional	Medicare claims	In-degree, In-strength, Out-degree, Out-strength, Eigenvector centrality	Do inpatient transfers contribute to the spread of nosocomial infections? Can network structure be leveraged to design efficient surveillance systems?	☐ Patient transfers between hospitals are associated with the spread of nosocomial infections. It may possible to develop a sentinel network at a few facilities to monitor for emerging nosocomial outbreaks.
Hollingsworth, Funk, Garrison, Owen-Smith, Kaufman, Landon, and Birkmeyer (2015)	USA	Cross-sectional	Medicare claims	Repeat-tie fraction, Clustering, External ties	Are there differences in the characteristics of physician social networks between communities by proportion of black residents?	☐ Physicians treating patients who underwent a coronary artery bypass grafting procedure in hospital service areas (HSAs) with more black residents exhibited different patient-sharing network structures those in HSAs with fewer black residents. ☐ After adjustment, physicians in HSAs with more black residents were exhibited a lower repeat-tie fraction (proportion of ties defined by sharing two patients versus one patient) and fewer ties to physicians working outside the hospital's core-based statistical area. ☐ After adjustment, physicians in HSAs with more black residents were more likely to exhibit tighter clusters.
Hollingsworth, Funk, Garrison, Owen-Smith, Kaufman, Pagani, and Nallamothu (2016)	USA	Cross-sectional	Medicare claims	Bipartite clustering coefficient	Is physician teamwork is a determinant of surgical outcomes?	☐ Health systems with physicians who tend to work together in tightly-knit groups during CABG episodes realize better surgical outcomes with respect to hospital readmission, emergency department use, and mortality.
Hussain, Hsien-Yen, Veestra, and Pollack (2015)	USA	Cohort	SEER-Medicare	Shared patients	Does surgical-oncologist patient-sharing relationships affect mortality in patients with stage III colon cancer?	☐ An increase in shared patients between medical oncologists and surgeons who care for Stage III colorectal cancer patients was associated with a significant decrease in the hazard of mortality. ☐ Patient sharing was not associated with differences in health care spending.
Iwashyna, Christie, Kahn, and Asch (2009)	USA	Cross-sectional	Medicare claims	Centralization, In-degree, Out-degree	Can network analysis be used to understand variations in hospital patient transfers? Can network analysis simulations of a hospital closure provide information on the importance of a hospital?	☐ In Connecticut, patients were generally transferred to hospitals with more resources. ☐ The classification of secondary and tertiary hospitals did not explain observed patient transfer patterns

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Kunz, Zupancic, Rigdon, Phibbs, Lee, Gould, Leskovec, and Profit (2017)	USA	Cross-sectional	California Perinatal Quality Care Collaborative Infant database	Adjusted Degree, Shared patients	What are the patterns of neonatal transfers in California in comparison to perinatal referral regions defined by the state of California? What are the patient-level factors associated with transport outside the empirical hospital network?	☐ Over 80% of observed neonatal acute transfers were within the state-defined perinatal hospital network regions. ☐ Out-of-subnetwork (defined using a hierarchical agglomerative algorithm) transfers were associated with the presence of a major congenital anomaly, need for surgery, and insurance as the reason for transfer.
Landon, Keating, Barnett, Onnela, Paul, I'Malley, Keegan, and Christakis (2012)	USA	Cross-sectional	Medicare claims	Adjusted physician degree, Shared patients, Relative betweenness centrality, Clustering coefficient	Do physician patient-sharing networks vary? What are the determinants of physician patient-sharing connections?	☐ Across 51 HRRs, the authors found substantial variation in physician network characteristics. ☐ Some network characteristics were influenced by network size: adjusted degree, clustering, and number of shared patients. Relative PCP centrality and relative medical specialist centrality were less influenced by network size. ☐ Physicians were more likely to share patients with physicians with similar individual (age, sex) and panel (race) characteristics.
Landon, Onnela, Keating, Barnett, Paul, O'Malley, Keegan, and Christakis (2013)	USA	Cross-sectional	Medicare claims	Adjusted degree, Shared patients, Relative betweenness, Clustering coefficient	Can network analysis identify physician networks well-suited to becoming accountable care organizations?	☐ Physician networks identified using a community detection algorithm (Girvan-Newman) captured a greater proportion of care delivered than physician networks determined using the extended hospital medical staff (EHMS) model. ☐ Community detection identified 416 communities compared to 273 identified by EHMS ☐ After adjusted for network size, physician communities accounted for a significantly greater share of hospital admissions, emergency room visits, physician visits, and PCP visits.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Lee, McGlone, Song, Avery, Eubank, Chang, Bailey, Wagener, Burke, Platt, and Huang (2011)	USA	Cross-sectional	California hospital discharge data	Geodesic distance, Network Diameter, Density, Degree, In-degree, Out-degree, Betweenness	What are the characteristics of patient-sharing between hospitals in Orange County, California?	☐ In Orange County, California hospital patient-sharing network characteristics were sensitive to the definition of a tie and thresholds. ☐ The authors found that hospital patient-sharing networks defined by any shared patient within 1-year connected 81% of hospitals while hospital patient-sharing networks defined by direct inter-hospital transfers connected 45.9% of hospitals. ☐ Higher patient-sharing thresholds (>10 versus >100) increased the likelihood that a hospital would send (out-degree) or receive (in-degree) a patient from a geographically proximate hospital. ☐ In multivariate models, hospital admission volume was associated with hospital in-degree, out-degree, and betweenness centrality and a hospital's percent of cancer patients was associated with in-degree and betweeenness centrality.
Lee, Song, Bartsch, Kim, Singh, Avery, Brown, Yilmaz, Wong, Potter, Burke, Platt, and Huang (2011)	USA	Cross-sectional	California hospital discharge data	Number of ties, Density, Reciprocity, Geodesic distance, Network diameter, Network Betweeness, In-degree, Out-degree, Ego network size, Ego network ties, Ego network density, Ego network betweenness	What are the characteristics and patterns of patient transfer between long term care facilities and acute care facilities in Orange County, California?	☐ In Orange County, California, including long-term care facilities in acute care facility patient-sharing networks added a substantial number of connections between acute care facilities. ☐ Hospital patient-sharing networks limited to direct inter-hospital transfers connected a hospital to an average of 3.5 facilities to 13.4 facilities.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Lomi, Mascia, Vu, Pallotti, Conaldi, and Iwashyna (2014)	Italy	Longitudinal	Italian National Health Service (Abruzzo)	Reciprocity, Assortativity by intensity, Assortativity by degree, Recurrence, Transitive closure, Cyclic closure, Out-degree, Wighted out-degree, In-degree, Weighted in-degree, Recent sending of a patient, Recent receiving of a patient	Do patient-sharing relationships between hospitals reflect hospital quality in a region in Italy? What are the organizational and historical factors that affect hospital patient-sharing relationships?	☐ Patients transferring between hospitals in Italy generally move to higher performing hospitals as defined by readmission rate. ☐ Leveraging longitudinal data on patient-sharing events, the authors find that past organizational and relational effects drive patient transfers.
Mandl, Olson, Mines, Liu, and Tian (2014)	USA	Cross-sectional	HealthCore Integrated Research Database	Collaborative pair, Collaborative triad, Constellation density, Provider network size, Provider network density, Shared pateints, Patient network density, Patient network size, Constellation composition, Other-patient sharing	What are the characteristics of physician patient-sharing relationships by U.S. region?	☐ Using a commercial claims data set, the authors report substantial variation in the organization of physicians. ☐ There was little evidence that patients' physicians are also connected through other patients suggesting little cohesion among physician teams.
Manuel, Lam, Maaten, and Klein-Geltink (2011)	Canada	Cross-sectional	Ontario Health Insurance Program	Interconnected partners	Can administrative patient-sharing data be used to measure how physicians are connected in Ontario, Canada?	☐ Physicians saw mainly their own patients, but did provide some care for the their partners' patients. ☐ The number of connected physicians was higher in group practices that had more physicians.
Mascia, Angeli, and Di Vincenzo (2015)	Italy	Cross-sectional	Italian National Health Service (Abruzzo)	Bonacich Centrality, Ego-network density	What is the relationship between hospital patient-sharing network characteristics and the likelihood of a hospital readmission?	☐ The characteristics of hospital patient-sharing networks influenced patient-level hospital readmission rates. ☐ After adjustment, hospital centrality was associated with readmissions. ☐ After adjustment, hospital ego-network density increased the likelihood of readmissions.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Merrill, Sheehan, Carley, and Stetson (2015)	USA	Cross-Sectional	EMR	Total degree, density, Diameter, Inverted betweenness, Centralization, Edge weight,	What are the observed patterns of service delivery for patients with congestive heart failure with respect to frequency and order of service use in the context of readmissions?	☐ In a cohort of congestive heart failure patients, there were differences in the order and frequency of services used by patient admission status (never admitted, admitted once, single re-admit, and multiple re-admit). ☐ Observed patterns of care captured in the order of patient transitions from service to service and the volume of patient transitions from service to service were validated by a clinical expert panel.
Moen, Austin, Bynum, Skinner, and O'Malley (2016)	USA	Cross-sectional	Medicare claims	Betweenness centrality, Closeness centrality, Eigenvector centrality, Node Strength, Degree, Edges, Alt-K-Star, Clustering coefficient	Do hospital or physician network measures account for some of the observed differences in evidence-based implantable cardioverter defibrillators therapy use between to hospital referral regions?	☐ Using nested models, the researchers found that the observed differences between the two regions in evidence-based implantable cardioverter defibrillator (ICD) therapy may be explained in part by differences in physician network structure, specifically node strength and closeness centrality of the ICD capable physicians. ☐ Physician node strength, the number of clinical encounters a provider has with shared patients in his or her hospital network was the only network measure to have a statistically significant association with the receipt of evidence-based ICD therapy.
Ong, Olson, Cami, Liu, Tian, Selvam, and Mandl (2016)	USA	Cross-sectional	HealthCore Integrated Research Database	Care density, Number of patients shared by two physicians, Percentage of patients shared by two providers, Jaccard similarity, Team Size	What is the relationship between physician patient-sharing relationships and the likelihood of multiple providers prescribing benzodiazepines?	☐ After adjustment, cohesion of a patient's physician team as measured by care density was negatively associated with receipt of overlapping benzodiazepine prescriptions. ☐ After adjustment, physician dyads who shared a greater number of patients were less likely to write overlapping benzodiazepine prescriptions.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Ong, Olson, Chadwick, Liu, and Mandl (2016)	USA	Cross-sectional	HealthCore Integrated Research Database	Constellation, network density, Care Density	What is the association of physician patient-sharing networks on the risk of multiple physicians prescribing of medications with known drug–drug interactions?	☐ Two percent of patients in a private insurer claims database received two or more medications with known drug to drug interactions from multiple physicians. ☐ After adjustment, a one-unit increase in the natural log of Care Density was protective against receipt of interacting medications from multiple physicians. ☐ In models stratified by constellation size (number of physicians involved in a patient's care), the risk of multiple physicians prescribing of interacting drugs decreased as constellation size increased.
Paul, Keating, Landon, and O'Malley (2014)	USA	Cross-sectional	Medicare claims	Network Density, Reciprocity, In-degree, Out-degree, Global triadic clustering	Is an estimation approach that accounts for dyadic and triadic dependence less biased than traditional dyadic independence models?	☐ Dyadic-dependence models yield less biased results than models that ignore dyadic dependence in physician patient-sharing networks.
Pollack, Weissman, Bekelman, Liao, and Armstrong (2012)	USA	Cross-sectional	SEER-Medicare	Number of urologists per community, Number of patients per community, Average urologist degree	Does localized prostate cancer care vary by physician patient-sharing networks?	☐ The network structures of physicians involved in prostate cancer care in three cities varied with respect to number of nodes and included a number of large subgroups. ☐ In adjusted analyses, the odds of receiving a prostatectomy varied significantly by urologist subgroup. ☐ Providers in the same practice were often in the same subgroup, but subgroups also included physicians from different practices.
Pollack, Weissman, Lemke, Hussey, and Weiner (2013)	USA	Cross-sectional	SEER-Medicare	Care density	Does localized prostate cancer care vary by physician patient-sharing networks?	☐ Among diabetes and congestive heart failure patients, care density - which measures the extent of patient sharing between a patient's care team – did not find an association between claims-based measures of continuity. ☐ After adjustment, high care density was associated with lower total health spending and inpatient health spending for both patients with congestive heart failure and diabetes.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Pollack, Frick, Herbert, Blackford, Neville, Wolff, Carducci, Earle, and Snyder (2014)	USA	Cohort	IMS Health Plan Claims Database	Care density	Do patients seeing physicians who share patients have lower costs of care and fewer hospitalizations?	☐ Among cancer survivors, care density ranged from 1 to 6. ☐ After adjustment, cancer survivors with the highest care densities were more likely to have lower odds of hospitalization and higher odds of diabetic eye examinations compared to cancer survivors with the lowest care densities.
Pollack, Wang, Bekelman, Weissman, Epstein, Liao, DuGoff, and Armstrong (2014)	USA	Cohort	SEER-Medicare database	Number of urologists per community, Number of patients per community, Average urologist degree	Do cancer survivors seeing physicians who share patients receive higher quality care and lower care costs?	☐ Unadjusted rates of complications following prostatectomy varied between subgroups of physicians who care for patients with prostate cancer across five cities. ☐ Using an intra-subgroup correlation coefficient, the authors report that physician subgroups explained as much as 13.5% of the variation in 30-day complications (City 3), 31.3% of the variation in late urinary complications (City 3), and 14.7% of the variation of long term incontinence (City 1). ☐ The relationship between network characteristics (e.g., average urologist degree) and complications were not consistent across cities.
Pollack, Lemke, Roberts, and Weiner (2015)	USA	Cross-sectional	SEER-Medicare	Care density	Are variations in patient-sharing networks associated with rates of complications following radical prostatectomy?	☐ Among all patients and patients with congestive heart failure, diabetes, and chronic obstructive pulmonary disease, bivariate analyses suggest that individuals with higher care densities have on significantly fewer hospitalizations than those with lower care densities ☐ After adjustment, among all individuals the highest care densities were associated with lower odds of having a preventable hospitalization or cervical cancer screening, and higher odds of a breast cancer screening. ☐ After adjustment, among individuals with diabetes, the highest care densities were associated with greater odds of receiving a diabetic eye exam, and lower odds of hospital readmission and preventable hospitalization.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Pollack, Soulos, Gross (2015)	USA	Longitudinal	SEER-Medicare		Does having a peer who was an early adopter of brachytherapy influence a surgeon's use of brachytherapy in a latter period?	☐ Among surgeons who treat women for breast cancer, exposure to peers who were early adopters of brachytherapy was found to be associated with the surgeon's use of brachytherapy in a later period.
Pollack, Soulos, Herrin, Xu, Christakis, Forman, Yu, Killelea, Wang, and Gross (2017)	USA	Cohort	SEER-Medicare		Does early adoption of MRI and PET for breast cancer care by physician peers influence the use of these services by non-early adopting physicians?	☐ Among breast cancer surgeons who did not use magnetic resonance imaging (MRI) and positron emission tomography (PET) scans in breast cancer care from 2004 to 2006, these surgeons were more likely to use these imaging modes in the follow up period if their peer group was in the highest use of MRI or PET compared to surgeons whose peers were in the lowest use group.
Ray, Lin, Weinstein, and Trick (2016)	USA	Cross-sectional	Extensively Drug Resistant Organisms Registry, Illinois Hospital Discharge Data	Degree centrality, Eigenvector centrality	Is patient sharing between hospitals and long term acute care hospitals associated with greater risk of Carbapenem-resistant Enterobacteriaceae infections?	☐ Among Illinois hospitals, higher degree centrality was associated with greater Carbapenem-resistant Enterobacteriaceae (CRE) rates. ☐ With each additional patient-sharing relationship to another hospital, the relative risk of CRE significantly increased by 1.056 among rural hospitals; and the relative risk of CRE significantly increased by 1.027 among Chicagoland,and 1.025 among non-Chicago urban facilities compared to rural hospitals.
Simmering, Polgreen, Campbell, Cavanaugh, and Polgreen (2015)	USA	Cross-sectional	Healthcare Cost and Utilization Project California State Inpatient Database	In-degree, Weighted in-degree	Does inter-hospital patient sharing affect the rate of C. difficile infection?	☐ In California, over seven years, 9.2% of all possible patient transfers between hospitals occurred at least once. ☐ Compared to multivariate negative binomial models accounting only for patient mix, hospital fixed effects, and time, models accounting for patient transfers received by a hospital defined as either in-degree or weighted in-degree, improved model fit. ☐ A one-unit increase in the log of in-degree was associated with a 4.8% increase in the mean number of Clostridium difficile (C. diff) cases. ☐ A one-unit increase in the log of weighted in-degree was associated with a 3.3% increase in the mean number of C. diff cases.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Stein, Mendelsohn, Gordon, Dick, Burns, Sobero, Shih, and Pacula (2017)	USA	Cohort	Medicaid claims		What are the rates of opioid prescribing to Medicaid-enrollees in the calendar year after an opioid use disorder diagnosis? What is the relationship of individual, county, and provider community factors with such prescribing opioid prescribing to Medicaid-enrollees in the calendar year after an opioid use disorder diagnosis?	☐ Using the modularity maximization community detection to identify physician communities to treat patients with opioid use disorders, the researchers identified 1081 distinct provider communities in 2009 in 12 different states. ☐ Among Medicaid beneficiaries in 12 states previously diagnosed with an opioid-use disorder, 45% filled a prescription for an opioid analgesic and 37% for a benzodiazepine in the year following their diagnosis. ☐ Rates of opioid and/or benzodiazepine rates varied substantially across provider communities; rates of opioid prescribing were 2.5 times here in the top quartile of prescribing physician communities compared to the bottom quartile and rates of benzodiazepine prescribing were 3 .3times higher in top quartile of prescribing physician communities compared to the bottom quartile.
Steitz and Levy (2016)	USA	Cross-sectional	Vanderbilt University Medical Center Tumor registry	Provider node size, Ratio of Providers to Patients, Ratio of provider edges to patients, Ratio of unique edges to patients, Edge size	Do provider relationships within and between institutions differ in strength? How does the connectedness of provider networks vary with changes in patient cancer stage?	☐ In a cohort of stage I to stage III breast cancer patients who saw at least one Vanderbilt University Medical Center (VUMC) provider, the patient-sharing network included 409 providers (medical oncology, surgical oncology, radiation oncology) who had 1,758 patient sharing relationships (edges). ☐ The majority (55 percent) of provider-provider patient-sharing relationships occurred between VUMC affiliated providers. ☐ Providers treating stage III breast cancer patients had the highest ratio of providers to patients, indicating a more tightly connected network than providers treating stage I or II patients.
Tranmer, Palloti, and Lomi (2016)	Italy	Cross-sectional	Italian health data	Edge weights	Do emergency and non-emergency transfers explain the variation in waiting times in emergency departments embedded within hospitals?	☐ Using Multiple Membership Multiple Classification models, the researchers find that variation in emergency department (ED) waiting time is determined in part by the multi-level network (emergency patient transfers between EDs and hospitals and non-emergency transfers between hospitals and hospitals) in which the EDs are embedded.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Uddin, Hossain, and Kelaher (2011)	Australia	Cross-sectional	Australian Insurer	Betweenness centrality, Density, Distance	What is the relationship between physician patient-sharing networks and patient outcomes?	☐ Using exponential random graph models, this study found that 2-star physician network structures were associated with hospital cost. Triangle structures, alternative k-star, and alternative k-2 paths were associated with hospital readmission rate.
Uddin, Hamra, and Hossain (2013)	Australia	Cross-sectional	Australian Insurer	Edge, 2-star, 3-star, Triangle, Alt-K-Stars, Alt-K-Triangles, Alt-K-2-Paths	What is the relationship between physician patient-sharing network characteristics on hospitalization cost and readmission rate?	☐ Among physicians who treat patients for total hip replacement, the structure of hospital-based physician networks were associated with hospitalization costs and readmission rates. ☐ Network characteristics (i.e., degree centralization, betweenness centralization, and network density) of physician networks defined by sharing a total hip replacement patient were weakly correlated with each other. ☐ In models adjusted for patient age and the interaction of age and the network measure, the coefficient for betweenness centralization and density were negatively associated with hospital cost. The interaction terms between these measures and age were positive and significant. ☐ Degree centralization, betweenness centraliziation and density were not associated with readmission rate in models controlling for patient age and the interaction of age and the network measure. ☐ Using ERGMs, the authors report that physician networks with high readmission rates were more decentralized while low readmission physician networks were more centralized.
Uddin, Hossain, Hamra, and Alam (2013)	Australia	Cross-sectional	Australian Insurer	Degree centralization, Betweenness centraliziation, Density, Edge, 2-star, 3-star, Triangle, Alt-K-Stars, Alt-K-Triangles, Alt-K-2-Paths	What is the relationship between physician collaboration network characteristics on hospitalization cost and readmission rate?	☐ In physician networks defined by shared total hip replacement patients, analyses suggest that physician networks with greater degree centrality and tie strength are positively associated with hospital length of stay. The relationship between network characteristics (degree centrality and tie strength) and hospital length of stay are moderated by patient gender. ☐ An ERGM analysis found that physician networks with high readmission rates had more closed triads – suggesting a flat organizational structure; centralization was associated with better performance (lower readmission rates)

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Uddin, Kelaher, and Piraveenan (2015)	Australia	Cross-sectional	Australian Insurer	Number of physician communities, Average number of physicians per community, Ratio of physicians to patients	What is the relationship between the number of subgroups on hospitalization cost and readmission rate?	☐ The authors identified 4.3 subgroups (ranging from 2–7) within 85 physician networks defined by hospitalized hip replacement patients. ☐ Simple linear regression models found that the number of subgroups was negatively associated with readmission rate, while the number of physicians per community was positively associated with readmission rate.
Uddin, Kelaher, and Srinivasan (2015)	Australia	Cross-sectional	Australian Insurer	Degree centrality, Tie strength	Do physician network measures derived from medical billing data predict a physician community's hospital length of stay and readmission rate.	☐ In physician networks defined by shared total hip replacement patients, analyses suggest that physician networks with greater degree centrality and tie strength are positively associated with hospital length of stay. The relationship between network characteristics (degree centrality and tie strength) and hospital length of stay are moderated by patient gender. ☐ An ERGM analysis found that physician networks with high readmission rates had more triangle structures – suggesting flat organizational structure – whereas centralization is thought to be associated with better performance (i.e., lower readmission rates)
Uddin (2016)	Australia	Cross-Sectional	Australian Insurer	Average number of physicians per community, Density	What is the relationship between physician collaboration network characteristics on hospitalization cost and hospital length of stay using multi-level regression models?	☐ Using multi-level models, the authors report found significant variations in the structure of physician collaboration networks with respect to density. ☐ The number of physicians in a physician network was significantly associated with hospital cost.
Veinot, Bosk, Unnikrishnan, and Iwashyna (2012)	USA	Cohort	Medicare claims	Patient sharing	How do community hospital staff implement hospital transfers for patients with acute myocardial infarction, and select destination hospitals?	☐ Using Medicare claims data, two-thirds of U.S. hospitals sent more than half of their acute myocardial infarction (AMI) patients to the same hospital (a "primary referral partner"). ☐ 72% of hospitals had the same primary referral partner across all 6-month time periods from 1996 to 2006.

Appendix 3 | Continued

Author(s) (Year)	Country	Study Design	Primary Study Data	Social Network Metrics	Research Question(s)	Key Findings
Yaraghi, Du, Sharman, Gopal, Ramesh, Singh, and Singh (2014	USA			Innovation coefficient, Imitation coefficient, Network externality, Direct network effects, Indirect network effects, Emulators		☐ Direct network effects caused by common patients among physicians are much more influential on HIE adoption as compared with previously investigated social contagion and external factors. ☐ Professional proximity due to common patients was not found to influence adoption decisions; the effect of geographical proximity was more stronger on rural than urban physicians.
Zand, Trayhan, Farooq, Fucile, Ghoshal, White, Quill, Rosenberg, Barbosa, Bush, Chafl, and Boudreau (2017)	USA	Cross-sectional	Medicare claims	Betweenness centrality, Component enumeration, Diameter, Degree assortativity, Reciprocity, Global clustering coefficient, Density, Largest component size, Edge, Edge weight	What are the topological differences in provider patient-sharing networks built from administrative claims data using binning, sliding frame, and trace-route construction approaches?	☐ Three different network construction approaches—binning, sliding frame, and trace-route—each produced substantial differences in the topology of patient-sharing networks with respect to the number of edges, density, assortativity, and clustering. ☐ The number of shared patients used to define an edge between two providers affects the topology of a network with respect to number of nodes and edges. Using the trace-route algorithm, physician patient-sharing networks with 12 or more shared patients included 2.3% of the edges and 49.9% of the nodes in comparison to networks using 1 or more shared patients. Similarly, using the sliding frame algorithm, physician patient-sharing networks using 12 or more shared patients included 2.1% of the edges and 31.2% of the nodes in comparison to networks using 1 or more shared patients.

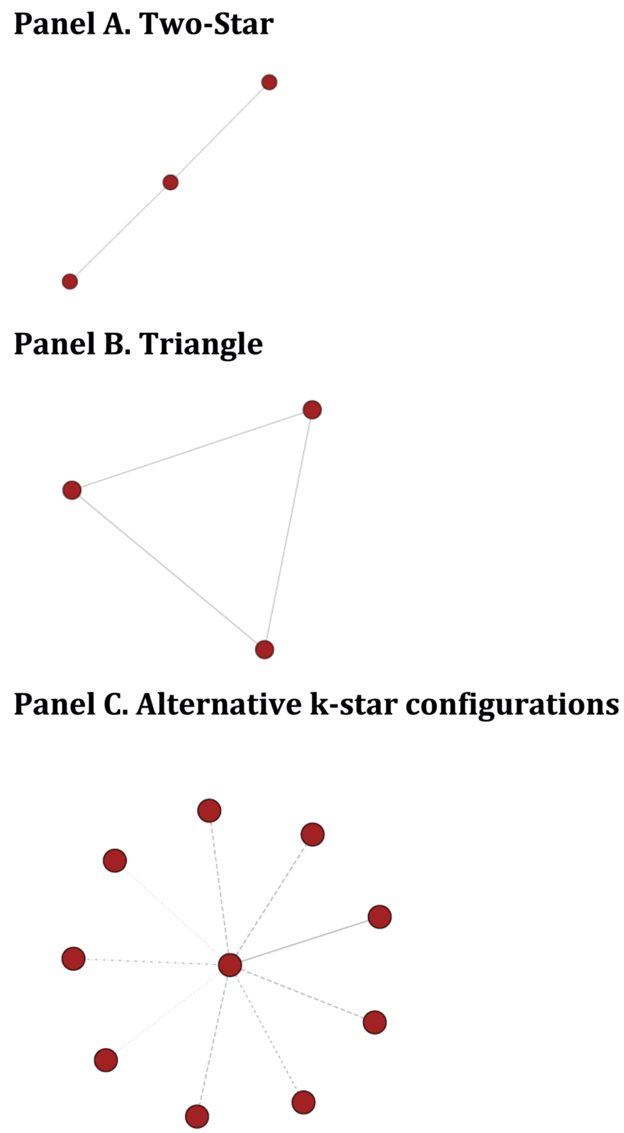

Fig A1 | Illustration of configurations for exponential random graph models. (A) Two-star. (B) Triangle

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