

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/6579948>

# Network Analysis in Public Health: History, Methods, and Applications

Article in *Annual Review of Public Health* · February 2007

DOI: 10.1146/annurev.publhealth.28.021406.144132 · Source: PubMed

CITATIONS

439

READS

918

2 authors:



Douglas A Luke

Washington University in St. Louis

172 PUBLICATIONS 7,587 CITATIONS

[SEE PROFILE](#)



Jenine Kinne Harris

Washington University in St. Louis

105 PUBLICATIONS 2,462 CITATIONS

[SEE PROFILE](#)

Some of the authors of this publication are also working on these related projects:



Investigation of Lead and other heavy metal exposures from lead in paint, and smelting and mining operations. [View project](#)



Ozioma CECCR project [View project](#)

# Network Analysis in Public Health: History, Methods, and Applications

Douglas A. Luke and Jenine K. Harris

Department of Community Health, School of Public Health, Saint Louis University, St. Louis, Missouri 63104; email: dluke@slu.edu

Annu. Rev. Public Health 2007. 28:69–93

The *Annual Review of Public Health* is online at <http://publhealth.annualreviews.org>

This article's doi:  
10.1146/annurev.publhealth.28.021406.144132

Copyright © 2007 by Annual Reviews.  
All rights reserved

0163-7525/07/0421-0069\$20.00

First published online as a Review in Advance on  
January 12, 2007

## Key Words

social networks, disease transmission, diffusion of innovations, social support, social capital

## Abstract

Network analysis is an approach to research that is uniquely suited to describing, exploring, and understanding structural and relational aspects of health. It is both a methodological tool and a theoretical paradigm that allows us to pose and answer important ecological questions in public health. In this review we trace the history of network analysis, provide a methodological overview of network techniques, and discuss where and how network analysis has been used in public health. We show how network analysis has its roots in mathematics, statistics, sociology, anthropology, psychology, biology, physics, and computer science. In public health, network analysis has been used to study primarily disease transmission, especially for HIV/AIDS and other sexually transmitted diseases; information transmission, particularly for diffusion of innovations; the role of social support and social capital; the influence of personal and social networks on health behavior; and the interorganizational structure of health systems. We conclude with future directions for network analysis in public health.

## INTRODUCTION

Over the past several decades researchers have placed increasing emphasis on using ecological models and methods in the health and social sciences in general, and public health in particular. The 2001 National Institutes of Health report “Toward Higher Levels of Analysis: Progress and Promise in Research on Social and Cultural Dimensions of Health” (110) lays out an ecological and multilevel national research agenda, and its recommendations include support for increased use of measurement at the “group, network, neighborhood, and community levels” (p. 3). This recommendation recognizes an important gap: Although ecological thinking is part of the mainstream in the health sciences (59), we lag behind in having a variety of ecological methods and tools that are routinely used in studies of health (95). In public health, much of what we study is inherently relational: disease transmission, diffusion of innovations, coalitions, peer influence on risky behavior, etc. Network analysis is a research approach that is uniquely suited to describing, exploring, and understanding these types of structural and relational aspects of health. This review outlines the history of network analysis, provides a brief overview of network methods, and shows where and how network analysis has been used in public health.

A network consists of actors that represent individuals, organizations, programs, or other entities. As this review shows, a network can be four different things: a conceptual model, a description of an existing real-world structure or system, a mathematical model, or a simulation. We typically depict a network as a set of actors connected by lines or arrows which show some relationship between them. For example, **Figure 1** shows tobacco control agencies in Oregon. The color and size of the nodes show the type of agency and its role within the network; the links between nodes represent contact between agencies.

Network analysis, then, is the field that concerns itself with relational data and research questions. More specifically, the network paradigm has four important features (51):

1. Network analysis is a structural approach that focuses in part on patterns of linkages between actors;
2. it is grounded in empirical data;
3. it makes frequent use of mathematical and computational models; and
4. it is highly graphical.

## HISTORY AND DEVELOPMENT OF NETWORK ANALYSIS

Network analysis has a long and complex history drawing on traditions in many different research disciplines. In some cases its development was stepwise, with new ideas building on existing work; other times concurrent development was occurring in different fields. The following brief overview highlights some of the major milestones in the development of social network analysis. For a more detailed treatment of the history of network analysis, see Freeman (51).

Eighteenth-century European mathematician Leonhard Euler used a visual representation of a network of bridges and rivers to solve the now famous Königsberg bridge problem (30). The problem asked if it was possible to walk around the town of Königsberg, crossing each of its seven bridges only once, and returning to the point of origin. By portraying the bridges and land as points with lines between them, Euler determined that no such path existed owing to the number of nodes and links. In doing so, Euler invented graph theory, which provides one of the mathematical foundations for network analysis. **Figure 2** shows a version of the Königsberg map and the network developed to explore the problem.

Throughout the 1800s and early 1900s social scientists posed questions about social

ties and developed theories and terminology to describe social connections and social structure (51). Renowned sociologists such as Comte and Simmel are often credited with many of the early ideas providing a foundation for social network analysis. Important contributions were also made during this time by lesser-known social scientists such as ethnologist Eilert Sundt, who studied the formation of social circles among rural Norwegian farmers (33).

In 1929 a new idea about ties between people was proposed in a short story by Hungarian writer Frigyes Karinthy. In the story, a character asserted that he could link anyone in the world to himself through at most five acquaintances, proposing what may be the first mention of the concept of six degrees of separation (109). In Karinthy's time this assertion became a popular game, and it remains a part of popular culture today. Recent appearances of the concept are found on numerous Web sites and in John Guare's play, *Six Degrees of Separation*. The concept of six degrees of separation was one of the first demonstrations that a network approach could be used to discover important characteristics of the natural world.

In the 1920s educational psychologists published a number of studies reporting on characteristics of social ties such as influence, interaction, and companionship (50). Although many important network ideas came from this early work, the studies are often overshadowed by the major contribution made in 1934 by psychiatrist Jacob L. Moreno (100). Moreno developed a new way of representing relationships on paper, called a "sociogram." A sociogram was a drawing with points representing people connected by lines representing interpersonal relationships. Moreno's work established network analysis as a unique discipline, and his sociograms were the first specific network analytic tool (141). In 1937 Moreno founded the journal *Sociometry*, which published many of the early studies taking network approaches or developing network methods.

From the mid 1950s to the early 1970s, fields such as sociology, anthropology, and mathematics contributed conceptual, theoretical, and methodological advances that helped to solidify the foundation of modern social network analysis (11, 61, 144). One of the landmark articles in *Sociometry* during this time was a study examining interpersonal communication among physicians and the diffusion of new drugs by Coleman, Katz, and Menzel (39). Coleman, Katz, and Menzel found that the number and types of social connections physicians had influenced their adoption of a new drug with close professional ties facilitating the earliest adoptions.

In 1959, mathematicians Paul Erdős and Alfréd Rényi proposed one of the first formal network models. The Erdős-Rényi model portrayed networks as completely random (9). Surprisingly they found with this model that the larger the size of the network, the fewer connections between network nodes were needed to have the network be completely linked. In fact, according to this model, connecting all six billion people in the world would require each person to have only about 24 random acquaintances (30). This random graph model was an early successful attempt to provide an explanation for how actual networks operate and paved the way for modern mathematical network theory (109).

In the early 1970s sociologist Mark Granovetter proposed a network model that accounted for some basic truths about human social ties (58). Although the Erdős-Rényi network explained why large networks can be connected with a small number of ties (i.e., the "small world" phenomenon), most individuals are not likely to be randomly connected to 24 others around the world. It is more reasonable to assume that people know their neighbors, coworkers, and families. Granovetter posited that, in addition to strong ties to families, neighbors, and coworkers, each person has weak ties to people such as casual acquaintances and that these weak ties held the network together. The acquaintances and friends of friends reached outside what might

otherwise be closed and segmented networks of strong ties, allowing a larger network to form (58).

Granovetter's work is important for several reasons. First, it helped develop a sophisticated and realistic model of network structure (58). More importantly for its subsequent utility for public health, Granovetter's work was among the first applications of network theory, which attempted to explain social structure and human behavior. Granovetter's theory of weak ties arose out of a simple question: "How do people find jobs?" The surprising answer that people find jobs through acquaintances rather than through close friends led to a deeper understanding of how knowledge and information can be efficiently passed through large social networks.

In recent years mathematicians and physicists have started examining the fundamental properties of theoretical and real-world networks. Drawing on the work of social scientists in measuring network centralization (49, 126) physicists developed models such as the small-world model and the scale-free model, which have been useful in describing very large networks (9, 143). In particular, scale-free networks have hubs, or a few nodes that have an unusually high number of links, whereas other nodes have a small and relatively consistent number of links. This structure has since been identified in diverse networks such as sexual partners in the early stages of the AIDS epidemic, the national and international network of airports and flights, and networks of large businesses (9).

Social network analysis rapidly developed as a distinct discipline in the decades following the 1970s (51). Important contributions were made from an extremely wide variety of fields, including sociology, psychology, political science, anthropology, communication, business, mathematics (especially graph theory), statistics, computer science, and physics. In 1977 the professional association for social network analysis was founded: the International Network for Social Network Analysis (INSNA). Shortly thereafter professional

journals focusing on network analysis appeared (e.g., *Social Networks*), and international conferences were established (i.e., the annual Sunbelt Conference). One critical aspect of the success of social network analysis was the development and availability of software packages, including UCINET (25) and Pajek (13). As network analysis grew and was applied in various mathematical, biological, behavioral, and organizational contexts, it became clear that it was not simply a new analytic tool, but a distinctive theoretical discipline. In fact, network analysis can be seen as a type of "normal" science, using Kuhn's terminology (65, 85). Network analysis, thus, provides public health with a new way of framing and answering important health questions. To introduce some of the major differences between network approaches and traditional research methodology, the next section contains an overview of network methods.

## A BRIEF OVERVIEW OF NETWORK ANALYSIS METHODS

The inherently relational quality of network methods requires a shift in thinking when it comes to research methodology. Network approaches focus on relationships between subjects rather than relationships between subject attributes (*i.e.*, variables). Study design, data collection, and data analysis incorporate this relational perspective, requiring unique approaches to each.

### Study Design and Data Collection

Traditional study designs in public health typically utilize attribute data at the individual level. For these types of designs, data can be collected from individuals before the entire sample has been identified, recruited, or interviewed. Data collection in network studies works quite differently. For many network studies, the entire network must be identified before data collection starts. For example, in a study of student friendships, students in

**Table 1** Comparison of attribute data format (top) and network data format (bottom)

Attribute data						
ID	Age	Gender	Educ.	# Partners	Diagnosed	
1	25	M	Low	7	Y	
2	32	F	Low	3	N	
3	33	F	High	4	N	
4	34	M	Med.	4	Y	
5	40	F	Med.	2	N	
6	37	M	High	5	N	

Network (friendship) data						
ID	Bob	Karen	Nancy	Peter	Roberta	Scott
Bob	0	0	0	1	0	1
Karen	0	0	1	1	1	0
Nancy	0	1	0	1	1	1
Peter	1	1	1	0	0	1
Roberta	0	1	1	0	0	1
Scott	1	0	1	1	1	0

particular classrooms would be identified before starting to collect network data. Then, every student in a classroom would be asked about every other student to ascertain the relationships. **Table 1** shows how the resulting data could be organized, comparing data from a traditional individual-level study design to relational data obtained in a network study. In individual attribute studies, the data are organized in an  $N$ -by- $k$  rectangular matrix, with  $N$  subjects measured on  $k$  attributes. In network analyses, data are typically organized in an  $N$ -by- $N$  square matrix. Thus, the data entries represent a relationship between a pair of actors (in this case, a friendship relation).

This type of network data collection is sometimes referred to as complete or bounded because it is based on prior identification of all network members. In many cases, network identification is straightforward, especially when boundaries are clear. For example, a network analysis of a substance abuse referral network would identify all social service agencies in a particular county that provide or receive referrals for substance abuse services. However, in many cases, network identification may not have clearly defined boundaries. One useful network sampling approach is snowball sampling or respondent-

driven sampling (43, 120). This type of sampling falls into the larger category of link-tracing designs (128). Here, the researcher starts with a small number of network members and asks them who else should be included in the network. These new network members are then approached and are in turn asked to nominate network members. Typically, after a small number of waves network members start nominating people who have already been nominated. For more information about network study design see the 2004 text by Morris (101) and the 1992 article by Doreian & Woodard (43).

### Data Analysis

Although many ways exist to analyze network data, three broad approaches to analysis are generally used. First, network visualization allows researchers and audiences to view various graphical depictions of networks. Second, descriptive analyses of network properties can reveal important details concerning the (a) position of network actors, (b) properties of network subgroups (called a subgraph), or (c) characteristics of a complete network (**Table 2** provides definitions and terms used at each level). Third, recent work in

**Table 2** Network levels of analysis with descriptions and network measures

Level	Definition and purpose		Standard network measures
Individual	A single actor or node  Identification of the position or location and characteristics of an actor within a network	Degree	Connectivity of a given actor or node given by the number of lines that are incident (connected) to the node
		Centrality	Importance or prominence of a given actor or node Following are several types of centrality: Betweenness: extent to which an actor lies between two nodes that would not otherwise be connected Closeness: how close an actor is to all other actors on the basis of distance between nodes Degree: extent to which an actor is connected to others; the simplest of the centrality measures Prestige: specifically for directed networks; extent to which other members choose a given actor or node
		Structural equivalence	Extent to which actors play similar roles within a network by having the same patterns of connections to other actors
Subgraph	A subset of the graph based on certain nodes or links  Examination of characteristics of a group	Dyad Triad	A pair of actors and the possible tie between them Three actors and the ties between them
		$k$ -core Clique	All nodes in a network with degree $\geq k$ Three or more actors connected by all possible connections
Network	The entire system of nodes and links  Description or inference based on the structure of the entire network	Density Diameter	Ratio of observed ties to possible ties Longest of all geodesics (shortest path between two nodes)
		Centralization	Extent to which the graph shows a hierarchical or centralized structure

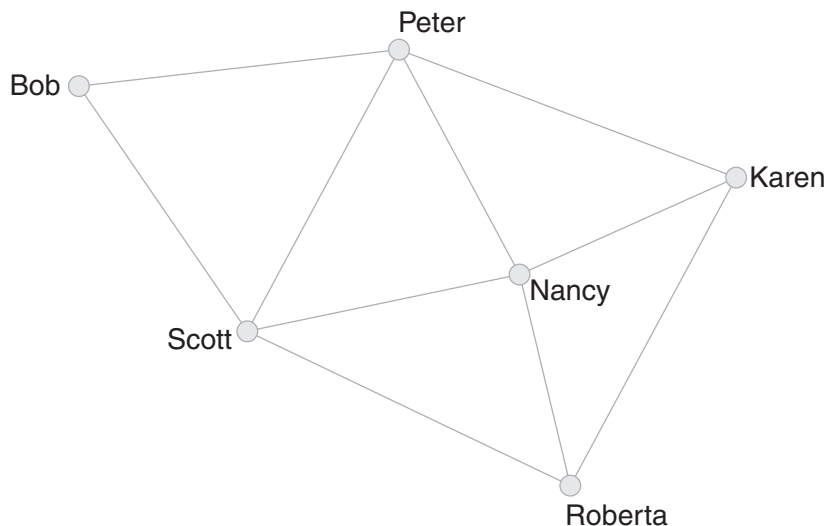
stochastic and longitudinal network methods allows investigators to build and test inferential and longitudinal network models.

**Network visualization.** Network visualization consists of presenting network information in graphic format and is a major part of social network analysis. **Figure 3**, for example, depicts the friendship network based on data from **Table 2**. Graphic representation allows researchers to ask and answer questions about the network that might not be statistically obvious. Modern network software incorporates layout and presentation algorithms that facilitate efficient and accurate interpretation of network graphs. This is important because networks can be displayed in a variety of ways. For example, **Figure 4** shows

two ways of displaying the same tobacco control network. On top is a ring network, where all the nodes are arranged in an oval. This configuration is limited in that it becomes hard to determine which nodes are more (or less) connected to others. In comparison, the bottom figure uses an energy or spring embedding algorithm to position more central nodes (those with more connections) toward the center of the network (54), making it easier to see the structure. Modern visualization techniques have been developed to display large and complicated networks in two- and three-dimensional space (68).

**Network description.** As **Table 2** suggests, network description can focus on the role of individual actors in the network, identification





**Figure 3**

This network graphic depicts the friendship ties between six individuals. This was developed by the authors for the purpose of demonstrating how network data is visualized. The data underlying the network can be found in **Table 2**.

and interpretation of subgroups (called a subgraph), and analysis of overall network structure. For a more formal and complete treatment of network methods, see the Wasserman & Faust text (141). Analysis at the individual level typically consists of identifying the position or location of an actor within a network. Traditionally, researchers have paid attention particularly to actors who play central roles, for example, those who are chosen more frequently by other network members (high prestige) or who act as brokers in communication or transmission networks (high betweenness). For example, in a study of adolescent smoking, Ennett & Bauman (45) identified three positions in social networks associated with transmission of health behaviors: isolate, bridge, and clique member. These positions were defined by the number and types of links individuals had to others in the network, and each position was associated with a different probability of adopting a particular health behavior. Ennett & Bauman found that isolates, or adolescents with few or no links to others, were more likely to be smokers than were adolescents in bridge or clique positions. A later study determined that, among middle school students, popular students with many links to others were more likely to become smokers (139).

Subgraph analysis consists of identifying and analyzing a subset of links and nodes from a network. This approach is used to understand cohesion in groups and to identify characteristics of dyads, triads, and other subsets (**Table 2**). For example, in an article about risk potential for HIV infection (53) Friedman et al. used subgraph analysis to find all the components comprised of individuals in the network that had two or more drug-injecting or sexual links. They determined that this subset of individuals was an appropriate target for HIV prevention efforts because they were more likely to be HIV positive or engage in high-risk behaviors.

Finally, network description can focus on the overall structure of the network. Network-level statistics provide insight into how connected a network is or how flat or hierarchical the relationship structure is. Analyses of public health systems often report network-level results because they are typically examining collaboration in a group of agencies (84, 115). For example, in an article about a health policy network addressing diabetes along the U.S.-Mexican border (115), Provan et al. compared the density of a network of agencies for four different relations: sharing information, sharing resources, working together on projects, and sharing



**STD:** sexually transmitted disease

referrals. They found that the information-sharing network had the highest density, suggesting that information was passed between agencies more frequently than were resources or referrals.

### Stochastic and longitudinal networks.

One limitation of the preceding methods is that they are fundamentally descriptive. Network data is, by definition, nonindependent, and thus traditional parametric models, that require independence of observations cannot be applied. In the past decade, however, researchers have developed stochastic network modeling methods, which can be used to test network hypotheses (142). Also, new methods have been developed that allow analysis of longitudinal network data (127). To date, only a handful of public health studies have utilized stochastic (102, 103) or longitudinal (111, 133, 134) methods.

## THE USE OF NETWORK ANALYSIS IN PUBLIC HEALTH

Public health has long recognized the importance of relational characteristics in understanding disease and health. The role of close physical contact in communicable disease outbreaks and the influence of peers on adolescent smoking and substance use are two notable examples. However, although public health has often adopted an ecological framework that recognized the importance of relational information, only relatively recently have scholars utilized a more explicit network analytic approach. Our review suggests that the use of network analysis in public health falls into three broad categories: transmission networks, social networks, and organizational networks (see **Figure 5**). This organization is not based on particular network analytic methods or theory per se; rather, it reflects how public health researchers have utilized network analytic tools to address public health problems.

## Transmission Networks

Analysis of transmission networks represents a common use of network analysis in public health. Transmission networks are social systems that structure the flow of some tangible element. Here the emphasis is on what flows between actors in a network. There are two major types of transmission networks studied in public health: disease transmission networks and information transmission networks.

**Disease transmission networks.** Friedman & Aral (52) defined disease transmission networks as risk potential networks, which are networks of individuals connected by ties that can spread infection. As Eames & Keeling pointed out (44), “A wide range of communicable human diseases can be considered as spreading through a network of possible transmission routes. The implied network structure is vital in determining disease dynamics...” (p. 13,330).

These ties include behaviors such as needle sharing or risky sexual activity, as well as seemingly less risky connections such as living in the same household or belonging to the same friendship group. In terms of risk potential, network analysis has been used primarily to look at the spread of HIV/AIDS, other sexually transmitted diseases (STDs), and other infectious diseases. Much of this research has highlighted differences between network approaches and traditional epidemiological models of STDs and HIV.

Traditional disease outbreak models examining person-to-person spread of infection typically consist of the frequency of cases over time (78), whereas network models of transmission show relationships among individuals. The difference can be seen in **Figure 6** with an epidemic curve showing the spread of syphilis on the left (34) and a network graph modeling the spread of syphilis (in a different population) on the right (119). The epidemiologic model is most useful for identifying the course of an outbreak or epidemic,

whereas the network model reveals the underlying transmission structure of the outbreak. The network model is useful particularly for planning interventions for the disease in question (147). These figures are included to allow the reader to compare traditional epidemiologic methods with network analytic methods.

Network-like diagrams depicting disease transmission appeared in print as early as 1940 (31). More recently, similar diagrams depicting the early spread of HIV/AIDS were presented as a tool for understanding and addressing this emerging health problem. In 1984, just as the American public became aware of the AIDS epidemic, Auerbach and colleagues published an article entitled "Cluster of Cases of the Acquired Immune Deficiency Syndrome" in the *American Journal of Medicine* (7). The article presented a diagram of 40 AIDS patients in 10 cities linked by sexual contact. This depiction was among the first evidence that AIDS was an infectious disease and was transmitted through sexual contact. In 1985 Klov Dahl took a network approach to analyzing the data from the Auerbach et al. study (80). His conceptualization of disease transmission as a social network allowed researchers the opportunity to consider disease in a new way, which marked a transition to wider use of network concepts and methods for studying infectious diseases. Since that time, numerous other studies have considered risk potential networks and HIV/AIDS transmission. These studies have focused primarily on sexual and needle-sharing networks and identified risk factors associated with network characteristics (41, 53, 87, 104). In addition, characteristics of network structure have been associated with the various stages of HIV epidemics (114).

Through analysis of HIV/AIDS risk potential networks, researchers have identified a number of network-related risk factors for HIV transmission, including network position and composition. In studies of street-level drug markets, researchers found that network position was associated with levels

of AIDS risk behaviors and HIV infection rates (41, 53). These studies, based on a population of 767 injecting drug users (IDU) in New York, reported that a higher percentage of core and inner periphery members were HIV positive. Core members were those considered "regular" members by others in the network, whereas inner-periphery members were those who had shared drugs with a core member in the past 30 days but were not in the core. In addition to having a higher rate of HIV, these core and inner-periphery network members were involved in risk behaviors such as sharing syringes more often than were network members in the outer periphery. Another study of IDUs found that individuals were more likely to share needles with strongly connected friends than with new friends or friends who were weakly connected (140). This factor reduced their short-term risk of HIV but not the long-term risk owing to the high level of turnover in friendships in this population. By examining the social networks of another population of IDUs, researchers also found that the larger and denser a person's drug network was, the more likely he/she was to share needles (87). In general, the more close or strong ties an IDU has, the more likely he/she is to share needles and to be at risk for HIV (140).

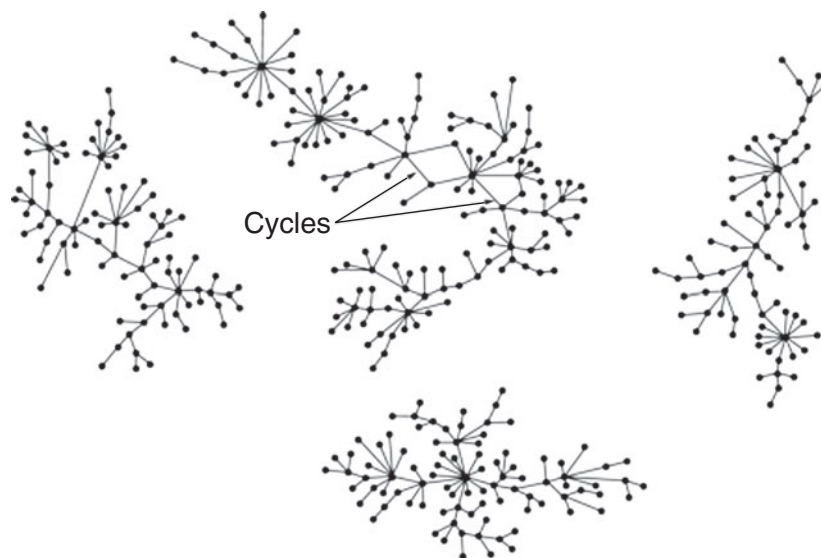
In addition to individual network position and composition, structural network properties have been associated with the epidemic stage or level of transmission of HIV within a population. The amount of assortative and disassortative mixing within the network and the presence of cyclic or dendritic structures are indicators of how HIV is spreading through the population (113, 114). Assortative mixing occurs when people who have something in common are connected to each other. That is, a network where "birds of a feather flock together" would be considered assortative, whereas a network where "opposites attract" would be considered disassortative (102).

By simulating the spread of HIV through networks of sexual relationships, Morris &

---

**IDU:** injection (or intravenous) drug user

---



**Figure 7**

A graph of the four largest chlamydia components in Colorado Springs. Adapted from (113).

Kretzschmar (102) found that, compared with random mixing, both assortative and disassortative mixing regarding the number of sexual partners increased the odds of a large epidemic once there had been an outbreak. Further evidence to support this comes from two studies that found that it was not just having more partners that was a risk factor for becoming HIV positive; in fact, it was disassortative sexual partnerships between younger men and older men that increased HIV risk (104, 122).

Mixing patterns are not the only factor influencing HIV transmission networks. In a study of network structure and STD, Potterat and colleagues (113) identified cyclic structures, or closed loops, within a network as being loci of epidemics that are often present early in an epidemic. Conversely, dendritic, or tree-like, structures appeared indicative of the later phases of an epidemic where the rate of new cases is decreasing (see **Figure 7**). In a later study in the same community, Potterat and colleagues found a mixture of these two structures in an HIV network. They suggested that the hybrid network structure was associated with the low-to-moderate spread of HIV observed in the community (114).

STDs have been another focus of public health network research. Research in this

area has focused on gaps in traditional epidemiologic methods of contact tracing for STD prevention and control (6, 67, 82, 119). The utility of network analysis for understanding STDs was strikingly demonstrated to researchers and the public in 1998 when Rothenberg and colleagues (119) published an article on a syphilis outbreak in young teenage girls in an affluent Atlanta suburb. A network of 99 teenagers connected by sexual contact was identified when six girls, most under the age of 16, were diagnosed with syphilis (**Figure 6b**). Although the high level of sexual activity among this group of young teenagers appeared unique, a 2004 study (15) of the population of students in a Midwestern high school found a sexual and romantic relations network (**Figure 8**) that included 288 of the 832 students interviewed. Like the teenagers in Atlanta, these students were involved in a single large connected component, putting them at much greater risk for contracting an STD.

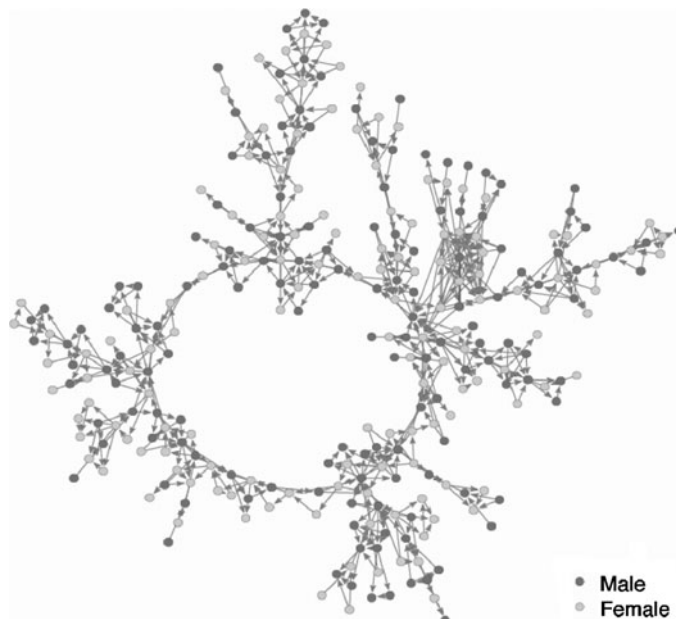
Similar to findings in HIV/AIDS research, the structure of an STD transmission network may be different depending on the stage of STD epidemic and the likelihood of assortative or disassortative mixing in various populations (89, 113). Laumann and colleagues

(89) found that the higher STD infection rate among African Americans could have a network explanation; specifically, within the African American population there is more disassortative mixing concerning the number of sexual partners. Those who had few partners were five times more likely to choose partners that had four or more partners in the previous year. Laumann and colleagues also found that this community was assortative regarding race in choosing sexual partners, keeping STD transmission within the African American community.

Network characteristics differ across different types of STD transmission networks. Networks depicting the spread of chlamydia, gonorrhea (130, 150), and syphilis (119) each have distinctive characteristics. Specifically, Stoner and colleagues (130) found that gonorrhea networks were larger than chlamydia networks and that individuals in gonorrhea networks had more sex partners. Wylie & Jolly (150) found that chlamydia networks had more disassortative mixing concerning the number of sexual partners and that individuals in chlamydia components were from fewer distinct geographical locations.

Identification of network characteristics can lead to development and implementation of more efficient and effective interventions (42, 82, 118, 136, 146, 150). Rothenberg & Narramore (118) describe changes in the approach of a Nashville STD control program based on their review of network research. The new approach allowed the intervention specialists to develop and maintain strong long-term connections in specific neighborhoods to get to know the inhabitants and identify more easily the social networks appropriate for intervention. Examination of other interventions found that network approaches utilizing peer networks were more effective in educating IDUs about risk behaviors and HIV (28, 88) than traditional approaches were.

Although most of the network research on disease transmission has been in the areas of HIV/AIDS and STDs, researchers



**Figure 8**

Romantic and sexual relationships among 288 students at "Jefferson High School." From <http://www.sociology.columbia.edu/pdf-files/bearmanarticle.pdf>.

have done some work on other types of disease transmission. In 2001, Klov Dahl and colleagues published an article using network methods to reconstruct an outbreak of tuberculosis in the mid-1980s (81). The research team used biological, epidemiological, and network information to identify the people and places involved in transmission. The authors found that by taking a network approach, they could assess the importance of people and places and could identify individuals that were not identified by the traditional contact-tracing procedures followed during the outbreak. This approach has since been adopted by the CDC in their guidelines and procedures for tuberculosis control; the new CDC contact-tracing form includes questions regarding places where tuberculosis may have been acquired (36).

Network models of disease transmission have been used to examine recent outbreaks of severe acute respiratory syndrome (SARS) (98). Like other risk potential network

---

**SARS:** severe acute respiratory syndrome  
**DOI:** diffusion of innovation

---

articles, this study supports the idea that epidemiologic models assigning an equal chance of spreading disease to each individual are unrealistic. Meyers and colleagues used information from observed SARS outbreaks in China and Canada to develop theoretical models of disease spread through different network configurations using information about real-life contacts among individuals. This approach allowed the investigators to use social network information from the first few cases of an outbreak to make predictions about the scale of the impending outbreak and about preventive measures that could impede the spread of disease. In addition, a 2003 *MMWR* report on the worldwide spread of SARS focused on contacts among individuals, connecting them through the places they had visited (35).

Finally, in a 2003 study on control measures for pneumonia outbreaks (97), Meyers et al. found that network theory and methods were useful to epidemiologists in modeling the spread of an infection in a health-care facility. From this model they determined that caregivers, although less likely to become ill, had higher rates of transmission to patients than did patients to caregivers. This finding allowed Meyers et al. to propose specific strategies for reducing the transmission of pneumonia in this setting.

In summary, network analysis has advanced epidemiologic work on disease transmission in three ways: by providing structural descriptions of transmission networks, by developing simulations and models that provide more accurate predictions of the course of a disease (112), and by suggesting new types of disease prevention interventions based on a relational approach.

**Information transmission networks.** In public health, like other fields, social networks facilitate the dissemination of information. A central goal of health communication and health education is to devise efficient and effective ways to translate and disseminate health information to practitioners, communities and consumers, which could reduce dis-

ease risk and promote health. These fields are making greater use of network analytic methods to shape how health information is transmitted through and to health consumers.

One early and influential work in this area was the 1955 book by Katz & Lazarsfeld on the two-step flow of information (73). Drawing on their studies of 1940s political campaigns, Katz & Lazarsfeld proposed that the impact of media messages is mediated by social relationships. The role of information networks can perhaps be seen most clearly in Rogers's theory of diffusion of innovations (DOI) (117) first published in 1962. According to Rogers, DOI consists of three major steps in the process of adopting an innovation: (*a*) become aware of and learn about the innovation, (*b*) develop a positive or negative attitude toward the innovation, and (*c*) put the innovation to use. Rogers also categorized the adopters of any new innovation or idea into five categories, each located along a bell-shaped curve in the following order: innovators, early adopters, early majority, late majority, and laggards. DOI is clearly, at least in part, a structural phenomenon. Network characteristics, such as the centrality of adopters, can influence the speed and breadth of the spread of the information. For a treatment of how networks structure information flow and adoption from the perspective of a public health researcher, see Valente (133).

An early and influential study of information diffusion was conducted by Coleman et al. in 1966. Coleman and colleagues (40) examined the diffusion of information about new drugs through the informal social networks of physicians. Since this study, social network analysis has been used to model the diffusion of public health innovations in several areas, including family planning (27, 99, 129), reproductive health campaigns (47, 138), and HIV education and prevention messages (28, 99). Several of the studies of diffusion of family planning information found that having a direct or indirect link to the source of information was associated with either having more knowledge



of family planning (27, 129, 138) or increasing the use of contraceptives (27, 138). Not only did having a link to the source of information make a difference, but the composition of an individual's personal network and an individual's position within that network also had some relationship to knowledge and behaviors. Two studies (27, 129) found that network position was associated with family planning knowledge, attitudes, and, possibly, use. Isolates, or those individuals without network ties, showed different patterns of knowledge and attitudes than did those who had discussed family planning within or outside the village. Namely, using a modern method of family planning was associated with having discussed family planning with someone outside the village (129).

In their 2006 article in *Sexually Transmitted Diseases*, authors Valente & Fosados describe the use of network models of DOI to enhance public health interventions (136). They assert that, although public health is moving forward by taking a more multimedia approach to disseminating interventions, the approaches are still often lacking an interpersonal communication component. The authors conclude that, "who delivers the message, and in what interpersonal context, may be just as, if not more important than the message itself, [and] may result in better, more relevant, and perhaps more effective programs" (p. 22).

Finally, network researchers have worked on developing simulations that reveal the properties of dissemination networks. Valente & Davis simulated diffusion networks and showed that innovation adoption was quickest if the early adopters were also opinion leaders in the network (135). More recently, sophisticated mathematical models of diffusion networks have incorporated differential costs of adoption, which appear to follow a fundamental power law (60).

As the field of public health has discovered more about network influences on information transmission, researchers and funders have started building their own net-

works to speed up the dissemination of public health knowledge. An example of this is the Centers for Disease Control and Prevention's Healthy Aging Research Network (63). Tobacco control has been in the forefront of establishing research and training networks to enhance information dissemination; examples include the National Cancer Institute's Tobacco Harm Reduction Network, the Tobacco & Health Disparities Research Network, and the Global Tobacco Research Network (108).

## Social Networks

Social networks represent the second major area for network analysis in public health. Research on social networks focuses less on the transmission of a specific tangible element and more on how social structure and relationships act to promote or influence health and health behavior. Specifically, public health researchers have examined the influence of social support and social capital on morbidity and mortality as well as on general well-being. Additionally, this research area has included numerous descriptive studies of social support networks in various populations, such as the chronically ill, depressed, homeless, or elderly. Researchers have also examined the relationship between social networks and specific health behaviors.

**Social support and social capital.** Along with disease transmission, using network analysis to understand how social support and social capital influence health has been one of the largest areas of network research in public health. Social support and social capital are related but distinct concepts. According to a recent review, social support is typically defined as the actual and perceived resources available to an individual from friends, family, and acquaintances (48). Much of the early work on social networks examined how different aspects of social support influenced mental health, physical health, and behavior (17, 79). Although this early work was often based

on sophisticated theories (for example, distinguishing the related concepts of social network from social support), the studies were limited by relatively crude network tools and research methods. The general results of this early work on social support indicated that greater social support [often measured simply as number of friends, frequency of contact with close family members, self-reports of quality of support received, etc. (94)] was strongly associated with greater mental health and reduced mortality (17). However, taken as a whole, the work on social support was less successful at revealing the mechanism or structure of the social connections and processes that appeared to influence health strongly.

With the introduction of the concept of social capital, investigators had a more sophisticated theoretical model that not only explained the health benefits of social support, but also proposed a more specific structural model that suggested a more dynamic process between persons and the social networks that they inhabit. Lin has defined social capital as “resources embedded in a social structure which are accessed and/or mobilized in purposive actions” (92, p. 35). Access to resources is thus a critical part of social capital, which includes the concepts of cooperation and collective action. Specifically, it is defined as membership in social networks that facilitate access to resources (24, 56, 75, 92, 151). One of the major differences between the two concepts of social support and social capital is the level of analysis. Whereas social support tends to be conceptualized and measured at the inter-individual level, social capital includes higher-level constructs such as neighborhood, group, or state (74). The research on social support and social capital is voluminous; the following section highlights how these concepts have been applied in public health.

Although there is some earlier research on the subject, the number of studies examining associations between social support and aspects of psychological and physical health increased dramatically following the publication

of three review papers (32, 38, 71) in the mid-1970s (29). Findings associating social support with health have ranged from determining that the risk of death was 2.3 times higher for men and 2.8 times higher for women considered “isolated” by a limited number of social and community ties (18) to the well-being of blind adolescents being more influenced by network characteristics than by personal attributes (77).

Several studies found that having a large network improved health and reduced mortality. For example, one early study (64) found that men reporting more social relationships and activities had lower levels of mortality over a lengthy follow-up period. In a study of how women’s social networks influence child survival in Mali, family network size significantly increased the odds of child survival after controlling for demographic characteristics (1). Having a large network lowered the risk of family homelessness in a population of homeless and never-homeless, low-income, single mothers (12), and denser networks led to longer-lasting ties for elderly patients in long-term care (14). In addition, social network characteristics impact success or failure in alcohol treatment (10), influence the level of satisfaction of caregivers (55), affect level of depression (57, 93), and predict blood pressure rates (22).

In general, individuals experiencing mental and physical health problems have smaller, less-dense, and disadvantaged social support networks. The social support networks for depressed patients showed deficits (5), social support networks for mental health patients tended to “burn out” over time (20), and social support networks of HIV+ individuals appeared smaller than those for other groups (123). A recent study by Knowlton examining the caregiver networks of low-income African American injection drug users with HIV/AIDS found that the support networks consisted disproportionately of other low-income, drug-using, HIV-infected African Americans (83). Investigators noted a similar phenomenon in social support in



employment referral programs among the urban African American poor. Job referral networks in populations of urban African American poor are deficient and may contribute to the problem of unemployment in this community (116). For example, African American mothers living in poorer neighborhoods have fewer employed and college-educated friends and more friends on public assistance than do those in wealthier neighborhoods (116). Job finding through word of mouth varies for different racial, ethnic groups and by gender, immigration status, and education, with wealthier individuals having more access to social support (125) that increased opportunities for employment. In general the characteristics of social ties with family and friends affect the scope and type of employment opportunities an individual has (91).

Directly and indirectly in a number of studies, researchers have linked social capital to health and well-being, typically finding that greater levels of social capital are associated with better health or well-being (75, 76, 121, 151). A 1997 study by Kawachi and colleagues (76) found that higher social capital, as measured by questions on the General Social Survey regarding trust, reciprocity, and group membership, was strongly associated with lower levels of mortality, even after adjusting for poverty rates and median income. A follow-up report in 1999 found that states with low social capital had more residents reporting fair or poor health (75). The researchers determined that the odds of reporting fair or poor health when living in a state with low social capital were similar to the odds of reporting fair or poor health among current smokers and obese individuals.

A 2005 study of the health implications of social capital found that regular involvement in informal networks (socializing with friends, family, neighbors, coworkers, etc.) was positively associated with better mental health, but not with better physical health (151). In a 1997 study of neighborhoods and violent crime, Sampson and colleagues determined

that social cohesion and trust predicted lower rates of neighborhood violence after adjusting for neighborhood composition, prior violence, and other potential confounders (121).

In general, social support and social capital are important factors in a population's health and well-being. Physical and emotional health along with general well-being all increased with increased social support or social capital. These findings are important for public health professionals developing interventions; building networks that increase the social support and social capital of individuals could be an effective way to combat poor health.

**Health behavior.** Research on how social networks influence health behavior has focused on social position and the topics of substance use and other risky behaviors. Starting with the 1993 Ennett & Bauman (45) article on peer groups and adolescent smoking, researchers using network analysis to understand health behaviors have often focused on how social position influences health behaviors. Ennett & Bauman used previously defined terminology to describe three major social positions that may be associated with health behavior: clique member, liaison, and isolate. Isolates were identified as having little or no interaction with peers and having higher odds of being a current smoker. Clique members, or groups of adolescents that spend more time with each other than with others, and liaisons, who interact with others but not a specific group, both had lower smoking rates.

Ennett & Bauman also found that liaisons may be at risk for substance use because they become exposed to the norms of different groups, any of which may support misuse (45, 137). Other studies during this time period concluded that having a best friend who smoked positively influenced outsiders (isolates) to smoke but did not show the same influence with those who were part of a friendship group (clique) (4). Later research found that popular students were more likely to smoke in general (139), or that popular students were more likely to smoke in

schools with high smoking prevalence and less likely to smoke in schools with low smoking prevalence (2). Another study confirmed that risk-takers accumulated in isolate positions and that individuals in isolate positions drifted toward risk-taking groups, whereas clique members shifted from nonrisk-taking behaviors to risk-taking behaviors over time (111).

Research using a network approach to examine health behaviors also includes studies about delinquency, STD risk, and health care utilization. First, two studies on the impact of network position on delinquent or bullying behavior showed that having friends who participated in bullying behavior was associated with being a bully (105), and, similarly, having friends who exhibited delinquent behavior was associated with delinquency (62). In a study of STD risks and social network influence on health behavior, investigators found that risk perceptions varied significantly across network position. Core and bridge individuals were likely to perceive lower levels of STD risk than were isolates, and those perceiving lower risk were less likely to have used condoms (19). In a network study of health screening, Allen (3) found that social network size was not associated with breast cancer screening practices among employed women, but peer perception of breast cancer screening as normative was predictive of regular screening. Finally, a study of racial differences in network influence on health behavior found that African Americans were less likely to know someone who had experienced surgical replacement of the hip or knee (21) and, as a result, were less likely to perceive this type of surgery as beneficial.

Among those associating peer influence with smoking, drinking, and drug behavior, researchers have discussed whether peer selection might be a result rather than a cause of behavior. According to researchers, similarity between friends could be due to selecting similar others for their friends, influencing each other during the friendship, and

discarding (or deselecting) dissimilar friends (4). In a 1997 study of friendship selection, Urberg et al. (132) found that friendship selection plays a stronger role in similarity between adolescents than does influence. Several additional studies reported similar findings regarding the large role selection plays in similarity between friends (4). Valente and colleagues (137) frame this as a chicken-egg argument, that is, does friendship grouping precede or follow substance use? Ennett & Bauman (46) and Kandel (70) found that it was neither the chicken nor the egg; both peer-group selection and influence within the peer group after selection affected behavior.

## Organizational Networks

Scholars in public health have moved toward taking a systems approach to design and evaluate public health programs. In their 2006 introduction to the *American Journal of Public Health* special issue on systems thinking (90), Leischow & Milstein described systems approaches as, “a paradigm or perspective that considers connections among different components, plans for the implications of their interaction, and requires transdisciplinary thinking as well as active engagement of those who have a stake in the outcome to govern the course of change” (p. 403). Fittingly, this approach is taking a more prominent role in public health at the same time that network analysis is becoming a more widely employed tool. Organizational network analysis differs from network analysis of transmission and social networks in that the networks are comprised of agencies or organizations rather than of individuals. Organizational network analysis has been used extensively in business and political science but has only recently appeared in public health studies (26).

Although limited research has applied network theory and analysis in the area of public health organizations, existing studies have considered a variety of health systems. Given

the prominence of HIV/AIDS in network research, it is no surprise that there have been multiple studies of HIV/AIDS service organizations (86, 124, 149). In addition, researchers have taken network approaches to understand better the public and private agencies serving the mentally ill and mental health (16, 107, 131), community agencies addressing child abuse (106), services for the health and social well-being of the elderly (23, 69), emergency preparedness and response (72, 37), tobacco control (84), cancer support (96), health policy (115), and health promotion (145).

Several of these studies found that in public health organizations, past relationships predicted partnering (96, 124), as did working on a common issue (23, 145) or exchanging/receiving funding (96, 106, 124, 148). Among health care systems providing services for specific populations—such as the elderly, mental health patients, or HIV/AIDS patients—links between agencies consist of sending and receiving client referrals (23, 86, 107, 145, 148), sending and receiving funding (84, 96, 106, 124, 148), and utilizing joint programs or providing service (23, 66, 84, 86, 148). Some researchers identified barriers to interorganizational relationships, namely that building relationships takes resources and can limit autonomy (23, 96). Several articles identified a core or lead agency or group of agencies within the system they were evaluating (72, 84, 86, 148); however, no other common organizational network characteristics were easily identified in this literature.

Organizational network analysis has given insight into the overall structures and types of relationships that exist in a variety of public health systems. This information provides a base for future research in this area that could include structural evaluation of public health systems and evidence-based recommendations for developing effective relationships within these systems.

## SUMMARY AND FUTURE DIRECTIONS

Over the past several decades network analysis has become an increasingly important analytic tool and research framework in public health. It has been widely used particularly to study disease and information transmission networks, to examine the role of social networks on health and health behavior, and to study interorganizational networks in public health systems. Throughout this work we can see that network analysis has been applied in three different ways: to study existing public health networks (e.g., service referral networks), to apply a network theory to a health phenomenon (e.g., examining whether a contagion hypothesis explains patterns of STD transmission), and to use a network approach for developing and implementing health interventions (e.g., using network characteristics to identify central actors to speed up diffusion of health information).

To build on these early successes and to realize further the potential of network analysis for public health, we make the following suggestions:

- Most of the application of network analysis in public health has been as an analytic tool to help us answer basic science questions about the social and ecological determinants of health. However, we are starting to see how the network paradigm is being used to shape public health surveillance and practice; for example, CDC now uses a network approach in their contact-tracing procedures for tracking infectious diseases such as tuberculosis (36). There are numerous opportunities in public health practice to implement our ecological, network discoveries. For example, as we learn more about the characteristics of health and naturally occurring networks, we can use this knowledge to build more effective community-based coalitions.

- Public health researchers should start moving beyond network descriptions and take advantage of the new stochastic and longitudinal network analysis models being developed. This allows us to pose specific ecological and structural research hypotheses that can be formally modeled and tested using advanced network methods.
- Network analysis should be included more often in the training and educational curricula for public health professionals. Although network thinking is becoming more common, network methods are still treated as specialized tools in public health education. Better and earlier training in these methods is a partial response to the NIH call for increased utilization of higher levels of analysis (110).
- Network data and visual depictions should be used more often as a dissemination tool. Network diagrams are often easily understood by community, agency, and funding partners.
- Public health scientists should identify areas of health research in which network analysis has been underutilized. In particular, we think that network analysis can make important contributions in the areas of public health preparedness, health policy, and health communication. For example, with the one exception of DOIs, we know very little about how social networks shape health communication among family members, friends, health professionals, and community organizations. Network analysis is an extremely flexible research tool and a rich theoretical paradigm: It will continue to be an important element of public health research and practice in the years to come.

## LITERATURE CITED

1. Adams AM, Madhavan S, Simon D. 2002. Women's social networks and child survival in Mali. *Soc. Sci. Med.* 54(2):165–78
2. Alexander C, Piazza M, Mekos D, Valente T. 2001. Peer networks and adolescent cigarette smoking: an analysis of the national longitudinal study of adolescent health. *J. Adolesc. Health* 29:22–30
3. Allen JD, Sorensen G, Stoddard AM, Peterson KE, Colditz G. 1999. The relationship between social network characteristics and breast cancer screening practices among employed women. *Ann. Behav. Med.* 21(3):193–200
4. Aloise-Young PA, Graham JW, Hansen WB. 1994. Peer influence on smoking initiation during early adolescence: a comparison of group members and group outsiders. *J. Appl. Psychol.* 79(2):281–87
5. Amann G. 1991. Social network and social support deficits in depressed patients: a result of distorted perception? *Eur. Arch. Psychiatry Clin. Neurosci.* 241(1):49–56
6. Aral SO. 1999. Sexual network patterns as determinants of STD rates: paradigm shift in the behavioral epidemiology of STDs made visible. *Sex. Transm. Dis.* 26:262–64
7. Auerbach DM, Darrow WW, Jaffe HW, Curran JW. 1984. Cluster of cases of the acquired immune deficiency syndrome. Patients linked by sexual contact. *Am. J. Med.* 76(3):487–97
8. Barabasi AL. 2002. *Linked: How Everything Is Connected to Everything Else and What It Means for Business, Science, and Everyday Life*. New York: Plume
9. Barabasi AL, Bonabeau E. 2003. Scale-free networks. *Scient. Am.* May:50–59
10. Barber G, Crisp BR. 1995. Social support and prevention of relapse following treatment for alcohol abuse. *Res. Soc. Work Pract.* 5:283–96

11. Barnes JA. 1954. Class and committees in a Norwegian island parish. *Hum. Relat.* 7:39–58
12. Bassuk EL, Buckner JC, Weinreb LF, Browne A, Bassuk SS, et al. 1997. Homelessness in female-headed families: childhood and adult risk and protective factors. *Am. J. Public Health* 87(2):241–48
13. Batagelj V, Mrvar A. 2005. *Pajek—program for large network analysis*. <http://vlado.fmf.uni-lj.si/pub/networks/pajek/>
14. Bear M. 1990. Social network characteristics and the duration of primary relationships after entry into long-term care. *J. Gerontol.* 45(4):S156–62
15. Bearman PS, Moody J, Stovel K. 2004. Chains of affection: the structure of adolescent romantic and sexual networks. *Am. J. Sociol.* 110(1):44–91
16. Becker T, Leese M, McCrone P, Clarkson P, Szmukler G, Thornicroft G. 1998. Impact of community mental health services on users' social networks. *Br. J. Psychiatry* 173:404–8
17. Berkman LF. 1984. Assessing the physical health effects of social networks and social support. *Annu. Rev. Public Health* 5:413–32
18. Berkman LF, Syme SL. 1979. Social networks, host resistance, and mortality: a nine-year follow-up study of Alameda County residents. *Am. J. Epidemiol.* 109:186–204
19. Bettinger JA, Adler NE, Curriero FC, Ellen JM. 2004. Risk perceptions, condom use, and sexually transmitted diseases among adolescent females according to social network position. *Sex. Transm. Dis.* 31:575–79
20. Biegel DE, Tracy EM, Song L. 1995. Barriers to social network interventions with persons with severe and persistent mental illness: a survey of mental health case managers. *Community Ment. Health J.* 31(4):335–49
21. Blake VA, Allegrante JP, Robbins L, Mancuso CA, Peterson MG, et al. 2002. Racial differences in social network experience and perceptions of benefit of arthritis treatments among New York City Medicare beneficiaries with self-reported hip and knee pain. *Arthritis Rheumat.* 47(4):366–71
22. Bland SH, Krogh V, Winkelstein W, Trevisan M. 1991. Social network and blood pressure: a population study. *Psychosom. Med.* 53(6):598–607
23. Bolland JM, Wilson JV. 1994. Three faces of integrative coordination: a model of interorganizational relations in community-based health and human services. *Health Ser. Res.* 29:341–66
24. Boneham MA, Sixsmith JA. 2006. The voices of older women in a disadvantaged community: issues of health and social capital. *Soc. Sci. Med.* 62:269–79
25. Borgatti SP, Everett MG, Freeman LC. 2002. *UCINET for Windows: Software for Social Network Analysis*. Harvard, MA: Anal. Technol.
26. Borgatti SP, Foster PC. 2003. The network paradigm in organizational research: a review and typology. *J. Manag.* 29:991–1013
27. Boulay M, Storey JD, Sood S. 2002. Indirect exposure to a family planning mass media campaign in Nepal. *J. Health Commun.* 7(5):379–99
28. Broadhead RS, Heckathorn DD, Weakliem DL, Anthony DL, Madray H, et al. 1998. Harnessing peer networks as an instrument for AIDS prevention: results from a peer-driven intervention. *Public Health Rep.* 113:42–57
29. Broadhead WE, Kaplan BH, James SA, Wagner EH, Shoenbach VJ, et al. 1983. The epidemiologic evidence for a relationship between social support and health. *Am. J. Epidemiol.* 117(5):521–37
30. Buchanan M. 2002. *Nexus: Small Worlds and the Groundbreaking Science of Networks*. New York: Norton
31. Burnet FM, White DO. 1972. *Natural History of Infectious Disease*. Cambridge, UK: Cambridge Univ. Press

32. Cassel J. 1976. The contribution of the social environment to host resistance. *Am. J. Epidemiol.* 104:107–23
33. Caulkins D. 1981. The Norwegian connection: Eilert Sundt and the idea of social networks in 19th century ethnology. *Connections* 4(2):28–31
34. Cent. Dis. Control Prev. 1998. Outbreak of primary and secondary syphilis—Guilford County. *Morb. Mortal. Weekly Rep.* 47(49):1070–73
35. Cent. Dis. Control Prev. 2003. Update: outbreak of severe acute respiratory syndrome—worldwide. *MMWR* 52(12):241–48
36. Cent. Dis. Control Prev. 2005. Guidelines for the investigation of contacts of persons with infectious tuberculosis. *MMWR* 54(15):1–72
37. Choi SO, Brower RS. 2006. When practice matters more than government plans: a network analysis of local emergency management. *Adm. Soc.* 37(6):651–78
38. Cobb S. 1976. Social support as a moderator of life stress. *Psychosom. Med.* 38:300–14
39. Coleman J, Katz E, Menzel H. 1957. The diffusion of innovations among physicians. *Sociometry* 20(4):253–70
40. Coleman J, Katz E, Menzel H. 1966. *Medical Innovation: A Diffusion Study*. Indianapolis, IN: Bobbs-Merrill
41. Curtis R, Friedman SR, Neaigus A, Jose B, Goldstein M, Ildefonso G. 1995. Street-level drug markets: network structure and HIV risk. *Soc. Netw.* 17:229–49
42. De P, Singh AE, Wong T, Yacoub W, Jolly AM. 2004. Sexual network analysis of a gonorrhoea outbreak. *Sex. Transm. Infect.* 80:280–85
43. Doreian P, Woodard KL. 1992. Fixed list versus snowball sampling. *Soc. Sci. Res.* 21:216–33
44. Eames KTD, Keeling MJ. 2002. Modeling dynamic and network heterogeneities in the spread of sexually transmitted diseases. *Proc. Natl. Acad. Sci. USA* 99:13330–35
45. Ennett ST, Bauman KE. 1993. Peer group structure and adolescent cigarette smoking: a social network analysis. *J. Health Soc. Behav.* 34:226–36
46. Ennett ST, Bauman KE. 1994. The contribution of influence and selection to adolescent peer group homogeneity: the case of adolescent cigarette smoking. *J. Person. Soc. Psychol.* 67(4):653–63
47. Entwisle B, Rindfuss RR, Guilkey DK, Chamrathirong A, Curran SR, Sawangdee Y. 1996. Community and contraceptive choice in rural Thailand: a case study of Nang Rong. *Demography* 33(1):1–11
48. Faber AD, Wasserman S. 2002. Social support and social networks: synthesis and review. In *Social Networks and Health*, ed. JA Levy, BA Pescosolido, pp. 29–72. Oxford, UK: Elsevier Sci.
49. Freeman LC. 1979. Centrality in social networks: Conceptual clarification. *Social Networks* 1:215–239
50. Freeman LC. 1996. Some antecedents of Social Network Analysis. *Connections* 19(1):39–42.
51. Freeman LC. 2004. *The Development of Social Network Analysis: A Study in the Sociology of Science*. Vancouver, Can.: Empirical
52. Friedman SR, Aral S. 2001. Social networks, risk-potential networks, health, and disease. *J. Urban Health; Bull. N. Y. Acad. Med.* 78:411–18
53. Friedman SR, Neaigus A, Jose B, Curtis R, Goldstein M, et al. 1997. Sociometric risk networks and risk for HIV infection. *Am. J. Public Health* 87:1289–96
54. Fruchterman TMJ, Reingold EM. 1991. Graph drawing by force-directed placement. *Software: Prac. Exp.* 21(11):1129–64



55. Fudge H, Neufeld A, Harrison MJ. 1997. Social networks of women caregivers. *Public Health Nur.* 14(1):20–27
56. Godoy R, Byron E, Reyes-Garcia V, Vadez V, Leonard WR, et al. 2005. Income inequality and adult nutritional status: anthropometric evidence from a preindustrial society in the Bolivian Amazon. *Soc. Sci. Med.* 61(5):907–19
57. Goldberg EL, Van Natta P, Comstock GW. 1985. Depressive symptoms, social networks and social support of elderly women. *Am. J. Epidemiol.* 121(3):448–56
58. Granovetter MS. 1973. The strength of weak ties. *Am. J. Sociol.* 78(6):1360–80
59. Green LW, Richard L, Potvin L. 1996. Ecological foundations of health promotion. *Am. J. Health Promot.* 10:270–81
60. Guardiola X, Diaz-Guilera A, Perez CJ, Arenas A, Llas M. 2002. Modeling diffusion of innovations in a social network. *Phys. Rev. E.* 66:026121-1–4
61. Harary F, Norman RZ, Cartwright D. 1965. *Structural Models: An Introduction to the Theory of Directed Graphs*. New York: Wiley
62. Haynie DL. 2001. Delinquent peers revisited: Does network structure matter? *Am. J. Sociol.* 106:1013–57
63. Healthy Aging Res. Netw. Writ. Group. 2006. The prevention research centers healthy aging research network. *Prev. Chron. Dis.* 3(1):A17
64. House JS, Robbins C, Metzner HL. 1982. The association of social relationships and activities with mortality: prospective evidence from the Tecumseh Community Health Study. *American Journal of Epidemiology.* 116(1):123–40
65. Hummon NP, Carley KM. 2003. Social networks as normal science. *Soc. Netw.* 15:71–106
66. Johanson J. 2000. Formal structure and intraorganisational networks. An analysis in a combined social and health organisation in Finland. *Scandinav. J. Manag.* 16:249–67
67. Jolly AM, Muth SQ, Wylie JL, Potterat JJ. 2001. Sexual networks and sexually transmitted infections: a tale of two cities. *J. Urban Health: Bull. N. Y. Acad. Med.* 78:433–45
68. Junger M, Mutzel P. 2003. *Graph Drawing Software*. Berlin: Springer
69. Kaluzny AD, Zuckerman HS, Rabiner DJ. Interorganizational factors affecting the delivery of primary care to older Americans. *Health Ser. Res.* 33:381–401
70. Kandel DB. 1985. On processes of peer influences in adolescent drug use: a developmental perspective. *Adv. Alcohol Subst. Abuse* 4(3–4):139–63
71. Kaplan BH, Cassel JC, Gore S. 1977. Social support and health. *Med. Care* 15(Suppl. 5):47–57
72. Kapucu N. 2005. Interorganizational coordination in dynamic context: networks in emergency response management. *Connections* 26:35–50
73. Katz E, Lazarsfeld P. 1955. *Personal Influence*. New York: Free Press
74. Kawachi I. 2000. *Social capital*. <http://www.macses.ucsf.edu/Research/Social%20Environment/notebook/capital.html>
75. Kawachi I, Kennedy BP, Glass R. 1999. Social capital and self-rated health: a contextual analysis. *Am. J. Public Health* 89(8):1187–93
76. Kawachi I, Kennedy BP, Lochner K, Prothrow-Stith D. 1997. Social capital, income inequality, and mortality. *Am. J. Public Health* 87(9):1491–98
77. Kef S, Hox JJ, Habekothé HT. 2000. Social networks of visually impaired and blind adolescents. Structure and effect on well-being. *Soc. Netw.* 22:73–91
78. Kelsey JL, Thompson WD, Evans AS. 1986. *Methods in Observational Epidemiology*. New York: Oxford Univ. Press
79. Kessler RC, Price RH, Wortman CB. 1985. Social factors in psychopathology: stress, social support, and coping processes. *Annu. Rev. Psychol.* 36:531–72

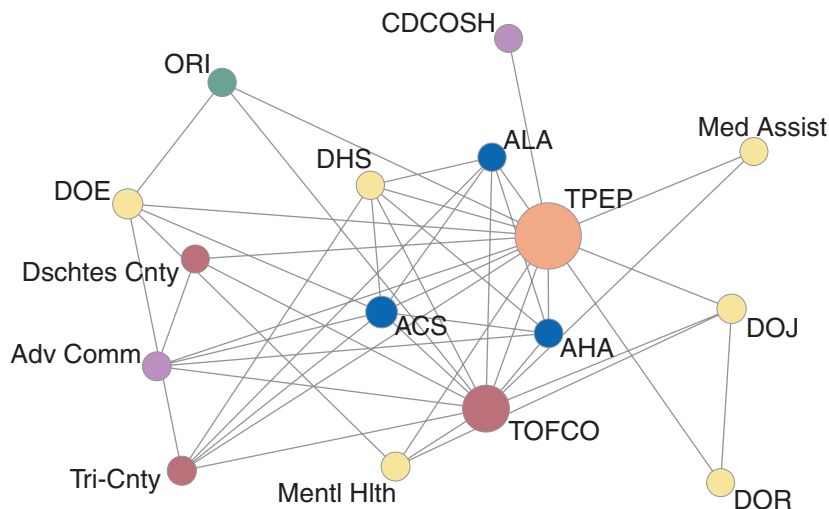


80. Klov Dahl AS. 1985. Social networks and the spread of infectious disease: the AIDS example. *Soc. Sci. Med.* 21(11):1203–16
81. Klov Dahl AS, Graviss EA, Yaganehdoost MW, Ross MW, Wanger A, et al. 2001. Networks and tuberculosis: an undetected community outbreak involving public places. *Soc. Sci. Med.* 52:681–94
82. Klov Dahl AS, Potterat JJ, Woodhouse DE, Muth JB, Muth SQ, Darrow WW. 1994. Social networks and infectious disease: the Colorado Springs study. *Soc. Sci. Med.* 38:79–88
83. Knowlton AR. 2003. Informal HIV caregiving in a vulnerable population: toward a network resource framework. *Soc. Sci. Med.* 56(6):1307–20
84. Krauss M, Mueller N, Luke D. 2004. Interorganizational relationships within state tobacco control networks: a social network analysis. *Prev. Chron. Dis.* 1(4):A08
85. Kuhn T. 1962. *The Structure of Scientific Revolutions*. Chicago: Univ. Chicago Press
86. Kwait J, Valente TW, Celentano DD. 2001. Interorganizational relationships among HIV/AIDS service organizations in Baltimore: a network analysis. *J. Urban Health: Bull. N. Y. Acad. Med.* 78:468–87
87. Latkin C, Mandell W, Vlahov D, Knowlton A, Oziemkowska M, Celentano D. 1995. Personal network characteristics as antecedents to needle-sharing and shooting gallery attendance. *Soc. Netw.* 17(3–4):219–28
88. Latking CA, Sherman S, Knowlton A. 2003. HIV prevention among drug users: outcome of a network-oriented peer outreach intervention. *Health Psychol.* 22(4):332–39
89. Laumann EO, Youm Y. 1999. Racial/ethnic group differences in the prevalence of sexually transmitted diseases in the United States: a network explanation. *Sex. Transm. Dis.* 26(5):250–61
90. Leischow SJ, Milstein B. 2006. Systems thinking and modeling for public health practice. *Am. J. Public Health* 96(3):403–5
91. Lin N. 1986. Access to occupations through social ties. *Soc. Netw.* 8:365–85
92. Lin N. 1999. Building a network theory of social capital. *Connections* 22(1):28–51
93. Lin N. 1999. Social support and depressed mood: a structural analysis. *J. Health Soc. Behav.* 40:344–59
94. Lin N, Ye X, Ensel WM. 1999. Social support and depressed mood: a structural analysis. *J. Health Soc. Behav.* 40:344–59
95. Luke DA. 2005. Getting the big picture in community science: methods that capture context. *Am. J. Commun. Psychol.* 35(3–4):185–200
96. McKinney MM, Morrissey JP, Kaluzny AD. 1993. Interorganizational exchanges as performance markers in a community cancer network. *Health Ser. Res.* 28(4):459–78
97. Meyers LA, Newman MEJ, Martin M, Schrag S. 2003. Applying network theory to epidemics: control measures for *Mycoplasma pneumoniae* outbreaks. *Emerg. Infect. Dis.* 9:204–10
98. Meyers LA, Pourbohloul B, Newman MEJ, Skowronski DM, Brunham RC. 2005. Network theory and SARS: predicting outbreak diversity. *J. Theoret. Biol.* 232:71–81
99. Mohammed S. 2001. Personal communication networks and the effects of an entertainment-education radio soap opera in Tanzania. *J. Health Commun.* 6(2):137–54
100. Moreno JL. 1934. *Who Shall Survive?* New York: Beacon
101. Morris M. 2004. *Network Epidemiology: A Handbook for Survey Design and Data Collection*. New York: Oxford Univ. Press
102. Morris M, Kretzschmar M. 1995. Concurrent partnerships and transmission dynamics in networks. *Soc. Netw.* 17:299–318
103. Morris M, Kretzschmar M. 1997. Concurrent partnerships and the spread of HIV. *AIDS* 11(5):641–48

104. Morris M, Zavisca J, Dean L. 1995. Social and sexual networks: their role in the spread of HIV/AIDS among young gay men. *AIDS Educ. Prev.* 7(Suppl. 5):24–35
105. Mouttapa M, Valente T, Gallahe P, Rohrbach LA, Unger JB. 2004. Social network predictors of bullying and victimization. *Adolescence* 39(154):315–35
106. Mulroy EA. 1997. Building a neighborhood network: interorganizational collaboration to prevent child abuse and neglect. *Soc. Work* 42:255–64
107. Nakao K, Milazzo-Sayre LJ, Rosenstein MJ, Manderscheid RW. 1986. Referral patterns to and from inpatient psychiatric services: a social network approach. *Am. J. Public Health* 76(7):755–60
108. Natl. Cancer Inst. 2006. *Tobacco control research—cancer control and population sciences: tobacco networks*. [http://dceps.nci.nih.gov/tcrb/tobacco\\_networks.html](http://dceps.nci.nih.gov/tcrb/tobacco_networks.html)
109. Newman M, Barabási AL, Watts DJ. 2006. *The Structure and Dynamics of Networks*. Princeton, NJ: Princeton Univ. Press
110. Off. Behav. Soc. Sci. Res. 2001. Toward higher levels of analysis: progress and promise in research on social and cultural dimensions of health. *NIH No. 01-5020*. Bethesda, MD
111. Pearson M, West P. 2003. Drifting smoke rings: social network analysis and Markov processes in a longitudinal study of friendship groups and risk-taking. *Connections* 25:59–76
112. Potterat JJ, Muth SQ, Brody S. 2000. Evidence undermining the adequacy of the HIV reproduction number formula. *Sex. Transm. Dis.* 27(10):644–45
113. Potterat JJ, Muth SQ, Rothenberg RB, Zimmerman-Rogers H, Green DL, et al. 2002. Sexual network structure as an indicator of epidemic phase. *Sex. Transm. Infect.* 78:i152–58
114. Potterat JJ, Phillips-Plummer L, Muth SQ, Rothenberg RB, Woodhouse DE, et al. 2002. Risk network structure in the early epidemic phase of HIV transmission in Colorado Springs. *Sex. Transm. Infect.* 78:i159–63
115. Provan KG, Harvey J, de Zapien JG. 2005. Network structure and attitudes toward collaboration in a community partnership for diabetes control on the US-Mexican border. *J. Health Organ. Manag.* 19(6):504–18
116. Reingold DA. 1999. Social networks and the employment problem of the urban poor. *Urban Stud.* 36:1907–32
117. Rogers EM. 2003. *Diffusion of Innovations*. New York: Free Press Glencoe. 5th ed.
118. Rothenberg R, Narramore J. 1996. Commentary: the relevance of social network concepts to sexually transmitted disease control. *Sex. Transm. Dis.* 23:24–29
119. Rothenberg RB, Sterk C, Toomey KE, Potterat JJ, Johnson D, et al. 1998. Using social network and ethnographic tools to evaluate syphilis transmission. *Am. Sex. Transm. Dis. Assoc.* 25:154–60
120. Salganik MJ, Heckathorn DD. 2004. Sampling and estimation in hidden population using respondent-driven sampling. *Sociol. Methodol.* 34:193–239
121. Sampson RJ, Raudenbush SW, Earls F. 1997. Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science* 277(5328):918–24
122. Service S, Blower SM. 1995. HIV transmission in sexual networks: an empirical analysis. *Proc. Biol. Sci./Roy. Soc.* 260:237–44
123. Shelley GA, Bernard HR, Killworth P, Johnsen E, McCarty C. 1995. Who knows your HIV status? What HIV+ patients and their network members know about each other. *Soc. Netw.* 17:189–217
124. Shumate M, Fulk J, Monge P. 2005. Predictors of the International HIV-AIDS INGO Network over time. *Hum. Commun. Res.* 31:482–510
125. Smith SS. 2005. “Don’t put my name on it”: social capital activation and job-finding assistance among the black urban poor. *Am. J. Sociol.* 111:1–57

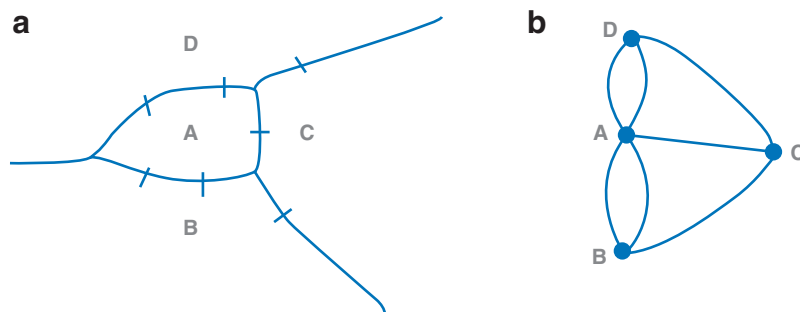
126. Snijders TAB. 1981. The degree variance: an index of graph heterogeneity. *Soc. Netw.* 3:163–74
127. Snijders TAB. 2005. Models for longitudinal network data. In *Models and Methods in Social Network Analysis*, pp. 215–47. Cambridge, MA: Cambridge Univ. Press
128. Spreen M. 1992. Rare populations, hidden populations, and link tracing designs: what and why? *Bull. Methodol. Sociolog.* 36:34–58
129. Stoebeu K, Valente TW. 2003. Using network analysis to understand community-based programs: a case study from Highland Madagascar. *Int. Fam. Plan. Perspect.* 29:167–73
130. Stoner BP, Whittington WL, Hughes JP, Aral SO, Holmes KK. 2000. Comparative epidemiology of heterosexual gonococcal and chlamydial networks: implications for transmission patterns. *Sex. Transm. Dis.* 27:215–23
131. Tausig M. 1987. Detecting “cracks” in mental health service systems: application of network analytic techniques. *Am. J. Commun. Psychol.* 15:337–51
132. Urberg KA, Degirmencioglu SM, Pilgrim JM. 1998. Adolescent friendship selection and termination: the role of similarity. *J. Soc. Person. Relationsh.* 15(5):703–10
133. Valente TW. 1995. *Network Models of the Diffusion of Innovations*. Cresskill, NJ: Hampton
134. Valente TW. 2005. Models and methods for innovation diffusion. In *Models and Methods in Social Network Analysis*, ed. PJ Carrington, J Scott, S Wasserman. Cambridge, UK: Cambridge Univ. Press
135. Valente TW, Davis RL. 1999. Accelerating the diffusion of innovations using opinion leaders. *Ann. Am. Acad* 566:55–67
136. Valente TW, Fosados R. 2006. Diffusion of innovations and network segmentation: the part played by people in promoting health. *J. Sex. Transm. Dis.* 32:S23–31
137. Valente TW, Gallaher P, Mouttapa M. 2004. Using social network to understand and prevent substance use: a transdisciplinary perspective. *Subst. Use Misuse* 39:1685–712
138. Valente TW, Saba WP. 2001. Campaign exposure and interpersonal communication as factors in contraceptive use in Bolivia. *J. Health Commun.* 6(4):303–22
139. Valente TW, Unger J, Johnson AC. 2005. Do popular students smoke? The association between popularity and smoking among middle school students. *J. Adolesc. Health* 37:323–29
140. Valente TW, Vlahov D. 2001. Selective risk taking among needle exchange participants: implications for supplemental interventions. *Am. J. Public Health* 91(3):406–11
141. Wasserman S, Faust K. 1994. Social network analysis: methods and applications. In *Structural Analysis in the Social Sciences*, ed M Granovetter. Thousand Oaks, CA: Sage
142. Wasserman S, Robins G. 2005. *An Introduction to Random Graphs, Dependence Graphs, and p\**. Cambridge, MA: Cambridge Univ. Press
143. Watts DJ. 2004. The “new” science of networks. *Annu. Rev. Sociol.* 30:243–70
144. White HC. 1963. *An Anatomy of Kinship*. Englewood Cliffs, NJ: Prentice-Hall
145. Wickizer TM, Von Korff M, Cheadle A, Maeser J, Wagner EH, et al. 1993. Activating communities for health promotion: a process evaluation method. *Am. J. Public Health* 83:561–67
146. Williams ML, Atkinson J, Klov Dahl A, Ross MW, Timpson S. 2005. Spatial bridging in a network of drug-using male sex workers. *J. Urban Health* 82:i35–42
147. Wohlfeiler D. 2000. Structural and environmental HIV prevention for gay and bisexual men. *AIDS* 14:S52–56
148. Woodard KL, Doreian P. 1994. Utilizing and understanding community service provision networks: a report of three case studies having 583 participants. *J. Soc. Ser. Res.* 18:1–41

149. Wright ER, Shuff IM. 1995. Specifying the integration of mental health and primary health care services for persons with HIV/AIDS: the Indiana integration of care project. *Soc. Netw.* 17:319–40
150. Wylie JL, Jolly A. 2001. Patterns of chlamydia and gonorrhea infection in sexual networks in Manitoba, Canada. *Sex. Transm. Dis.* 28(1):14–24
151. Ziersch AM. 2005. Health implications of access to social capital: findings from an Australian study. *Soc. Sci. Med.* 61:2119–31



**Figure 1**

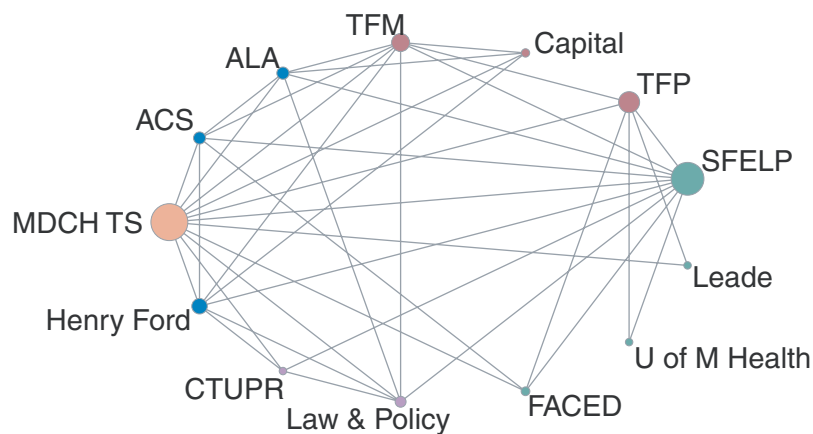
A graphic representation of the key players in Oregon's tobacco control program. The underlying data came from a project conducted in 2005 by this review's authors and funded by The American Legacy Foundation and the Association of State and Territorial Chronic Disease Program Directors.



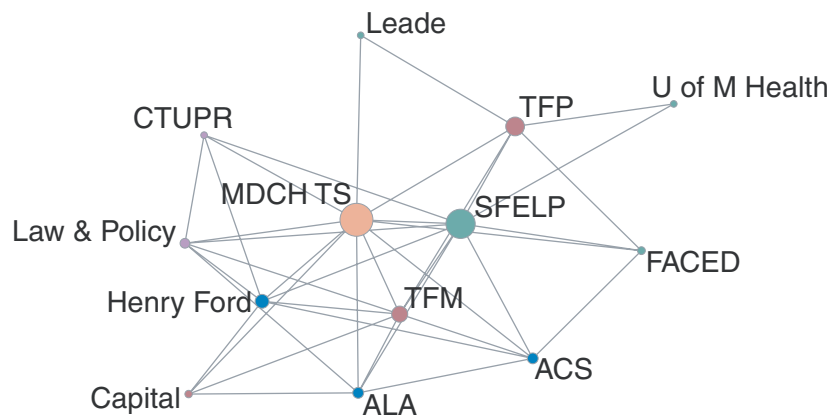
**Figure 2**

A simplified map of the Königsberg bridges (*a*) and the corresponding graph used by Euler to examine the Königsberg bridge problem (*b*). This graphic was adapted from <http://www.amt.canberra.edu.au/euler.html>.

a) Ring format

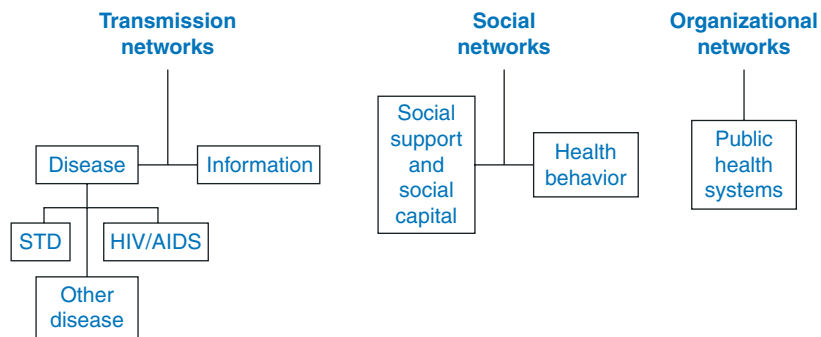


b) Iterative format



**Figure 4**

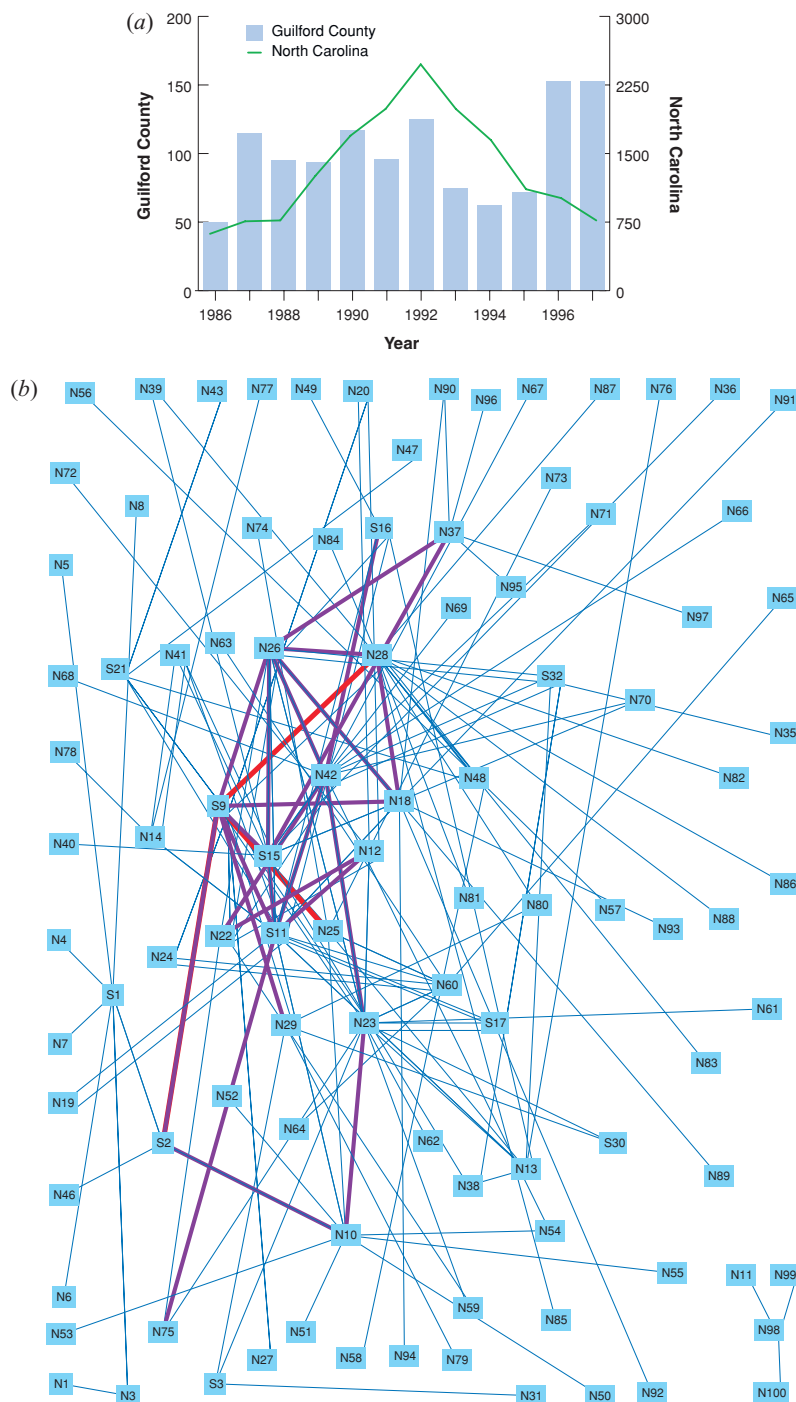
Two ways of visualizing the same network of state tobacco control agencies. The agencies are key partners in the Michigan tobacco control program. The underlying data came from a project conducted in 2005 by the authors and funded by The American Legacy Foundation and the Association of State and Territorial Chronic Disease Program Directors.



**Figure 5**

Categorization of network analysis applications in public health.





**Figure 6**

A comparison of (a) an epidemiologic model of syphilis transmission adapted from the *MMWR* (34) and (b) a network model of syphilis transmission from <http://www.pbs.org/wgbh/pages/frontline/shows/georgia/outbreak/details.html>.



# Contents

## Symposium: Public Health Preparedness

Introduction: Preparedness as Part of Public Health <i>Nicole Lurie</i> .....	xiii
Assessing Public Health Emergency Preparedness: Concepts, Tools, and Challenges <i>Christopher Nelson, Nicole Lurie, and Jeffrey Wasserman</i> .....	1
Quality Improvement in Public Health Emergency Preparedness <i>Michael Seid, Debra Lotstein, Valerie L. Williams, Christopher Nelson, Kristin J. Leuschner, Allison Diamant, Stefanie Stern, Jeffrey Wasserman, and Nicole Lurie</i> .....	19
Risk Communication for Public Health Emergencies <i>Deborah C. Glik</i> .....	33
First Responders: Mental Health Consequences of Natural and Human-Made Disasters for Public Health and Public Safety Workers <i>David M. Benedek, Carol Fullerton, and Robert J. Ursano</i> .....	55

## Epidemiology and Biostatistics

Network Analysis in Public Health: History, Methods, and Applications <i>Douglas A. Luke and Jenine K. Harris</i> .....	69
Methods for Improving Regression Analysis for Skewed Continuous or Counted Responses <i>Abdelmonem A. Afifi, Jenny B. Kotlerman, Susan L. Ettner, and Marie Cowan</i> .....	95
New Challenges for Telephone Survey Research in the Twenty-First Century <i>Angela M. Kempf and Patrick L. Remington</i> .....	113
Seasonality of Infectious Diseases <i>David N. Fisman</i> .....	127

Health Impact Assessment: A Tool to Help Policy Makers Understand Health Beyond Health Care <i>Brian L. Cole and Jonathan E. Fielding</i> .....	393
---	-----

## **Social Environment and Behavior**

Physical Activity and Weight Management Across the Lifespan <i>Jennifer H. Goldberg and Abby C. King</i> .....	145
The Hitchhiker's Guide to Tobacco Control: A Global Assessment of Harms, Remedies, and Controversies <i>Ronald M. Davis, Melanie Wakefield, Amanda Amos, and Prakash C. Gupta</i> .....	171
Youth Violence Prevention Comes of Age: Research, Training, and Future Directions <i>Kara Williams, Lourdes Rivera, Robert Neighbours, and Vivian Reznik</i> .....	195
Church-Based Health Promotion Interventions: Evidence and Lessons Learned <i>Marci Kramish Campbell, Marlyn Allicock Hudson, Ken Resnicow, Natasha Blakeney, Amy Paxton, and Monica Baskin</i> .....	213
Risk Communication for Public Health Emergencies <i>Deborah C. Glik</i> .....	33

## **Environmental and Occupational Health**

The Epidemiology of Autism Spectrum Disorders <i>Craig J. Newschaffer, Lisa A. Croen, Julie Daniels, Ellen Giarelli, Judith K. Grether, Susan E. Levy, David S. Mandell, Lisa A. Miller, Jennifer Pinto-Martin, Judy Reaven, Ann M. Reynolds, Catherine E. Rice, Diana Schendel, and Gayle C. Windham</i> .....	235
Beryllium: A Modern Industrial Hazard <i>Kathleen Kreiss, Gregory A. Day, and Christine R. Schuler</i> .....	259
Adverse Late Effects of Childhood Cancer and Its Treatment on Health and Performance <i>Kirsten K. Ness and James G. Gurney</i> .....	279
First Responders: Mental Health Consequences of Natural and Human-Made Disasters for Public Health and Public Safety Workers <i>David M. Benedek, Carol Fullerton, and Robert J. Ursano</i> .....	55

## **Health Services**

Managed Behavioral Health Care Carve-Outs: Past Performance and Future Prospects <i>Richard G. Frank and Rachel L. Garfield</i> .....	303
---	-----

Rationale and Public Health Implications of Changing CHD Risk Factor Definitions <i>Robert M. Kaplan and Michael Ong</i> .....	321
Delivery of Health Services to Migrant and Seasonal Farmworkers <i>Thomas A. Arcury and Sara A. Quandt</i> .....	345

## Public Health Practice

Lessons from Cost-Effectiveness Research for United States Public Health Policy <i>Scott D. Grosse, Steven M. Teutsch, and Anne C. Haddix</i> .....	365
Health Impact Assessment: A Tool to Help Policy Makers Understand Health Beyond Health Care <i>Brian L. Cole and Jonathan E. Fielding</i> .....	393
How Can We Increase Translation of Research into Practice? Types of Evidence Needed <i>Russell E. Glasgow and Karen M. Emmons</i> .....	413
Community Factors in the Development of Antibiotic Resistance <i>Elaine Larson</i> .....	435
Assessing Public Health Emergency Preparedness: Concepts, Tools, and Challenges <i>Christopher Nelson, Nicole Lurie, and Jeffrey Wasserman</i> .....	1
Quality Improvement in Public Health Emergency Preparedness <i>Michael Seid, Debra Lotstein, Valerie L. Williams, Christopher Nelson, Kristin J. Leuschner, Allison Diamant, Stefanie Stern, Jeffrey Wasserman, and Nicole Lurie</i> .....	19

## Indexes

Cumulative Index of Contributing Authors, Volumes 19–28 .....	449
Cumulative Index of Chapter Titles, Volumes 19–28 .....	454

## Errata

An online log of corrections to *Annual Review of Public Health* chapters (if any, 1997 to the present) may be found at <http://publhealth.annualreviews.org/>