Interorganizational Network Structures and Diffusion of Information Through a Health System

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Objectives. I used computational models to test the relationship between interorganizational network structures and diffusion of moderate- to high-priority health information throughout a system. I examined diffusion effects of mean and variance in organizational partnering tendencies, arrangement of ties among subgroups of the system, and the diffusing organization's effective network size.

Methods. I used agent-based models to simulate local information-sharing processes and observe the outcomes of system-level diffusion. Graphs of diffusion curves demonstrated differences among intergroup structures, and regression models were used to test effects of parameterized and emergent network variables on diffusion.

Results. The average tendency of participating organizations to engage in partnerships with other network members influenced diffusion of information, but variance in partnering tendencies had little effect. Fully connected subgroup structures outperformed hierarchical connections among subgroups, and all outperformed group-to-group chains. Introduction of a small proportion of randomness in connections among members of the chain structure improved diffusion without increasing network density. Finally, greater effective size in the diffusing organization's network increased diffusion of information.

Conclusions. Small interventions that build connecting structures among subgroups within a health system can be particularly effective at facilitating natural dissemination of information. (*Am J Public Health.* 2007;97:1684–1692. doi:10.2105/AJPH.2005.063669)

A public health system, defined by the Institute of Medicine as a "complex network of individuals and organizations,"[1] can include government agencies, health care delivery systems, businesses, media, nonprofit organizations, private health practitioners, and academia. A better understanding of public health networks is needed, but research efforts are complicated by the enormity of each network, the cost of obtaining data, and the impossibility of measuring enough complete systems to compare effects among them. Although qualitative information about organizational partnering contributes to our understanding of public health networks, it is inadequate to create measurable standards and actionable guidelines for network development. Actual tests of network effects on variables that influence public health could provide foundations for such action. These tests can be accomplished through computational modeling of individual and dyadic activities that accumulate to create system-level outcomes. Results provide benchmarks for building health networks.

The computational models ("simulation models") reported here address a question raised by an official in a county-level public health department. I asked the official to identify key issues regarding the overall public health network in her area, and one of her primary concerns was information delivery. In particular, she asked what her organization could do to improve the flow of information without relying on personal relationships or sending a nurse to knock on every physician's door. She explained that her staff invest a lot of effort to maintain direct relationships with health organizations, but there are many others that they cannot contact directly. She was particularly concerned about getting health information to people and organizations that are not currently involved with her department.

I examined the issue from 2 angles. First, how do prototypical network structures affect the diffusion of moderate- and high-priority health information from an initial source to a set of interrelated but independent organizations? Second, how can a health organization adjust its networking strategies to increase the likely distribution of its information without increasing its networking expenditures?

NETWORKS AND THEIR ROLES

Organizations that support the health of a population often develop relationships with each other. The relationships form patterns of interaction and exchange that compose the public health network. Relationships between organizations can support collaboration,[2] knowledge sharing,[3] and access to resources.[4] By providing crucial communication channels, networks of relationships enable diffusion of products,[5] practices,[6] and information.[7] Characteristics of the network structure influence the availability of information to individual organizations[8] and to the system as a whole.[9] As a result, interorganizational network structures influence the systemwide ability to distribute information.

NETWORK STRUCTURES AND DIFFUSION OF INFORMATION

People form subgroups within a network because of business demands, social similarities, proximity, profession, complementary needs or goals, and ease of communication. Homophily, or preference for others whom we see as similar to ourselves, plays a large role in relation-building.[10] People who see themselves as members of a particular group are likely to identify with other members of that group[11] and to prefer them because of social identification.[12] Dense connections form within clusters of health organizations that share a common purpose,[13] operate in the same geographic region, or benefit from joint action.[14]

This tendency toward subgroup adhesion permeates health systems, but the interaction patterns and levels of centralization vary among networks.[15] In a study of relationships between state and local health agencies in the United States, 16 of the public health systems were decentralized, 16 included a mixture of decentralization and centralization, and 10 were centralized.[16] Community-based networks form a variety of substructures, including hierarchical, factional, and amorphous decentralized tendencies.[17]

In this study, I modeled the diffusion of information through 5 prototypical structures among 10 subgroups that include 20 organizations each. Graphs depicting examples of all 5 structures are available as online supplements to this article at http://www.ajph.org. These prototypes represent a variety of situations that can occur among organizations.[18] The first prototype is an "unconstrained" network in which organizational attributes alone create the structure; no preference exists for in-group members, and no social, institutional, or geographic barriers limit partnerships with members of other subgroups. It is likely to support rapid diffusion of information, but diffusion is not likely to occur naturally. The unconstrained structure serves as a point of reference for comparing effects of the other, more obtainable, structures.

In the second, "fully connected" structure, clustering patterns arise from in-group preferences, shared interests, and functional demands, but interactions occur among all groups. A fully connected structure may arise from interventions that invite members of organizational, ethnic, professional, and geographic subgroups to participate in joint discussions or to join task forces on public health issues. It is unlikely to occur without interventions because people are inclined to create ties to geographically or socially adjacent groups but disinclined to build ties with members of distant or dissimilar groups.

In the third structure, members prefer other groups that are near or similar to themselves, creating a "chain" of adjacent groups that interact among themselves and with their immediate neighbors. Chain structures can occur, for example, in rural areas populated by small communities, in urban areas where ethnic subgroups interact mainly with similar others, or among specialists who interact primarily within their own and related specialties. In the fully connected and chain networks, members of each group have equal opportunities to find partners, but in the chain network, their partners are socially or geographically proximate to themselves.

The fourth structure depicts "hierarchy" among groups. This pattern occurs when a central group holds the majority of influence but interacts with some members of allied or dependent groups, and some members of those second-tier groups then interact with members of peripheral groups. This scenario is particularly likely to occur where central organizations—often public health agencies, hospitals, and health maintenance organizations—share information, resources, and collaboration opportunities with in-group members, and other groups find themselves on the fringes of the system.

The final structure represents "connected clusters." This situation occurs when subgroups form clusters, and a portion of each cluster maintains ties to a central group that connects the clusters. In the hierarchy and connected clusters structures, members of the central and bridging groups have more partnering opportunities.

Because existing relationships foster subsequent ties,[19] small interventions that build new relationships have the potential to change broad network structures over time. Public health organizations may improve transfer of information and other network-dependent functions of a system by supporting the development of effective network structures.

HEALTH ORGANIZATIONS' INDIVIDUAL NETWORKS AND DIFFUSION OF INFORMATION

Within the overall health system, public health organizations build their own partnerships, the number and pattern of which influence an organization's ability to distribute information. Each organization's degree of centrality (number of ties to others) limits the extent to which it can diffuse information directly. In addition, the pattern of its ties may influence the speed and extent to which information flows outward through the system. By creating partnerships with organizations that are not already connected to its existing partners, an organization increases its potential for broad distribution of information. This concept of network effectiveness has been applied to obtaining information and opportunities through a network,[8] but it could prove equally important for distributing information. The key thought is that the "effective size" of a network is smaller than the number of ties if those ties provide redundant access to the same parts of the system. Broader networking patterns by public health organizations are therefore likely to increase information flow through the system.

HYPOTHESES

The simulation models tested the following hypotheses:

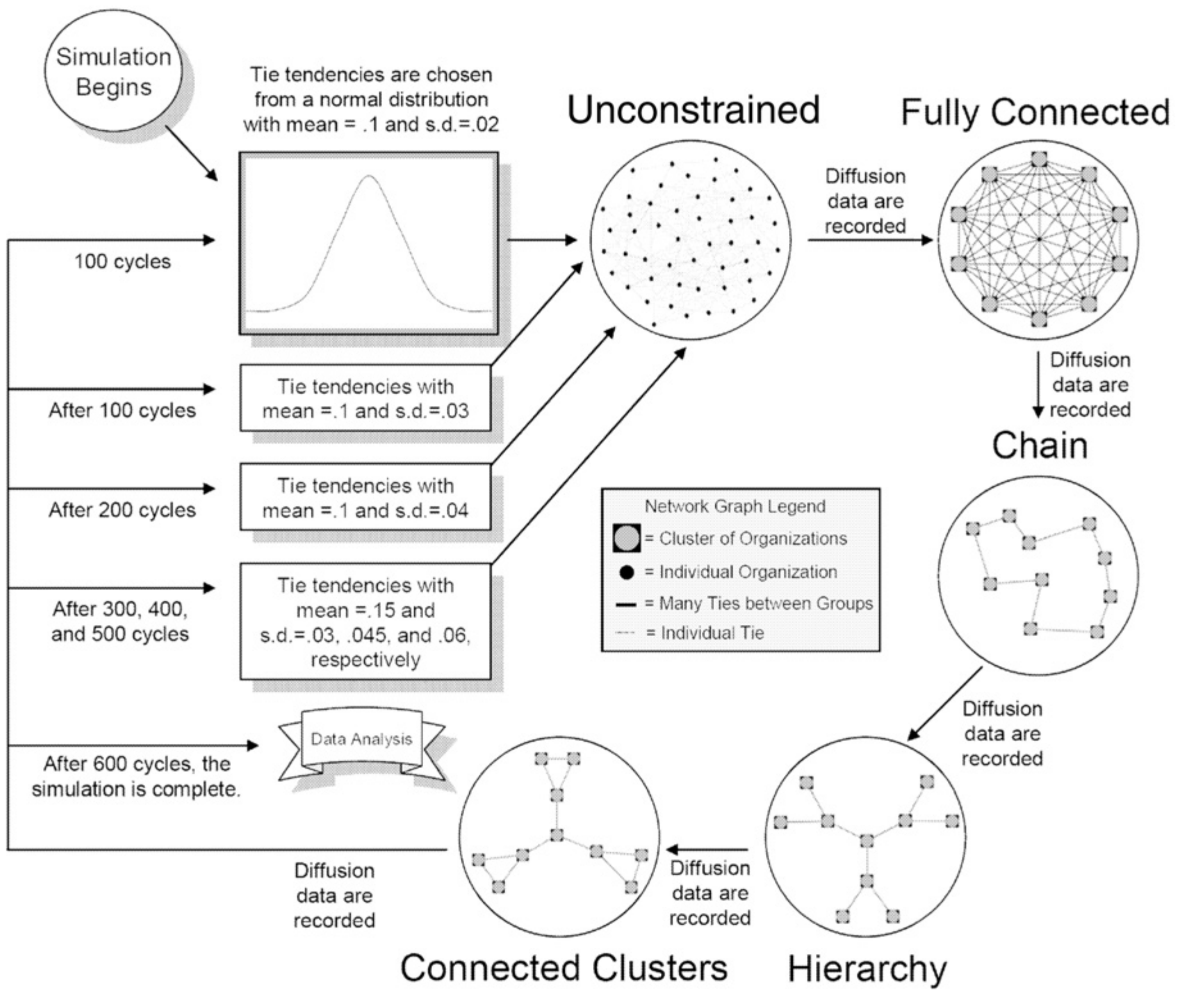
1. The mean and SD of partnering tendencies influence systemwide diffusion.
2. The pattern of ties among subgroups influences systemwide diffusion.
3. The degree and effective size of the information diffuser's network positively influence systemwide diffusion.

METHODS

Model Development, Parameters, and Measured Variables

For each of 100 trials, I modeled diffusion from a central source to members of a health system that varied systematically in overall mean and variance of partnering tendencies. Within every combination of means and variances, each organization retained its partnering tendency while I redistributed the pattern of ties into each of the 5 types of intergroup network structures (Figure 1). This yielded 3000 system-level data points. The procedure ran once for diffusion of medium-priority information and once for high-priority information.

Approximate network densities of 0.10 and 0.15 were chosen because real-world networks are sparse relative to the number of potential contacts.[21] Larger systems tend to be less dense than smaller systems because the number of possible ties increases dramatically with the number of participants. To represent natural variation, each organization's tendency to create ties was randomly drawn



Structure	PWG	PAG
Unconstrained	1	1
Fully Connected	5	0.578
Chain	5	2.6
Hierarchy	5	2.889
Connected Clusters	5	2.167

Group	1	2	3	4	5	6	7	8	9	10
1	5	2.6	0	0	0	0	0	0	0	2.6
2	.58	5	2.6	0	0	0	0	0	0	0
3	.58	.58	5	2.6	0	0	0	0	0	0
4	.58	.58	.58	5	2.6	0	0	0	0	0
5	.58	.58	.58	.58	5	2.6	0	0	0	0
6	.58	.58	.58	.58	.58	5	2.6	0	0	0
7	.58	.58	.58	.58	.58	.58	5	2.6	0	0
8	.58	.58	.58	.58	.58	.58	.58	5	2.6	0
9	.58	.58	.58	.58	.58	.58	.58	.58	5	2.6
10	.58	.58	.58	.58	.58	.58	.58	.58	.58	5

Above, left: Tie probability weightings within (PWG) and across (PAG) groups.

Above, right: Blocked probability matrix for Fully Connected (bottom-left) and Chain (top-right) structures.

Right: Blocked probability matrix for Hierarchy (bottom-left) and Connected Clusters (top-right) structures.

Network graphs were drawn using NetDraw.[29]

Group	1	2	3	4	5	6	7	8	9	10
1	5	2.17	2.17	0	0	0	0	0	0	0
2	2.89	5	2.17	0	0	0	0	0	0	2.17
3	0	2.89	5	0	0	0	0	0	0	0
4	0	0	0	5	2.17	2.17	0	0	0	0
5	0	0	0	2.89	5	2.17	0	0	0	2.17
6	0	0	0	0	2.89	5	0	0	0	0
7	0	0	0	0	0	0	5	2.17	2.17	0
8	0	0	0	0	0	0	2.89	5	2.17	2.17
9	0	0	0	0	0	0	0	2.89	5	0
10	0	2.89	0	0	2.89	0	0	2.89	0	5

Note. Network drawing created using Netdraw software.[20]

FIGURE 1—Parameters and procedures for a simulation model testing the effects of organizational partnering tendencies, the diffusing agency's structural position, and interorganizational network structures on diffusion of health information throughout a public health system.

from a normal distribution having the mean equal to the desired network density and a range from 0 to 1. SDs in organizations' tie tendencies were modeled at 3 levels in each density setting (SD=0.2×density, 0.3×density, and 0.4×density). Within each of these conditions, for every cycle of the simulation, every organization was assigned a partnering tendency, and pairwise averages were assigned to dyads as the probability that they would form a reciprocal relationship. The simulation then created intergroup structures based on existing models.[18]

Studies that measure health networks generally define those networks narrowly, such that member organizations tend to be similar, connected by formal structure, or focused on 1 particular aspect of health. These networks are small and fairly dense. For example, Johnsen et al. found that information networks among child health organizations ranged in density from 0.49 to 0.68.[13]

The current problem requires a broader focus because a county-level public health system includes a variety of organization types. Such a system is nearly guaranteed to include dense subgroups, with limited interaction among them. This pattern was reflected in the simulation design by increasing the likelihood of within-group ties while decreasing the probability of across-group ties in all but the unconstrained structure. The simulation presented here multiplied the probability of within-group ties by 5, but a parallel simulation was run as a sensitivity test using within-group probability weightings of 4. Each structure was generated within each centrality distribution by scaling (s_i) partnering tendencies (t_i), maintaining an average partnering tendency (d, network density) of approximately 0.1 in the first condition and 0.15 in the second condition:

$$\frac{1}{n}\sum_{i=1}^{n} s_i t_i = d \equiv 0.1,\ 0.15. \tag{1}$$

The exact probability weightings and the resulting structures appear in Figure 1. The unconstrained, fully connected, and chain networks have normally distributed partnering tendencies that are not moderated by intergroup structures. The hierarchy and connected clusters structures create disparity in centralities, as occurs in scale-free networks. In a scale-free network, the majority of nodes have low degree (few connections) while 1 or more heavily connected, high-centrality hubs bridge the gap between many lower-degree peripheral nodes.[22] Community networks often exhibit normally distributed ties,[23] but larger systems are sometimes scale-free. The fully connected and chain structures are decentralized and "scale-rich" according to the definition by Alderson et al.[24] The connected clusters structure is less scaled, and the hierarchy structure is closer to scale-free, with a central hub and smaller branches.

Degree of centrality (number of ties) and effective network size (degree minus the average number of ties among the organization's contacts)[8] were measured for each diffusing organization. Diffusion level was defined as the number of organizations in the population that received the information.

Simulation Procedures

The virtual experiment, comprising 2 densities×3 levels of networking variance×5 intergroup structures, ran for 100 cycles under each condition as follows:

1. Draw networking tendencies from a normal distribution.
   a. Networking tendency has means of 0.1 and 0.15 (yielding densities of approximately 0.1 and 0.15, respectively) and SDs at 0.2, 0.3, and 0.4 of the mean.
2. Generate ties among 200 organizations.
   a. Probability of a tie between any 2 organizations is equal to the average of their individual partnering tendencies.
   b. Weighting of probabilities within groups versus between groups creates a prototypical structure (each of 5 structures under each networking tendency in each cycle).
   c. Structural position of information source is recorded.
3. Determine diffusion.
   a. Information source distributes health alert to all contacts at time 1 with $p=.5$ for medium-priority information or .95 for high-priority information.
   b. Each organization communicates with 1 contact per time period.
   c. If initiator of the contact has the information and the contact does not, transfer occurs with $p=.5$ (medium priority) or 0.95 (high priority); after the information is received, it cannot be forgotten.
   d. The knowledge-holder matrix updates.
   e. This process repeats for 30 time periods, recording information diffusion at each time period.
4. Reset parameters and return to step 1 until all conditions have run.

Analyses

Ordinary least squares regression analyses tested the effects of parameterized and emergent variables on the diffusion level of medium-priority information after 10 time periods and of high-priority information after 5 and 10 time periods. (A time period is a unit in which 1 round of events is allowed to occur. Because this is a simulation, a time period doesn't map onto a specific number of hours or days.) Diffusion curves depict the average level of information diffusion over time through each intergroup structure.

RESULTS

Tables 1 and 2 show means, SDs, and correlations among variables. Regression results appear in Table 3. Because of the large number of data points, only relations that were significant at $P<.001$ were considered meaningful. Medium-priority information diffusion data appear in Table 1; high-priority information data appear in Table 2. Variable means and SDs in the medium-priority condition appear in the second column. Variable means and SDs in the high-priority condition appear under the column headers across the top of the table.

Mean partnering tendency, which is directly responsible for overall network density, positively influenced diffusion. Although SD in partnering tendencies correlated positively with diffusion level, its effect was small and inconsistent in the regression models predicting level of diffusion after 5 and 10 time periods. Intergroup structures and diffusers' effective networks, by contrast, had large effects on diffusion processes. The chain structure inhibited diffusion of information, as did the hierarchy and connected clusters to lesser extents. The fully connected intergroup structure served nearly as well for distributing

TABLE 1—Means, Standard Deviations (SDs), and Correlations for Diffusion of information under the Medium-Priority Condition, by Predictor Variable

Variable	Mean (SD)	Diffusion after 5 time periods[a]	Diffusion after 10 time periods[a]	Diffusion after 15 time periods[a]	Mean partnering tendency	Partnering tendency SD	Unconstrained structure	Fully connected structure	Chain structure	Hierarchy structure	Connected clusters structure	Diffuser's degree centrality	Diffuser's effective network
Diffusion after 5 time periods[a]	45.915 (14.026)		0.811*	0.571*	0.476*	0.267*	0.136*	−0.002	−0.340*	0.171*	0.035	0.702*	0.706*
Diffusion after 10 time periods[a]	120.699 (27.922)	0.811*		0.886*	0.343*	0.177*	0.351*	0.211*	−0.682*	0.048	0.072*	0.459*	0.469*
Diffusion after 15 time periods[a]	173.227 (23.337)	0.571*	0.886*		0.194*	0.088*	0.337*	0.295*	−0.855*	0.084*	0.139*	0.287*	0.292*
Mean partnering tendency	0.125 (0.025)	0.476*	0.343*	0.194*		0.585*	0.000	0.000	0.000	0.000	0.000	0.644*	0.587*
Partnering tendency SD	0.038 (0.013)	0.267*	0.177*	0.088*	0.585*		0.000	0.000	0.000	0.000	0.000	0.360*	0.321*
Unconstrained structure	0.200 (0.400)	0.136*	0.351*	0.337*	0.000	0.000		−0.250*	−0.250*	−0.250*	−0.250*	−0.118*	−0.093*
Fully connected structure	0.200 (0.400)	−0.002	0.211*	0.295*	0.000	0.000	−0.250*		−0.250*	−0.250*	−0.250*	−0.146*	−0.114*
Chain structure	0.200 (0.400)	−0.34*	−0.682*	−0.855*	0.000	0.000	−0.250*	−0.250*		−0.250*	−0.250*	−0.143*	−0.139*
Hierarchy structure	0.200, (0.400)	0.171*	0.048	0.084*	0.000	0.000	−0.250*	−0.250*	−0.250*		−0.250*	0.363*	0.355*
Connected clusters structure	0.200, (0.400)	0.035	0.072*	0.139*	0.000	0.000	−0.250*	−0.250*	−0.250*	−0.250*		0.044*	−0.009*
Diffuser's degree centrality	26.118, (7.973)	0.702*	0.459*	0.287*	0.644*	0.36*	−0.118*	−0.146*	−0.143*	0.363*	0.044*		0.993*
Diffuser's effective network	22.153, (6.203)	0.706*	0.469*	0.292*	0.587*	0.321*	−0.093*	−0.114*	−0.139*	0.355*	−0.009*	0.993*	

Note. n = 3000 observations for each variable.
[a]A time period is defined as a unit in which 1 round of events is allowed to occur.
*Significant at $P < .001$.

TABLE 2—Means, Standard Deviations (SDs), and Correlations for Diffusion of information under the High-Priority Condition, by Predictor Variable

Variable	Mean (SD)	Diffusion after 5 time periods[a]	Diffusion after 10 time periods[a]	Diffusion after 15 time periods[a]	Mean partnering tendency	Partnering tendency SD	Unconstrained structure	Fully connected structure	Chain structure	Hierarchy structure	Connected clusters structure	Diffuser's degree centrality	Diffuser's effective network
Diffusion after 5 time periods[a]	112.911 (25.858)		0.797*	0.519*	0.376*	0.183*	0.398*	0.235*	−0.721*	0.009	0.079*	0.516*	0.532*
Diffusion after 10 time periods[a]	187.015 (17.432)	0.797*		0.705*	0.116*	0.042	0.293*	0.288*	−0.926*	0.143*	0.202*	0.217*	0.218*
Diffusion after 15 time periods[a]	199.203 (1.751)	0.519*	0.705*		0.148*	0.025	0.182*	0.186*	−0.541*	0.066*	0.107*	0.193*	0.194*
Mean partnering tendency	0.125 (0.025)	0.376*	0.116*	0.148*		0.585*	0.000	0.000	0.000	0.000	0.000	0.651*	0.594*
Partnering tendency SD	0.038 (0.013)	0.183*	0.042	0.025	0.585*		0.000	0.000	0.000	0.000	0.000	0.356*	0.316*
Unconstrained structure	0.200 (0.400)	0.398*	0.293*	0.182*	0.000	0.000		−0.250*	−0.250*	−0.250*	−0.250*	−0.101*	−0.073*
Fully connected structure	0.200 (0.400)	0.235*	0.288*	0.186*	0.000	0.000	−0.250*		−0.250*	−0.250*	−0.250*	−0.149*	−0.118*
Chain structure	0.200 (0.400)	−0.721*	−0.926*	−0.541*	0.000	0.000	−0.250*	−0.250*		−0.250*	−0.250*	−0.138*	−0.134*
Hierarchy structure	0.200 (0.400)	0.009	0.143*	0.066*	0.000	0.000	−0.250*	−0.250*	−0.250*		−0.250*	0.344*	0.333*
Connected clusters structure	0.200 (0.400)	0.079*	0.202*	0.107*	0.000	0.000	−0.250*	−0.250*	−0.250*	−0.250*		0.043	−0.009*
Diffuser's degree centrality	26.066 (7.867)	0.516*	0.217*	0.193*	0.651*	0.356*	−0.101*	−0.149*	−0.138*	0.344*	0.043		0.993*
Diffuser's effective network	22.119 (6.112)	0.532*	0.218*	0.194*	0.594*	0.316*	−0.073*	−0.118*	−0.134*	0.333	−0.009*	0.993*	

Note. n = 3000 observations for each variable.
[a]A time period is defined as a unit in which 1 round of events is allowed to occur.
*Significant at $P < .001$.

TABLE 3—Regression Models Using the Diffusing Agency's Network Position and Structural Characteristics of a Public Health Network to Predict Systemwide Information Diffusion

Variable	Medium Priority[a]		High Priority[b]		High Priority[a]	
	Model 1[c,d]	Model 2[c,e]	Model 1[c,d]	Model 2[c,e]	Model 1[c,d]	Model 2[c,e]
Mean partnering tendency	0.364*	0.104*	0.409*	0.087*	0.138*	0.072*
Standard deviation in partnering	−0.036	−0.022	−0.056	−0.032*	−0.038	−0.033*
Fully connected structure		−0.105*		−0.112		−0.001
Chain structure		−0.810*		−0.870*		−0.970*
Hierarchy structure		−0.396*		−0.479*		−0.155*
Connected clusters structure		−0.252*		−0.282*		−0.078*
Diffuser's effective network		0.429*		0.518*		0.107*
R^2 model	0.119	0.726	0.144	0.877	0.014	0.889
F statistic for R^2 (*df*)	202.018* (2, 2997)	1133.179* (7, 2992)	251.081* (2, 2997)	3046.901* (7, 2992)	21.818* (2,2997)	3443.272* (7, 2992)
R^2 change		0.607		0.733		0.875
F statistic for change in R^2 (*df* change)		1326.895* (5, 2992)		3567.624* (5, 2992)		4742.814* (5, 2992)

Note. A time period is defined as a unit in which 1 round of events is allowed to occur.
[a]After 10 time periods.
[b]After 5 time periods.
[c]Standardized regression coefficients are reported to enable direct comparison of effect sizes across variables.
[d]Model 1 uses mean organizational partnering tendencies and SDs in organizational partnering tendencies to predict diffusion.
[e]Model 2 includes variables from Model 1 as well as structure types and the diffuser's effective network to predict diffusion.
*P < .001.

information as did the unconstrained structure. Inclusion of intergroup structures and diffusers' effective networks in the regression models increased the R^2 for the medium-priority diffusion by 0.607 and the R^2 for the high-priority diffusion by 0.733 at time 5 and by 0.875 at time 10.

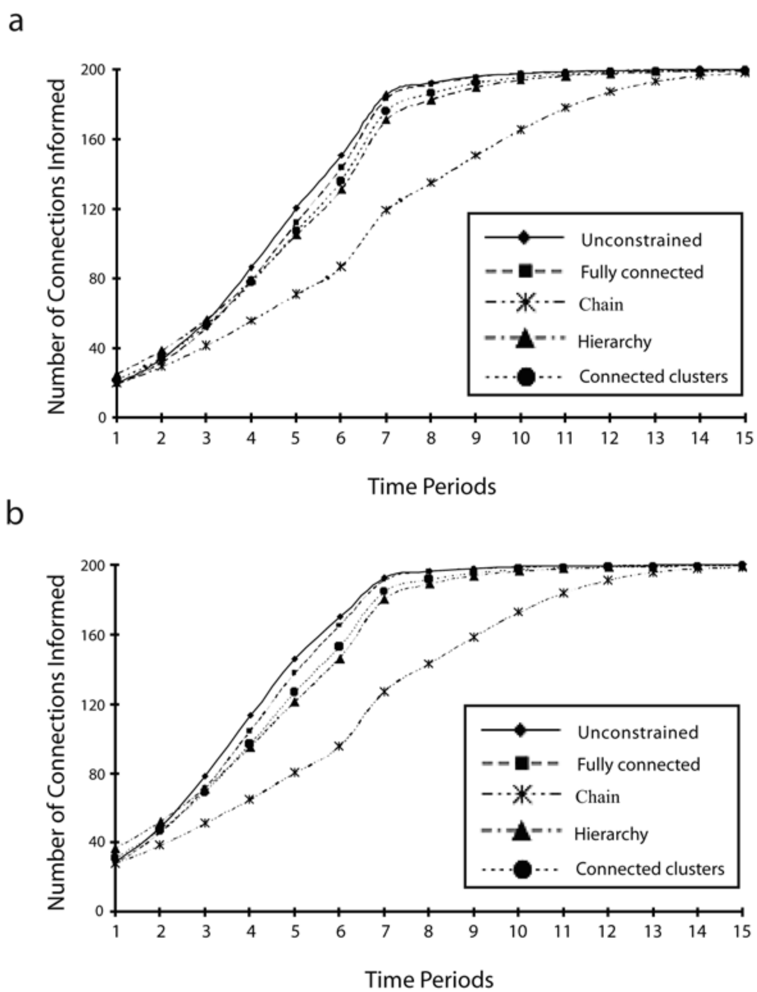
Diffusion curves in Figure 2 demonstrate differences in diffusion of high-priority information through the 5 intergroup structures. Networks that directly connect all subgroups outperformed more constrained networks. The hierarchy and the connected clusters both outperformed the more egalitarian chain structure, which performed significantly worse than the others. Diffusion curves (available as an online supplement to the article at: http://www.ajph.org) extending over a somewhat longer term span, depict similar structure effects on medium-priority information diffusion. These results were paralleled in the alternative simulation model that weighted in-group tie probabilities by 4 instead of 5 and adjusted across-group ties accordingly.

In addition to systemwide network structures, the number and pattern of ties maintained by the information source influenced diffusion. Diffuser's degree centrality and effective network had a predictably strong effect on early diffusion, and their influence continued throughout the diffusion process. Because of extremely high correlation (r= 0.993 in both data sets) and resultant multicollinearity, I could not include degree and effective size of network in the same regression model. To determine which was most indicative of diffusion outcomes, I ran stepwise regressions. In all cases, the effective size of the network was a better predictor than simple degree, indicating that diversity in partnerships improves capacity for information diffusion.

Simulated Bridge Building

Although the chain structure performed noticeably worse than did the others, small amounts of bridge building should be able to improve its diffusion capacity. To determine how much health systems would gain from a few unconstrained ties, I ran a simulation that introduced small amounts of randomness to the partner selection process in the chain structure. This simulation (using mean partnering tendency=0.1, SD=.03) began with 100 iterations of high-priority diffusion under the chain structure. It then ran another 100 iterations of high-priority diffusion, replacing 0.5% of the ties in each chain with randomly placed ties that were not constrained by the chain structure. The process continued, increasing the random "rewiring" by 0.5% increments in each subsequent model until the final model included 20% random ties amid 80% chain-based ties. The number of ties is retained through this process, but the pattern of ties is slightly altered.

The results of simulated bridge-building appear in Figure 3. The first graph shows percentage of randomness on the horizontal axis and diffusion level on the vertical axis. Lines in the graph represent time periods, where the bottom line is time 1, the next line is time 2, and so on. Following a line from left to right enables one to track the difference in diffusion at that time on the basis of percentage of random ties introduced to the chain structure. The steepest improvement occurs from 0% to 3.5% randomness; modest improvements continue until about 10.5%, and there is little effect beyond that point. The second graph shows diffusion curves beginning with the chain structure at the bottom, and each succeeding line shows diffusion given 1% more randomness. Counting up from the bottom, there were distinct improvements from each 1% increase in random ties up to 3.5%, after



Note. Each curve represents the average level of diffusion at each time period (a unit in which 1 round of events is allowed to occur) during 300 simulated diffusion processes.

FIGURE 2— Diffusion of high-priority information over time for varying network structures with a network density of 0.1 (a) and 0.15 (b).

which the diffusion curves improve only slightly.

DISCUSSION

Results of the simulation models indicate that intergroup structure and the information source's effective network have a greater influence than does the density of the network or variance in partnering tendencies on information diffusion. Increasing direct ties from the diffuser to others can facilitate the spread of information, but selection of partners that are not already involved with one's current contacts is likely to be most helpful. This principle applies to intergroup structures as well. A little networking effort can have a significant effect if it yields ties between previously disconnected subgroups. In lieu of bridging ties among all groups, a central group that creates ties to disparate parts of the network may also improve the effectiveness of the system for information transfer. Both of these approaches shorten path lengths between members of the system, but direct connection of subgroups may create less demand on intermediaries and fewer bottlenecks in the system when information flows are high.

Practical Applications

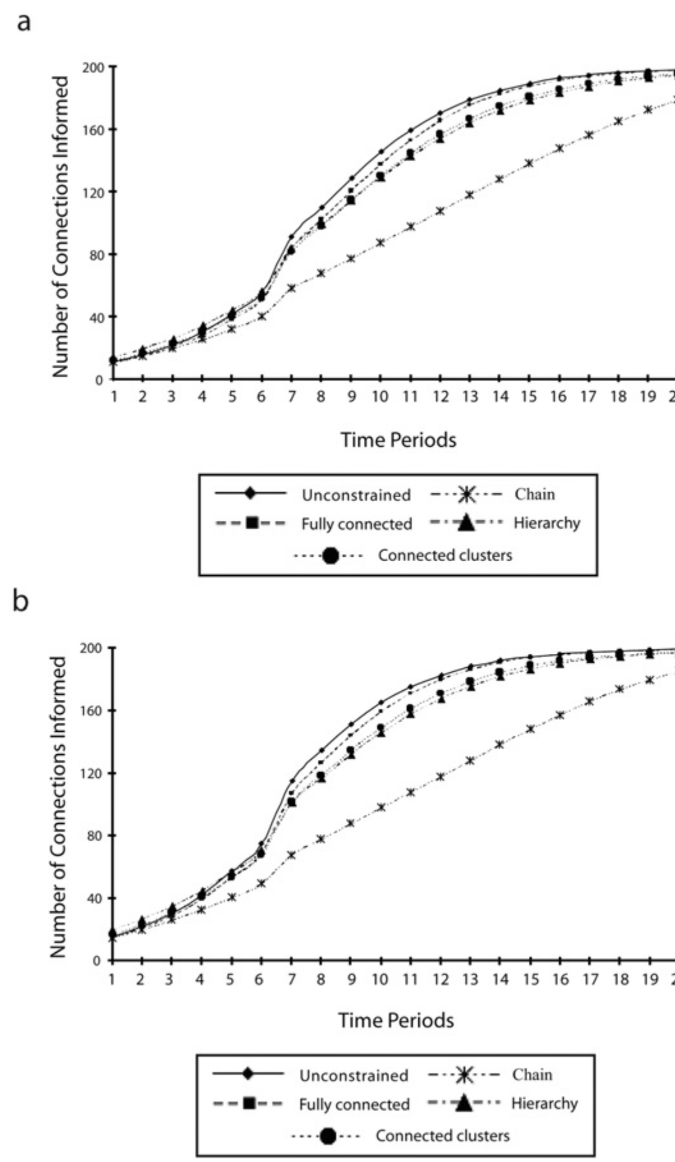
By testing alternative scenarios, simulations provide information and benchmarks to guide policymakers and practitioners. For example, the current results suggest that public health agents may be able to increase the dissemination capacity of their community's health network without acquiring more direct ties of their own. One strategy is to connect members of different subgroups with each other, as modeled by introducing randomness to the chain structure. Another strategy is to direct networking efforts toward disparate groups, thus increasing the agency's effective network size and connecting the clusters.

In Monterey County, California, Dona Putnam, public health program manager and director of nursing, has worked to help members of the community develop a better-connected network. In 2006, she invited stakeholders in maternal, child, and adolescent health issues to a meeting of the Monterey County group, where the 35 attendees selected 3 priority issues for the county. The people at the meeting brainstormed about other organizations that could be invited to collaborate, which subpopulations were currently outside their reach, and how to intervene. Small groups began working on the 3 topics, identifying categories of organizations (e.g., schools, churches, social service agencies) as well as dozens of specific organizations (e.g., YMCA, Boy and Girl Scouts, Department of Motor Vehicles) that could be contacted.

According to Putnam,

> Participants were asked 'who's out there' so we could include them. . . . It became apparent that each agency needed to share its resources and begin to collaborate together to ensure that the impact would be maximized. One of the outcomes from our collaboration discussion was the realization that most of our outreach efforts were concentrated in the largest city and the greatest need was in the outlying smaller cities. Identifying this gap of service sparked dialogue among the agencies represented to begin to investigate how they could effectively coordinate their efforts to address these needs. (D. Putnam, personal e-mail, January 2006)

By providing a forum for stakeholder interaction, Putnam is helping members of the collaboration to build bridges among geographically, socially, and professionally



Note. Each curve represents the average level of diffusion at each time period (a unit in which 1 round of events is allowed to occur) during 300 simulated diffusion processes.

FIGURE 3—Diffusion of medium-priority information over time for varying network structures with a network density of 0.1 (a) and 0.15 (b).

distinct subgroups of the county. In addition to connecting organizations that already work on child and adolescent health issues, the collaboration is finding and reaching out to subpopulations that were not previously included in the network.

Over time, efforts to connect subgroups of a health system can increase communication, inclusive decisionmaking, and development of community-based programs. For example, Community Voices Miami (CVM) convened a multiagency consortium of approximately 90 health and human service providers, foundations, and community-based organizations over a period of 3 to 4 years, and it jointly produced the Miami Action Plan (MAP) for access to health care. According to program director Leda Perez (L. Perez, personal e-mail, January 2006), a valuable component of the effort was "a community dialogue process. This was about talking to folks in different neighborhoods, in different settings about their realities accessing health care. The result is that we talked to around 700 people over the course of 6–8 months and conducted about 19 dialogues and 3 focus group-like follow-ups. All of these elements contributed to the MAP."

Continuing their networking efforts, CVM is coordinating efforts by community organizations to develop a training program for community health workers. Perez explained that "the training, curriculum, leadership of this has been very much community-driven and driven by CHWs [community health workers] themselves. CVM has been able to play a role in creating the space, facilitating the meetings, providing the follow-up and momentum and negotiating with the community college." (L. Perez, personal e-mail, January 2006)

Comparing these approaches for network building, we see that the Monterey County group is striving toward a fully connected network, while CVM builds consortia to connect clusters of organizations. Both approaches may be effective.

Limitations and Future Research Directions

The usefulness of simulations for improving public health systems depends on integration with fieldwork that tests and validates recommendations derived from the simulations. By taking an iterative approach to modeling and field research, we can obtain practical insights that could not be obtained by either approach alone.

Variance in the size of subgroups and systems might be an interesting aspect of future research. Another important issue for public health partnerships and networks that might be addressed through simulation modeling is the effect of competition, mutual aid, and bounded rationality on growth of collaborative networks. Butler has suggested that increasing complexity demands more feedback and collaboration, which leads organizations to operate collectively.[25] Yet limited resources and existing structures may constrain members' future opportunities. Central organizations tend to remain central, but we may find in public health, as in biotechnology, that organizations with more diverse relationships obtain more subsequent partners.[26]

The effects of technology on mitigating constraints on partnering time and resources also merit further investigation. In conjunction with this line of research, ongoing attention to the distribution of centralities may be needed. A wide variety of real-world systems form scale-free networks, including sexual networks[27] and the World Wide Web.[22] One might fruitfully apply knowledge about scale-free networks to widespread global, national, or regional public health systems. Recent research indicates that extremely large scale-free networks include subnetworks that are not scale-free,[28] so mixed models of large public health systems could be appropriate. Practitioners and field researchers could gain substantially by investing in online forums for measuring and supporting such community networks.

By incorporating qualitative understanding of local processes into computational models, we learn more than we could through qualitative or quantitative research alone. Researchers performing site-based investigation and intervention in current activities, practices, events, and so on can then take recommendations derived from the simulations into the field. Through this cooperative process, we may develop interventions that will enable the networks to better serve everyone in the system. ■

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