Network Interventions

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Science **337**, 49 (2012);
DOI: 10.1126/science.1217330

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The term "network interventions" describes the process of using social network data to accelerate behavior change or improve organizational performance. In this Review, four strategies for network interventions are described, each of which has multiple tactical alternatives. Many of these tactics can incorporate different mathematical algorithms. Consequently, researchers have many intervention choices at their disposal. Selecting the appropriate network intervention depends on the availability and character of network data, perceived characteristics of the behavior, its existing prevalence, and the social context of the program.

The importance of social network influences on behaviors is well established, and the advantages of network approaches to understanding a wide variety of phenomena are clear (*1–7*). Recent research on social networks and networking has shown that people can be influenced by their social networks to adopt new practices that affect their personal lives (*1*). There is widespread recognition that behavior and organizational change programs should be implemented and/or delivered by members of the group undergoing the change; i.e., the peers (*8*, *9*). This accumulated body of evidence indicates that social networks can be leveraged to accelerate behavior change, improve organizational efficiency, enhance social change, and improve dissemination and diffusion of innovations. The purpose of this Review is to assess what is known from prior research on network interventions, provide a framework for organizing such efforts, and suggest promising new areas for future research and application.

Network interventions are purposeful efforts to use social networks or social network data to generate social influence, accelerate behavior change, improve performance, and/or achieve desirable outcomes among individuals, communities, organizations, or populations. Several caveats regarding network interventions are warranted: First, network interventions are not agnostic or impartial, but depend on the goals and objectives that initiate the intervention. For example, when the goal is to disrupt disease transmission, the intervention will be based on different tactics than an intervention with the goal of accelerating the adoption of disease-prevention measures (*10*). Second, scientific theory regarding how individuals or organizations change or can be changed is critically important for choosing the right type of network intervention and the correct mix of promotional elements and materials (for instance, how much training of change agents, what type of media to use, and so on). Third, the interventionist should not only use the network as a delivery vehicle but also be prepared to use network information to learn from the community and to better serve community needs.

Network interventions are based on the diffusion of innovations theory, which explains how new ideas and practices spread within and between communities (*11*, *12*). Though diffusion and other mechanisms of social influence explain the process of change, they do not provide guidance on how to use that information to accelerate change. Here, we present four strategies that capitalize on network data to develop planned change programs. The criteria for the categories are: (i) identifying individuals (called "nodes" within the network) who are selected on the basis of some network property; (ii) segmentation, in which the intervention is directed toward groups of people; (iii) induction, in which excitation of the network occurs such that novel interactions between people (links in the network) are activated; and (iv) alteration, interventions that change the network. The interventions are listed in order of increasing complexity, though not necessarily according to their efficiency. Each strategy has multiple tactical alternatives. For example, many programs identify individuals to act as "champions." Tactically, however, the individuals who are identified might be opinion leaders, or they might be bridges between groups. Further, for each tactic there may be multiple definitions of the concept. For example, leaders are often defined as individuals who are most central in the network, yet there are at least a dozen different definitions and formulas used to measure centrality.

Figure 1 displays a hypothetical network used to illustrate the interventions, with solid circles designated as users of the behavior. This example, as well as many early network interventions, used relatively small networks such as classrooms ($n \approx 30$ people) or organizations ($n \approx 100$), but more recent studies have used online communities with thousands of members. The supplementary materials contain an R script file that can be used to replicate the calculations presented in this paper, as well as network graphs illustrating most of the interventions presented here.

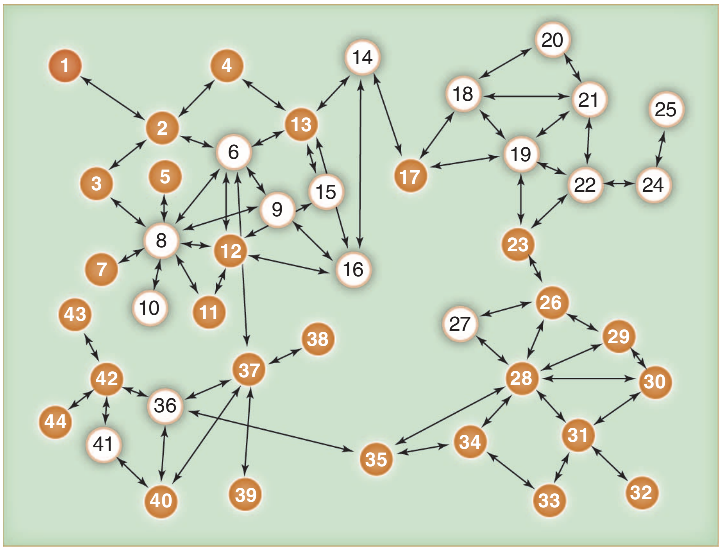

Fig. 1. Hypothetical network used to illustrate intervention techniques. Orange circles denote users (adopters); white circles indicate nonusers (nonadopters).

Intervention Types

Individuals. In the most basic network intervention, network data are used to identify individuals to act as champions. The most frequent intervention of this type is the use of opinion leaders (*13–15*). At least 20 published studies have used nominations by members of the social network to identify leaders to promote behavior change. Most of the studies were randomized control trials designed to increase the uptake of evidence-based medical practices. In all cases, those who received the most nominations up to some threshold, the top 10 to 15%, were identified as leaders (nodes 28, 8, 13, 37, 19, and 6 in Fig. 1).

In addition to counting nominations, there are many mathematical algorithms available to identify central nodes based on different conceptions of centrality (*16*). For example, "centrality closeness" nodes (nodes 6, 37, 36, 13, and 35) can reach everyone else in fewer steps, on average, than other nodes. "Centrality betweenness" nodes occupy critical gate-keeping positions by most frequently lying on the shortest path connecting other nodes (numbers 6, 37, 36, 28, and 35). Other centrality measures (e.g., eigenvector, power, information, flow, etc.) might be

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used depending on the goals and objectives of the program.

Borgatti suggested that the most critical nodes for behavior change programs can be identified by finding those that most optimally span the network (*10*). Furthermore, Borgatti observed that the most central nodes can sometimes be linked to the same people (*6*, *8*); thus, using the number of links a node has to identify key players may not identify the best nodes to disseminate information or, if removed, fragment the network most efficiently. The KeyPlayer software (*17*) was developed to identify nodes that would be the best seeds for spreading a behavior (nodes 6, 22, 28, and 36) and those best for disrupting its spread (nodes 13, 23, 35, and 37).

Leaders may not always be the best change agents. Leaders have a vested interest in the status quo, whereas bridging individuals (who link non- or loosely connected groups) may be more amenable to change and may be in a better position to change others. For example, when diffusion between groups is expected to be difficult, bridging individuals may be more effective change agents (*18*, *19*). Bridging individuals may be preferred as change agents when the behavior or policy is controversial or not likely to be well accepted initially. Bridging nodes can be identified as brokers (*20*) (nodes 8, 28, 6, 37, 19, and 13) who have many connections to people who are not directly connected or as bridges whose connections maximally increase network cohesion (*18*) (nodes 14, 37, 24, 6, and 35). In this case, node 37 has been identified as a leader and a bridge, indicating that this person is potentially in the best position to lead a change program because of his/her prominence and diversity.

Low-threshold change agents should be recruited when the researcher wants to create early momentum for the change and accelerate the time to reach a critical mass or tipping point. Low-threshold adopters are individuals willing to adopt a new idea earlier than their peers (*21*). If node 19 were to adopt an innovation, he/she would be doing so under the condition that two of his/her five contacts (nodes 17 and 23) were previous adopters. Exposure would thus be 40% and, having adopted, the threshold would also be 40% (thresholds equal exposure at time of adoption). For person 20, his/her adoption at the same time would have been done with no adopters and, hence, an exposure and threshold of zero. In contrast, adoption by 27 and 36 would yield thresholds of 100%. Thus, nodes 19 and 20 have low thresholds (less than 50%), whereas 27 and 36 have high thresholds. Identifying low-threshold adopters as change agents would thus require some prior knowledge of behavioral adoption of a related innovation.

People on the margins of the community or organization may also be identified by change programs, because they are potentially excluded from services or the positive supports derived from community participation, not for their ability to persuade others. Individuals on the periphery of a network learn about new ideas or practices later than their better-integrated peers and hence may suffer disadvantages from their exclusion. For example, in two classic studies of diffusion of innovation through social networks, social isolates were significantly less likely to adopt new farming practices or modern methods of contraception (*12*). In some cases, peripheral individuals may be important to identify, as they are often the source of new ideas and innovations because they have contacts with other communities and/or are free from the social pressure to conform.

Segmentation. In contrast to individual approaches in which certain individuals are recruited to be change proponents, segmentation approaches identify groups of people to change at the same time. For example, companies often introduce new procedures at separate locations sequentially rather than having all locations adopt the new procedures simultaneously. In some cases, behavior change is a group decision owing to the interdependent nature of the innovation or behavior change process (*22*). People often view themselves as members of a community of practice (*23*) with established norms and processes that can only change when the whole group changes (*24*). For example, a new workflow practice or technology standard may be difficult to adopt unless the entire group agrees to use the system at the same time. Communication technologies such as fax machines, texting, and social networking (for example, Facebook) increase in value as more users adopt the technology or standard (*25*, *26*). Groups can either be mutually exclusive or "cliques," which allow for overlapping group membership (*27*).

Group-detection algorithms create mutually exclusive groups and an overall index indicating how well the groups represent the overall network structure (*28*). The mutually exclusive groups defined from the data in Fig. 1 are illustrated in Fig. 2 and consist of (i) 3, 5, 7, 8, 9, 10, and 11; (ii) 1, 2, 4, 6, 12, 13, 14, 15, and 16; (iii) 17, 18, 19, 20, 21, 22, 23, 24, and 25; (iv) 26, 27, 28, 29, 30, 31, 32, 33, 34, and 35; and (v) 36, 37, 38, 39, 40, 41, 42, 43, and 44. Interventions can be delivered to the groups separately or sequentially.

A group structure that occurs in many inter- and intraorganizational networks is a core-periphery structure in which core members are densely connected to one another and peripheral members are connected to the core but not to each other (*29*). Mobilizing networks that have a core-periphery structure may be accomplished by focusing resources on the core members or by ensuring that the core members have sufficient resources or diversity to achieve network goals (*30*). For example, community coalitions are often composed of hundreds of organizations and/or individuals, yet the core working group may consist of no more than 20 organizations. Understanding who is part of this core and their distribution of assets is critical to coalition success. A study of a community coalition designed to improve health insurance coverage for children was deemed successful because the core organizations spanned all of the services and functions needed to expand health care access (*30*).

Segmentation may also be designed to identify nodes that occupy the same roles in the organization or community (*31*, *32*). For example, a new sales product might be communicated differently to the sales and technical teams. Similarly, in human service organizations, employees may be divided into positions such as line-service personnel, program managers, and program directors.

Induction. Induction interventions stimulate or force peer-to-peer interaction to create cascades in information/behavioral diffusion. Word-of-mouth (WOM) interventions stimulate interpersonal communication to persuade others to adopt the new behavior. Media marketing campaigns are often designed to generate buzz about their products, with the goal of increased sales (*33*), and frequently encourage users to recommend products to their friends and family (*34*). Often referred to as "going viral," these interventions do not necessarily use network data, but they depend on the network for their effects. Research has shown that the success of WOM is a function of the network position of initial adopters and the incentives they have to recruit others (*35*, *36*).

In respondent-driven sampling [(RDS), also known as "snowball methods"], individuals recruit others to participate in a study (for instance, a clinical trial) or receive an intervention (*37*, *38*). In RDS, an initial set of people who are members of the community or population to be influenced are selected and identified as "seeds." These seeds then recruit members of their social networks who subsequently encourage additional people to participate, and so on. Researchers can use coupons or cards as a means to track who recruited whom. Additionally, researchers must decide on the number of seeds to start with and how many others each seed can be expected to recruit. RDS is quite effective at connecting with hard-to-reach individuals who might not otherwise receive services. This is achieved by initiating recruitment with people who are members of this marginalized group. One of the initial studies applying RDS to the recruitment of injection drug users (IDUs) showed that an unbiased sample of IDUs could be recruited within three to five waves of recruitment (*38*). This tactic enables researchers to generalize their study results to a broader group of IDUs and ensures that interventions for IDUs reach everyone they are intended to reach. Adhering consistently to study procedures and protocols over these three to five waves of data collection can be challenging, however. One participant generated more than 100 recruits of varying ethnicity, gender, and place of residence. RDS differs from WOM in that RDS interventions require the seeds to recruit their closely-associated peers, whereas WOM interventions work by sparking interpersonal communication among any and all social ties.

Network outreach is similar to RDS, except that the network seeds recruit members of their personal networks to participate in an intervention together, in which the behavior change messages can be delivered to the entire group. Network outreach is expected to be more effective than individual interventions because the motivations and lessons (such as preparation of healthy food) are delivered in a group context, and the group reinforces the positive behavior change (*39*, *40*).

Leaders can be identified and groups matched or assigned to them, or the groups can be identified first and a leader selected afterward. Two randomized studies creating school-based substance abuse prevention programs using network analysis matched leaders to groups (*41*, *42*). In both cases, the effects were dependent on contextual factors (who delivered the program and the social context of delivery) (*41*, *42*). Figure 2 illustrates how leaders within groups are identified and expected to induce behavior change within their local networks (*43*, *44*). The combination of different group-segmentation and leader-identification techniques provides a few dozen operational variations.

Alteration. Strategies one through three generally assume a static network (or ignore network dynamics). Many interventions deliberately alter the network to improve efficiency. Three different tactics might be considered: (i) adding/deleting nodes, (ii) adding/deleting links, or (iii) rewiring existing links. Adding nodes is an important and long-standing behavior change approach with outside change agents, expert consultants, and lay health advisors (LHAs) being deployed in many settings to accelerate behavior change. Many studies have used LHAs, who are community members trained in behavior change techniques (*45*). These LHAs fan out into the community, often going from door to door, to inform individuals and groups about health and other topics to promote behavior change. LHAs may sometimes work within their existing social networks or approach strangers at their homes, places of business, or in public areas. Politicians and advocacy groups often mount "get out the vote" campaigns consisting of door-to-door appeals, which have been shown to increase voter participation and diffuse to other household members (*46*). Support groups, such as Alcoholics Anonymous, are often used to add new people to a person's network to facilitate behavior change. Node-addition interventions often create connections randomly, yet it is probably preferable to add nodes to the network selectively on the basis of network position. New individuals should be added to a network to bridge disconnected or loosely connected groups (*47*).

Node-deletion interventions remove nodes that occupy critical positions in a network (*48*, *49*). Nodes are then ranked on the degree to which their removal changes the network statistic. Node-deletion interventions have been embraced by antiterrorist agencies to degrade terrorist network organization (*50*). Removing critical nodes from sexual contact networks is an effective way for public health agencies to reduce disease spread and protect communities. In such cases, it is not always physical node removal but rather the use of protective behaviors (such as condom use) that inhibits transmission by the node. Node-deletion interventions change the focus of study from individual behavior to system dynamics in attempts to understand how communities or organizations respond to the removal or alteration of critical nodes. In the hypothetical example in Fig. 1, the nodes that fragment the network most when removed are 6, 37, 36, 35, 8, 14, 17, 26, 23, and 28.

As with node deletion, network measures can be used to determine optimal connections to add or remove. Networks can be modified so that they have increased redundancy of the paths that connect individuals or how individuals connect to resources (*51*). For example, a 9-month study conducted in a global consulting agency revealed two distinct subgroups in the organization that did not communicate with one another (*52*). The intervention created extensive linkages between the two subgroups so that members throughout the organization knew the resources and assets available throughout the entire organization, not just within their own subgroup. Changing network structure is probably more difficult than using existing network structures (induction), because networks are often formed for a myriad of individual, relational, attitudinal, and environmental reasons.

Finally, networks can be rewired to increase efficiency or improve performance based on certain goals. For example, teachers often randomize classroom networks so that ability levels are randomly distributed in the network. As with node and link changes, the researcher can also maximize the network on one or several metrics. Watts has suggested that optimal networks are those with short average distances between nodes and a high degree of clustering (*53*). These small-world networks maximize bridging and bonding opportunities in the network. Finally, rewiring may be conducted to connect individuals with different attributes (e.g., a buddy system).

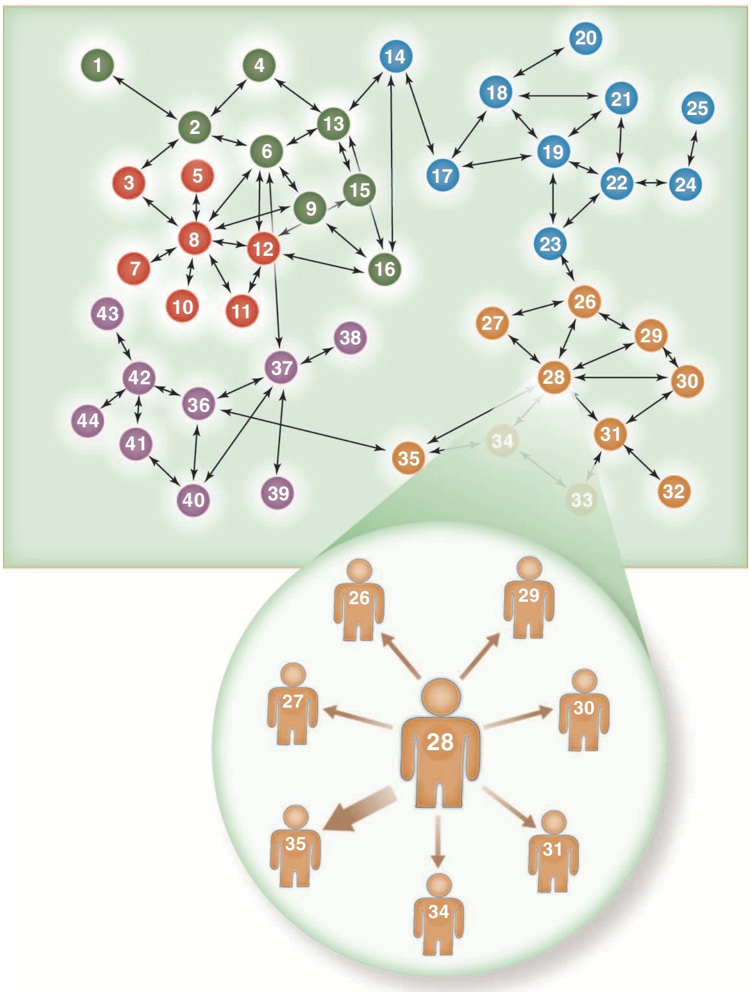

Fig. 2. Network segmentation, with each group represented by a distinct color (**top**). For induction, each group has a leader, and that leader influences the other group members (**bottom**). Node 28 can directly influence those immediately connected to him/her. Indirect influence will be required to reach those not directly connected to a leader. Different colors represent mutually exclusive groups.

Selecting an Intervention

Selecting an appropriate network intervention depends on many factors, including the type and character of available network data, the type of behavior change being promoted, and the environmental or situational context. Network data can be derived from many sources, including archived communications (such as phone, e-mail, text messaging, and listserve postings), participant observations, published sources (such as corporate board membership), and survey data. Due to the plethora of network data sources, studies may vary considerably in their ability to assess the validity and reliability of the data. Indeed, an objective standard for what constitutes a social relation may or may not exist, depending on the social relation. For example, being friends with a person is somewhat subjectively defined, whereas having lunch together constitutes a known and certifiable relationship. Consequently, methods for assessing network validity and reliability are, by nature, incomplete. Evidence from survey research indicates that social networks can be measured validly and correspond to behavioral observations (*54*). From survey data, we know that people are more likely to recall strong ties as opposed to weak ones (*55*) and are reliable when using free recall or a list of names (*56*).

The classic medical innovation study conducted in the mid-1950s measured network connections among primary care physicians in four Illinois communities (*57*). The researchers asked physicians to name other physicians in their community with whom they discussed medical issues, turned to for advice, and considered as friends. The study concluded that social networks were associated with adoption of a new drug and that the advice and discussion networks were influential early in the process, whereas friendship mattered later. Advice networks identify people who are expert and credible sources of information and who usually have considerable technical knowledge about the idea or product (*58*). Discussion networks, in contrast, identify relations that are high in trust, mutual understanding, and interpersonal affect in which communication and persuasion flow easily. Discussion relations are mutual and close physically; advice relations are more likely to be asymmetric and distant. When barriers to adoption are technical or the innovation is complex, advice networks should be used for the intervention. In contrast, when barriers to adoption are primarily cultural, discussion networks may be more appropriate. Network interventions should measure different types of networks using the data for different strategies and tactics.

Geographic distance also plays a role: Smaller, local organizations will generally rely on trusted peers for information and not depend on geographically distant leaders, because local leaders provide advice that is more sensitive to local conditions and culture. Geographically distant leaders are still quite important, however, and they might have more technical knowledge than local leaders, which would make them valued sources of information. In addition to network type, overall network properties influence strategy selection. When network data indicate that the network is nonexistent, too fragmented, too centralized, or otherwise dysfunctional, there is a need for network change. The interventionist should use induction or alteration techniques to create a network amenable to change. Once the network is built or restructured, identification and segmentation tactics can be used to accelerate change. Network structure also matters. For example, a highly centralized network may profit from leader identification tactics, whereas a decentralized network will not gain much from using leaders, and instead the analyst must rely on segmentation or induction strategies.

Characteristics of the behavior being studied also affect intervention choice (*11*). A program designed to spread information of a readily accepted idea can rely on easily identified opinion leaders, whereas one that requires complex organizational and personal changes may need dynamic rewiring and/or matching of change agents.

Interdependent behaviors are those that increase in value as more people adopt them. For example, Facebook becomes more appealing as more of one's friends use this social networking site. Interdependent behaviors often have slow initial uptake because there are few advantages to being an early adopter. Thus, interdependent innovations benefit from segmentation strategies, induction matching, or rewiring so that the interdependence can be explicitly addressed.

Prevalence also affects intervention choice. At high levels of prevalence (greater than 75%), network interventions can be used to find individuals who have not yet adopted the behavior in question, perhaps due to their network position. At low prevalence (less than 15%), network interventions can identify whether early users are leaders and, thus, are well positioned to accelerate behavior spread or whether they are on the periphery and hence likely to be slowly imitated.

Perceived political support or acceptability of the new behavior can also influence intervention strategy. For example, in a study of public health officials in the 1960s, Becker (*59*) showed that opinion leaders were early adopters of measles immunization programs that were culturally compatible with the public health establishment, but these same leaders were later adopters of diabetes screening, which was perceived to be less compatible and riskier to adopt. In general, behaviors that are likely to be readily accepted are likely to be adopted early by leaders. Controversial change processes will need to invest in network feedback and employ segmentation tactics to reduce resistance. Programs perceived as being driven by a central authority are usually resisted.

Resistance to change and susceptibility to change are influenced by many non-network factors as well. It is critical for program staff to develop an extensive understanding of the variables that influence adoption. Well-articulated behavior change theory is critical to designing effective network interventions.

Existing evidence indicates that network interventions are quite effective. Leader-matching studies returned significant reductions in self-reported smoking and substance use rates compared those from with control groups (*41*, *42*). Online peer-persuasion interventions have been shown to increase adoption of new products (*34*), and experiments manipulating social network exposures indicate that both peer persuasion and the network interconnectivity of those peers influence behavior change (*60*). Yet, the science of how networks can be used to accelerate behavior change and improve organizational performance is still in its infancy.

Research is clearly needed to compare different network interventions to determine which are optimal under what circumstances. The challenge of distinguishing causation from correlation is exacerbated when making causal inferences from network associations. Linked individuals who exhibit the same behavior may do so because they influence one another, are influenced by others they have in common, or select one another to be friends based on the behaviors (i.e., two people who wish to smoke become friends to smoke together) (*61*). Some scientists have criticized causal inferences made from regression-type models (*62*), and statisticians have built elegant but complex models to address these challenges (*63*, *64*). Although most interventions would benefit from such data in their evaluation, because network interventions are based on accelerating social influence, they require a deeper understanding of the social mechanisms driving behavior change. Further, such analyses may be critical in comparison of network interventions with non-network ones.

The options for network interventions have been dramatically enhanced by communication and information technologies that enable policymakers to identify critical nodes and network groups and to enhance diffusion within naturally occurring social networks. Electronic communications (social media, e-mail, text messaging, etc.) permit large-scale unobtrusive measures of social networks along with behavior change information. These technologies enable network interventions to go "to scale" and to be implemented beyond small-scale community groups or organizations.

However, these assets do not come without costs. Computer-mediated communications remove the richness of face-to-face interaction and were traditionally thought to be less effective for persuasion than interpersonal interaction. Moreover, many populations now live in media-saturated environments, making it hard to attend to any one message or medium. Research is needed on whether electronic networked interventions are more effective or efficacious than traditional face-to-face interaction (that is, does the increased reach compensate for the diminished effectiveness?).

Still, these electronic networks are often composed of friends (sometimes close friends), and much affective communication now occurs over electronic media. These socially mediated communications may be more relevant than mass media messages (*65*). Further, network interventions within computer-mediated environments can take advantage of data not previously available. For example, smart phone interventions can incorporate geographic location information that can be directly linked to the intervention. A network intervention promoting health screenings can include information on where and when screenings are available. Hence, the message encouraging screening comes from a friend and contains pertinent "point-of-sale" information reducing barriers to behavior change. For example, a prototype system now in development uses wearable sensors to constantly monitor and communicate individual health data to the patients' health care providers (*66*).

The strategies and tactics presented in this Review can be implemented within an electronic environment. Individuals occupying critical nodes of various types (for instance, leaders or bridges) in electronic communications can be identified. Subgroups can also be identified and, using chatroom–like technologies, actually formed into groups with specific names; individuals within the groups can be encouraged to jointly adopt new behaviors and discuss their experiences. Many companies (e.g., Amazon, StubHub, etc.) already employ various induction strategies—for example, these companies may prompt individuals to share new purchase information with their Facebook friends or Twitter followers. In short, electronic communications already incorporate many types of network interventions, and many more can now be tested.

Empirical and theoretical work on network dynamics has shown that networks evolve in both predictable and unpredictable ways (*63*, *67*, *68*). Still, we currently have little understanding of how network evolution and dynamics may impact the effectiveness of these efforts. For example, does the network position of change agents differ if they act as sponsored change agents? It is the possibility of such a change that inhibits many leaders from participating in interventions. A leader who enjoys widespread power and control is unlikely to support interventions designed to change the status quo.

A further concern is that simply soliciting network information and/or feeding it back to community organizations can generate positive results. Network interviews prompt individuals to consider their interpersonal context, potentially making them aware of the contacts and ties they do and do not possess, which may affect their ability to achieve programmatic goals. Displaying network diagrams to agencies and organizations may thus prompt individuals to create or dissolve ties that alter network structure, regardless of any other programmatic activities.

The benefits of network interventions do not come without some risks. Organizational or community members may be reluctant to have their position in the network known by others. Some people may rightfully fear that their status or jobs may be jeopardized if the network data show them to be less (or more) important than expected. A person identified as an informal leader may be seen as threatening to management or demand a raise as a result.

The studies reviewed here indicate that networked interventions are more effective than non-network alternatives. To date, however, few of the many network intervention alternatives have been tested in laboratory or real-world settings, and it is unclear which network interventions work best under what conditions. There are many strategic, tactical, and operational choices to be made when implementing a network intervention. Appropriate choices depend considerably on data availability, the behaviors under study, and the social context of the setting. Thus far, results suggest that these efforts will yield considerable scientific knowledge regarding the behavior, evolution, and malleability of socio-technical systems. By understanding how social networks can be used to improve learning, performance, and organizational outcomes, we can use the power of human interaction to improve the human condition.

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Acknowledgments: This work was supported by NIH grant number 1RC1AA019239-01 (from the National Institute on Alcohol Abuse and Alcoholism). I thank A. Heckert for help with Fig. 2 and R. Davis, L. Koehly, W. Loges, P. Matous, J. Okamoto, and three anonymous reviewers for comments on earlier drafts.

Supplementary Materials

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Supplementary Text
Figs. S1 to S22
Tables S1 and S2
Computer Code and Data

10.1126/science.1217330