COMMENTARY

Putting the network in network interventions

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The article by Chami et al. (1) in PNAS provides another example of the potential effectiveness of using network theory and data to implement health-promoting interventions. There are many such examples across the health and medical literatures addressing a variety of health behaviors. While the study by Chami et al. (1) uses a strategy of individual change agent identification, other strategies and tactics using network concepts and data have been used (2).

Advances and progress with network interventions have been slowed precisely due to the variety of applications and the variety of approaches. Example applications include HIV/sexually transmitted infections; contraceptive use; tobacco, alcohol, and other substance use; physician behaviors regarding reproductive health; acute myocardial infarction; and kidney disease. So, rather than advancing network intervention theory, scientists continue to replicate approaches in new settings and new applications. Consequently, we now know that selecting influential nodes in a network results in superior intervention effectiveness. We also know that even slightly better nodes from a network perspective are better than nodes chosen randomly: a finding demonstrated with simulations (3) and empirical examples (4).

The many studies identified by Valente and Pumpang (5) over 10 y ago and the more recent review by Flodgren et al. (6) have shown that using sociometric network data to identify peer opinion leaders has been a successful strategy across a wide variety of topic areas. This later wave of two studies by Kim et al. (4) and Chami et al. (1) has sacrificed some of the theoretical effectiveness of choosing strategically located nodes in favor of implementing a technique that is more feasible: recruiting the friends of randomly chosen seed nodes who, on average, will be of higher degree than the seeds. These studies are commendable for they make more feasible the idea of using network theory to improve public health. As Chami et al. (1) show, recruiting the friends of randomly selected individuals and removing them from the network is an efficient way to fragment a network, thus inhibiting disease spread.

However, I think the field needs to trend in a different direction, namely, comparing different network intervention approaches against one another. Dozens of network intervention tactics and operationalizations have been identified, yet we continue to focus on selecting influential nodes and are focused on identifying key influencers in networks (7). However, other tactics such as respondent-driven sampling, network segmentation, network outreach, and network manipulation have been shown to be effective in some settings and some applications (2). A second much needed development is the alignment of behavioral and epidemiological theory with intervention choice. The theoretical mechanisms responsible for generating the network and/or those generating the behavioral distributions should be articulated, and the appropriate network intervention should be chosen to match them (8).

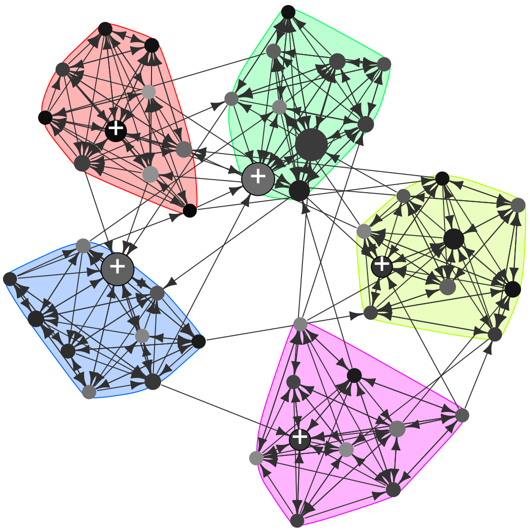

Fig. 1. Random network with leaders identified within groups by a "+" sign; shading indicates threshold level, with lighter shades having lower thresholds. Leaders are more likely to be effective persuading others in their group and more effective among those with lower thresholds. Figure courtesy of George Vega Yon (University of Southern California, Los Angeles, CA).

Chami et al. (1) also show that removing structurally important nodes decreases the extent to which others

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are exposed to disease, diarrhea in this case. This is significant in that it shows that removing key nodes from a network can disrupt transmission by both reducing potential transmission links and reducing exposures from others in the community. The finding is consistent across both friendship and advice networks, and as Chami et al. (1) note, degrading advice networks was more easily accomplished in the simulations than degrading friendship ones. Advice networks are less likely to be symmetrical, are less likely to contain transitive triplets, and are more hierarchical than friendship ones, and so should be easier to work with in real-world settings.

Another consideration for future development is the combination of individual identification tactics with group-based approaches. Many interventions rely on the cohesion, social support, and increased social capital created in group-based interventions to promote behavior change. Leaders do not lead in a vacuum; rather, the social context of their interactions with their followers is a prime consideration to their effectiveness. So, rather than identifying leaders independent of their own social networks, some researchers recommend identifying groups first and selecting leaders from within these groups (9). As Fig. 1 shows, selecting leaders and incorporating information on the overall group structure of the network enables leaders to know whom they are leading. Armed with this information, they can more effectively promote healthier behaviors and tailor their promotion messages to their peers in different ways.

This raises another issue worthy of theoretical development. Often left unsaid in behavior change interventions is what to do with these leaders once they are identified. We do not have enough research to know the level of active versus passive persuasion required for effective behavior change leadership. There is little to no evidence on what level of training is necessary for identified leaders to be effective change agents. There is undoubtedly variation among leaders in their ability to convince their colleagues to try new things.

We know there is variability among individuals in their receptivity to new ideas and practices. Thresholds are the number or proportion of one's network neighbors required for an individual to adopt a new behavior (10). Low-threshold adopters are willing to adopt innovations before any or most of their peers are willing to do so, and they may be necessary to get some innovations "off the ground." A leader surrounded by high-threshold peers is unlikely to be successful at changing their behaviors. Leaders themselves may have high or low thresholds, and old research has shown that leaders tend to follow the norms of the community when deciding whether to embrace new ideas early (11). In sum, there are many contextual, theoretical, and practical factors that affect the ability of identified change agents to persuade their peers to adopt new practices (12).

Finally, although the present commentary focuses on network interventions, researchers have noted that networks can play a fundamental role in all stages of behavior change promotion, including intervention, design, development, implementation, and monitoring (13). Identifying change agents is thus but one step in a series of actions needed to create and implement effect change programs. Ideally, a constant and regular recording of community networks would be conducted to optimize diffusion of multiple innovations addressing health, economics, political involvement, and many other social goods. In this way, some individuals would provide leadership in domains in which they are considered expert and other individuals would provide leadership in other areas. This would create a constant learning community.

The rationale for the simulations reported by Chami et al. (1) is based, in part, on the argument that collecting complete sociometric network data is difficult and time-consuming. This argument warrants discussion. In many settings and in many communities and populations, network data are quite easy to collect. Students in schools readily know who their friends are and report an eagerness to indicate so in field studies. Indeed, friendship is a concept that they are familiar with from a young age, and it is a more sensible thing for them to report than agreement on Likert scales and other complex measures (e.g., their family income). Increasingly, even in low-income settings, mobile devices that readily store network data are being used and can be used for ecological momentary assessment of networks (14). Additionally, several academic groups are currently busy developing new network assessment tools for mobile devices. In sum, complete sociometric data are becoming more readily available every day.

Chami et al. (1) provide valuable data showing that network information can readily be incorporated into behavior change interventions and that it works better than current approaches relying on community members who hold prominent positions. This commentary is designed to push us to do more than identify leaders to act as change agents by noting the importance of networks in all stages of program design and implementation and noting additional contextual factors that may affect leader effectiveness. It is clear there is much work to be done, but it should also be clear that there is great benefit in doing so.

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