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Journal of Public Health Research 2012; volume 1:e12

Article

Interpersonal influence among public health leaders in the United States Department of Health and Human Services

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Significance for public health

Influence can facilitate the spread of new ideas or opposition to ways of doing things. Influential leaders in government settings may contribute to how programs and policies are adopted, implemented, and evaluated. Despite these important characteristics, we know little about influence among government public health officials. Using a unique approach, we found that having and sharing certain professional characteristics like job rank and agency affiliation were associated with influence in the United States Department of Health and Human Services. Understanding these influence patterns allows more strategic development of organizational structures to strengthen national and global public health leadership.

Abstract

Background. In public health, interpersonal influence has been identified as an important factor in the spread of health information, and in understanding and changing health behaviors. However, little is known about influence in public health leadership. Influence is important in leadership settings, where public health professionals contribute to national policy and practice agendas. Drawing on social theory and recent advances in statistical network modeling, we examined influence in a network of tobacco control leaders at the United States Department of Health and Human Services (DHHS).

Design and Methods. Fifty-four tobacco control leaders across all 11 agencies in the DHHS were identified; 49 (91%) responded to a web-based survey. Participants were asked about communication with other tobacco control leaders, who influenced their work, and general job characteristics. Exponential random graph modeling was used to develop a network model of influence accounting for characteristics of individuals, their relationships, and global network structures.

Results. Higher job ranks, more experience in tobacco control, and more time devoted to tobacco control each week increased the likelihood of influence nomination, as did more frequent communication between network members. Being in the same agency and working the same number of hours per week were positively associated with mutual influence nominations. Controlling for these characteristics, the network also exhibited patterns associated with influential clusters of network members.

Conclusions. Findings from this unique study provide a perspective on influence within a government agency that both helps to understand decision-making and also can serve to inform organizational efforts that allow for more effective structuring of leadership.

Introduction

Theories of social influence pervade social science fields. Early studies of influence by psychologist Solomon Asch demonstrated people's tendency to base their interpretations on the interpretations of those around them.[1] Later work by Milgram found that people in positions of authority have some degree of influence over their subordinates, even in ethically challenging situations.[2] Sociologists have differentiated between power and social influence, defining the latter as *change in an individual's thoughts, feelings, attitudes, or behaviors that results from interaction with another individual or a group*.[3] These changes are often made based on observations of others who are in the majority, similar to the individual, experts, or otherwise desirable.[4] Some research has shown that people may be influenced by their perceptions of the behaviors and attitudes of others, regardless of whether those perceptions are correct.[5,6]

Interpersonal influence can facilitate the spread of new ideas or oppose new ways of doing things.[7] Within groups, influence can result in members of a group developing a shared attitude or norm, thereby reducing any conflict or uncertainty about a topic among group members.[8] Influence may also reinforce ideas an individual already holds.[9] In public health, interpersonal influence has been demonstrated as important in the spread of health information[10-12] and in explaining or changing health behaviors and characteristics such as cancer screening,[13] smoking,[14-17] adolescent drug and alcohol use,[18-21] physical activity,[22] and obesity.[20,23] However, little attention, if any, has been paid to influence among national public health leaders. Influence is important to understand in public health leadership, where influential individuals may facilitate the adoption and diffusion of public health programs, policies, and resources.

Models of influence

Since influence is a relational concept, theories and approaches that account for the complexity of social ties are important in modeling influence.[24] Sociological theories such as Rogers' diffusion of innovations (DOI)[7] and Granovetter's threshold models of collective behavior[25] have helped explain adoption of new attitudes and behaviors as a result of influence stemming from a person's social ties. DOI focuses on influential individuals, or *opinion leaders*, who facilitate the spread of attitudes and behaviors in a social system. Threshold models propose that there is a point at which an individual changes their behavior based on the behavior of a large enough proportion of others within a group of which they are member.

Network models have been a useful tool for examining thresholds and DOI.[26-28] Valente identified relational, positional, and central network characteristics as indicators of social influence related to adoption of an innovation.[27] According to Valente, relational influence occurs through links an individual has with others, indirect ties (the friend of a friend) within the larger system, or joint participation with others in groups or events. Positional influence occurs when an individual shares a similar pattern of links with another person in the network, or is close to another network member. Finally, network centralization, or the extent to which a single person or small group of people is most central to the network, may indicate the presence of influential opinion leaders. Burt identified structural equivalence, or being in a similar social position within a network, as a driving factor in the adoption of a new drug across a network of physicians.[24,29] Consistent with the qualities identified by Burt and Valente, Friedkin demonstrated three structural characteristics associated with influence in a network of teachers involved in a resolution process in a public school: cohesion, similarity, and centrality.[9,30] That is, a teacher who was central (centrality) to the network was influential; teachers who shared similar social positions (similarity) within the network influenced one another; and network members who were part of a well-connected group influenced one another (cohesion).[9,30] In 1998, Friedkin formalized these three structural aspects of influence into structural social influence theory, which explained social influence as dependent on three specific structural qualities of network relationships: i) structural centrality; ii) structural similarity; iii) social cohesion.[9]

Although some studies have examined the structural characteristics of government and policy networks,[31,32] little is known about the structural characteristics of influence among government professionals in these networks.[32] The goal of this study is to examine influence in a United States (US) government network of public health leaders. To this end, we developed a model of influence in a network of 54 employees in leadership positions in a single policy area (tobacco control) across all 11 operating agencies (Table 1) of the US Department of Health and Human Services (DHHS).

Materials and Methods

Network measures describing the position of a given network member have been used in numerous network studies of influence.[14,29] While useful in identifying influential network members, these measures are limited in that they examine characteristics or measures associated with influence (e.g., centrality) one at a time. In contrast, to explain influence in a network using all three components of structural social influence theory, Friedkin (1998) proposed a logistic regression model incorporating aspects of structural centrality, structural similarity, and social cohesion to predict interpersonal influence. In using logistic regression with network data, this approach violates the assumption of independence of observations unless *all* variables associated with interdependence are included in the model.[9] It is difficult to identify and measure all reasons for interdependency existing in any

Table 1. Agencies with tobacco control leadership in the United States Department of Health and Human Services (2005).

Agency	Full name	General description	Dedicated office for tobacco	Number included in network
ACF	Administration for Children and Families	ACF supports programs that promote the economic and social well-being of children, families and communities and administers the state-federal welfare program.	No	2
AHRQ	Agency for Healthcare Research and Quality	AHRQ provides evidence-based research on health care systems, health care quality and cost issues, access to health care, and effectiveness of medical treatments.	No	4
CDC	Centers for Disease Control and Prevention	CDC works with states and other partners to monitor, develop, and implement disease prevention and health promotion strategies designed to improve the health of the people of the United States.	Yes	12
CMS	Centers for Medicare & Medicaid Services	CMS administers the Medicare and Medicaid programs, which provide health care to about one in every four Americans, and is responsible for the State Children's Health Insurance Program.	No	2
FDA	Food and Drug Administration	FDA is responsible for assuring the safety of foods and cosmetics, and the safety and efficacy of pharmaceuticals, biological products, and medical devices.	No	2
HRSA	Health Resources and Services Administration	HRSA provides access to health care services for people who are low-income, uninsured or who live in rural areas or urban neighborhoods with limited health care services.	No	3
IHS	Indian Health Services	IHS works with tribes to provide primary care and public health services for American Indians and Alaska Natives of more than 550 federally recognized tribes.	No	2
NIH	National Institutes of Health	NIH is the primary agency for conducting and supporting medical research. NIH provides leadership and financial support to researchers in every state and throughout the world through 27 institutes and centers.	Yes	16
SAMHSA	Substance Abuse and Mental Health Services Administration	SAMHSA supports the improvement and availability of quality substance abuse prevention, addiction treatment, and mental health services.	No	3
OGC	Office of the General Council	OGC provides representation and legal services to the DHHS and supports the development and implementation of programs.	No	3
OS	Office of the Secretary	OS is responsible for the management and coordination of programs and operations of the DHHS that help facilitate achieving the nation's public health mission	No	5
Total		Sources: DHHS Website: http://www.hhs.gov/about/whatwedo.html/		54

given network. Fortunately, recent advances in network analysis offer statistical models that can handle multiple terms and which account for the interdependencies inherent in network data.[34-36]

One of these advances, exponential random graph (p*) modeling (ERGM), is a stochastic method that can be used to examine how a single observed network differs from a random network. Observed networks are typically different from random networks in two major ways: i) the distribution of links throughout the network; and ii) the presence of triangle structures (transitivity) in the network. In a random network, each network member has an equal likelihood of being connected to any other network member and typically all network members have approximately the same number of links. Observed networks often have a small group of network members who are highly connected, while most others in the network have very few links. In addition, observed networks often include many triangle structures, depicting the transitive property of the-friend-of-my-friend-is-my-friend. More complex ERGM models can incorporate properties of overall network structure, network member attributes, and attributes of relationships among network members to explain the differences between an observed network and a random network.[37-39] Although ERGM accounts for the complex interdependencies inherent in networks, it produces models that are similar in structure and interpretation to a standard binary logistic regression model. This familiar form and interpretation makes ERGM an especially accessible and powerful tool for conducting and reporting inferential network analysis.

While the development of ERGM began in the 1980's,[40,41] the lack of accessible software to conduct ERGM prevented its widespread use in applied research until recently. To date the majority of publications utilizing ERGM are focused on developing the theory and methods,[39] are published in journals specific to researchers specializing in social network analysis (e.g., *Social Networks*), or have the primary goal of explaining how to conduct ERGM in recently released software packages.[36,37,42-44] Applied articles using ERGM approaches are still relatively uncommon outside these areas, although there are exceptions.[34,45-47] In public health, ERGM is just beginning to be used to examine topics like network influences on individual behavior,[20] and inter-organizational collaboration among public health organizations.[33,45] In this study we will use ERGM to examine professional influence among tobacco control leaders across the Department of Health and Human Services. This is the first study that we know of to use an ERGM approach to examine public health leadership. In addition to being an applied use of ERGM to examine influence among public health leadership, it is important to note that we are also examining a network comprised of influence nominations. Most prior public health research examining influence in social networks has focused on identifying influential individuals based on their position in networks of informal social ties like communication[6] and friendship, or behavioral ties like needle sharing.[48] In this case, we measured influence in a network of professional ties among public health leaders by asking network members who in the network is influential. So, instead of attempting to identify influential individuals in a network based on their network position (e.g., centrality), we begin knowing who is perceived as influential and examine the contributions of network member attributes and network structures in explaining these influence nominations.

Data collection

In 2005, the lead tobacco control representative from each Department of Health and Human Services operating agency was asked to identify: i) individuals most knowledgeable about tobacco activities in their agency, and ii) other DHHS individuals who were considered important in tobacco control at Department of Health and Human Services, had primary responsibility for directing tobacco activities in their group, or made recommendations to the Department of Health and Human Services on tobacco policy, practice, or research. This resulted in 95 total individuals; those with three or more nominations were retained leaving 54 public health professionals invited to participate in the survey. Forty-nine participated for a 91% response rate. Table 1 shows the distribution of participants across agencies.

Measures

Four survey questions asked participants about their career and time at the Department of Health and Human Services: i) How long have you been employed at your agency? ii) How long have you been in your current position? iii) How long has your work included a focus on tobacco? and iv) How much of your work week is spent on tobacco-related activities? Participants were also asked questions about working with others members of the network. The first relational question, *Are you aware of the following individuals' work regarding tobacco control?*, was followed by a list of all 54 participants and was used as a screening question. Anyone a participant was aware of was kept in the list for the subsequent network questions:

Contact frequency: On average, how often have you had personal contact (e.g., meetings, phone calls, faxes, letters, or emails) with each of the following individuals within the past year? (Do not count listservs or mass emails). Response options*: daily, weekly, monthly, quarterly, yearly, and no contact.*

Influence: How influential has each of the following individuals' work been on your own tobacco work? Response options: *not at all, a little, somewhat, moderately, extremely.*

Finally, job rank (Director or Assistant Director, Branch Chief, Other) of each individual was collected through archival data.

Data management

Prior to developing the statistical models we dichotomized the influence measure with a cut-off of moderate influence. That is, on the scale of 0 to 4, all nominations of 3 or 4 were recoded as 1 and nominations with an influence value of 0, 1, or 2 were recoded as 0. This resulted in a binary network with directed ties having the values of 1 and 0, where 1 represents at least moderate influence and 0 represents less than moderate influence.

Directed networks are networks where A→B and A←B represent two different links. There are three possible states for the relationship between A and B in the DHHS directed network: i) no link; ii) a unidirectional link from A to B (A→B) or B to A (A←B) demonstrating that A nominated B as influential or B nominated A as influential; or iii) a bidirectional link (A B) demonstrating that A and B have mutually nominated each other as influential.

Complete data for node attribute measures is necessary for model development. We were missing five participant responses for two attributes: i) How long has your work included a focus on tobacco? and ii) How much of your work week is spent on tobacco-related activities? We imputed missing values with the mean of individuals from the same agency with the same job rank.

Statistical network modeling

Using ERGM, we predicted the likelihood of an influence nomination between tobacco control professionals in the Department of Health and Human Services based on characteristics associated with structural centrality, structural similarity, and social cohesion. There are several types of structural centrality that can be measured in a social network.[5] Friedkin's regression model used *indegree centrality* of a network member to measure structural centrality. Indegree centrality is the number of incoming links a network member has out of the total number of incoming links they could have. Because the links in the Department of Health and Human Services network measure influence nominations, indegree centrality measures the proportion of people in the network who nominated a network member as moderately or extremely influential.

Structural similarity or structural equivalence indicates the extent to which two network members share similar positions. Specifically, two network members are structurally similar if *their normative, material, or interpersonal circumstances in the social structure are similar.*[9] In the case of the Department of Health and Human Services network, one example of a structural similarity (homophily) would be if network members A and B were both in the same job rank or were both working for the same agency. Sharing ties to the same people in the rest of the network is also an indicator of structural similarity.

Structural cohesion occurs when members of a network share membership in a tightly linked sub-group (strong component) within a network. Measures of structural cohesion in networks are often defined in terms of the minimum number of network members in a group that would disconnect the group if removed.[49] However, frequent communication has also been used as an indicator of structural cohesion, since those who are in tightly linked sub-groups are likely to communicate with one another more frequently.[9,50]

The network model of influence was developed in four steps. First, we accounted for network member indegree centrality (being nominated as influential). In the Department of Health and Human Services network, indegree centrality is, by definition, an indicator of influence. We examined whether the following characteristics of network members were associated with indegree (and therefore influence): agency affiliation, job rank, length of time in tobacco control, and time per week spent on tobacco related work. We hypothesized that:

H1: Network members working in agencies with dedicated tobacco control offices (Centers for Disease Control and Prevention, National Institute of Health), with higher job ranks, and spending more time (per week or overall) in tobacco control are more likely to be nominated as influential than other network members.

Second, homophily of characteristics, such as sharing the same job rank, is a material indicator of structural similarity.[9] Agency affiliation, job rank, time in tobacco control, and time spent per week were added to the model as *mutual terms*. In a directed network like the Department of Health and Human Services influence network, mutual terms account for the frequency with which A B and A B both exist. By specifying a node attribute in the mutual term, the coefficient for the mutual term will quantify the extent to which nodes with the same specified attribute nominate one another as influential. We hypothesized that:

H2: Network members in the same job rank, working for the same agency, or spending the same amount of time on tobacco control (weekly or overall) were more likely to influence one another than people not in similar positions.

Third, we used frequency of contact as a proxy for social cohesion since those who communicate more often are likely to belong to a cohesive group.[9] We hypothesized that:

H3: Network members communicating with each other more frequently were more likely to nominate each other as influential than network members communicating less frequently.

Finally, global structural network terms were entered into the model to account for underlying network structures often seen in social systems. Terms included a geometrically weighted term for the distributions of indegree (GWIDegree) and another for outdegree (GWODegree), and two types of clustering (Geometrically Weighted Edge-wise Shared Partnerships [GWESP], Geometrically Weighted Dyad-wise Shared Partnerships [GWDSP]). These global terms (pertaining to the overall network structure) aid in detecting underlying patterns of influence across the entire network. For example, GWESP accounts for transitivity in the network. Transitivity, or the friend-of-my-friend-is-my-friend property, is seen more often than would be expected by chance in social structures and was the source of degeneracy for many early statistical network models. When used with GWESP, GWDSP accounts for the distribution of open triangles. GWDSP may be considered an indicator of the presence and amount of structural similarity (or structural equivalence) because it identifies pairs of unlinked actors who are tied to the same other actors.[36] In accounting for triangles (transitivity), GWESP quantifies clustering in the network and may be considered an indicator of structural cohesion. Following Goodreau,[36] we built the model by first adding local terms (individual characteristics and frequency of contact between individuals) followed by global predictors. This allows an assessment of the role of global structures above and beyond what individual characteristics and local partnering explain. To examine their relative contributions, terms representing different aspects of influence were added in consecutive blocks. Model fit was examined at each step. Although statistical measures of model fit such as the Aikake Information Criterion are commonly used to compare nested statistical models like these, these measures rely on independent data and so were not used.[51] Instead, goodness-of-fit (GOF) plots comparing observed network characteristics to the characteristics of networks simulated based on each model were used. A GOF percentage was also calculated to quantify the proportion of observed network measures fitting within the confidence intervals of simulations based on the models.

Network characteristics

Network size was 54 with 336 influence nominations for a density of 0.12. Indegree, or the number of influence nominations each network member received, ranged from zero to 29 with a median of 5.5 nominations. Outdegree, or the number of influence nominations made by each member, ranged from zero to 28 with a median of four. Figure 1 shows the influence network with arrows representing influence nominations, labels showing agency affiliation, size showing number of influence nominations, and color depicting job rank. Larger nodes shown in Figure 1 depict the individuals who received more influence nominations. Agencies in the network with the highest average job rank were Office of the Secretary, Centers for Disease Control and Prevention, Agency for Healthcare Research and Quality, and the Food and Drug Administration. Because job rank is represented by color in Figure 1, and darker colors are higher job ranks, these organizations were represented more often by darker colors. Agencies with employees having the most experience in tobacco control were the Centers for Disease Control and Prevention, Indian Health Services, and Health Resources and Services Administration; agencies where individuals spent the most time per week on average on tobacco control were the Centers for Disease Control and Prevention, Indian Health Services, and National Institutes of Health. Experience in tobacco control was not demonstrated in Figure 1.

Results

Odds ratios and 95% confidence intervals based on coefficients and standard errors for all terms in each of the models are shown in Table 2. Graphic and statistical measures of goodness-of-fit measures revealed that Model 4 was the best fit. Specifically, the goodness-of-fit percent (Table 2) increased from 61.9% for the null model to 87.6% for Model 4. The graphic measures of fit can be used to visualize this large increase; for example, Figure 2 shows the increase in fit for edge-wise shared partnerships, or shared partners for two linked network members, in the four models as a demonstration. Moving from panel 2a to 2d the observed network (black line) measure of edgewise shared partnerships increasingly falls inside the 95% confidence interval (gray lines) for this measure based on network simulations.

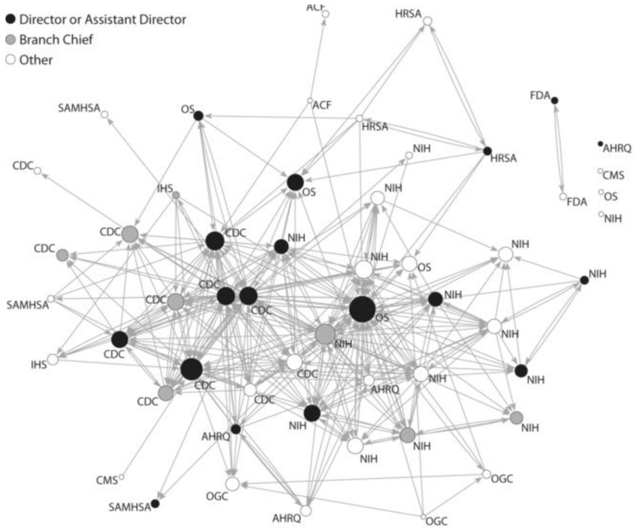

Figure 1. Network of influence ties among Department of Health and Human Services tobacco control professionals. A link from A→B indicates that A nominated B as influential. Node size shows how many influence nominations were received by each individual

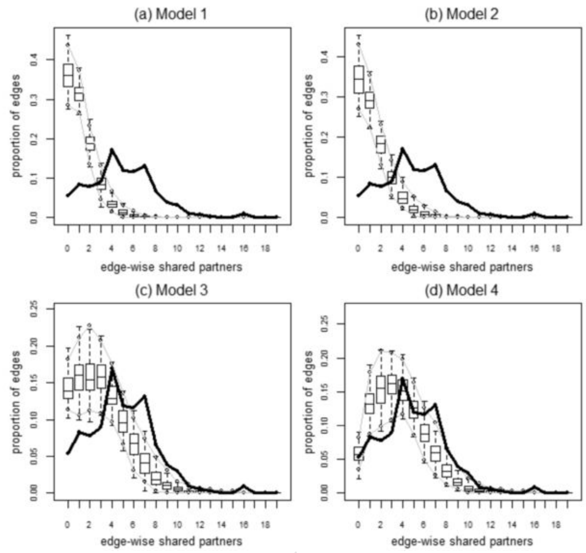

Figure 2. Model fit comparing observed network characteristics (black lines) and simulated network characteristics (boxplots) for the distribution of edge-wise shared partners (ESP) for each model tested as a demonstration of the increase in model fit across the four models.

Table 2. Statistical models of influence among tobacco control professionals in the Department of Health and Human Services.

	(a) Model 1	(b) Model 2	(c) Model 3	(d) Model 4
Local terms	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**
Edges	0.04 (0.02-0.08)	0.03 (0.02-0.04)	0.01 (0.01-0.02)	0.007 (0.004-0.01
Structural centrality (in-degree)				
Agency affiliation				
ACF	0.23 (0.03-1.70)	0.31 (0.05-1.88)	0.44 (0.06-3.26)	1.56 (0.27-29.67)
AHRQ	0.40 (0.21-0.76)	0.54 (0.28-1.00)	.65 (.33-1.25)	1.56 (0.27-9.19)
CDC	0.81 (0.59-1.12)	1.07 (0.81-1.41)	1.17 (.83-1.65)	1.35 (0.97-1.88)
CMS	na	na	na	na
FDA	0.22 (0.05-0.96)	0.35 (0.10-1.27)	1.12 (0.26-4.76)	3.26 (0.91-11.69)
HRSA	0.35 (0.14-0.88)	0.45 (0.20-1.04)	0.50 (0.19-1.31)	1.96 (0.90-4.28)
IHS	0.32 (0.13-0.81)	0.33 (0.11-.99)	0.82 (0.27-2.45)	1.70 (0.68-4.22)
NIH	ref	ref	ref	ref
OGC	1.35 (0.64-2.87)	1.24 (0.59-2.61)	1.75 (0.76-4.03)	3.78 (2.03-7.03)
OS	1.40 (0.94-2.09)	2.11 (1.47-3.02)	3.47 (2.12-5.67)	3.90 (2.48-6.14)
SAMHSA	0.18 (0.07-0.77)	0.20 (0.06-.60)	0.86 (0.26-2.80)	0.65 (0.31-1.38)
Other job characteristics				
Job rank	0.66 (0.57-0.77)	0.75 (0.71-0.79)	0.87 (0.75-1.04)	0.83 (0.81-0.85)
Hours per week on tobacco control	1.81 (1.54-2.14)	1.38 (1.36-1.40)	1.02 (1.00-1.04)	1.11 (1.10-1.13)
Years in tobacco control	1.18 (.99-1.26)	1.16 (1.14-1.17)	1.09 (1.08-1.11)	1.09 (1.07-1.10)
Structural similarity (mutuality)				
Agency affiliation		13.04 (11.04-15.40)	3.47 (3.03-3.98)	4.70 (4.10-5.40)
Job rank		2.76 (2.33-3.26)	1.16 (0.96-1.39)	1.16 (0.96-1.41)
Hours per week on tobacco control		6.36 (5.40-7.49)	3.05 (2.57-3.61)	1.70 (1.43-2.02)
Years in tobacco control		1.57 (1.23-1.99)	1.04 (.82-1.33)	0.81 (.64-1.04)
Social cohesion				
Frequency of contact			36.68 (34.18-39.35)	19.57 (12.91-29.67)
Global terms				
GWDSP				0.93 (0.92-0.94)
GWESP				2.48 (2.37-2.59)
GWODegree				0.05 (0.04-0.07)
GWIDegree				2.18 (1.46-3.25)
Model fit				
Goodness-of-fit	61.9%	65.7%	81.0%	87.6%

The odds ratios and confidence intervals for Model 4 in Table 2 identify the specific individual, dyadic, and network characteristics significantly contributing to influence among the Department of Health and Human Services tobacco control professionals. Significant factors included several of the individual attributes, the structural similarity terms for agency affiliation and time per week spent on tobacco control, the social cohesion term (frequency of contact), and all of the global structural terms. The sections that follow examine the strength and direction of the relationship between each significant predictor and influence.

Structural centrality

Our results were partially supportive of hypothesis 1, which stated that network members from agencies with dedicated tobacco control offices (Centers for Disease Control and Prevention; National Institutes of Health), higher job ranks, and more time devoted to tobacco control would be more likely to be influential. With the highest job classification coded as 1 and the lowest coded as 3, the protective odds ratio for job rank (OR=.83; 95% CI=.81-.85) indicates that, for every one unit decrease in job classification score there was a 17% decrease in the likelihood of an influence nomination. So, Branch Chiefs were 17% less likely to be influential than Directors, and Other job classifications were 34% less likely to be influential than Directors. Spending more hours per week (OR=1.11; 95% CI=1.10-1.13) and more years overall (OR=1.09; 95% CI=1.07-1.10) on tobacco control were both associated with an increased likelihood of influence. Specifically, for every one unit increase in hours per week spent on tobacco, an individual was 11% more likely to be identified as influential. Similarly, for every one unit increase in years in tobacco control, an individual was 9% more likely to be influential. Two specific agencies also demonstrated significant main effects for structural centrality (Office of the General Council, Office of the Secretary). Compared to those working for the National Institutes of Health (the reference group), individuals at the Office of the General Council and Office of the Secretary were 3.78 (95% CI: 2.03-7.03) and 3.90 (95% CI: 2.48-6.14) times more likely to be nominated as influential, respectively.

So, while higher job rank and more time in tobacco control were associated with higher likelihood of influence, employees of the agencies with tobacco control offices were not more likely to be influential. Instead, they were no different from employees of most the agencies, and less likely than members of two of the agencies. Significant results for agency affiliation and hours per week in tobacco must be interpreted with caution given the significant structural similarity terms for each of these; structural similarity terms are higher-order dyad-level terms.

Structural similarity

Hypothesis 2, which stated that network members sharing certain characteristics (job rank, agency affiliation, time in tobacco control) were more likely to be mutually influential than those not sharing these characteristics, was also partially supported. The agency affiliation and hours per week similarity terms were positive and significant. Having the same agency affiliation increased the likelihood of mutual influence nomination by 4.70 times. Working the same hours per week increased the likelihood of mutual influence 1.70 times. Working the same number of years in tobacco control and having the same job rank were not significant predictors of mutual nomination. So, two network members who were both working for the Centers for Disease Control and Prevention would be 4.70 times more likely to nominate each other as influential as two network members working for two different agencies. Likewise, if two network members were both working full-time on tobacco control they would be 70% more likely to nominate each other as influential as a full-time tobacco control professional and someone spending a portion of their time on tobacco.

Structural cohesion

Hypothesis 3 stated that network members who communicated more frequently were more likely to nominate each other as influential compared to those not communicating as often. This hypothesis was supported. The network predictor of contact frequency was positive and significant (OR=19.57; 95% CI: 12.91-29.76), indicating a very strong association between influence and contact. Specifically, for every one unit increase in the frequency of contact between two network members, the likelihood of influence nomination increases more than 19 times. If two network members had weekly contact, they would be 19 times more likely to have an influence nomination between them as two network members communicating on a monthly basis.

Global structural terms

The significant odds ratio of 0.93 for GWDSP indicated that unlinked dyads were generally *unlikely* to have shared influence links to others. That is, there is an overall lack of structural similarity in the network once local terms are accounted for. The significant odds ratio of 2.48 for GWESP indicates an increased likelihood for connected dyads to have links to the same other network members. This is an indicator of some clusters of influence beyond what was accounted for by local terms. Finally, the GWIDegree term was significant and greater than one, indicating that after accounting for local terms; individuals were more likely than chance to have many influence nominations. GWODegree also had an odds ratio less than one, indicating that individuals were less likely than chance to make numerous influence nominations once local terms were accounted for.

Discussion

Network approaches have been used to examine influence, which is an inherently relational concept. Network theories such as diffusion of innovations and social structural influence theory have associated influence with characteristics of individuals, dyads, and network structures. Unlike standard network methods, recent advances in ERGM allow for hypothesis testing to determine whether such characteristics and structures in an observed network explain differences between the observed network and a random network of the same size.[51] We used this unique stochastic approach to examine how the characteristics of individuals, their relationships, and global network structures aid in explaining influence in a network of public health leaders. Most studies of influence in networks rely on examining networks comprised of social ties such as communication or friendship. In contrast, we measured perceived influence directly through a survey question about professional influence. In doing so, the network models developed in this study not only contribute to a better understanding of influence among government leaders, but may also add to, and aid in validating, existing literature explaining influence in social networks.

The statistical network model of influence among professionals working across all 11 agencies of the Department of Health and Human Services identified significant contributions from individual attributes, structural similarity, and social cohesion in predicting influence nominations. Specifically, we found that individuals who shared characteristics, like agency affiliation and time spent on tobacco control, and communicated with one another more frequently were more likely to be seen as influential by their peers in the public health leadership. In the context of occasional criticism of government for being out of touch or making decisions without knowledge of a particular content area, these results suggest that – at least with respect to tobacco control - organizations within the Department of Health and Human Services valued expertise and organizational communication in the process of meeting the nation's public health needs.

While we did not directly test network diffusion of innovations or threshold models, based on our results, these theories might predict that a new innovation or idea adopted by a full-time tobacco control professional at the Centers for Disease Control and Prevention might first spread among influence ties throughout the Centers for Disease Control and Prevention and among full-time tobacco control professionals across the network. Depending on how many of the network members adopted the idea, thresholds for adoption among others in the network might eventually be met and facilitate additional spread of the idea or innovation throughout the network. The primary limitation of this study is that it is cross-sectional. In addition, there may be variables that were not included in this study, like shared employment history,[52] that help to drive perceptions of influence.

Given the role of the DHHS as a national leader in United States tobacco control, it is important to understand existing patterns of influence across the network, how they may facilitate the adoption of new ideas and strategies nationwide, and how they may shift over time. For example, consider the role of the National Institutes of Health (Table 1) in the Department of Health and Human Services and in this network (Figure 1; Tables 1 and 2). The majority (n=11) of National Institutes of Health participants in the network were from the National Cancer Institute, which is housed within the National Institutes of Health. Traditionally, tobacco control professionals at the National Cancer Institute primarily work on the discovery end of the Discovery-Development-Delivery continuum, while tobacco control professionals at Centers for Disease Control and Prevention and Agency for Healthcare Research and Quality focus more on development and delivery. Specifically, National Cancer Institute tobacco control professionals work in an organization funding the generation of much of the data upon which development and delivery efforts are subsequently based. Currently, the National Institutes of Health are considering moving addiction-related activities from across the National Cancer Institute, National Institute on Drug Abuse, and National Institute on Alcohol Abuse and Alcoholism into a newly created substance abuse and addictions institute by 2014 (http://feedback.nih.gov). Such a shift will result in numerous structural changes across the network. If the relocation occurs, interpersonal ties facilitating the communication of tobacco-related discovery from National Cancer Institute to Centers for Disease Control and Prevention and Agency for Healthcare Research and Quality would likely change and new ties would form between the Centers for Disease Control and Prevention, the Agency for Healthcare Research and Quality, and the new institute.

Because frequency of contact is associated with influence, changes in communication structures could result in entirely new patterns of influence among individuals and agencies involved in Department of Health and Human Services tobacco control leadership. Changes in the distribution of job rank and other characteristics of individuals involved in tobacco control would also likely occur (e.g., individuals moving from one organization to another) and would further change the influence structure of the network. These sorts of structural changes should be considered as re-organization plans are developed. In addition to aiding the Department of Health and Human Services in its organization efforts, this study has relevance to other government organizations because it highlights relationships involved in decision-making processes relevant to government effectiveness. It is not clear that the network relationships observed in the current study generalize to other health problems, or government agencies, but our results provide metrics for measuring communication and collaboration that can serve as a foundation for future efforts designed to make the government function more effectively.

Finally, in addition to the Department of Health and Human Services playing a leadership role in tobacco control nationally, it has the potential to play a leadership role in tobacco control globally.[54] This role is especially important, as new global initiatives are being developed to address non-communicable diseases.[55] To fulfill these leadership opportunities, the Department of Health and Human Services needs to have well-coordinated decision-making processes and effective leadership structures in place. Understanding influence across the network is one piece of the puzzle to consider when making strategic organizational decisions that would allow the Department of Health and Human Services to become a global leader in tobacco control.

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Key words: influence, exponential random graph modeling, leadership, network.
Contributions: JKH, instrument development, data collection and management, manuscript conceptualization, analyses performance, manuscript writing and editing; BJC, analyses performance, manuscript writing and editing; LMW, SCS manuscript writing and editing; SJL, study leading, data collection, manuscript sections writing.
Conflict of interest: the authors declare no conflicts of interest.
Received for publication: 1 November 2011.
Accepted for publication: 1 February 2012.

Journal of Public Health Research 2012; 1:e12
doi:10.4081/jphr.2012.e12

References

1. Asch SE. Effects of group pressure upon the modification and distortion of judgments. In: HS Guetzkow (ed.) Groups, leadership and men; research in human relations. 1951, Carnegie Press, Pittsburgh, USA.
2. Milgram S. Behavioral study of obedience. J Abnorm Soc Psych 1963;67:371-8.
3. Rashotte L. Social influence. In: G Ritzer (ed.) Blackwell encyclopedia of sociology. 2007, Blackwell Publ., Malden, USA, pp. 562-563.
4. Marsden PV, Friedkin NE. Network studies of social influence. In: S Wasserman, J Galaskiewicz (eds.) Advances in social network analysis. 1994, Sage Publ., Thousand Oaks, USA.
5. Valente TW. Social networks and health: models, methods, and applications. 2010, Oxford University Press, Oxford, UK.
6. Valente TW, Watkins SC, Jato MN, Van Der Straten A, Tsitsol LM. Social network associations with contraceptive use among Cameroonian women in voluntary associations. Soc Sci Med 1997 9;45:677-87.
7. Rogers EM. Diffusion of innovations, 5th Edition. 2003, Simon & Schuster, New York, USA.
8. Friedkin NE. Norm formation in social influence networks. Social Networks 2001;23:167-89.
9. Friedkin NE. A structural theory of social influence. 1998, Cambridge University Press, Cambridge, UK.
10. Valente TW, Saba WP. Mass Media and interpersonal influence in a reproductive health communication campaign in Bolivia. Commun Res 1998;25:96-124.
11. Starkey FF. Identifying influential young people to undertake effec-

tive peer-led health promotion: the example of A Stop Smoking In Schools Trial (ASSIST). Health Educ Res 2009;24:977-88.
12. Latkin CA. Outreach in natural settings: the use of peer leaders for HIV prevention among injecting drug users' networks. Public Health Rep 1998;113(Suppl.1):151-9.
13. Davis DT. The urban church and cancer control: a source of social influence in minority communities. Public Health Rep 1994;109:500-6.
14. Hall JA, Valente TW. Adolescent smoking networks: the effects of influence and selection on future smoking. Addict Behav 2007;32:3054-9.
15. Ennett SST. The contribution of influence and selection to adolescent peer group homogeneity: The case of adolescent cigarette smoking. J Pers Soc Psychol 1994;67:653-63.
16. Fagan P, Eisenberg M, Stoddard AM, et al. Social influences, social norms, social support, and smoking behavior among adolescent workers. Am J Health Promot 2001;15:414-21.
17. Sorensen G, Emmons K, Stoddard AM, et al. Do social influences contribute to occupational differences in quitting smoking and attitudes toward quitting? Am J Health Promot 2002;16:135-41.
18. Knecht AAB, Burk WJ, Jeroen W, Steglich C. Friendship and alcohol use in early adolescence: a multilevel social network approach. J Res Adolesc 2011;21:475-87.
19. Rice RE, Donohew L, Clayton R. Peer network, sensation seeking, and drug use among junior and senior high school students. Connections 2003;25:32-58.
20. Valente TW. Adolescent affiliations and adiposity: a social network analysis of friendships and obesity. J Adolesc Health 2009;45:202-4.
21. Eggert LL, Thompson EA, Herting JR, et al. Preventing adolescent drug abuse and high school dropout through an intensive school-based social network development program. Am J Health Promot 1994;8:202-15.
22. Troped PJ, Saunders RP. Gender differences in social influence on physical activity at different stages of exercise adoption. Am J Health Promot 1998;13:112-5.
23. Christakis NA, Fowler JH. The spread of obesity in a large social network over 32 years. N Engl J Med 2007;357:370-9.
24. Robins GG. Network models for social influence processes. Psychometrika 2001;66:161-89.
25. Granovetter M. Threshold models of collective behavior. Am J Sociol 1978;83:1420-43.
26. Valente TW. Network models of the diffusion of innovations. 1995, Hampton Press, Cresskill, USA.
27. Valente TW. Social network thresholds in the diffusion of innovations. Social Networks 1996;18:69-89.
28. Carrington PJ, Scott J, Wasserman S. Models and methods in social network analysis. 2005, Cambridge University Press, Cambridge, UK.
29. Burt RS. Social contagion and innovation: Cohesion versus structural equivalence. Am J Sociol 1987;92:1287-35.
30. Friedkin NE. Structural bases of interpersonal influence in groups: a longitudinal case study. Am Sociol Rev 1993;58:861-72.
31. Berry FS, Brower RS, Choi SO, et al. Three traditions of network research: what the public management research agenda can learn from other research communities. Public Admin Rev 2004;64:539-52.
32. Leischow SJ, Luke DA, Mueller N, Harris JK, Ponder P, Marcus S, Clark PI. Mapping U.S. government tobacco control leadership: Networked for success? Nicotine Tob Res 2010;12: 888-94.
33. Leischow SJ, Best A, Trochim WM, Clark PI, Gallagher RS, Marcus SE, Matthews, E. Systems thinking to improve the public's health. Am J Prev Med 2008;35:S196-S203.
34. Luke DA, Harris JK, Shelton S, et al Systems analysis of collaboration in 5 national tobacco control networks. Am J Public Health 2010;100:1290-7.
35. Harris JK, Luke DA, Zuckerman RB, Shelton SC. Forty years of secondhand smoke research: the gap between discovery and delivery. Am J Prev Med 2009;36:538-48.
36. Goodreau SM. Advances in exponential random graph (p*) models applied to a large social network. Social Networks 2007;29:231-48.
37. Goodreau SM, Handcock MS, Hunter DR, et al. A statnet tutorial. J Stat Softw 2008;24:1-26.
38. Morris M, Handcock MS, Hunter DR. Specification of exponential-family random graph models: terms and computational aspects. J Stat Softw 2008;24:1548-7660.
39. Snijders TAB, Pattison PE, Robins GL, Handcock MS. New specifications for exponential random graph models. Sociol Methodol 2006;36:99-153.
40. Frank O, Strauss D. Markov Graphs. J Am Stat Assoc 1986;81:832-42.
41. Holland PW, Leinhardt S. An Exponential Family of Probability Distributions for Directed Graphs. J Am Stat Assoc 1981;76:33-50.
42. Handcock MS, Hunter DR, Butts CT, et al. statnet: software tools for the representation, visualization, analysis and simulation of network data. J Stat Softw 2008;24:1548-7660.
43. Hunter DR, Handcock MS, Butts CT, Goodreau SM, Morris M. ergm: a package to fit, simulate and diagnose exponential-family models for networks. J Stat Softw 2008;24:nihpa54860.
44. Shumate M, Palazzolo ET. Exponential Random Graph (p*) models as a method for social network analysis in communication research. Communication Methods and Measures 2010;4:341-71.
45. Steven M. Goodreau SM. Birds of a feather, or friend of a friend?: Using exponential Random Graph Models to investigate adolescent social networks. Demography 2009;46:103-25.
46. Harris JK, Cyr J, Carothers BJ, et al. Referrals among cancer services organizations in an underserved urban area. Am J Public Health 2011;101:1248-52.
47. Wimmer A. Beyond and below racial homophily: ERG models of a friendship network documented on Facebook. Am J Sociol 2010;116:583-642.
48. Valente TTW. Selective risk taking among needle exchange participants: implications for supplemental interventions. Am J Public Health 2001;91:406-11.
49. Moody J, White DR. Structural Cohesion and embeddedness: a hierarchical concept of social groups. Am Sociol Rev 2003;68:103-27.
50. Wasserman S, Faust K. Social network analysis: methods and applications. 1994, Cambridge University Press, Cambridge, UK.
51. Hunter DR, Goodreau SM, Handcock MS. Goodness of fit of social network models. J Am Stat Assoc 2008;103:248-58.
52. Scott J, Carrington PJ. The SAGE handbook of social network analysis. 2011, Sage Publ., Thousand Oaks, USA.
53. Hatmaker DM, Rethemeyer RK. Mobile trust, enacted relationships: social capital in a state-level policy network. Int Public Manag J 2008;11:426-62.
54. Bollyky TJ, Gostin LO. The United States' engagement in global tobacco control: proposals for comprehensive funding and strategies. JAMA 2010;304:2637-8.
55. Beaglehole R, Bonita R, Horton R, et al. Priority actions for the non-communicable disease crisis. Lancet 2011;377:1438-47.