Frontiers in Public Health Services and Systems Research

Volume 2 | Number 5 Article 3

8-12-2013

Diffusion of Innovation Across a National Local Health Department Network: A Simulation Approach to Policy Development Using Agent-Based Modeling

Mark Orr
Columbia University, mo2259@columbia.edu

Jacqueline Merrill RN, MPH, DNSc
jam119@columbia.edu

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Abstract
The network that local health officials use to communicate about professional issues is sparsely connected, which may limit the spread of innovative practices. We used agent-based simulation modeling to find out if a policy to promote more connections improved the network's capability to diffuse innovation. We found that unanticipated effects could result, depending on the requirements of the policy and the proportion of health officials involved. With carefully crafted assumptions and reliable data it is possible to untangle complex processes using simulation modeling. The results represent how the world might actually work which may provide useful decision support for policymakers with further research.

Keywords
Public health systems, policy, decision support, diffusion of innovation, computer simulation, non-linear models, complex systems, agent-based modeling, networks

Professional communication networks are conduits for the spread of best practices and innovation [1]. The network that the officials of local health departments (LHDs) use to communicate about policy and practice was recently analyzed using data from the 2010 National Profile of Local Health Departments (2010 NPLHD). The network is directed and sparsely connected, with small groups of two or three health officials communicating locally, mainly within state boundaries [2,3]. This pattern suggests limited capability for innovative practices to disseminate widely via the existing communication links between health officials.

Policy makers interested in developing high performing public health systems may wonder if it is possible to change this communication pattern in a way that is both feasible from a policy perspective and increases the potential for practice innovations to diffuse across the network, from one innovation in one local health department (LHD) ultimately throughout the national system of LHDs. This is particularly important given that interpersonal communication with trusted peers is known to determine the spread and shape of diffusion in a social system through a process of social contagion [4].

We approach this question using a computational modeling technique from the field of complex systems. In particular, we constructed an agent-based model (ABM) to simulate interactions between health officials (the "agents") in the 2010 NPLHD network (n=1999, [2]). Using this ABM, we examined the effects, on the diffusion of innovation, of a policy that generated more cross-state connectivity among LHDs via the recently inaugurated national accreditation process. In essence, we explored the question of whether increasing the cross-state connectivity among LHDs would make a practice innovation, e.g., regulatory limits on sales of high sugar beverages, more or less likely to propagate across the network of LHDs over time.

METHODS

We conducted a policy experiment in which a selected proportion of the network nodes were forced to make new out-of-state network ties (called *rewiring* the network) while dropping some of the current existing network ties. This was intended to represented a national policy where LHDs applying for accreditation were required to partner in cohorts each located in a different state. We hypothesized that diffusion across the network would improve if the degree of connection was maintained (the number of old ties was equal to the number of replaced ties), but occurred across a wider geographic area.

There were two experimental factors: *Percent Rewired* and *Number Ties*. We manipulated the percent of network nodes (each represented a local health official) selected for the policy intervention, (*Percent Rewired)*, from zero to 80 by intervals of 5%. Also, we manipulated the number of network ties that were added for each selected node, called *Number Ties*, from one to five by intervals of two. When we rewired the network, we removed *n* old ties (picked at random) for each selected node and replace them with *n* new ties to nodes that were randomly chosen but out-of-state relative to the selected node. The new ties were always reciprocal (information could flow both ways) between the selected node and the new nodes to which it was connected. Thus, we used a 3 (Number Ties) x 17

(Percent Rewired) factorial design for a total of 51 conditions (3 times 17). Each condition was simulated 100 times.

Simulations were conducted in two steps. First, we rewired the network (zero Percent Rewired, by definition, was the only level that was not rewired). Second, we seeded one LHD in the network with an "innovation" and allowed the innovation to diffuse through the network using a probabilistic contagion mechanism (similar to infectious disease contagion). Specifically, during each time step of the simulation, the probability that a node would adopt the innovation from its neighboring nodes was 0.70 and was computed independently for each neighboring node. Although other diffusion mechanisms are possible (e.g., thresholds or social learning, see [5] for a review) the assumptions of the contagion model fit how we conceptualized the diffusion process on this particular empirical network.

During the simulation, we tracked the proportion of LHDs in the network that adopted the innovation. The primary outcome variable, called *Prevalence of Innovation*, was defined as the proportion of LHDs that adopted the innovation by the end of the simulation—i.e., this was a measure of how much diffusion occurred as a result of the experimental manipulation.

We also considered two properties of the simulated networks: *Reciprocity* measured the number of bi-directional ties between health officials and is a proxy for collaboration; the *Clustering* coefficient measured the connections between direct neighbors, which typically supports locally shared communication and limits more globally shared communication.

RESULTS

We first present the diffusion process in raw form. Figure 1, Panel A, shows the baseline diffusion process without any policy manipulation (100 runs are shown). Panels B, C, and D show increasing levels of the Number Ties factor (one, three and five-ties) for the 30% level of Percent Rewired; each panel shows 100 runs of each condition. Notice that, for all panels, there are a number of simulations that did not show any degree of diffusion—i.e., the Prevalence of Innovation was near zero. This was due to the initial seed being a health official with few or no network ties. Thus, it is quite possible that a single innovation may not diffuse at all, no matter what or how strong the policy manipulation may have been.

Next, in Figure 2, across three panels we show three direct effects of the policy manipulation and, in a fourth panel, the relation between the network properties and the Prevalence of Innovation. Panels A and B show the effects of the policy manipulation on the two network measurements, Reciprocity and Clustering coefficient, both of which were strongly affected by the policy manipulation. Of particular interest is the inverted-U shape of the Reciprocity curves and the fact that the Clustering coefficient dramatically changed at three and five-tie levels of Number Ties. These two panels show how the policy manipulation affected the structure of the health officials' network.

Panel C shows the policy effect on the Prevalence of Innovation at the end of the simulation. Here, we provide a detailed statistical analysis on the effect of policy on innovation diffusion. There was an effect on both Number Ties and Percent Rewired, $F(2, 5081) = 810.30$, $p < 0.001$, and $F(16, 5081) = 13.77$, $p < .001$, respectively. Furthermore, there was an interaction between these two experimental factors, $F(32, 5049) = 11.38$, $p < .001$. The interaction model explained more variance in Prevalence of Innovation than the non-interaction model (from 27% to 32 %, $p < .001$).

Visual inspection provides four further main points. First, the one-tie level of Number Ties does not diffuse more than the baseline condition (zero Percent Rewired), suggesting that the implementation of the policy did not have a linear, incremental effect on diffusion. Second, the shapes of the three-tie and five-tie level curves were markedly different: five-tie was a non-linear, inverted-U, shape; three-tie was a monotonic increasing shape. Third, from 65% to 80% Percent Rewire, the five-tie level had a lower degree of Prevalence of Innovation than the three-tie level. That is, the five-tie and three-tie graph lines actually crossed paths. The last two points taken together suggest that to maximize the potential for diffusion, it is important to know both the percent of LHDs involved and the requirements of the policy regarding rewiring of the network.

Panel D shows the effects of the network properties on Prevalence of Innovation which helps to explain the variation in diffusion that the policy manipulation produced in the network. There is a clear *increase* in diffusion as Reciprocity (collaboration) increases and a *decrease* in diffusion as the Clustering coefficient (local communication) increases. Thus, taken with the other results in Figure 2, it appears that the effect of our policy worked by changing these properties of the network. Further analysis elucidated that the effects of Reciprocity and Clustering on diffusion operate differently. As shown in Table 1, either an increase in Reciprocity or a decrease in Clustering lead to an increase in the probability that a large degree of diffusion might occur, i.e., that the Prevalence of Innovation would be relatively high (e.g., above 0.50). However, an increase in Reciprocity had a very small effect on the magnitude of Prevalence of Innovation for the subset of simulations that reached this relatively high degree of prevalence; in contrast, a decrease in Clustering still had a strong effect for this subset. In short, in these simulations the effect of Reciprocity was limited to affecting the chances that a single innovation in one LHD might cascade into a large-scale diffusion process that captures a large degree of the network; Clustering did not show this limitation. It should be recognized that the findings regarding Reciprocity and Clustering are probably specific to the initial conditions of this empirical network, which is both sparse and highly clustered within and not between states[2].

IMPLICATIONS

There are two key implications of this work. First, when a policy has more than one component or decision point, the potential exists for interactions which may produce unanticipated changes in the outcomes of interest. Thus, it is important to understand the joint effects across policy decision points. In our simulation, for example, imagine that it was only feasible to require local health departments to make a maximum of three new network connections (instead of five). Under that condition, to maximize the potential for innovation diffusion, our model suggests that to produce the best results we should involve the highest possible proportion of LHDs. On the other hand, if it was feasible from a policy perspective to enforce a higher number of connections, then only a moderate (about 30%) of the network should be involved—beyond 30%, the payoffs are less.

Second, simulation of policy effects can provide insight toward novel policy efforts. Our simulation provided a mechanistic explanation of how policy affects network structure and, in turn, affects innovation diffusion—via network reciprocity and clustering. Any policy that changes these two network properties in the right direction likely has potential to increase diffusion of innovations through the health officers' communication network. However, this conclusion is highly provisional at this point and warrants further research into the details of how Reciprocity and Clustering are working to increase diffusion.

In summary, with carefully formulated requirements and reliable data, it is possible to untangle complex processes using simulation modeling [6,7]. The results represent how the world might actually work and, thus, provide useful decision support for policymakers.

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Figure 1. Diffusion as a function of simulation time. Each panel represents 100 runs within one condition. See text for details on the conditions.

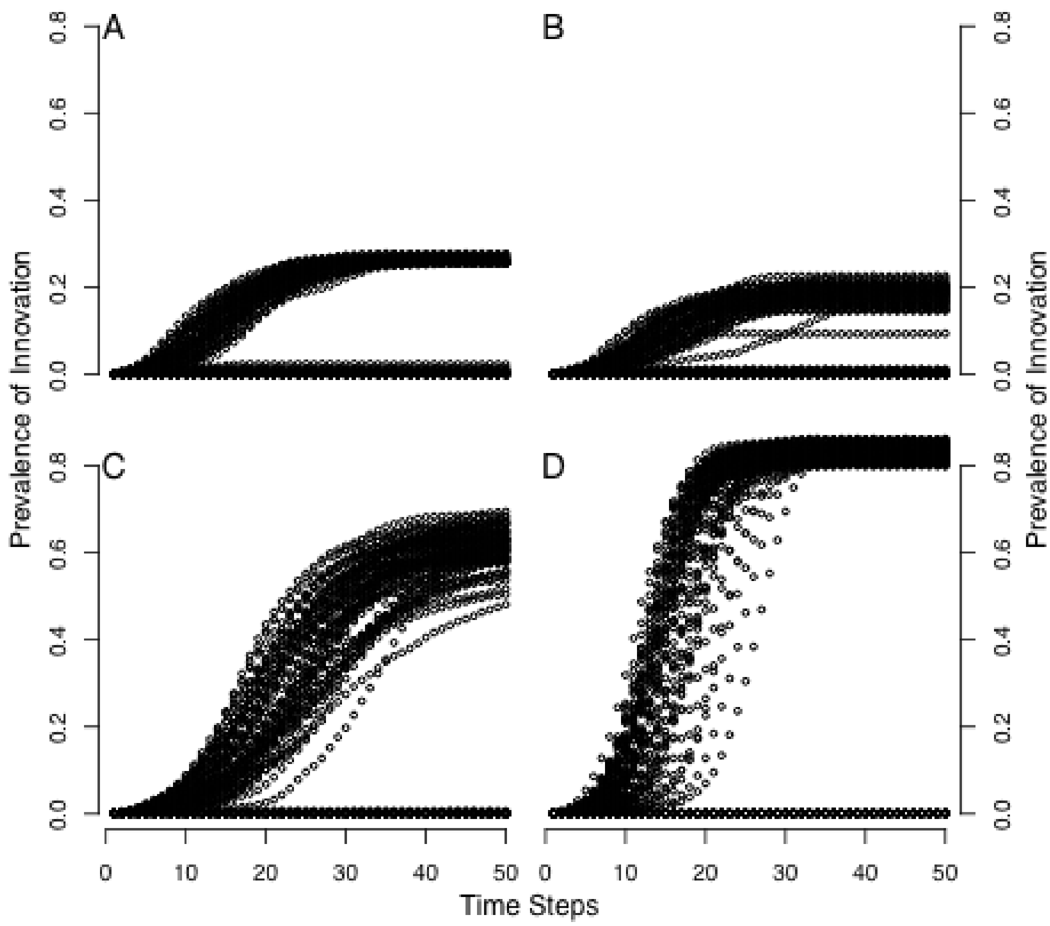

Figure 2. Panels A – C illustrate the effects of the policy manipulations on three separate metrics, Reciprocity, Clustering and Prevalence of Innovation, respectively. The Percent Rewired is on the x-axis; the metrics on the y-axis. Each level of Number Ties is represented by the data point symbol type (see the key in Panel A). Panel D shows the relationship between the network measures and Prevalence of Innovation. The x-axis shows equal-spaced bins of the network measures. The type of network measure is represented by the data point symbol type (see the key in Panel D).

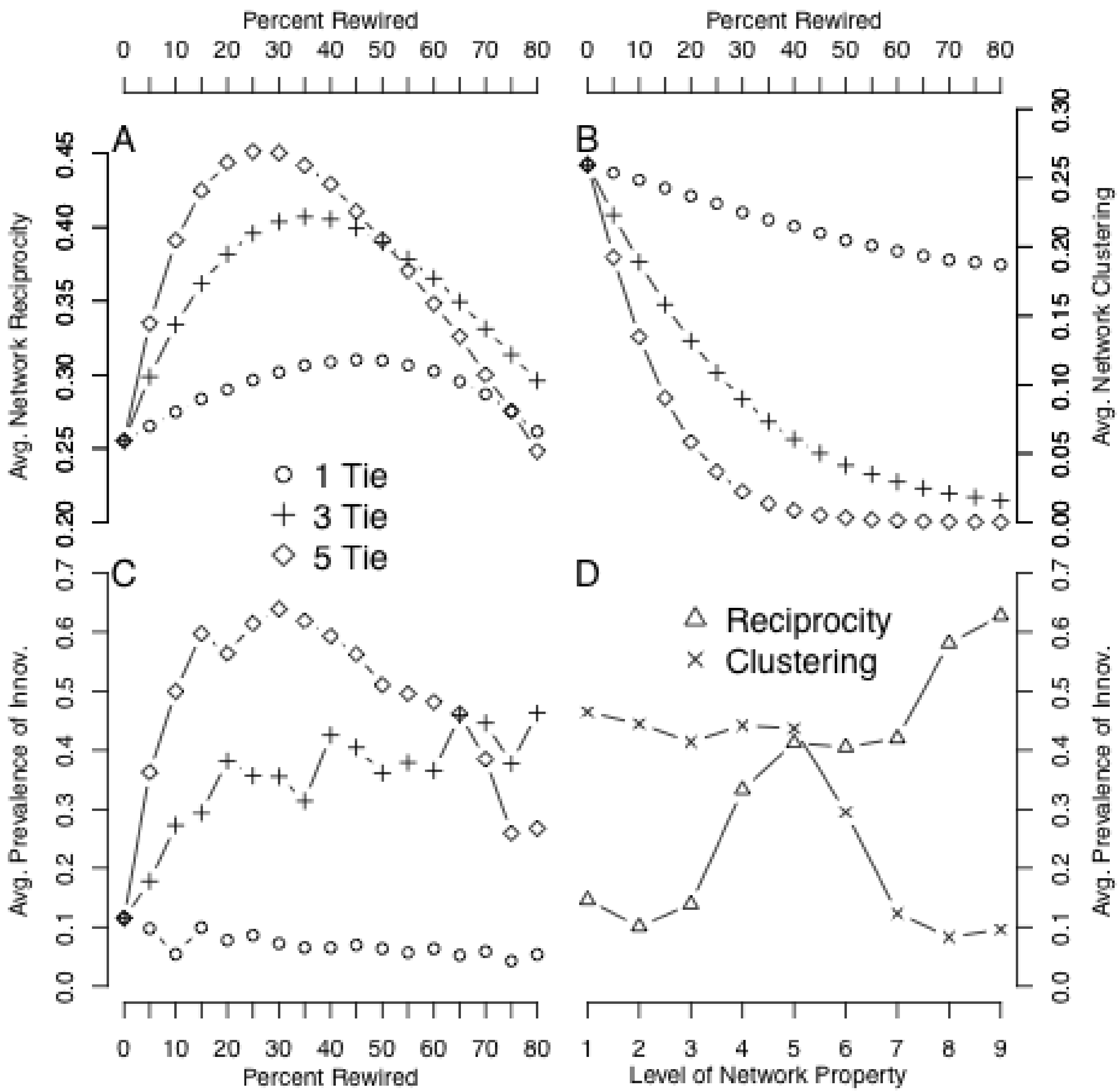

Table 1. Proportion of Simulations Diffused to a Prevalence Above .50 and the Average Prevalence of Innovation for The Same Simulations Across the Nine Levels of Clustering and Reciprocity.

		Level of Network Property								
		1	2	3	4	5	6	7	8	9
Proportion Diffused > .50	Clustering	0.56	0.60	0.59	0.65	0.66	0.43	0.10	0	0
	Reciprocity	0.07	0.05	0.09	0.38	0.54	0.57	0.6	0.72	0.76
Ave. Prev of Innov | Diffused > .5	Clustering	0.83	0.73	0.69	0.67	0.65	0.56	0.60	0	0
	Reciprocity	0.86	0.86	0.85	0.76	0.74	0.70	0.69	0.81	0.82