

Dissemination and Implementation Research in Health: Translating Science to Practice

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Viewing Dissemination and Implementation Research through a Network Lens

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Abstract and Keywords

Dissemination and implementation (D&I) are complex social and organizational processes by which new scientific discoveries and advances can be translated and transferred to people, settings, and communities to affect and improve public health. Despite their complexity, D&I processes can be viewed as a type of information transmission. A new scientific discovery (or innovation) is a piece of information that needs to be transferred to a different part of society, which can put that information to use. It turns out that this type of information transmission has important structural and relational properties that can best be understood using a relatively new systems science tool: network analysis. This chapter proposes a network analytic model of D&I and illustrates how network analysis can be used both to study and shape D&I processes and outcomes. Understanding the D&I process more fully through network analysis can be an important domain of D&I research.

Keywords: D&I, network analysis, scientific discovery

Introduction

Dissemination and implementation (D&I) are complex social and organizational processes by which new scientific discoveries and advances can be translated and transferred to people, settings, and communities to affect and improve public health. Despite their complexity, D&I processes

can be viewed as a type of information transmission. A new scientific discovery (or innovation) is a piece of information that needs to be transferred to a different part of society, which can put that information to use. It turns out that this type of information transmission has important structural and relational properties that can best be understood using a relatively new systems science tool: network analysis. The purpose of this chapter is to propose a network analytic model of D&I and illustrate how network analysis can be used both to study and shape D&I processes and outcomes. Understanding the D&I process more fully through network analysis can be an important domain of D&I research.

For an orienting example, consider the ride of Paul Revere, a part of American history that many of us learn about in primary school. On the evening of April 18th, 1775, Paul Revere and his compatriot William Dawes rode from Boston to Lexington, warning people of the mobilizing British forces. Paul Revere's ride is a classic dissemination problem: how to get new important information (“The British are Coming!”) disseminated quickly, reliably, and broadly. Although lanterns were actually hung in Christ Church in Boston at the beginning of the ride, Revere and Dawes disseminated the information by riding and stopping at towns and farmhouses along the way to Lexington (Figure. 8-1), “alarming” the patriots there, many of whom set off on horseback on their own to further spread the message. Thus, Paul Revere's ride was an early type of “phone tree” where a message could be spread quickly through a network of people. Figure. 8-2 shows schematically how the Paul Revere dissemination network was structured, and illustrates the relational and structural nature of dissemination. For example, we can see that the success of Paul Revere's ride rests not only on how many towns Revere and Dawes could reach in one night, but also in how many patriots hear the message in each town, and how many of them spread the message further. More specifically, this example suggests that in order to understand dissemination, and design more effective dissemination processes and structures, it is important to be able to study and analyze the structural and relational aspects of dissemination networks. The rest of this chapter describes how network analysis can be used in this way to study D&I. (p. 155)

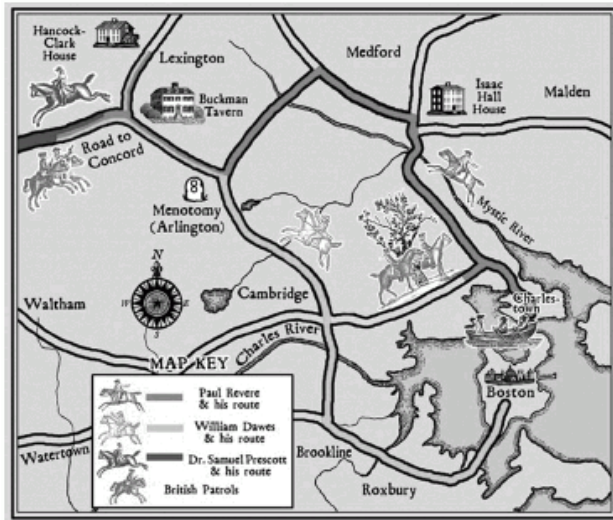


Figure 8-1. Map of Paul Revere's ride (www.paulreverehouse.org).

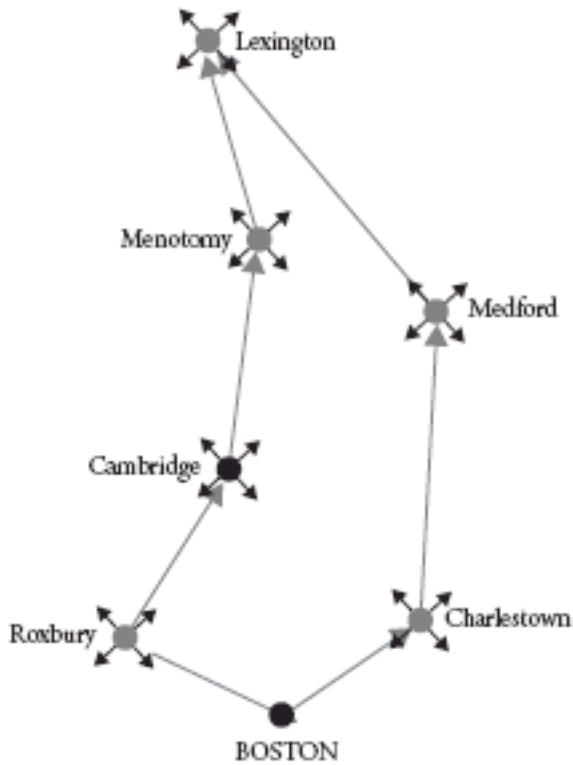


Figure 8-2. Network analytic depiction of Revere's and Dawes's ride.

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Network Analysis Fundamentals

Network analysis is not just a set of quantitative techniques—it is a paradigmatic approach to the social and health sciences that embodies a fundamentally different view of social phenomena.¹ The unit of analysis in network science is a relationship between social objects, not an object or characteristic of an object. Relationships can be many things—friendship, money exchange, an e-mail transmission, disease transmission, and so on. Because of this shift in focus from the object to relationships among objects, network analysis is one of the most useful tools for studying context, environment, process, and social structure.² Network analysis has been used widely in public health and health sciences to study infectious disease transmission, social influences on health behavior, social support and social capital, organizational systems, and Diffusion of Innovations.³

To support the rest of this chapter, it is helpful to understand basic network analysis terminology. A network is made up of a set of nodes and ties that connect the nodes. A node can be almost any type of object—a person, organization, state, country, animal, computer, and so on. Similarly, a tie can represent almost any type of relationship. Nodes are also called actors, members, or vertexes. Ties are sometimes called links, arcs, or edges. Networks can include directed or nondirected relationships. A directed tie (usually indicated by an arrow in a network graph) shows what direction the relationship goes in. For example, money exchange is usually measured and analyzed as a directed tie. Money is given from one node and received by another node. Many other types of relationships are nondirected. For example, organizational collaboration is typically viewed as a nondirected relationship. Two organizations work together on a common project, and it does not make sense to think of the direction of that collaboration. Nondirected ties are usually indicated by straight lines (without arrowheads) in a network graphic. For those interested in more in-depth treatment of network data collection and analysis, see books by Wasserman & Faust, Valente, or de Nooy.^{4 - 6}

Connecting Dissemination and Implementation Theories to Network Theories

Diffusion of Innovations

Probably the most important and influential theoretical framework relevant to D&I is the theory of Diffusion of Innovations⁷ (see also [Chapter 3](#)).⁸ Rogers

defined Diffusion of Innovations as “the process by which an innovation is communicated through certain channels over time among the members of a social system.” The early work on Diffusion of Innovations emphasized the types of members (Figure. 8-3) as well as the cumulative adoption over time (Figure. 8-4). Thus, early understanding of dissemination of scientific findings concentrated on the roles that different members of society played (e.g., innovators vs. opinion leaders) or the amount of time it took for an innovation to be disseminated and adopted in clinical or community practice.

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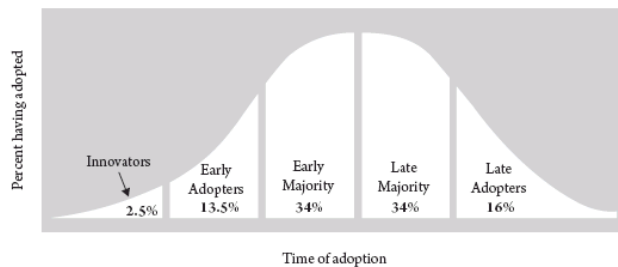


Figure 8-3. Distribution of role types according to time of adoption (based on Bohlen et al., 1962).⁹

However, this emphasis on types of persons involved in diffusion or the amount of time it takes for a discovery to be completely adopted begged the question about what processes drove diffusion in the first place. That is, what distinguishes early adopters from opinion leaders other than their simple temporal ordering in the diffusion process? This question did not start to get answered until Diffusion of Innovations theory started incorporating structural and relational aspects.¹⁰

This can be seen most clearly by actually looking at one of the well-known diffusion networks studied by social scientists: the adoption of new hybrid seed corn among Iowa farmers.^{9 , 11} In this diagram (Figure. 8-5), arrows connect the farmers and scientist, and the arrows point to the source of the information about the innovation. The diagram shows us that Farmer #1 was the innovator and the first to adopt the farm practice in 1948. However, most of the farmers did not learn about this new technology from him. Instead, it wasn't until after 1950 when Farmer #2 (the opinion leader) had adopted the new technology that the practice became more widespread. This network and geography map reveals that there is not just a temporal structure to the diffusion process, but also a relational structure. The opinion leader is much more densely connected to the rest of the diffusion network than the

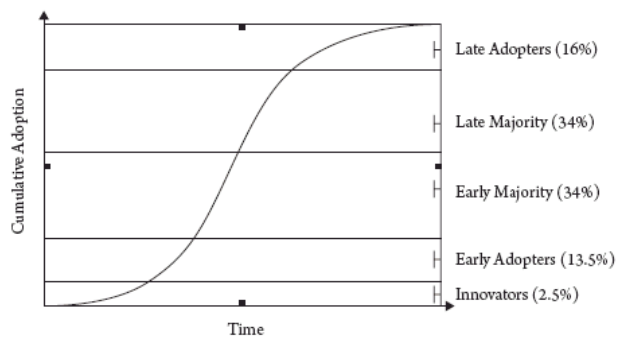


Figure 8-4. S-shaped diffusion of innovation curve (adapted from Rogers, 2003).⁷

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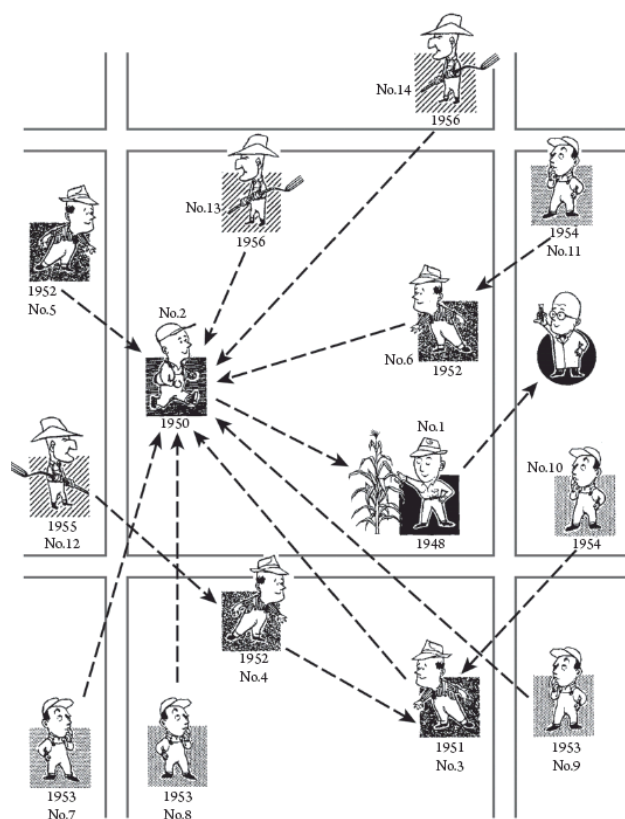


Figure 8-5. Dissemination of hybrid-seed corn information (from Bohlen et al., 1962).⁹

innovator is. That is, the pattern of informational ties can be used to understand the diffusion process. Consistent with U.S. federal definition

and those described in [Chapter 2](#) of this book, elsewhere in this chapter the broader term “dissemination” is used, which includes diffusion concepts.

Dissemination and Implementation Frameworks

Implementation science is a newly emerging discipline that focuses, in part, on the discovery and identification of social, organizational, and cultural factors affecting (p. 159) the uptake of evidence-based practices and policies.¹² Although the early developers of this field have recognized the importance of systems thinking and methods,¹³ there has been a lack of explicit discussion or demonstration of the utility of network analysis methods for implementation science. However, close examination of new D&I science theoretical models makes it clear that network analysis could be a powerful tool.

For example, Proctor and colleagues have introduced an implementation research framework that groups outcomes into three categories: implementation outcomes, service outcomes, and client outcomes.¹⁴ A number of the implementation outcomes, including penetration, acceptability, sustainability, and uptake, could be examined using network methodology. Tenkasi and Chesmore provide a good example of this in their study of implementation outcomes among 40 units of a multinational corporation.¹⁵ They found that both between-unit and within-unit density of strong ties predicted change implementation cycle time (penetration) and change use (uptake).

The utility of network analysis for studying implementation is made more explicit in the theoretical framework proposed by Feldstein & Glasgow: the Practical, Robust Implementation and Sustainability Model (PRISM).¹⁶ As suggested in Figure. 8-6, when studying the implementation process of a new treatment or intervention, the social networks of both the organization members and patients are important tools for understanding predictors of adoption, implementation, and maintenance outcomes. In a successful empirical application of the PRISM model, Beck and colleagues further demonstrated the usefulness of network analysis.¹⁷ Organizational

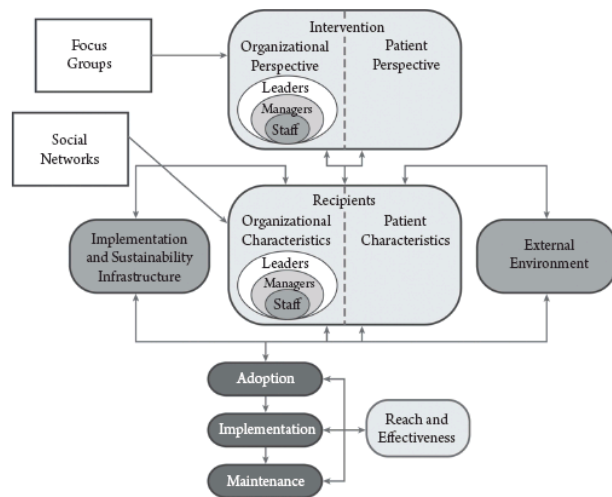


Figure 8-6. The Practical, Robust Implementation and Sustainability Model (PRISM) (adapted from Feldstein & Glasgow, 2008).¹⁶

(p. 160) advice-seeking patterns among clinicians and staff at two HMO sites were identified using network analysis. These network maps were then used to help drive the subsequent implementation of a new well-child care intervention.

Both of these examples utilize frameworks of implementation processes and outcomes. There have been fewer theoretical treatments of dissemination that highlight the role of network analysis. One exception is Wandersman and colleagues' Interactive Systems Framework for Dissemination and Implementation.¹⁸ In their critical analysis of existing frameworks, they note that traditional models of dissemination tend to ignore the infrastructure and systems that support the dissemination processes. In arguing for a more dynamic and interactive model of D&I, they recognize the importance of network-related concepts such as social capital, community capacity, and collective efficacy.

Although network analysis has not been used widely in D&I science, this is likely to change as more researchers come to grips with the systems approach to studying dissemination and implementation processes and outcomes.

Using Network Analysis for Dissemination and Implementation Research

In the previous section, we have seen how a network theoretical framework can be useful for framing research questions about D&I processes and outcomes. This leads to scientific studies of D&I that collect and analyze data quite differently than in traditional social and health science research. The fundamental difference is the unit of analysis: traditional research poses questions about the attributes or characteristics of individual objects (i.e., people, organizations, etc.), whereas in network analysis the questions are about relationships among those objects. In the rest of this chapter, we will consider a number of network analysis techniques that are most useful for exploring D&I.

Network Description and Visualization

To provide a real-world example for the next two sections, data are shown from an ongoing evaluation of how state tobacco control programs use evidence-based guidelines such as CDC's *Best Practices for Comprehensive Tobacco Control Programs-2007*.¹⁹ States are implementing new policies and practices based on these guidelines, and the successful implementation is supported by broad dissemination of these guidelines through state and community agencies.²⁰ A main goal of this evaluation was to assess the dissemination networks in each state to help CDC improve tobacco control D&I activities.

In D&I research or evaluation, the first analytic task is often to simply describe the basic dissemination structures or processes. For example, who is involved in the dissemination network? Who in this network has been actively involved with dissemination? How tightly connected is the dissemination network? How efficient is the network? All of these questions can be addressed with basic network analytic and visualization techniques.

(p. 161) For example, Figure. 8-7 presents the *Best Practices* dissemination network for the Oregon state tobacco control program. Each node in the graphic is a critical agency or partner in the state program. Nodes are connected by a line if they have communicated with each other about CDC's *Best Practices* guidelines in the past year. The nodes are colored to indicate type of agency, and they are sized to reflect network prominence (see below.) This type of network graphic can reveal a lot about dissemination structures and processes. In this case we can quickly see that most of the Oregon partners have communicated about *Best Practices* with multiple other partners. There is one isolated agency (DHS MedAsst). The lead agency for the state program (TPEP) is highly interconnected. Contractors and

grantees show a lower level of dissemination connections than other types of agencies such as advocacy groups.

Although network graphics such as this one can be constructed by hand for small networks, typically specialized network software such as Pajek or UCInet is used. Network software uses specialized visual display algorithms that can enhance the interpretability of the graphics—for example, by placing highly interconnected nodes in the center of the graph, placing disconnected nodes along the periphery, and minimizing crossing lines.²¹

In addition to network graphics, there are a number of useful basic network descriptive statistics that can be used to summarize important network properties. The two most useful of these are network density and diameter. Network *density* is a measure of the overall interconnectedness of the network. It is defined as the proportion of observed network ties to the total number of possible network ties.

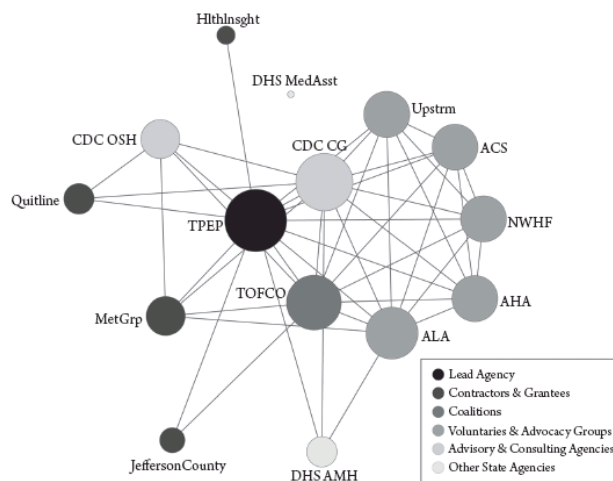


Figure 8-7. Oregon tobacco control dissemination network.

(p. 162) Oregon's dissemination network has 15 members, and there are 45 observed dissemination ties. For a nondirected network, the total number of possible ties is $k*(k-1)/2$, with k being the number of nodes. So the density of Oregon's network is $45/105$, or 0.43. Density can range from 0 to 1, and as networks get larger, the density tends to get smaller. Experience suggests that the density of Oregon's dissemination network (0.43) indicates a highly interconnected network.

Network size, in and of itself, is often not a very interesting statistic. The network size can be driven by a number of factors totally unrelated to the

relation of interest (here, dissemination), including geographic boundaries, funding patterns, legislative mandates, or even study design issues. Instead, we can look at a measure of network efficiency designed to tell us how easy it is to get from one part of the network to any other part. The network *diameter* is the longest path between all pairs of a connected network.²² One of the major discoveries of network science is that even in very large networks (such as the Internet with millions of nodes), the network diameter can be quite small.²³ In fact, the “small-world” phenomenon is based on this property of large networks with small diameters.

For the Oregon network, the diameter is defined as infinity, because of the disconnected node (DHS MedAsst). That is, because this node is not connected to the rest of the network, we cannot go from one node to any other node in the network. If we drop this node and just consider the rest of the connected network, then we can calculate the diameter as 2. Because TPEP is connected to every other agency in the network, it only takes two steps or hops to reach another node from any starting node. The diameter of the Oregon network (more than the rough measure of its size) indicates that this is a highly interconnected network.

With network visualization, and measures of network density and diameter, we can summarize the basic characteristics of a dissemination network. This can help us understand whether an organizational or informational system is ready to support widespread and efficient dissemination of new programs, policies, and innovations.

Prominence

As we saw earlier, our current understanding of how Diffusion of Innovations works includes structural and relational elements. In particular, as Figure. 8-7 suggests, particular members of a dissemination network may play specific roles in the dissemination process, and these roles are determined in part by how they are connected (or not connected) to others in the network. Network analysis provides a number of useful tools to assess the roles that individual members play in a network. Possibly the most popular and flexible of these tools is the set of network statistics designed to measure the *prominence* of individual network members.

A network member is seen as prominent in the network to the extent that she (or it) is visible to others in the network. The most commonly used class of prominence measures is *centrality*, where network members are central

when those members have high involvement in many relations with other network members. Centrality can actually be measured in a number of different ways—Table 8-1 presents three different centrality statistics for the Oregon dissemination (p. 163)

Table 8-1. Centrality Measures for Oregon Dissemination Network

Agency	Centrality		
	Degree	Closeness ^a	Betweenness
TPEP	0.928	1.000	0.294
Metropolitan Group	0.357	0.619	0.003
American Lung Assoc.	0.643	0.765	0.033
Health InSight	0.071	0.520	0.000
Jefferson County Dept of Health	0.143	0.542	0.000
Tobacco Free Coalition	0.714	0.812	0.072
American Heart Assoc.	0.500	0.684	0.000
Upstream Public Health	0.500	0.684	0.000
American Cancer Society	0.500	0.684	0.000
Northwest Health Foundation	0.500	0.684	0.000
DHS-Addictions & Mental Health Div.	0.214	0.565	0.000
DHS-Medical Assistance	0.000	—	0.000
CDC-Office on Smoking and Health	0.357	0.619	0.007
CDC-Community Guide	0.786	0.867	0.096

Free & Clear	0.214	0.565	0.000
Overall Network Centralization	0.577	0.703	0.279

^aCloseness centrality calculated after dropping the isolate: DHS-Medical Assistance.

network: *degree* centrality, *closeness* centrality, and *betweenness* centrality.²⁴ For all three measures, scores can range from 0 to 1, with numbers closer to 1 indicating greater centrality. Degree centrality is the easiest to understand—it is based on the number of direct connections (degree) that a network member has with other members. The lead agency, TPEP, has the highest overall degree (13), so it also has the highest degree centrality (0.93). Closeness centrality takes into account not just direct ties, but also indirect ties. A network member will have high closeness centrality if it lies close to all other members in the network. Closeness is measured by the smallest path that connects two nodes. For the Oregon network, closeness centrality can only be calculated after dropping the single isolate (DHS-Medical Assistance), because closeness is only defined for a connected network. TPEP has the highest possible closeness centrality because it is directly connected to every other network member. Health InSight, on the other hand, has the lowest closeness centrality because it has to go through TPEP to get to any other member of the network. Finally, betweenness centrality is another centrality measure that takes both direct and indirect ties into account. A node will have high betweenness if it sits in between many other shortest paths between network members. Betweenness is usually interpreted as control over the flow of information in a network.²⁵

As Table 8-1 illustrates, these three measures of centrality give similar, but not identical information. What is the best measure to use? Each measure is based on a different aggregation of information about network ties (only direct ties considered vs. all ties) and network structure (distance vs. location). A researcher should use a measure of centrality that most closely matches the theoretical framework being used. For dissemination studies, if the focus were on identifying network members who are most responsible for driving the dissemination, then perhaps degree centrality would be most appropriate. If the interest were more in the flow of dissemination across an entire network, then betweenness centrality would (p. 164) be useful. Finally, if the researcher were more interested in dissemination efficiency (how quickly or easily the entire network can be reached with the information), then closeness centrality would be a good candidate.

Centrality measures are useful for identifying critical network members, such as TPEP in the Oregon dissemination network. TPEP's prominence makes sense given that it is the lead agency for the state's tobacco control program. Part of the Oregon analysis was to understand the impact of the CDC's Community Guide, which is a comprehensive systematic review of a whole range of public health interventions.²⁶ The centrality measures revealed that the Community Guide is playing an important role in the dissemination of Best Practices, which makes sense given the Community Guide's focus on evidence-based strategies.

Prominence measures can also be very useful for making comparisons across different networks or among different types of relationships in the same network. First, individual node-level centrality measures can be aggregated into network-level *centralization* indices. These are presented for the Oregon dissemination network at the bottom of Table 8-1. These numbers are actually measures of the variability of the node-level measures and also range from 0 to 1. Higher numbers indicate greater variability of centrality. This is usually interpreted as greater hierarchy in the communication structure. That being said, it is often difficult to interpret a single measure of centralization—instead, these numbers are more useful when making comparisons. For example, consider Figure 8-8, which compares the centralization

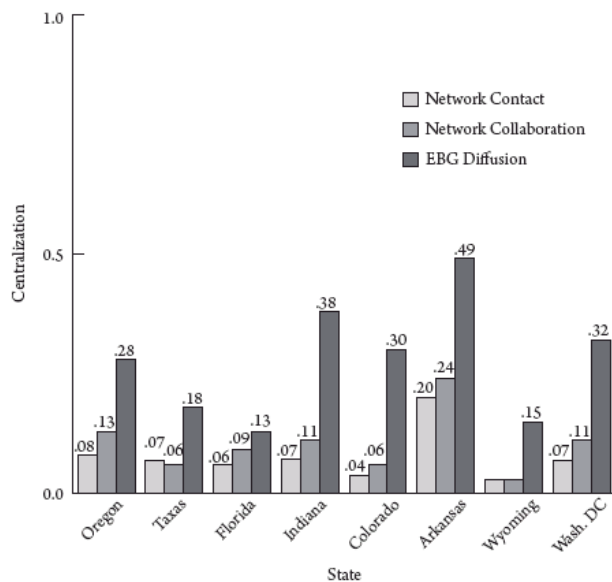


Figure 8-8. Betweenness centralization for eight tobacco control programs and three network relations.

(p. 165) of three types of network relations for eight different state tobacco control programs. Contact is simply how often two agencies talk to each other, collaboration is how extensively the two agencies work together on common projects, and EBG diffusion is whether the two agencies have talked to each other about CDC's *Best Practices* guidelines. The graphic shows a striking pattern: across all eight state programs, EBG diffusion shows much higher betweenness centralization than for contact or collaboration. This suggests that contact and collaboration are shared among state partners in comparable ways, but a small number of agencies are driving the *Best Practices* diffusion process in each state. This fits a staged communications model of Diffusion of Innovations, where interagency communication and collaboration must precede the more challenging task of broad dissemination of practice and policy innovations.

Analyzing Diffusion Processes

The previous two sections have shown that basic node-level and network-level statistics can provide information relevant to studies of D&I processes and structures. More advanced network analysis techniques are available that can help analyze or model more specific diffusion processes in social or organizational networks: main path analysis and threshold modeling.

Main path analysis

Diffusion occurs across time, and this time dimension can be taken into consideration with network analysis of diffusion processes. If we want to trace diffusion across a network, then we will be dealing with a network structure that has two important properties. First, the network will be directed; the ties between nodes will go *from* one actor *to* another actor. The Iowa farmers network (Figure. 8-5) is an example of a directed network, while the Oregon tobacco control network is nondirected. Second, diffusion processes usually move in one direction over time; they do not double back. That is, once Farmer B learns about a new innovation from Farmer A, later on Farmer A will not learn about the same innovation again from Farmer B. This produces what are known as *acyclic* networks; these are networks without loops.⁴

Main path analysis was developed by Hummon and his colleagues and was used to trace the development of the theory of DNA.²⁷ Citations among scientific papers are a particular type of diffusion process, where scientists form the dissemination community. Main path analysis can be used to

identify the most important path of information flow through a connected set of scientific papers. Figure. 8-9 shows the main path through the DNA literature identified by Hummon (indicated by the thick black line). This main path includes Crick & Watson's famous 1953 paper describing the structure of DNA (node #27).

We can see how main path analysis works by turning back to the Iowa farm network as a simple diffusion process example. Although the Iowa farmers are not a citation network, this diffusion network meets the requirements for main path analysis: the network is directed, and acyclic (no loops). The main path in a (p. 166)

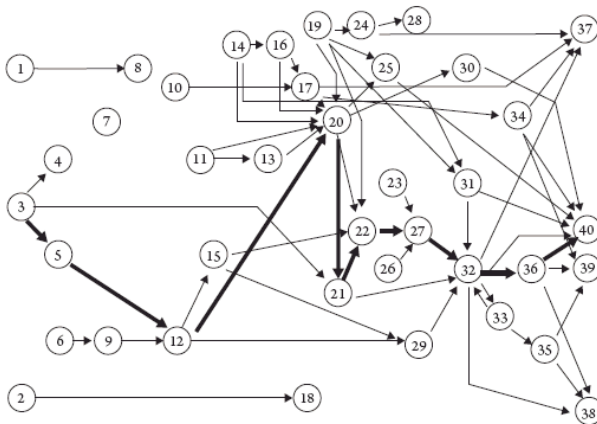


Figure 8-9. Main citation path of DNA research (reprinted from Hummon and Doreian, 1989).²⁷

diffusion network is the set of links through which most of the information flows. The analysis works by first identifying sources and sinks. A source node is one that has no links coming into it, only links leaving it. That is, a source link is a place where information starts flowing in a network. A sink is the opposite: a node that only has links coming into it. A sink is therefore a final stopping place for information flow. Once sources and sinks are identified, the entire network is examined to see which ties account for the largest proportion of information flow from all sources to all sinks in a network. Figure. 8-10 shows the results of the main path analysis for the Iowa farmers. (The arrows have been reversed to make the direction of the diffusion flow clearer.)

Along each diffusion link in the graph, the traversal weight is shown. The higher this number (up to 1) indicates, the higher proportion of information flow. The main path, identified by the thicker black line, is the path from a

source node to a sink node with the highest traversal weights on its links. So, we can see here that the main path of diffusion in the farmers network starts with the scientist, flows through the most centrally connected farmer (#2), and ends with farmers #10 and #12. This type of network analysis can be very useful for larger, more complicated diffusion networks, as long as you have the appropriate data to allow for directed, acyclic networks.

Threshold models of diffusion

Another approach to understanding the structural and relational determinants of D&I is to more explicitly examine how network characteristics influence the **(p. 167)**

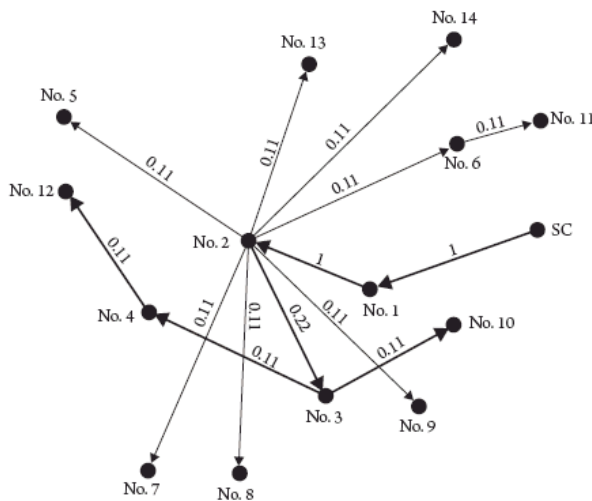


Figure 8-10. Main dissemination path of Iowa farmers.

likelihood of adoption (of some new idea, technology, behavior, or policy) over time. These are variously called contagion, threshold, or exposure models.^{1, 5} The central ideas of these models are that diffusion occurs over time, network characteristics influence the diffusion processes over time, and that there are thresholds that occur at specific points in time.⁵ Many of these models examine the influence of network exposure. Exposure can be defined in a number of ways but is most simply seen as the proportion of an actor's social network that has already adopted the behavior of interest. The usual hypothesis is that as exposure increases over time, the likelihood of adoption for any actor in a network will also increase.

Much of the empirical work testing these threshold models in public health comes from Valente and his colleagues. For example, he has shown that exposure helps explain the diffusion of new family planning information

among Korean families, but it did not predict diffusion of new medical technologies among doctors.¹⁰ In a more recent example, an exposure model was used to explore how network ties influenced the ratification of the Framework Convention on Tobacco Control among 168 nations.²⁸ They were able to show that exposure to other countries who were members of GLOBALink (an online network of global tobacco control researchers) was significantly associated with ratification of the FCTC treaty (AOR = 2.92; 95% CI = 1.25, 6.78). Many of these threshold studies use longitudinal logistic regression or survival analysis. Although these models are fairly sophisticated in combining relational and attribute data, the models can be hard to refute and are fraught with concerns about nonindependence.⁵ Newer statistical models of network processes and structure help avoid these technical problems, as described in the next section. (p. 168)

Statistical Modeling of Networks

Our previous examples of network analytic techniques have been primarily descriptive. They can be incredibly useful for exploring hypotheses about D&I processes, but they are limited in their ability to more formally test statistical hypotheses. Recent statistical and computational advances, however, now allow us to build and test statistical models of social networks.²⁹ These are new techniques that are just starting to be used in public health research.³⁰

These statistical models are relational models—they work by predicting the likelihood that a network tie exists between two network members.³¹ The attraction of these models for D&I research is threefold. *First*, and most important, the models allow for relational and actor predictors. This means that characteristics of the network member can be used in the model. So, for example, we can determine if participation in dissemination training results in a greater likelihood of dissemination activity. *Second*, despite the complexity of the underlying statistical computations, these models produce confidence intervals and *p*-values, which can be used to support traditional hypothesis testing. *Finally*, the models can use simulation techniques to provide goodness-of-fit tests, which are invaluable for model testing and model comparisons.

To see how this type of model can be used to test hypotheses about diffusion processes, consider Figure 8–11. This shows a main path citation network of 40 years of secondhand smoke research.³² The dark blue nodes in the upper part of the graph are the basic science (i.e., epidemiology and biology) studies, and the lighter blue nodes at the bottom are the

intervention, prevention, and policy studies. The red dashed lines were the only direct citations of the basic science literature from the policy and prevention literature. We had a hypothesis that there was a “discovery-to-delivery” diffusion gap in the secondhand smoke literature. The citation network suggests that this gap was real, that the secondhand smoke policy, prevention, and intervention studies were not directly citing the basic science upon which their interventions were based.

We used these new statistical network-modeling techniques to test this hypothesis. Table 8-2 summarizes the main modeling results. We found that secondhand smoke articles that were published in high-impact journals were more likely to be cited, regardless of type of study. However, we also found that there was little cross-citation between discovery and delivery research. In particular, a delivery article was 64.3% less likely (OR = 0.36, CI = 0.33-0.39) to cite a discovery article than a discovery article was to cite another discovery article. This statistical analysis supports a hypothesis of an important diffusion gap, that basic science information may not be quickly or easily disseminated to the practice community.

Summary

One persistent challenge in the health and social sciences is the mismatch between theory and methods. Many important behavioral and organizational theories in public health embrace the importance of context, assume that behavior changes over time, and assume that these changes are dynamic in nature and have complex interrelationships with other dynamic systems. Yet, despite calls for increases in **(p. 169)**

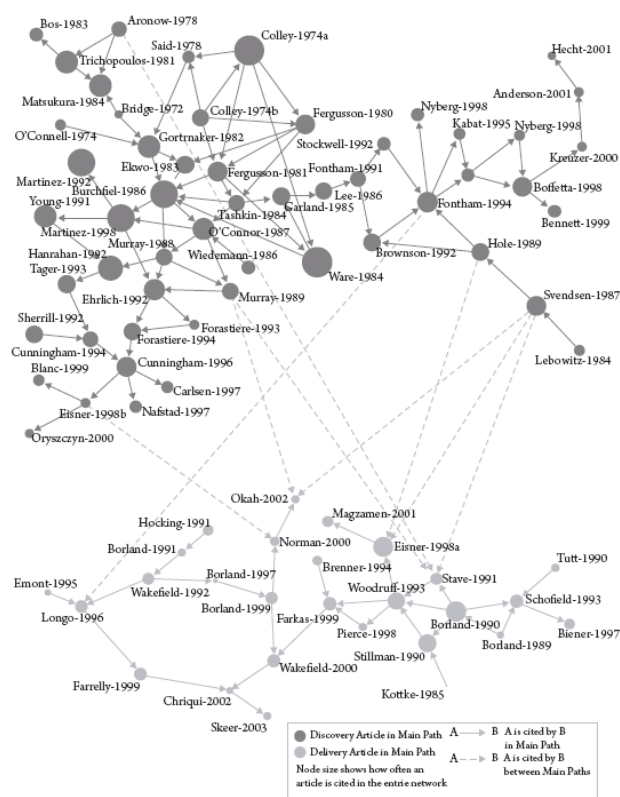


Figure 8–11. Dissemination of information among secondhand smoke research (adapted from Harris et al., 2009).³²

multilevel and ecological approaches to public health science,³³ we still tend to use research methods and analytic techniques that ignore context, focus on single snapshots in time, assume processes only operate at a single level of analysis, and are not dynamic.² Dissemination and implementation in public health is still in many ways an emerging discipline, but the important theoretical and conceptual frameworks guiding this new field all recognize that D&I are complex and dynamic social and organizational processes. (p. 170)

Table 8–2. Likelihood of Citation Relation among Secondhand Smoke Studies (Adapted from Harris et al., 2009).³²

	Model 1				Model 2			
Coefficient	Logit	SE	OR	95% CI	Logit	SE	OR	95% CI
Edges/Arcs	-5.27	0.10	0.005	0.004–0.006	-5.14	0.10	0.006	0.005–0.007

**Year
Citation
Patterns**

Cites articles by year (indegree)	-0.10	0.001	0.905	0.903-0.907	-0.10	0.001	0.905	0.903-0.907
Cited by year (outdegree)	0.04	0.002	1.041	1.037-1.045	0.04	0.002	1.041	1.037-1.045

**Journal
Citation
Patterns**

Cites articles (indegree)							—	
Ref	—	—	—	Ref	—	—	—	—
Impact factor # 3								
Impact factor 3-5	0.79	0.03	1.259	1.187-1.335	0.80	0.03	2.226	2.098-2.360
Impact factor # 5	1.58	0.03	4.855	4.578-5.149	1.61	0.03	5.003	4.717-5.306
Cited (outdegree)								
Ref	—	—	—	Ref	—	—	—	—
Impact factor # 3								
Impact	0.23	0.03	1.259	1.187-1.335	0.22	0.03	1.246	1.176-1.322

factor 3-5	0.32	0.04	1.377	1.273- 1.489	0.31	0.04	1.363	1.261- 1.475
Impact factor # 5								
<i>Subfield citation patterns</i>								
					Ref	—	—	—
Discovery cites discovery								
					-1.80	0.09	0.165	0.139- 0.197
Discovery cites delivery								
					-1.03	0.04	0.357	0.330- 0.386
Delivery cites discovery								
					1.47	0.04	4.349	4.021- 4.704
Delivery cites delivery								

(p. 171)

As seen in this chapter, network analysis is a very useful tool for studying how new scientific discoveries and evidence-based policies and practices are disseminated to target audiences and implemented by communities, organizations, and governments. If appropriate network data are collected from these D&I activities, then a number of empirical possibilities open up. Network visualization can be used to map and describe the dissemination networks themselves. Network descriptive statistics such as density and diameter can be used to summarize and compare these networks. More specific network concepts such as prominence can be used to identify important elements or characteristics of the network. For example, network centrality and centralization can be used to identify important gaps or

gatekeepers in a dissemination network. Specific theories of D&I process, such as Diffusion of Innovations, can be developed and tested using network methods. Finally, new statistical and computational abilities allow us for the first time to build and test statistical models of D&I network processes.

There is much that remains a mystery about how to build and sustain successful D&I in public health. However, it is clear that successful D&I happens in a social and organizational context (see [Chapter 7](#))³⁴ and that the relationships among those persons and organizations can make or break the entire enterprise. Network analysis is uniquely suited to elucidating these relationships and thus is an important tool for future D&I research.

Suggested Readings

Suggested Readings

Goodreau S. Advances in exponential random graph (p^*) models applied to a large social network. *Social Networks*. 2007;29:231–248.

This article describes recent advances in statistical network analysis. The ability to apply exponential random graph models to large datasets offers many practical applications for drawing inferences and represents real progress in the field.

Luke DA. Getting the big picture in community science: Methods that capture context. *American Journal of Community Psychology*. 2005;35:185–200.

This article presents a review of empirical community psychology articles showing that social scientists utilize a narrow range of statistical tools that are not well suited to analyze contextual data and effects. The paper recommends a broader set of analytic approaches to understand the effects of context on health behavior, including multilevel modeling, geographic information systems, cluster analysis, and social network analysis.

Luke DA, Harris JK. Network analysis in public health: History, methods and applications. *Annual Review of Public Health*. 2007;28:69–93.

Luke and Harris describe the basics of network analysis and how its techniques are applied to public health problems. Historically, network analysis has been used in public health to examine the transmission of HIV and other STDs, the diffusion of innovations, and how social support and social capital impact public health outcomes.

Rogers EM. *Diffusion of Innovations*. 5th ed. New York: Free Press; 2003.

Rogers's classic text on how ideas and opinions diffuse over time through various communication channels and networks. Because many new ideas involve taking a risk, people seek out others who have already adopted it. As a result, the new idea is spread through social networks over a period of weeks, months, or years.

(p. 172) Valente TW. *Network Models of the Diffusion of Innovations*. Cresskill, NJ: Hampton Press; 1995.

Diffusion of innovations refers to the idea of certain concepts or opinions spreading rapidly throughout society. This process is dependent on the presence of social networks. Valente's text presents an examination of this process and methods for estimating how fast or slow diffusion occurs; to be used by students, researchers, and policymakers.

Valente TW. *Social Networks and Health: Models, Methods, and Applications*. New York: Oxford University Press; 2010.

Networks, by definition, focus on connections between individuals, organizations, or other units. Valente describes how social network models can be used to understand and even change a range of human health behaviors.

Wasserman S, Faust K. *Social Network Analysis: Methods and Applications*. New York: Cambridge University Press; 1994.

Wasserman and Faust's reference on social networks can be used as a comprehensive review or to recommend specific network analysis methods for researchers who have already gathered network data. The book is divided into six parts, providing a broad overview of social network's properties, types of network data, and statistical methods, accompanied by substantive examples.

Selected Websites and Tools

INSNA—International Network for Social Network Analysis #<http://www.insna.org>#. INSNA is the primary professional association for network analysis and network science. In addition to useful data and software resources, the INSNA website provides information on the main network

analysis professional and scientific journals (*Connections* and *Social Networks*) as well as the annual international *Sunbelt Conference*.

Complexity and Social Networks Blog # <http://www.iq.harvard.edu/blog/netgov/#>. An interesting blog that covers a wide variety of network analysis and complexity science topics.

Pajek Wiki #<http://pajek.imfm.si/doku.php?id=start#>. Main support website for Pajek, a widely used free software package for network analysis.

Support website for *statnet* #<http://csde.washington.edu/statnet/#>. This website provides information on, background material for, and access to the *statnet* suite of packages for network analysis. The packages are written for the *R* statistical computing environment. Statistical modeling of networks can be done using procedures in *statnet*.

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