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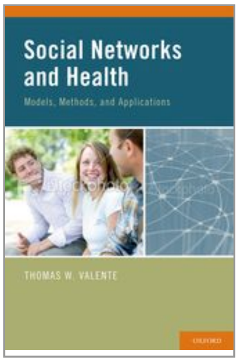

Social Networks and Health: Models, Methods, and Applications

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Diffusion of Innovations

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Abstract and Keywords

This chapter reviews diffusion of innovations theory which has been the theory that has used network principles and perspectives most extensively. An introduction to the theory and a review of its principles is provided. The chapter then reviewed the 4 major classes of diffusion models (1) integration/opinion leadership, (2) structural models, (3) critical levels, and (4) dynamic models. All four models explicitly account for network diffusion dynamics, but vary in their mathematical rigor and complexity. The chapter also introduced the calculation of infectiousness and susceptibility which dynamically account for adoption behavior and in-degree and out-degree, respectively. Empirical data illustrating network exposure effects are presented as well as the calculation and interpretation of network thresholds. The chapter closes with a brief critique of the theory.

Keywords: network diffusion, diffusion networks, diffusion of innovations, threshold, infectivity, susceptibility, dynamic models, behavior change

This chapter reviews the diffusion of innovations theory, which has been the theory that has used network principles and perspectives most extensively. An introduction to the theory and a review of its principles are provided. The chapter then covers the major models used to understand how diffusion through networks occurs. Empirical data illustrating network exposure effects are presented as well as the calculation and interpretation of network thresholds. The chapter closes with a brief critique of the theory. Many concepts related to diffusion have been interspersed throughout this volume, but this chapter delves deeper into the issues.

Behavior change theories are used to understand how social change occurs (Valente, 2002). The most prominent behavioral application of network analysis is the study of the *diffusion of innovations,* which explains how new ideas and practices spread within and between communities. Diffusion of innovations theory has provided the theoretical underpinnings to research how networks affect behavior and behavior change. Diffusion theory is one of the most widely used theories in public health (Glanz et al., 2002). It has its roots in anthropology, economics, geography, sociology, marketing, among other disciplines (Brown, 1981; Hägerstrand, 1967; Katz, 1962; Katz et al., 1963; Robertson, 1971; Rogers, 2003) and has in some ways been adapted from epidemiology (e.g., Bailey, 1975; Morris, 1993). The premise, confirmed by **(p. 173)** empirical research, is that many new ideas and practices spread through interpersonal contacts largely consisting of interpersonal communication (Bass, 1969; Beal & Bohlen, 1955; Katz et al., 1963; Ryan & Gross, 1943; Rogers, 2003; Valente, 1995, 2005; Valente & Rogers, 1995).

A new idea or practice may originate in another community and be transported to the host community, or it may originate, be invented in, the community where it diffuses. Ideas and innovations enter communities from external sources such as the mass media, via labor exchanges, technological innovations and shifts, cosmopolitan contact, and many other sources. The critical element for diffusion is that information about the new idea or practice spreads through interpersonal contact networks. (Many diffusion studies have not measured social networks and how information flows through networks and a purist might argue that these studies fall into the realm of behavior or social change studies and not diffusion.)

In their pioneering study, Ryan and Gross (1943) laid the groundwork for the diffusion paradigm by showing that, among other things, social factors rather than economic ones were important influences on adoption (Valente & Rogers, 1995). Hundreds of diffusion studies were conducted in the 1950s and early 1960s to examine the diffusion process in more detail across a variety of settings (Rogers, 2003). Many studies sought to understand how information created in government or otherwise sponsored programs could be disseminated more effectively. Diffusion research peaked in the early 1960s but has been reinvigorated recently with the advent of more sophisticated network models and technology, making it possible to study the diffusion process more explicitly.

Most diffusion studies focus on trying to understand the factors that lead some members of a population to adopt a new idea, while others do not. Further, studies try to understand why some people adopt the behavior early while others wait a substantial amount of time before accepting the new practice. Forexample, Ryan and Gross (1943) wanted to know why some farmers purchased hybrid seed corn almost immediately upon its availability while others waited until almost all the farmers purchased it before they were willing to do so. Similarly, Coleman and others (1966) wanted to know why some physicians began prescribing tetracycline as soon as it was available, while others waited until most physicians prescribed it before they were willing to do so.

The five main elements of the diffusion model are (Rogers, 2003) that (1) perceived characteristics of the innovation affect its rate of adoption; (2) diffusion occurs over time so that rate of adoption often yields a cumulate adoption S-shaped pattern, and individuals are classified as early or late adopters; (3) individuals pass through stages during the adoption process typically classified as knowledge, persuasion, decision, implementation, **(p.174)** and confirmation; (4) people can modify the innovation and sometimes discontinue its use; and (5) mathematical models can be developed to measure the rate and character of diffusion curves (Mahajan & Peterson, 1985; Valente, 1993; Young, 2006).

Some scholars have treated the rate of new adopters as normally distributed, and in such cases adopters can be classified in terms of their innovativeness or how early or late they are in the diffusion process relative to the population. By treating the new adopters, the incidence curve, as normally distributed, adopters are classified as early adopters (first 16%), early majority (17% to 50%), late majority (51% to 84%), and laggards (85% to 100%). Diffusion is usually a very slow process, taking years and decades for many significant innovations. For example, the telephone took decades from its invention to widespread acceptance.

The prototypical diffusion study was Ryan and Gross' (1943) study of factors that influenced rural Iowa farmers to adopt the use of hybrid seed corn (Box 10–1). Hybrid seeds took decades to be developed and perfected **(p.175)** in experimental lab stations. Once the hybrids were ready, it then took years, and in some cases decades, for these innovative seeds to diffuse among famers. In the Ryan and Gross (1943) study, there was a 14-year time span between the first and latest adopters even though the innovation was patently advantageous.

Box 10–1. Ryan and Gross and the History of Diffusion

Bryce Ryan studied sociology and economics at Harvard University and obtained his first faculty appointment at Iowa State University. He was assigned a doctoral student named Neil Gross. Ryan was casting about for a study topic and noticed that there was a lot of corn in Iowa. Throughout the early part of the twentieth century, scientists had been creating various hybrid corn seeds, which replaced open pollinated varieties. Hybrid seeds were a radical departure for farming since they required the purchase of seeds each year, that the farmer then planted in contrast to using his or her own crop to provide the seeds for each year's planting.

Hybrids had higher yields and were more drought resistant than open pollinated varieties, so they were a seemingly advantageous innovation. Yet it took decades for hybrids to be adopted by farmers in the United States and internationally. To spur diffusion, the U.S. Agricultural Extension Service was created to publish information on hybrid seed productivity, and private seed companies often distributed free samples to farmers.

Ryan launched a study in two Iowa communities to determine factors associated with the adoption of hybrid corn seed (Ryan & Gross, 1943). They contrasted economic variables (e.g., size of farm) with social ones (e.g., readership of farm bulletins). The Ryan and Gross study became a classic as it was a model for the study of behavior change and how new ideas and practices within and between communities (Crane, 1972). The diffusion of hybrid corn seed among the 257 farmers Ryan and Gross was textbook diffusion in action.

It should also be noted that diffusion typically takes a long time. Hybrid seed corn was under development for decades before it became commercially viable and seed companies had to give away samples for years before farmers would pay for it (Crabb, 1947). The telephone took decades to diffuse widely in the United States, and the VCR, while seemingly an innovation that diffused rapidly, took decades to reach a majority of households. To be sure, some innovations diffuse rapidly, but only rarely, and usually only under extraordinary conditions. The slow pace of diffusion is often a result of network structures that often inhibit diffusion. The advent of computer communications seems to have accelerated the spread of information and in many cases adoption of technologies and other products. Facebook, for example, spread to hundreds of millions of users in a few years (http://www.facebook.com/press.php).

The second element of diffusion theory is that adoption does not occur immediately after someone first learns about a new product; rather people pass through stages in the adoption process from becoming aware, to learning more information about it, making a decision to adopt it, trying it, and eventually confirming their use. These stages can be used for market segmentation as well as measuring progress toward behavior change. Most behavior change models describe stages in the adoption process (Valente, 2002; Valente et al., 1998). Diffusion of innovations is studied in many different fields, but here the discussion is primarily concerned with how social networks affect adoption and diffusion of disease and/or associated risk behaviors. The starting point is referred to as the homogeneous mixing model.

Homogeneous Mixing

Homogeneous mixing can be demonstrated with a simple spreadsheet exercise illustrated in Table 10–1. Assume a hypothetical population of 100 people at time 1 (year 1, for example), and 5 people adopt a new idea or practice. These 5 initial adopters may adopt because they are persuaded by the mass media to adopt or because they are willing and perhaps eager to try new things. These 5 initial adopters have random interactions with the 95 who have not yet adopted and they persuade them to adopt at a rate of 1%. The product (5 × 95 × 0.01) yields 4.75 new adopters at the end of time 1. At the start of time 2, there are 9.75 (5 + 4.75) adopters interacting randomly with **(p.176)**

Table 10–1. Homogeneous Mixing Sample in Excel

Adopters	Rate	Nonadopters	New Adopters
5.00	1%	95.00	4.75
9.75	1%	90.25	8.80
18.55	1%	81.45	15.11
33.66	1%	66.34	22.33
55.99	1%	44.01	24.64
80.63	1%	19.37	15.62
96.25	1%	3.75	3.61
99.86	1%	0.14	0.14

Adopters	Rate	Nonadopters	New Adopters
100.00	1%	0.00	0.00

the 90.25 left in the population, and they convince them to adopt at a rate of 1% and we get 8.8 new adopters, or 18.55 total adopters.

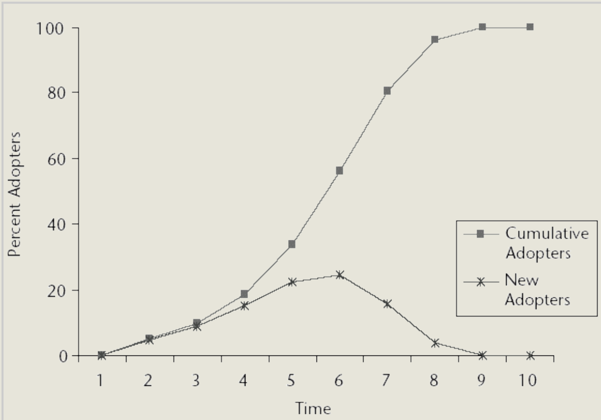

Figure 10–1. Typical diffusion and adoption curves (generated from hypothetical data). In this hypothetical scenario, five initial adopters interact and convince the remaining 95 nonadopters at a rate of 1%. The subsequent adoptions and interactions result in a cumulative growth curve resembling a logistic function with everyone converted by 10 time periods.

Figure 10–1 shows the incidence and prevalence graphs for this hypothetical scenario. The growth in adoption occurs gradually at first and then accelerates toward the middle of the diffusion process and then tapers off as the pool of nonadopters shrinks. The model assumes no one dis-adopts (quits using) and assumes uniform conversion rates (1% throughout the process). **(p.177)** One can change the conversion rate to generate different curves. The model also provides an example how an epidemic can spread in a population.

Unfortunately, or fortunately depending on the setting, diffusion is not as simple as the homogeneous model implies. For one, people do not interact randomly as noted in the sections on homophily, reciprocity, transitivity, and so on. Two, conversion rates are not likely to be uniform for everyone; some people have more resistance than others. Three, the media and other external factors influence perceptions about appropriate behaviors and may differentially affect people's adoption decisions. In particular, there has been some research on how media influences and social networks interact to collectively bring about behavioral and societal change (Box 10–2 on two-step flow hypothesis). Diffusion network scholars have developed a set of approaches and theories **(p.178)** **(p. 179)** about how social networks influence diffusion of innovations. There are four classes of models for network diffusion: (1) integration and opinion leadership, (2) structural models, (3) critical value models, and (4) dynamic models.

Box 10–2. Two-Step Flow Hypothesis

During the 1940s and 1950s, Paul Lazarsfeld (often with his colleague Robert Merton) had established a tradition of research studying the effects of the mass media on many behaviors including voting patterns and consumer behavior. Lazarsfeld and Merton were based at Columbia University and were joined by Elihu Katz in the mid-1950s. The team pioneered many research innovations with their primary focus being research on how radio and TV influenced mass audiences.

Although the prevailing view was that the mass media influenced people directly, Lazarsfeld thought that media effects were mediated by interpersonal influence. People who were exposed to media messages did not automatically believe them and did immediately accept the information provided to them. Instead, people digested media information within the context of their social networks. One specific hypothesis of theirs was the two-step flow hypothesis. The two-step flow hypothesis stated that the media influenced opinion leaders who in turn influenced others. Opinion leaders paid attention to the media at a greater rate than others and were thought to be more informed on many topics than opinion followers. Opinion leader use of media and other sources of information enabled them to be more knowledgeable and hence influence others.

Opinion leaders were found to receive more media and were more aware of current events than were nonleaders. To persuade others to follow their opinions, opinion leaders used media communications to buttress their arguments. Gladwell (2003) writes, “These mavens make extensive use of the media to stay expert on their favorite subjects and become trusted sources of information for others.” It may be that media influence opinion leaders who influence others that influence others—a three-step or even multistep flow. Furthermore, it may be that some opinion leaders influence one or a few others, whereas others have much higher multiplier effects, influencing five, ten, or hundreds of others. These opinion leader models, however, neglect to consider a number of other factors regarding the media influence process.

First, it is likely that opinion leaders are influenced by others as much as others are influenced by them and that media shape their messages in accordance with what they think the audience wants to see or hear. In summary, to say that media communications can influence person A who influences person B may be an oversimplification. Second, individuals are embedded within complex social network structures. Some people have small networks, whereas others have quite large ones. Some social networks are integrated (their friends know each other), whereas others are radial (their friends do not know one another). What follows are three ways in which social network structures can affect media processes First, Potterat and others (1999) proposed that network structure, especially the cohesiveness of an individual's network, is associated with STD/HIV risk for the individual. The authors report that lower cohesiveness of network members is associated with lower STD/HIV transmission, even in a high-risk population. Second, the norms held within social networks alter the media influence process. For example, if a social network composed of young adults has negative safer sex norms, a media campaign designed to target and change these norms may increase condom use (Friedman et al., 2001). Third, as mentioned earlier, homophily affects the flow of ideas and behaviors. Information flows and persuasion occur more readily among homophilous dyads, that is, people who are like one another, rather than among heterophilous ones. Consequently, diffusion tends to occur along sociodemographic lines because social networks are contoured by sociodemographic characteristics. Finally, the media influence process may vary by the degree of risk taking and risk avoidance in the population, their personal network thresholds.

These four factors, and perhaps others, suggest that the relationship between mass media and interpersonal communication is complex. Unlike the simple opinion leader model, it is more likely that people attend to media communication, and then interpret and discuss it in unanticipated ways. For example, an antitobacco campaign may be parodied by the intended audience, resulting in boomerang (opposite) effects rather than antitobacco effects. This boomerang effect has also occurred with HIV campaigns. Some members of the gay community have begun to refuse participation in safer sex behaviors because of the widespread access to antiretroviral drugs, believing the risk for HIV to be diminished (Bertrand et al., 2004). In other words, the effect of media communications on individuals is a function of how the messages are interpreted within the context of people's social networks —how, with whom, and in what ways the messages are discussed.

Integration and Opinion Leadership

Early diffusion network studies noted that those people who are integrated into a community generally adopt behaviors earlier than those who are less integrated. For example, Coleman and others (1966) in their study of network influences on physician adoption of a new drug showed that physicians who received three or more nominations as advice and discussion partners had a faster diffusion than those who received none. Figure 10–2 illustrates the diffusion curves for integrated physicians compared to nonintegrated ones. Coleman and others (1966) concluded that the new drug spread through the connections among the physicians in a snowball process (also see Coleman et al., 1957).

Other studies also confirmed that people who are well integrated into the community were likely earlier adopters than those on the margins (Rogers & Kincaid, 1981). In general, it was discovered that opinion leaders, those who

(p.180) received many choices as discussion partners from their colleagues, were earlier, but not the earliest, adopters of new ideas and practices. Rogers and Kincaid (1981) also discovered that study villages could be characterized by specific contraceptive methods which became widespread within each village. For example, in some villages, the IUD would be the most prevalent method whereas in others the pill or withdrawal would predominate. Opinion leaders seemed to play a role in this process since oftentimes the most prevalent method in a community was also the one being used by those women most frequently nominated as discussion or advice partners. Research of course is needed to determine whether these opinion leaders merely reflect the normative practices of their communities or whether their behavior is being imitated by others in the community. The role of opinion leaders is also likely to vary based on characteristics of the innovation.

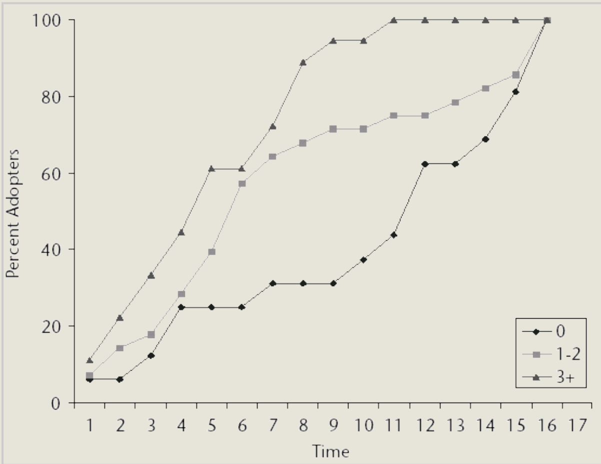

Figure 10–2. Diffusion of tetracycline among physicians by their integration in social networks. (Data from the classic network diffusion study of medical innovation by Coleman, Katz, and Menzel [1966].)

Becker (1970) questioned whether opinion leaders would always be earlier adopters of innovations. Becker (1970) hypothesized that opinion leaders would be earlier adopters of innovations that were compatible with the community norms but later adopters of innovations perceived to be incompatible. He studied public health officers’ adoption of two behaviors: measles immunization, which was compatible with the mission of public health officers, and diabetes screening, which was not. Becker (1970) showed that opinion leaders, measured with in-degree centrality, delayed their adoption of diabetes screening because they perceived it to be incompatible with the norms of public health at that time.

The importance of opinion leaders is hard to overstate. It is also important to note that opinion leaders are not necessarily the earliest adopters of innovations. Opinion leaders need to reflect the norms of their community and they cannot deviate too much from what is accepted in the community or they will lose their privileged position in the network. Thus, they can lead but not too far ahead of the group. Typically, the earliest adopters are innovative and often on the margins of the community; they innovate because they are different. The opinion leader then translates this innovation for the rest of the community. Translation is one of the skills associated with being a good opinion leader. Opinion leaders are admired by many and are good at scanning the environment because they are connected to lots of people.

Once opinion leaders embrace a new idea, diffusion can accelerate. Leaders are connected to many others; hence, once they embrace the idea, the number of relationships involving adopters and nonadopters increases dramatically. Not all adopters are equal, so while the earliest adopters may be the first to adopt, their behavior does little to influence the rest of the system because they are not role models for many others. The leaders, however, represent a shift from adoption on the margins of the network to the center and accelerate the behavior change process.

(p.181) Structural Models

Opinion leadership and integration have obvious implications and effects on diffusion—as those who occupy prominent roles in a community adopt, the balance of information and persuasion in the community tilts toward the new idea. Granovetter (1973) focused on a different aspect of the diffusion problem by showing that other people in a community can occupy critical positions in the network that affect diffusion at the macro level. Granovetter's (1973) strength of weak ties argument has both micro and macro levels of analysis and implications for both.

Granovetter (1973) noted the tendency for homophily and stated that two people who are friends are also likely to be friends with a third person (see Chapter 8 for information on triads). The tendency for triads to be closed is an important property used in the study of network evolution (see Chapter 8 and Kossinets & Watts, 2006). Networks thus tend to close in tightly formed pockets since friends tend to introduce people to one another. Granovetter argued that because of this triadic closure tendency, only some people will have networks that do not close around them but instead are open and connect different groups in the network. Granovetter presented the example in Figure 10–3 and argued that nodes A and B constitute a weak tie because they connect two different groups in the network.

Granovetter's central insight is that the friends of my friends typically know the same people I know and have access to the same information. Consequently, information received from my close personal networks tends to be redundant. New information comes from weak ties, people one sees **(p.182)** only occasionally or who are connected tangentially through acquaintances. The original data Granovetter collected for this thesis came from interviews with people who had recently obtained new jobs, and many of them reported weak ties as the source of information about the new job (Granovetter, 1974). Weak ties are strong in information because weak ties connect people to others to whom one is not normally connected.

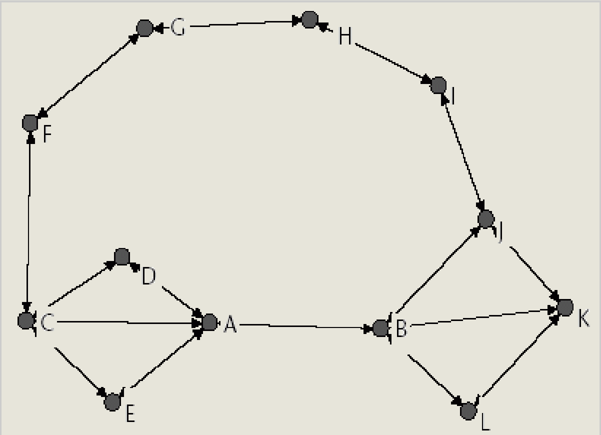

Figure 10–3. Granovetter's (1972) illustration of weak ties, in which the link between A and B creates shorter path lengths connecting others in the network.

The applicability of the weak ties argument was widespread. Weak ties clearly had implications for diffusion since the presence of weak ties would create bridges connecting different segments of a network and hence enable diffusion to traverse group boundaries. Weak ties were also instrumental in learning new information because, as stated, weak ties are connections to people different from one's usual conversation partners and so they have access to novel information. Finally, the identification of weak ties has implications for community mobilization and performance since organizations (and individuals) need to maintain a diverse set of contacts to be able to access resources and information critical to survival and success (Burt, 1992; Valente & Foreman, 1998; Valente et al., 2007a).

Granovetter's (1973) strength of weak ties article is one of the most widely cited articles in social science research, but it is important to be clear about what it says. For one, the main argument is that weak ties have implications for diffusion at the macro level, not the micro level. That is, weak ties enable diffusion to traverse bridges and connect otherwise disconnected or distally connected groups. It does not imply that weak ties are more persuasive adoption influences at the micro level, for individuals. Second, the main argument for the strength of weak ties is with information diffusion, not necessarily behavioral adoption. Weak ties may be very effective at communicating information but may be less effective at persuasion. Precisely because weak ties are weak and because they may contain less trust and reinforcement than strong ties, they are less likely to be conduits for behavior change.

Finally, weak ties are often measured in two different ways: structurally and relationally. Structural measures of weak ties are derived from sociometric data and can be measured as links between individuals connected in different triads. A structural measure of a weak tie would be a bridge that spans otherwise disconnected, or distally connected subgroups. Chapter 11 provides an explicit measure of bridges based on the weak tie concept. Relational measures of weak ties are derived from individual reports of frequency of interaction or emotional/affective closeness. Weak ties are those with whom one is less close and interacts with less frequently.

The weak ties argument was developed further by Ron Burt with his measures of structural holes and constraint (Burt, 1992, 2005). Burt noted that weak ties were ties that spanned structural holes in the network. This directed researchers to look at the white space in the network diagrams and **(p.183)** find those nodes or people who had links that spanned the holes in the network. People who occupy structural holes occupy critical positions in the network that enable them to excel. Burt created a measure called *constraint,* which calculated how well a person's ties reached out into the network and provided access to novel sources of information. Burt (2005) has shown how people who score high on constraint, span structural holes, have received higher pay, and gained better promotions in organizations.

The structural basis of diffusion and the role of weak ties were also developed by Duncan Watts (1999) in his analysis of the small world introduced in Chapter 1. Watts and Strogatz (1998) introduced a measure called the clustering coefficient (CC) defined as:

10–1

$$CC = \frac{2T_i}{k_i(k_i - 1)}$$

where T_i is the number of connections between the direct ties of each node, and $k_i(k_i - 1)$ is the maximum number of possible connections between each node's direct ties. A high (closer to 1) clustering coefficient indicates that a person's friends know one another, whereas a low coefficient indicates that a person's friends are unlikely to know one another. The clustering coefficients for all nodes in a network are averaged to calculate the overall clustering in the network.

As shown in Chapter 8, clustering provides a measure of network structure somewhat independent of its size (the number of nodes), the density (the number of links), and its centralization. Clustering provides a measure of “clumpiness” of the network. A random network will look the same everywhere, but one that is clustered has pockets of interconnectivity, with some nodes having more clustering and others less. Clustering and centralization give rise to the small world phenomenon because they increase the likelihood that two people who meet will have friends in common.

Critical Levels

The Nobel Laureate Thomas Schelling published *Micromotives and Macrobehavior* (1978), in which he coined the term “the tipping point.” Schelling showed that seemingly rational and obvious behaviors by individuals can create unexpected outcomes for the system. For example, while most individuals in a community might be considered tolerant with regard to living in mixed ethnic communities, the individual actions by everyone can create strongly segregated communities. Schelling found tipping points in the distribution of behaviors such that once a certain level of the behavior was reached, it had ongoing momentum that kept it going and was hard to reverse.

(p.184) Tipping points (Gladwell, 1999) have subsequently been discovered to apply to many different phenomena and seem nearly ubiquitous. Gladwell showed how opinion leaders can have a strong influence on others’ behavior and can make the difference between a product having no sales or taking off. Gladwell's contribution to diffusion network models was to show how the concepts can be scaled up to a population level. While many scholars had been focusing on behavior within small self-contained communities, Gladwell generalized these principles on a large, national, and international scale, and to a wider range of behaviors.

A number of researchers have developed diffusion models that emphasize the importance of critical levels or tipping points. These tipping points exist at both the micro (individual) and macro (system or community) levels (Valente, 1995). Scholars had long recognized that the diffusion curve (any growth curve for that matter) contained *inflection points*, times where the curve accelerated or decelerated dramatically (Hamblin et al., 1973; Mahajan & Peterson, 1983). Marwell, and others (1988) wrote persuasively about the importance of the critical mass for achieving collective action. Once critical mass was reached, momentum toward achieving collective goals would propel the social movement forward. Markus (1987) argued that interdependent innovations (telephone, fax, e-mail, Facebook, and so on) were particularly prone to critical mass effects because once a technological medium was adopted by a large enough number of people, it would be too difficult for them to defect to another medium and there were inherent advantages to subsequent adopters to adopt the technology.

Identifying critical values at the individual and system levels provides an understanding for how diffusion occurs. Individual tipping points, *thresholds,* enable researchers to identify different types of adopters, low- and high-threshold ones, who might have different motivations to adopt (Valente & Saba, 1998). Similarly, individual influences and motivations on adoption behavior are likely quite different before and after a system has reached its tipping point. Adoption before the tipping point carries more risk than after it.

Dynamic Models

All of the models presented in this chapter are dynamic in that time is specified—diffusion occurs over time, the structural characteristics (weak ties, holes) have consequences for how diffusion occurs over time, and the critical levels occur at a point in time. There have been a series of models created that treat time more explicitly in the sense that they model what happens at the micro (individual) level at each point in time during diffusion. The basic building block of these models and for much diffusion research **(p.185)** is network exposure (Burt, 1987; Marsden & Friedkin, 1993; Marsden & Podolny, 1990). Network exposure is the influence of a person's social network, measured with the following equation:

10–2

$$E_i = \frac{\sum W_{ij} y_j}{\sum W_i}$$

where *W* is the social network weight matrix, and *y* is a vector of adoption behavior. For a person with five friends in a network, network exposure (E_i) is the proportion of those friends who have adopted a behavior. Figure 10–4 provides a graphical display of how Equation 10-2 works. The network is represented as “W” because it is conceived as a weight matrix. For now, the W network will represents direct contacts, a person's five closest friends. Later, we show how W can represent different kinds of network properties, or weights (W), such as the degree of similarity between two nodes (alluded to in Chapter 4). To calculate network exposure, the network (W) is multiplied by y_j, which is a vector (column) of behavior scores.

If y_j represents smoking, for example, the numerator is a calculation of the number of one's friends who smoke. To control for the number of friends named, we divide the numerator by the number of friends to get a percent. Network exposure, then, is the proportion of friends who smoke, friends being those people with whom the respondent indicated he or she was a friend.

Figure 10–5 displays network exposure for one person who has three friends at three points in time. This person has one adopter at the first time point, so exposure is 33%. At the next time point, there are two adopters,

(p.186) so exposure increases to 66%, and then after all three friends adopt, it is 100%. As diffusion occurs, everyone's network fills with adopters. For each person in a community, we can track the percentage of their contacts who have learned about the new product or adopted the behavior based on those persons' self-reports. If diffusion for 30 people occurs over 10 time periods, say 10 months, then at each month, the percentage of each person's network who adopted is calculated.

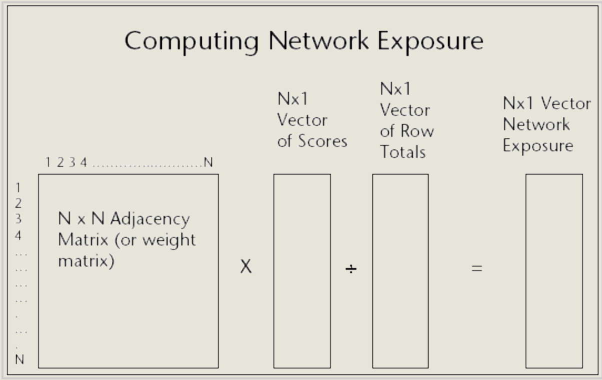

Figure 10–4. Illustration of network exposure calculation. The $N \times N$ adjacency matrix is multiplied by a binary vector of behavior and then divided by the number of people each person named to get a percentage of personal network exposure to the behavior.

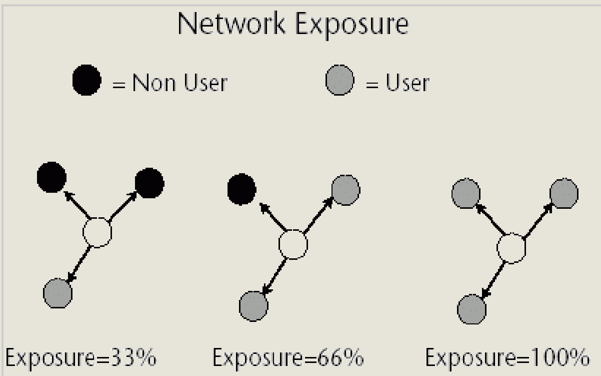

Figure 10–5. Network exposure is the proportion of a person's personal network who have adopted the behavior.

Calculating a person's adoption status at each time period is referred to as *event history analysis* (Allison, 1984). Event history analysis is the process of constructing data for each person at each point in time. So in diffusion studies, we can analyze for each person whether he or she has adopted the innovation and how many of his or her network partners have adopted it. The data are not measured at each time period in the study; rather the existing data are reshaped to replicate what happened over time. For example, suppose data were collected at the end of the year on whether each person in a school heard a rumor and the month they heard it. Suppose further that network data were collected in the school. How the rumor spread through the network can be replicated by reshaping the data and constructing the network exposure model. (Multiple measures of the network would be necessary to determine the network structure and how it varied over the year.)

To model the rumor spread, the information on which month each person heard the rumor would be converted to a set of vectors (columns) with a 0 for not heard, and a 1 for heard at each month. The network would be multiplied by each of these vectors and divided by the number of friends each person reported. Any updates or changes to the network can be incorporated in the network over time. This will provide a measure of the percent of each person's personal network who heard the rumor for each month. So if there are a 100 students and 12 months, the new database will have 1,200 cases, 100 **(p.187)** students at each month, and at each month we know how many of a student's friends were aware of the rumor. Chapter 12 shows how rumor spreading in the school can be simulated by using this network exposure model.

Empirical Estimates Using Diffusion Network Data

The network exposure model in the event history framework has been used to calculate empirical estimates for social influence in diffusion. Three datasets have collected social network data and time of adoption (Valente, 1995). These three datasets are quite varied in where they collected the data and the behaviors of study, but they all have the common features of measuring the network and the time of adoption. The event history framework was used to reshape the datasets and calculated the percentage of adopters in each person's personal network at each time point. Adoption behavior was then regressed on the percentage of adopters in each person's personal network. These estimates then determine if being exposed to the innovation through the network affected adoption in a dynamic way, one that considers each person's social network at each point in time.

Table 10–2 reports the regression results. The associations between network exposure and adoption varied across the thre datasets. In the medical

Table 10–2. Event History Analysis of Factors Associated with Adoption for the Three Diffusion Network Datasets

	Medical Innovation	Brazilian Farmers	Korean Family Planning
No.	947	10,092	7,103
Time	132.7**	5.14	4.34
Cumulative adoption	0.03	2.27	0.32
Number sent	1.04	0.99	1.02
Number received	1.05	1.01	1.05**
Cohesion exposure	1.05	1.93**	2.08**
Structural equivalence exposure	1.04	5.01**	1.34
Science orientation	0.65**		

	Medical Innovation	Brazilian Farmers	Korean Family Planning
Journal subscriptions	1.67		
Cosmopolitan-ness		1.00	
Income		1.14**	
Number of children			1.23**
Media exposure			1.03*

Coefficients are adjusted odds ratios for likelihood of adoption. Estimates adjusted for clustering within community.

(*) $p < .05$;

(**) $p < .01$.

(p.188) innovation data, network exposure via cohesion (direct ties) and structural equivalence (SE) were not associated with adoption. This result is consistent with analysis reported elsewhere (Van den Bulte & Lillien, 2001). Adoption was associated with exposure via SE in the Brazilian farmers' dataset, indicating that farmers who occupied similar social network positions were more likely to adopt hybrid-seed corn at the same time than those who occupied different social network positions. Adoption was associated with exposure via cohesion (direct ties) and SE in the Korean family planning dataset, indicating that family planning adoption was associated with both types of network influence in the Korean family planning data.

These results should be interpreted as suggestive rather than definitive. There are many choices made to build the model, all of which can be varied to derive different empirical results. First, in all three studies the networks were measured only once, assuming they are static, when evidence would indicate that people's networks change. Second, time of adoption was assumed to occur at monthly or yearly intervals so that two people who adopted in different months in the same year were given the same adoption time (in the medical innovation study, the data were collapsed into months). These broad time intervals forced calculating exposure contemporaneously rather than as a lagged effect. Most models regress adoption on exposure in the prior time period, the last month. Third, there are missing data, and no provision was made for the behavior of those not interviewed. Finally, there might be errors in people's recall of adoption (the Korean family planning and Brazilian farmer data used recall for time of adoption) or their specification of the networks.

In one sense it is surprising that the association between adoption and network exposures is not stronger. The diffusion model has long specified, and logic has long dictated, that the more people in a person's social network, the greater is the likelihood of adoption. Diffusion and most behavior change models believe that the greater the exposure, the greater is the likelihood of adoption (Gross et al., 2002; Valente et al., 1997). For example, many studies have shown that students who smoke are more likely to have friends who smoke (Alexander et al., 2001; Urberg et al., 1997). Recent studies of a large social network over time has shown that obesity and smoking cessation are more likely once one's social networks become obese or quit smoking (Christakis & Fowler, 2007, 2008). One would expect this result to be replicated in these three datasets, which measured time of adoption and social networks.

Interestingly, the failure of exposure to predict adoption in the medical innovation could have been discovered as early as 1957 when the data were first analyzed. The inability of computer programs to analyze network data prevented diffusion scholars from discovering this lack of association between exposure and adoption, which might have created a crisis in the **(p.189)** diffusion field, giving it new life. If exposure does not lead to adoption in some or many cases, what is the role of social networks?

Extensions to Exposure

The network exposure model is very flexible, as mentioned in Chapter 4. With egocentric data, network exposure model provides a measure of social influence based on ego's perceptions. Network exposure model may be weighted by many factors including the frequency of interaction or the similarity between ego and the named alters. With sociometric data, however, many types of social influence weights can be used and estimated. Virtually any theoretical mechanism of social influence can be modeled.

Network exposure model can be calculated on outgoing or incoming ties. Using outgoing ties models the influence of the people whom the focal individual names, who he or she thinks are his or her friends. For most analysis, using outgoing ties is probably the most appropriate way to calculate network exposure model because people are probably more strongly influenced by those they perceived to be their friends rather than by those who name them as a friend (incoming ties). Network exposure model is calculated on the named friends' self-reports.

Network exposure model can be calculated on incoming ties to model the influence of those who name the focal individual. Hall and Valente (2007) referred to incoming ties as *influence* and outgoing ties as *selection*, as the incoming ties are the ones who want to influence the focal individual. Incoming behavioral exposures may represent pressures to conform directed to the focal individual or the potential for the focal individual to access information and behavior from adopters. Further research is needed to understand how outgoing and incoming exposures compare.

Other network measures can be used to calculate social influences based on network concepts of position and influence. For example, suppose it is hypothesized that central members are more influential than peripheral ones. Exposure can be weighted by the centrality scores of friends in the network or even the difference in centrality scores. To weight exposures by centrality scores, the adjacency matrix (the matrix of direct connections) is multiplied by the centrality scores, which is then multiplied by the behavioral indicator (and optionally divided by the row sum to normalize).

As mentioned in Chapter 4, exposure can also be calculated on structural equivalence and other measures of role equivalence (see Chapter 7). Recall that structural equivalence measures the extent to which two people occupy the same position in the network. Exposure calculated on structural equivalence models the influence on the focal person of those who are similarly located in the network. Structural equivalence exposure can be a good **(p.190)** measure of competitive influences on adoption because people who occupy the same position but are not directly connected to one another are often competitors. This is particularly true, for example, in networks of firms and organizations.

Exposure can also be calculated on any attributes, attitudes, or behaviors of the people in the network. For example, a researcher who has measured ethnicity can construct a network based on ethnic similarity and this multiplied (element-by-element multiplication) by the friendship network to calculate network exposure indicating being exposed to the behavior by those of the same ethnicity. Measures of positive attitudes toward a behavior can also be used to construct exposure by friends with positive attitudes.

One of most promising ways to calculate network exposure is using affiliations to construct two-mode data. Fujimoto and others (submitted) have conducted affiliation exposure analysis among in-school adolescents using joint membership in clubs and sports. The analysis showed the utility of affiliation exposure and showed that adolescent smoking was associated with belonging to extracurricula groups that had a lot of smokers. Wipfli and others (in press) used membership in an online community over time to construct a weight matrix, which varied over time.

Infection and Susceptibility

The simultaneous inclusion of behavior and network structure in the modeling of diffusion dynamics has considerable appeal given the rich variety of theoretical processes that can be modeled. As mentioned so far, many theoretical influences can be included to construct the exposure term. One significant advance in this regard is the ability to model the extent to which individuals are infectious or susceptible to behavioral influence (Myers, 2000; Strang & Tuma, 1993). [As a side note, Strang and Tuma (1993) also proposed that time intervals can be included in these estimates so researchers can estimate short- or long-term infectiousness and susceptibility.] Infectiousness and susceptibility constitute two specific mechanisms that have public health analogs.

Infectiousness and susceptibility are measured as the extent many others adopt after or before the focal individual adopts the behavior. The researcher can specify whether there is some characteristic associated with infectiousness or susceptibility. For example, the researcher might specify that people who are popular are infectiousness in high schools. Popularity is often measured as the number of nominations received, in-degree, and analysis conducted to determine if the number of adoptions increases after high in-degree individuals adopt. Any individual characteristic can be used to determine its association with infectiousness and/or susceptibility. From a **(p.191)** network perspective, however, in-degree and out-degree are the logical candidate attributes to use.

Valente (1995) introduced a critical mass index that is a network-weighted adoption score. Not all adoptions are equal, and the critical mass index captured the notion that high in-degree adopters might contribute disproportionately to the diffusion process. The critical mass index is the ratio of adopter-nonadopter dyads in the network. Rather than measure diffusion as the number or percentage of individuals who have adopted, the critical mass index focused on the dyads or interactions and measured the percent of interactions which have the potential to result in further adoptions (those between adopters and nonadopters).

Thresholds

It may be naïve to think that exposure leads to adoption the same way for everyone. If everyone required a majority of their network to adopt before they were willing to, diffusion would never get started. Some people need to be willing to take risks and adopt new behaviors before their peers are willing to do so. These early adopters relative to their peer group are labeled low-threshold adopters. Granovetter (1978) proposed that the distribution of thresholds in the community affects the likelihood of diffusion. If no one is willing to adopt before their peers, diffusion will never get started. Further, if there is a discontinuity in the threshold distribution, diffusion can fail to take off.

Granovetter (1978) used the example of rioting. If the distribution of those willing to riot is distributed such that the number of people required to see rioting before a person is willing to do so was distributed as 0, 1, 2, 3, 4,…. *N,* then a riot can occur because the person with a 0 threshold initiates a riot and the person with a threshold of 1 see this and riots, and so on. However, if there is discontinuity in the distribution such as thresholds distributed as 0, 1, 2, 4, 4,…. *N,* then the first three people begin rioting because their thresholds are reached, but no one else does because their thresholds are not reached. Thresholds can be calculated relative to social networks as well by determining for each person the number or percent of adopters in his or her personal network required for him or her to adopt.

The trouble with calculating network thresholds is that it is hard to refute it. That is, if diffusion occurs completely irrespective of networks, one can still calculate how many people were in everyone's network when they adopted, regardless of whether those people had any influence on a person's adoption. Yet, the concept has appeal, mainly because it resonates as true; we know people who are eager to be early adopters among their peers so they can show others how something works or be the first to use it. We also know **(p. 192)** people who wait until they see all of their peers adopt before they are willing to do so. So the network threshold concept has appeal. Disproving network thresholds may be difficult, but they can be calculated and the resulting variable used in subsequent analysis. (It might also be possible to measure network thresholds using a Likert-type scale and treat it as an attribute.)

Network thresholds were calculated for the three empirical diffusion network datasets. Figure 10–6 plots the thresholds for one village of the Korean family planning study (village 24). The *y*-axis is the threshold, the proportion of each person's network who adopted before or at the same time the focal person adopted, and the *x*-axis is time, the year each person adopted. A cumulative adoption curve was overlaid on the graph to show the average expected exposure at each time period. For example, at year 5, about 50% of the community will have adopted family planning, so exposure at that time will be 50%, on average. We can see, however, that many people have thresholds above and below this expected value indicating that they adopted after 100% of their network adopted (person 59) or when 20% of their network adopted (person 19).

The average threshold values for the three datasets were MI, 55%; BF, 62%; and KFP, 63%. These values are inflated somewhat by the recoding of nonadopters to the last time period. For example, all nonadopters in the medical innovation data were recoded to 18 (the last month of data collection). Average thresholds excluding nonadopting cases were MI, 49%; BF,

(p.193) 51%; and KFP, 46%. Not surprisingly, thresholds are strongly correlated with time of adoption, with earlier adopters much more likely to have very low thresholds than later adopters.

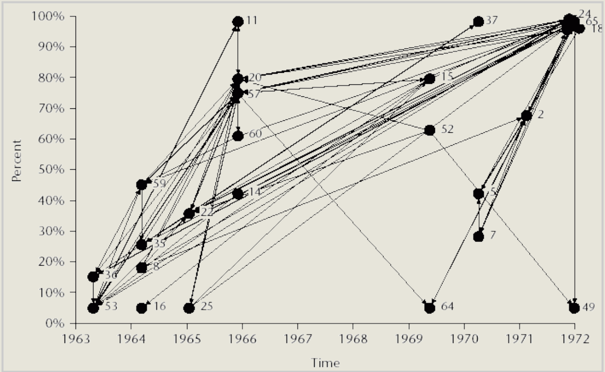

Figure 10–6. Graph of thresholds for one village in the Korean Family Planning study. The *x*-axis indicates year of adoption, and the *y*-axis, thresholds, the percentage of network contacts who adopted before each individual. Woman 31 was an early adopter and earlier than her peers, whereas person 59 was an early adopter but late relative to her peers.

If thresholds exist, we might expect people with low thresholds to turn to the media or other outside sources of information to learn about these new ideas. This occurs in part because low-threshold adopters have had few peers to turn to for advice about the new idea before deciding to adopt. Diffusion scholars have postulated change occurs when individuals come into contact with others outside their normal sphere of influence and learn about new ideas and practices from these other communities. They then transport the ideas to their host community, acting as bridges. Media theories propose that the mass media and other focused communications can act as the agent of change as well, disseminating information about new idea and practices. Change agents then are the people willing and/or able to accept these new ideas in the media and transmit them to others in their communities.

This hypothesis was tested in an evaluation of the Bolivia National Reproductive Health media campaign in which interviews were conducted with two samples of urban Bolivian residents. One sample consisted of three waves of independent (cross-sectional) residents in seven cities, and the other was a panel (following the same people over time) in one city (Valente & Saba, 1998). Low- and high-threshold adopters were calculated. Low-threshold adopters were Bolivian women who adopted a contraceptive method during the time of the study with a minority of their peers who had adopted previously, whereas high-threshold adopters had a majority of their peers who had adopted previously. We found that low-threshold adopters, in both the urban cross-sectional and panel samples, reported more media campaign exposure than high-threshold adopters (Table 10–3).

Calculating thresholds enabled measuring the two-step flow hypothesis of media influence. Katz (1957) had proposed that the media do not influence everyone, but rather they influence opinion leaders who in turn use

Table 10–3. Association between Campaign Exposure and Adoption for Low- and High-Threshold Adopters, Bolivia Media Campaign

	Cross-Sectional Data (n = 611)		Panel Data (n = 141)	
	Low-Threshold Adopters	High-Threshold Adopters	Low-Threshold Adopters	High-Threshold Adopters
Campaign Exposure	2.36**	1.92	1.71*	1.26

(*) $p < .05$;

(**) $p < .01$.

Note: Regression controls for education, age, income, and number of children.

(p.194) the information in the media to persuade others. Thus, media influence, and diffusion of new ideas and attitudes, spreads in a two-step process: first the media influence leaders and these leaders in turn influence others. The leaders that will be influenced by the media are those with low thresholds, and once they adopt, these low-threshold leaders can influence many others. Thresholds explain how diffusion jumps from innovators to early majority opinion leader adoption. If the thresholds of opinion leaders remain high for a particular issue, then diffusion is delayed.

Limitations to Diffusion Theory

Diffusion of innovations has been a theory with considerable explanatory power and predictions extend beyond available data at this time. There are several limitations to the theory, however. First, as just stated, the data required for complete testing of diffusion postulates and hypotheses are quite high. It requires data at multiple points that include behavioral adoption decisions as well as social network contacts. This can be further complicated by the long time span required for most innovations to diffuse. Further, a comprehensive study will require multiple communities studied simultaneously so the results span beyond a simple case study. Thus, it is difficult to get data over time on behavior and social networks.

A second limitation is that diffusion theory has focused more on system-level properties of diffusion at the expense of studies designed to understand individual decision making. For example, it is easier to hypothesize that diffusion occurs more rapidly in dense or centralized networks than in sparse or decentralized ones. How these postulates influence individual decision making, however, is much less often explored. For example, do individuals increase their resistance to social influence in dense networks? A third limitation is that diffusion theory to date has not hypothesized how the network changes as a consequence of innovation diffusion. For example, does adoption change one's status in the network, thus affecting the network structure? Most diffusion studies investigate how networks affect diffusion rather than how diffusion affects networks. New research in actor-oriented models may shed light on the dynamic interplay between networks and behavior.

Summary

This chapter reviewed diffusion of innovations theory which use social network analysis as a major causal mechanism. Diffusion of innovations theory is the most prominent network theory, as diffusion explains how new ideas **(p.195)** and practices spread through social networks. The chapter presented the five elements of diffusion: (1) perceived characteristics of the innovation affect its rate of adoption; (2) diffusion occurs over time so that rate of adoption often yields a cumulate adoption S-shaped pattern, with individuals are classified as early or late adopters; (3) individuals pass through stages during the adoption process typically classified as knowledge, persuasion, decision, implementation, and confirmation; (4) people can modify the innovation and sometimes discontinue its use; and (5) mathematical models can be developed to measure the rate and character of diffusion curves.

The chapter then reviewed the four major classes of diffusion models: (1) integration/opinion leadership, (2) structural models, (3) critical levels, and (4) dynamic models. All four models explicitly account for network diffusion dynamics but vary in their mathematical rigor and complexity. Dynamic models using the network exposure model were explained. Network exposure influences can be varied to model different social influence mechanisms. The chapter also introduced the calculation of infectiousness and susceptibility which dynamically account for adoption behavior and in-degree and out-degree, respectively. Infection is measured by examining the degree to which others adopt the innovation after the focal person has adopted, and susceptibility is the extent to which a person adopts after others adopt. The chapter closed with a presentation of network thresholds and limitations of diffusion theory.