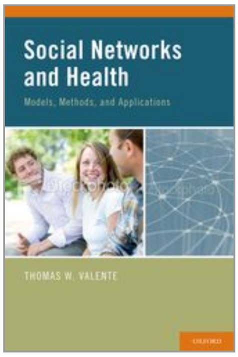

Social Networks and Health: Models, Methods, and Applications
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Print publication date: 2010
Print ISBN-13: 9780195301014
Published to Oxford Scholarship Online: May 2010
DOI: 10.1093/acprof:oso/9780195301014.001.0001

Centrality

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DOI:10.1093/acprof:oso/9780195301014.003.0005

Abstract and Keywords

This chapter provides background on the calculation, interpretation, and uses of various measures designed to determine which nodes occupy the center of a network. The chapter focuses on the three most common centrality measures developed by Freeman (1979): degree, closeness, and betweenness. Other centrality measures are also listed. The distinction between centrality and centralization is made and extent of correlation among centrality measures reported. The chapter reviewed how each of these centrality measures might function in the diffusion of innovations and behavior change and discussed the roles of opinion leaders in the behavior change process.

Keywords: network centrality, opinion leaders, centralization

This chapter provides background on the calculation, interpretation, and uses of various measures designed to determine which nodes occupy the center of a network. The chapter focuses on the three most common centrality measures developed by Freeman (1979): degree, closeness, and betweenness. Other centrality measures are also listed. The distinction between centrality and centralization is made, and extent of correlation among centrality measures reported. The chapter closes with a discussion of centrality and behavior change and how central individuals may affect the behavior of others.

When people are shown network diagrams, they frequently focus their attention on the nodes located in the center. Typically, people view being in the center of a network as a positive trait and see it as a good thing. Measuring the extent to which a node occupies a central position has been a critical focus of the network field. Central people often occupy important positions of prestige and visibility and, as noted in diffusion studies, may be influential in the spread of ideas and behaviors. Network analysts have developed numerous ways to measure centrality in a network (Borgatti & Everett, 2006).

Centrality measures for social networks were first developed in the 1950s by Bavelas, Sabidussi, and many other scholars from many disciplines (Borgatti & Everett, 2006; Freeman, 1979). The different measures and algorithms were summarized, expanded, and developed into an influential article by Freeman **(p.82)** (1979), in which Freeman introduced the modern typology of network measures by specifying that a centrality measure can have three properties:

1. It can be calculated on individuals referred to as point or node centrality.
2. This point centrality measure can and often should be normalized by the size of the network so calculations from different networks can be compared.
3. A network-level centralization score can be calculated indicating the degree of centralization derived from a specific measure.

Degree

The most frequently used centrality measure is degree, and it is an intuitive measure, easily calculated and easy to understand. *Degree* is the number of links to and from a person. In a directed (asymmetric) network, *in-degree* is the number of ties received and *out-degree* is the number of ties sent. Degree is characterized as a local centrality measure because it can be calculated without reference to the overall structure of the network. In other words, one can put a lens over a node's immediate ties and calculate centrality. Other centrality measures require information on the pattern of ties in the entire network to be calculated.

In-degree counts the number of times a person is nominated by others in the network. To make this measure comparable between networks of different sizes, this count is divided by the maximum number possible, which is N – 1. Theoretically, a person can be nominated by everyone else in the network. So the maximum possible in-degree is N – 1. The normalized degree centrality measure varies from 0 to 1. The formula for normalized degree is (Freeman, 1979):

5–1

$$C_D = \sum \frac{d_i}{N-1}$$

In-degree is a very useful measure, probably the most useful measure available to researchers. In-degree identifies opinion leaders in a network, and in friendship networks it indicates popularity. For example, popular adolescents are defined as those who received many choices as “friends” from their peers. In-degree can be used as a measure of social integration and used to identify opinion leaders to promote behavior change (see Chapter 11). In-degree is also a useful measure because a person can be nominated (and thus have an in-degree score) even if he or she does not complete a survey.

Out-degree is the number of names a person provides in response to a network question. Out-degree can be calculated as the total number of names **(p.83)** provided or restricted to the number of names provided in the network (ignoring ties to people not predefined as being part of the network). In nomination studies (see Chapter 3), out-degree is often restricted to some maximum number. For example, a survey may ask people to name up to seven of your closest friends. In a roster study, out-degree can be as high as N – 1 (every other person but himself or herself). In a study assessing the number of sexual partners, out-degree is the number of sexual partners, which is a very important variable for understanding disease risk.

Out-degree is sometimes needed as a control variable in statistical analysis. For example, analysis showing that a network measure is associated with some outcome should include out-degree as a control variable because it may be that the measure of interest is related to the outcome because a person selected a large number of others in response to the network question. Out-degree is also used as a denominator when calculating network exposure or network composition terms to control for the size of one's network. Out-degree measures, to some extent, a person's socialness or sociality. Out-degree is often referred to as expansiveness.

Out-degree is also sometimes a useful indicator for personal attributes. For example, a network study can ask for the names of others to whom people go to for emotional support. Counting the number of others provides a measure of the size of one's emotional support network and this variable can be expected to correlate positively with health outcomes. Out-degree centrality provides a measure of network size, which can be very important. Out-degree, like in-degree, can be normalized by dividing scores by N – 1, the maximum possible. Degree scores can be calculated within standard statistical packages such as SAS, SPSS, and STATA when the data are dyadic (Box 5–1).

Closeness

Degree, as mentioned earlier, is considered a local centrality measure. Other measures of centrality require information on the pattern of links in the entire network. Freeman (1979) introduced two other centrality measures: closeness and betweenness. *Closeness* measures the average distance a node is from all other nodes in the network. It is calculated by summing these distances and then inverting the value to change the measure from a distance one to a closeness one. Point closeness then is the inverted sum of the distances, and normalized closeness is N – 1 divided by the sum of distances, making it an average closeness measure. Normalized closeness is calculated as (Freeman, 1979):

5–2

$$C_c = \frac{N-1}{\sum D_{ij}}$$

(p.84)

Box 5–1. Reshaping Data from Wide to Long and Calculating Degree

Using a simple dataset of nominations, the data are reshaped to dyadic format. If there are multiple networks in the data, the collapse command below is modified to include a variable indicating the separate networks. In this example, the data contain nominations of up to five alters.

```
/* Make Dyad */

use c:\data

reshape long nom, i(net_id) j(alt 1-5)

drop if nom==.

sort net_id

save c:\dyad, replace

/* Calculate indegree from dyad data */

use c:\dyad

gen one = 1

collapse (sum) one, by(nom)

ren one no_recvd

ren nom net_id

sort net_id

save c:\indegree, replace

/* Calculate outdegree from dyad data */

use c:\dyad, replace

gen one = 1

collapse (sum) one, by(net_id)
```

```
ren one no_sent

sort net_id

save c:\outdegree, replace

/* Merge In and Out Degree scores with data */

use c:\data

sort net_id

merge net_id using c:\outdegree

tab _merge

drop _merge

sort net_id

merge net_id using c:\indegree

tab _merge

drop _merge

save, replace
```

(p.85) The maximum possible closeness score in any network is $N - 1$. When the distances to all nodes are summed and divided into $N - 1$, it provides a normalized version of closeness that varies from 0 to 1. Closeness has intuitive appeal as a centrality measure since someone who is closer to everyone else, on average, is in a central position. In geography, for example, St. Louis is in a central position in the United States because it is closer, on average, to all other U.S. cities. Los Angeles, on the other hand, may be near some cities, but it is far from many other cities, making it less central.

Unlike geography, however, social space is non-Euclidian; that is, the distance from A to B is not necessarily the same as the distance from B to A. Because networks are possibly asymmetric, the path from one person to another follows a direction along the lines. If one of those links is asymmetric, the path cannot be reversed. So the distance from one point to another may not be the same as the distance from that point to the original one (the distance from A to B is not necessarily the same as the distance from B to A).

Consequently, closeness centrality has a direction. One can calculate closeness based on the links directed to a person (in-closeness) or based on the links coming from a person (out-closeness). The calculations are the same (Equation 5-2) but are based on the direction of the person's direct links. The highest out-closeness is the person who can reach others in the fewest number of steps, while the highest in-closeness is the person others can reach in the fewest number of steps. Closeness has not been as useful a measure of centrality as in-degree and this may be in part due to its calculation.

Inverting the distance sums to calculate closeness is useful, but at the same time it can distort the measure in a nonlinear way. For example, a distance of 2 becomes ½ and a distance of 3 becomes and so on. While inverting the distances and dividing into N – 1 (the maximum closeness possible) enables comparison between networks of different sizes, it also may not be the best way to convert distance into closeness. Valente and Foreman (1998) suggested *reversing* distances to make them closeness scores. Reversing distances entails subtracting the distances from the maximum possible in the network, N – 1. Valente and Foreman (1998) called this measure *integration* when calculated on in-distances and *radiality* when calculated on out-distances. The integration and radialiaty measures were found to correlate better with outcomes than closeness calculated by inverting distances.

Distances for Unconnected Nodes

One difficulty inherent in distance calculations for networks is the calculation of distances for disconnected nodes. Nodes that cannot reach one another in a network are an infinite distance from one another. Using infinity **(p.86)** for the distance between disconnected nodes creates intractable mathematics for whole network calculations, however. Thus, some finite number is often used to represent the distance between disconnected nodes. The substitution of a constant for infinity is reasonable for several reasons. First, although the nodes are not reachable in this particular network, they might be reachable if the network was measured again or measured in a slightly different way. For example, two people might be connected in a friendship network but disconnected (unreachable) in an advice-seeking network. Given that they are reachable in another network, it seems logical to consider nodes as reachable in all networks.

A second reason to treat disconnected nodes as reachable rather than infinitely far apart is practical. Many network calculations require adding or inverting distances. Adding infinity to anything equals infinity and thus the calculations become meaningless. A third justification is that the lack of connectedness may be due to measurement error and the substitution minimizes the impact of this measurement error. Finally, on philosophical grounds, substituting a number for infinity may be justified because any person included in the study is thought to be somehow connected to the group and not disconnected from it entirely.

In sum, most network analysts treat unreachable nodes as being far away, but not infinitely far. Three obvious measures of distance for unreachable nodes are (1) $D + 1$ where D is the longest distance between connected nodes (the diameter) and (2) N or $N – 1$ (where N is network size). $D + 1$ assumes that two disconnected nodes are one step farther apart than the longest distance in the network. This works well for many applications because the disconnected nodes do not distort the distribution of distances too much. The disadvantage of $D + 1$ is that this distance is not a theoretical maximum. Another drawback is that since different networks within the same community or study may have different diameters, unreachable nodes in one network within the same community may have shorter distances than unreachable nodes in another. For example, a school friendship network may have a diameter of five and advice-seeking a diameter of seven and so students unreachable in the friend network may be calculated as closer than advice seekers reachable via six steps.

To address the limitations of D + 1, many researchers use N – 1 as the distance between disconnected nodes. N – 1 is the theoretical maximum distance for disconnected nodes because that is the maximum number of steps between any two nodes in a network. To understand how N – 1 can be the farthest distance, consider a set of nodes arranged in a line as a network that has the maximum distance between nodes. The distance from one end of the line to the other is N – 1. The drawback to using N – 1 is that average distances between nodes in a network of even moderate size can become quite **(p.87)** large even with only a few unreachable nodes. These larger than expected averages hamper interpretation when reporting results and can distort analysis conducted with the metrics (for example, in a regression analysis).

In sum, researchers need to be conscious of the network structure and specifically aware if the network contains isolates or disconnected groups. Researchers needing to analyze the whole network including these isolates or dis-connections may prefer using a finite number rather than infinity for these distances. D + 1 has the advantage of providing average distances close to the existing average in the connected components but cannot be compared between networks. N – 1 as a value can be compared between networks of different sizes but inflates distance values considerably and so may perturb further analysis of the data (e.g., in regression equations).

Betweenness

The third measure Freeman (1979) proposed was centrality betweenness measured as the frequency a person lies on the shortest path connecting everyone else in the network. The concept of *betweenness* is very appealing as it measures the degree a node occupies a strategic position in a network, somewhat akin to bridging and centrality combined. Like the other measures, one can calculate a point measure and its normalized version. Point betweenness is calculated by counting the frequency a node lies on the shortest paths connecting all other nodes in the network. Normalized betweenness centrality is calculated as (Freeman, 1979):

5–3

$$C_b = \frac{\frac{g_{ij} p_k}{g_{ij}}}{n^2 - 3n + 2}$$

where g_{ij} p_k counts the number of times point k lies on the geodesic (shortest path) connecting all other nodes (i and j) and g_{ij} is the number of geodesics in the network. Betweenness is the frequency a node lies on the shortest path connecting other nodes in the network. The maximum possible value that the numerator $[(g_{ij}\ p_k)/g_{ij}]$ can reach is $n^2 - 3n + 2$ and so this is the normalization factor (Freeman, 1979). Betweenness centrality is inherently directional since the geodesic (the shortest path) is directional. Consequently, separate calculations for in and out directions are not needed. Betweenness centrality captures the notion that a person with strategic contacts, say nominations received from leaders of two factions, inhabits a strategic position in the network even if his or her volume of contacts is not large.

(p.88) One shortcoming of Freeman's (1979) betweenness measure is that it relies on the *geodesic,* the shortest path connecting nodes. It may be that some nodes occupy critical betweenness locations but not on the geodesic. Another criticism is that it takes a long time to calculate betweenness for networks larger than a few hundred members. Newman (2005) provided an alternative measure of betweenness calculated similarly but, rather than relaying shortest paths, samples all paths connecting two nodes. Brandes and Erlebach (2005) offered an algorithm that is more efficient for larger networks.

Although degree, closeness, and betweenness measure centrality, they each capture slightly different conceptions or functions of centrality. Degree, for example, measures local centrality, the extent to which a node is connected to many other nodes regardless of the location/position of those other nodes. In contrast, Freeman (1979) stated that betweenness centrality captured a gate-keeping function—if members high in betweenness opposed an idea, its diffusion to other segments of the group might be blocked. Closeness centrality captured a communication role such that people high in closeness can communicate an idea to many others rapidly.

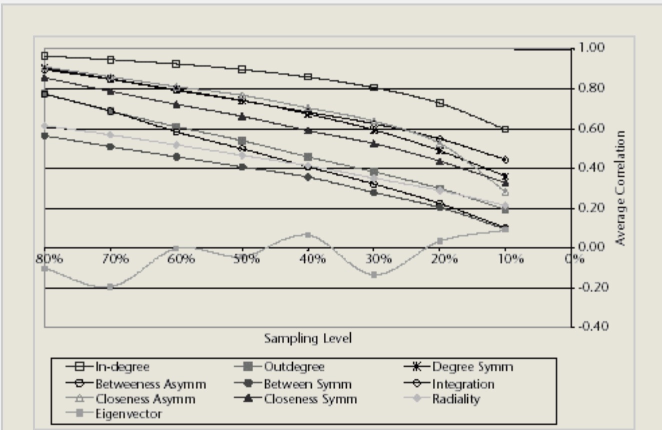
The three measures, degree, closeness, and betweenness, often identify different nodes as being the most central and of course are not perfectly correlated. For example, the networks in Figure 1–1 displays friendship choices for sixth-graders in one middle school in southern California. Centrality (and other) scores were calculated for this network and the links and measures are reported in Appendix C. Students 21 and 7 have the highest degree scores each receiving 11 friendship nominations. These two students have the highest centrality in-degree. In this study, students were asked to name up to five of their closest friends and many of the students named five so they all have the same out-degree score. In sum, the three most prominent centrality measures identify different individuals as being most central and two of these measures, degree and closeness, are asymmetric, yielding different nodes as being most central depending on the direction of the links. Further, closeness and betweenness have several different ways they can be calculated. In addition to imperfect correlation, it is also the case that centrality measures vary in their robustness to missing data (Box 5–2).

The most central nodes on in-closeness were 29 and 10. These two nodes have the shortest average number of steps to be reached by everyone else in the network. Closeness centrality is an asymmetric measure; distances in one direction can be different than distances in the other direction. The in-closeness centrality measure determines the distances “to” each node and is based on the ties being directed to each node. Messages from other students can reach 29 and 10 more quickly, on average, than they can reach other students. Out-closeness centrality is highest for students 35 and 2. Notice that 35 makes five nominations and two of these nominations are **(p.89)** **(p.90)** students 2 and 23, who then link directly to the other group. Messages *from* student 35 can reach other students more quickly than messages originating from anyone else. In this case, in-closeness and out-closeness identify different nodes as the ones being most central. Substantively, this can be very important depending on whether one is concerned about sending messages or getting messages received or on transmitting infection or receiving it.

Box 5–2. Robustness of Centrality Measures with Missing Data

One nagging concern in the social network field has been missing data. Because sociometric studies use census sampling, it is desirable to interview all members of the community. Each person contributes N – 1 bits of information to the data, the ties or non-ties to everyone else. There has always been a feeling that response rates of 70% or 80%, although high by most scientific standards, are inadequate for network analysis and might make most network measures invalid.

To assess the effect of missing data on networks measures, a study was conducted using social network data from eight studies and 58 different networks (Costenbader & Valente, 2003). Centrality measures were calculated on all the networks; then 20% of the people were removed from the network, and the centrality measures were recalculated, and then correlated with the original measure. The process was repeated 25 times at each sampled level to get an average of the correlations. The average correlation indicates how well centrality measures assess centrality under conditions of missing data, that is, if the response rates were lower.



The exercise was repeated reducing the sample (i.e., increasing the missing data rate) to 70%, 60%, 50%, 40%, 30%, and 20%. Figure 5–1 shows the average correlations at decreased sample sizes averaged across all the datasets. The centrality measures were surprisingly robust. In-degree centrality was the most robust. The actual in-degree score and the one calculated on the 30% sample had a correlation of 0.80. Closeness and integration, the two distance-based measures, do the next best decreasing in the correlation linearly with the decrease in sample size. Betweenness does less well, correlating at less than 0.60 with the 80% sample and decreasing steadily to about 0.30 at 30%. The most

Figure 5–1. Correlations between centrality measures calculated on the complete network and that calculated on a sample decremented by 10% and repeated 25 times at each sampling level. Results show that in-degree is the most robust when sampled; it is 60% accurate when as little as 10% of the original network is used. In contrast, integration, radiality, and betweenness do less well, in part because these measures reflect more of the network structure. Eigenvector centrality seems to do the least well when the network is sampled.

disappointing measure was eigenvector centrality which correlated poorly with the measure from the full sample at even the highest sampling rate and correlated erratically throughout the experiment. The conclusion from this exercise is that those centrality measures which tap into the structure of the network the greatest are the most vulnerable to missing data and that simple measures like degree and closeness are the most robust under conditions of missing data.

The empirical analysis showed that no one factor was uniformly associated with measure instability. Response rate, density, centralization, and dummy variables for the various studies were all tested for their effect on measure instability. No one factor emerged that affected centrality measure robustness. Borgatti and others (2006) conducted similar analyses with similar results on simulated data.

Betweenness centrality identifies node 27 as the most central. Student 27 lies on the shortest path connecting other students more frequently than any other node. If all the shortest paths connecting the people in this network were written out, student 27 would appear most often. In this case, 27 occupies a strategic position of importance by being the node that messages must pass through as they circulate through the network. If one wanted to disrupt communication flow, student

27 would be a critical person to inoculate with a specific message. If one wanted to disrupt the spread of infections, person 27 would be the most logical to immunize.

(p.91) In sum, the three most prominent centrality measures identify different individuals as being most central, and two of these measures, degree and closeness, are asymmetric, yielding different nodes as being most central depending on the direction of the links. Further, closeness and betweenness have several different ways they can be calculated.

Which students are the most central? There are five: 21 and 7 (in-degree); 29 (in-closeness); 35 (out-closeness); and 27 (betweenness). Each one serves different functions in the overall structure of the network and each potentially can be used in different ways to mobilize action or accelerate change in the network. The different centrality measures might capture the different kinds of leaders one would expect to adopt an innovation or be used to promote it during different stages of diffusion. For example, since people high on betweenness act as bridges, perhaps they could be recruited to carry the innovation from the innovative stage to early adopters. Or these bridges should be inoculated so that diseases do not get transmitted from one group to another. People high on in-degree centrality can then be recruited during the early adoption stage to be champions since they are role models for many people. High in-degree people act as champions that move the innovation from the early adoption stage to the early majority stage. They can be proponents that can establish a critical mass in favor of the new behavior. As diffusion progresses, people high in closeness centrality can be recruited to ensure diffusion spreads to the maximum number of people. Although it is unlikely such data would be available to implement such a project, in an ideal world this is how diffusion might be managed.

One limitation to carrying out such a project is the intensity of the monitoring and data collection necessary to complete it. A second is that the three centrality measures (degree, closeness, and betweenness) are highly correlated (Valente et al., 2008), and so a person high on betweenness is often high on closeness or degree. Still if one wanted to maximize diffusion, such a project, or a variation on it, should be considered. (A variation might be using high in-degree champions but continuously reassessing the identification of leaders using the different centrality measures.)

Correlation among Centrality Measures

Although the three centrality measures discussed so far are correlated, the correlation is far from 1. To measure their correlation, the centrality measures degree, closeness and betweenness were calculated on 58 networks collected in eight studies (Costenbader & Valente, 2003). The correlations among these centrality measures within each network was then calculated **(p.92)**

Table 5–1. Average Correlations between Centrality Meas-ures (*N* = 58)

	1	2	3	4	5	6	7	8	9	Total
1. In-degree										
2. Out-degree	0.30									
3. Degree	0.78	0.71								
4. Betweenness	0.62	0.54	0.70							
5. Symmetric betweenness	0.69	0.50	0.85	0.67						
6. Closeness-in	0.55	0.16	0.45	0.37	0.30					
7. Closeness-out	0.18	0.81	0.56	0.39	0.38	0.01				
8. Symmetric closeness	0.40	0.64	0.66	0.37	0.44	0.42	0.65			

	1	2	3	4	5	6	7	8	9	Total
9. Eigenvector	0.71	0.69	0.92	0.64	0.72	0.44	0.55	0.63		
Average correlation	0.59	0.58	0.70	0.54	0.57	0.34	0.44	0.54	0.67	0.54
Standard deviation of correlations	0.21	0.21	0.15	0.14	0.18	0.18	0.26	0.13	0.15	0.14

and averaged across the 58 networks (Valente et al., 2008). The average correlations are presented in Table 5–1 and are generally pretty high, ranging from 0.18 to 0.92. The correlation between in- and out-degree was modest, 0.30, for example. Betweenness centrality was strongly correlated with degree and eigenvector (0.64) but not with closeness centrality. Closeness centrality was also associated with degree and with eigenvector centrality. The overall average correlation among all centrality measures was 0.54, indicating that these different centrality measures seem to represent a fairly consistent concept, centrality, but with some distinctiveness to the individual measures. Overall, degree had the highest average correlation (0.70) with the other measures (Valente et al., 2008).

Reciprocity was strongly associated with centrality measure correlations. If there were many reciprocated relationships in the network, the centrality measures were highly correlated. This strong correlation could be a function of the symmetry status of the various measures—networks with higher levels of reciprocity will have higher correlations between asymmetric measures than those with lower levels of reciprocity. For example, the correlation between in-degree and out-degree will be one when the network is perfectly symmetric because the in- and out-ties are identical. In addition, correlations between symmetrized measures were associated with the number of components and network density, while asymmetric measures were not. Symmetrizing matrices before making centrality calculations should thus be done with caution and only if justifiable substantively. In addition, **(p.93)** un-symmetrized centrality measures might be more distinct in densely connected networks with more components. The findings demonstrated that symmetrizing network data creates disparities between symmetric and asymmetric centrality measures (Valente et al., 2008).

Other Centrality Measures

Degree, closeness, and betweenness constitute the three main centrality measures, but at least seven other centrality measures have been developed, including eigenvector centrality (Bonacich, 1972; Seary & Richards, 2003), entropy (Tutzauer, 2007), information (Stephenson & Zellen, 1989), flow (Freeman et al., 1991), power (Bonacich, 1987), and complement (Cornwell, 2005). All of these centrality measures can be calculated in UCINET (Borgatti et al., 2004) and many other software programs (Huisman & van Duijn, 2005). Before using these measures, researchers should understand the advantages and properties of each measure. Eigenvector centrality is useful because it measures the centrality of a node based in part on the centrality of its neighboring nodes. Eigenvector centrality, however, uses symmetric data and is not robust to missing data. Power is very useful as a measure because it allows the researcher to vary the extent to which the centrality of one's neighbors is included in the calculation.

Link or Edge Centrality

Of interest in some applications is treating the links as nodes and the nodes as links. Link centrality analysis enables the researcher to determine which connections are most central in the network. Every link will have a degree of two (two nodes), but one can calculate closeness, betweenness, and other centrality measures based on the network of links. This might be useful if, for example, a researcher wants to identify which relationships are the most central. For example, a network of sexual contacts may be converted to links and the most central relationships might be the ones most effectively eliminated to stem the flow of STDs.

In the network of Figure 1–1, betweenness centrality was calculated on the links. (Degree centrality is not important as all links have degree one or two.) The link (edge) with highest betweenness centrality score was the link connecting students 27 and 29. Visual inspection confirms this is indeed an important link as it connects the girls on the left with the boys on the right. Removing this link would disrupt the flow of communication (or disease transmission) more so than the removal of any other link.

(p.94) Centrality versus Centralization

Centrality measures can also be used to describe the extent to which a network is centralized. *Centralization* is the extent to which network links are focused on one or a few nodes in the network. A *centralized network*, sometimes referred to as a *hierarchical* one, concentrates links on one or a few people, while a *decentralized network* has links evenly distributed among the nodes.

A centralized network has most of its links connected to one or a few nodes. A star network (Figure 5–2) is a perfectly centralized network, whereas a wheel is decentralized. In the star, one node controls all of the activity, whereas in the wheel, every node is equally in control and has equal access to all others. Centralized networks are characterized by large variance in the individual centrality scores (some large and many small values), whereas decentralized ones have little variance in centrality measures (everyone has the same or similar scores). The star has one node with four links and four nodes with one link. In contrast, the wheel network has an equal number of links, two, for all five nodes.

One way to measure centralization is to calculate the standard deviation of the centrality scores (Wasserman & Faust, 1994). A centralized network will have a high standard deviation of centrality scores because some individuals have high centrality while many others have low centrality. A decentralized network, in contrast, has a low standard deviation of centrality scores because everyone has very similar scores. A network of five nodes in which everyone is connected to everyone else is perfectly decentralized and everyone has the same centrality degree score. In contrast, a network of five people in which four of them are all connected to one and the same person is perfectly centralized on that person and the standard deviation of the degree distribution is high.

A normalized centralization score is possible to calculate by taking the difference between the maximum score in the network and all other scores

(p.95) (see Chapter 8). This sum is then divided by the maximum value possible for a network. This centralization calculation logic is similar to using a standard deviation, which is a sum of differences, but instead divides by the maximum difference possible so the values range from zero to 1, with a perfectly centralized network having a centralization score of 1. The important concept to retain here is that centrality refers to the node or person-level measure and centralization to the network-level one. In other words, a person can have high centrality within a centralized or decentralized network.

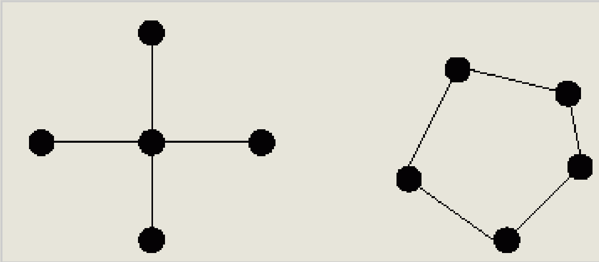


Figure 5–2. A perfectly centralized network on the left (a star) and a decentralized one on the right (a chain).

Centrality and Behavior

Early studies showed that centrality was linked to task performance. Experimental studies showed that centralized groups completed tasks more efficiently than decentralized groups, although the centralized ones reported less satisfaction with the task (Shaw, 1971). Organizational behaviorists debate the merits of decentralized versus centralized decision-making with some industries favoring centralization while others favor decentralization. Trade flows and traffic research have an inherent interest in centrality as trade centers usually occupy central positions. At the same time, centralized traffic systems are subject to congestion and bottlenecks. Pitts (1979) showed that the city of Moscow emerged as an important and large city in part because of its position in the river trade network.

City planners need to calculate centrality on traffic grids to decide where to locate fire stations, police stations, and hospitals, as these should be in the center of their catchment areas. Central members can be drivers of diffusion, and those at the center of disease risk networks are at greater risk for the disease than those on the periphery. Ellen and others (2005) showed that adolescents in high STD prevalence communities who had larger social networks were more likely to contract an STD than those with smaller social networks. Rogers' (1962, 2003) studies of the diffusion of innovations concluded that opinion leaders, who are often at the center of networks, were more likely to be earlier adopters of innovations than were non–opinion leaders.

Rogers and Kincaid (1981) studied the adoption of contraceptive practices in 25 Korean villages from data collected in 1973. They found that there was usually a certain contraceptive method—IUD, condom, or withdrawal—that would become widespread in a village and this method would be the one also chosen by the women who received the most nominations as a family planning discussion partner. Again, in-degree centrality was associated with behavioral adoption, and in this case evidence that perhaps the behavior of the opinion leaders was imitated by many others.

(p.96) Alexander and others (2001) found that popular students, measured as those who received many friendship nominations, were more likely to smoke than their less popular peers. Alexander and others (2001) also found that popular students were more likely to smoke in schools where the smoking prevalence in the school was high and less likely to smoke where the smoking prevalence in the schools was low. This cross-sectional study could only show a correlation between popularity and smoking but suggests that popular students embrace behaviors consistent with cultural norms and in turn may contribute to normative persistence.

Valente and others (2005) showed that adolescents popular in the sixth grade were more likely to become smokers in the seventh grade. Popular students were also more likely to become more susceptible to smoking (as measured by their refusal to state they would not smoke in the future) than their less popular peers. These effects held for change in smoking status as well as when restricted to nonsmokers in the sixth grade (smoking initiation). These analyses controlled for the many other factors associated with smoking including parental and sibling smoking, socioeconomic status, ethnicity, academic performance, age, and sex.

Why do popular students start smoking before their less popular peers? In part this perhaps is a function of the popular students' frame of reference. They anticipate that smoking will become widespread in their schools and so want to be earlier adopters of this behavior so they seem “hip” or “cool.” They also want to retain their positions of popularity and so need to be trendsetters, and smoking will enable them to be seen as the trendsetters. In schools in which smoking will be seen as deviant behavior, popular students will not be more prone to smoke. It may also be that they possess some other characteristics that make them both popular and become smokers.

In-degree centrality is the most frequently used network measure of opinion leadership and has been used for decades. As early as the 1950s, researchers counted the number of choices each person received and used this count to indicate opinion leadership. Rogers and Cartano (1962) conducted an early study comparing the in-degree measure of opinion leadership with other measures such as self-assessment via survey. They found that the measures were somewhat correlated ($r = 0.35$) but not as strong as one might expect them to be. In more recent research, we conducted a survey of physicians using a validated leadership scale and found it correlated with in-degree centrality at 0.43 (Van den Bulte, et al., 2008).

The smoking studies showed that opinion leaders, defined as popular students, started smoking earlier than their less popular peers. These studies, and many others, describe a general model in which opinion leaders evaluate the relative compatibility and appeal of new behaviors as they are introduced into a community. If that new behavior seems to be one that will be embraced **(p.97)** by the community, the opinion leader will adopt earlier than most everyone else in the community. In other words, if the behavior is culturally compatible, opinion leaders will adopt it early. Subsequently, many others will see the behavior of these opinion leaders, which will reinforce the acceptability of the new behavior, and its adoption by others will be accelerated.

Central people are in an advantaged position for access to information about what is happening in the community. They can scan the environment more effectively than others because of the many contacts they have and this scanning enables them to judge whether the new behavior will be acceptable to the community at large. Once central people sense or believe there will be widespread acceptance of the new behavior, they are likely to adopt it.

In turn, because of their central position, many others watch the central people to see how they will react to the new idea. The centrals are “on stage” more often than their peers and their behavior is monitored by more other people than nonleaders. As others monitor and emulate the behaviors of central people, their status as leaders becomes enhanced. Often then, widespread diffusion hangs in the balance while opinion leaders judge the acceptability of the new idea. Their endorsement means more than just another adoption, it signals community acceptance. This suggests that degree centrality would be an indicator more highly associated with accelerating diffusion than other centrality measures.

Not all opinion leaders are equal. Some leaders are local leaders while others are regional and still others national leaders. There are some leaders who command attention within their local community but not much beyond that. Still other leaders have regional influence so that they are well known and emulated by colleagues locally and regionally. National leaders have the most prominence. These leaders are recognized trendsetters and gatekeepers on a national level. National leaders may not be seen as local leaders within the community precisely because their contacts are outside the community. Since many people's adoption decisions are driven by their close personal networks, they may recognize national leaders as leaders, but perhaps will not emulate their behavior.

Behavioral diffusion is driven in large part by the behavior of local leaders. National leaders are usually perceived to be too different than those in the community and often do not provide the best role models as diffusion agents. National leaders function much like the mass media—their behavior may spread awareness about a new idea and legitimize it, but they often do not have direct influence on many others. The people they do influence are more likely to be regional and local leaders rather than nonleaders.

There is an element of network trust implied in these conjectures. People are influenced by those they trust. It is difficult to develop a trust relationship with a national leader whose sphere of influence is quite large. Local leaders **(p.98)** can develop trust within the community and so their opinions are often more valued, and behaviors more often emulated than those of national leaders. Trust is often a prerequisite condition for interpersonal influence to occur.

Characteristics of Opinion Leaders

Leaders are just like followers, only more so. Leaders are often of slightly higher status than their followers but not much higher. National leaders are often perceived to be different than everyone else, but local leaders often have just a bit higher status than the people they lead in their community. Typically, leaders have slightly more education, have slightly higher incomes, and/or are somewhat better read on the topic. This happens because most people like to look up to others who are like themselves, only a little better in some way. It is difficult for people to relate to others who are very different from themselves. On the other hand, people can relate to others who are just one rung above them on the socioeconomic or status ladder.

Research also shows that leaders are more empathetic and good listeners; they learn from other people. Leaders are good communicators, enjoying interpersonal interaction. They are "people" people. Leaders also attend to media more, which provides them with the information they need to lead and to stay abreast of what is happening. The importance of opinion leaders for behavior change has led to the creation of opinion leader interventions designed to accelerate behavior change (see Chapter 11).

It should also be noted that leadership is sometimes distinguished between formal and informal leadership. Formal leaders are identified by their occupation (elected officials, company presidents, media personalities), whereas informal leaders are often harder to identify. At least 10 different techniques have been used to identify leaders (Valente & Pumpuang, 2007), and these different approaches often yield different types of people who may be differentially suited to different tasks.

Leader characteristics and abilities may also depend in part on the overall network structure within which the opinion leaders function. Being a central node in a centralized network has different implications than being a central node in a decentralized network. A central node in a centralized network can exercise considerable more power and influence than a central node in a decentralized network. Moreover, centralization may also influence how noncentral nodes relate to central nodes because noncentral members may feel vulnerable or dependent on the central members' attitudes. In essence, noncentral members may feel more empowered in decentralized networks than in centralized ones.

(p.99) Summary

This chapter introduced the concept of centrality in social networks. The chapter provided the equations for the three most frequently used centrality measures—degree, closeness, and betweenness (Freeman, 1979). The extent correlation among centrality measures was presented as well as factors that influence correlations among measures. Overall, the correlation is quite high, 0.54, but far from unity and varies considerably between measures. There are also network properties such as reciprocity that affect the correlation among centrality measures. The greater the tendency toward reciprocity in the network, the higher is the correlation among measures. Thus, researchers should use caution when symmetrizing networks.

The chapter reviewed how each of these centrality measures might function in the diffusion of innovations and behavior change and discussed the roles of opinion leaders in the behavior change process. The distinction between centrality and centralization was emphasized. The interplay between centrality and centralization was discussed. Centrality measurement has been a key development in the network field. The central importance of central nodes and people in networks means that it is likely to continue this prominent role.