Nonrespondents in Communication Network Studies

PROBLEMS AND POSSIBILITIES

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This article explores problems caused by nonrespondents in sociometric studies of organizational communication and describes how networks that include nonrespondents can be analyzed. An illustrative example is used to conceptualize the problems and issues in analyzing such networks. An empirical study is described that operationalizes the decision criteria for choosing a method of analysis. Suggestions are offered for the design of communication network studies that may enhance response rates and provide the information needed to justify how incomplete network data sets may be analyzed.

Both researchers and consultants are finding network metaphors and network methods to be useful ways to conceptualize and operationalize patterns of communication, influence, friendship, and authority in organizations. Network methods have been used in empirical studies of innovation and the introduction of new technologies (Albrecht & Ropp, 1984; Burkhardt & Brass, 1990; Burt, 1987a; Papa, 1990; Rice & Barnett, 1985; Van de Ven & Rogers, 1988), commitment (Eisenberg, Monge, & Miller, 1983; Hartman & Johnson, 1989), individual influence (Brass, 1984; Tushman & Romanelli, 1983), organizational structure (Roberts & O'Reilly, 1978), turnover (Krackhardt & Porter, 1986), quality circles (Stohl, 1989), and research and development project performance (Katz & Tushman, 1979; Tushman, 1979a, 1979b). They have also been used as tools in organizational development (Monge & Eisenberg, 1987; Wigand, 1988) – for structural diagnosis, coalition identification, and the analysis of intergroup relations (Nelson, 1988, 1989). Comparing actual communication networks to the formally defined

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structure of an organization is a "powerful and heuristic method for redesigning a social system" (Wigand, 1988, p. 340).

Network theory emphasizes relationships "between two or more objects or individuals over the attributes of these objects" (Contractor & Eisenberg, 1990, p. 151). Methods of network analysis are used to create descriptions of patterns of relationships. Often, these patterns—the networks whose properties are of interest to the researcher or consultant—become visible only to an observer with a "bird's-eye view of the social landscape" (Alba, 1982, p. 58). The goal of network analysis is to create, from raw relational data, a useful description of a system of relationships.

The most common method for collecting communication network data is the sociometric survey in which individuals are asked to describe their relationships of communication with other organizational members (Dean & Brass, 1985; Nelson, 1989; Rogers & Kincaid, 1981; Tichy, Tushman, & Fombrun, 1980). Using this methodology, communication networks in organizations can be identified at three different levels of analysis. These include the personal or ego network, the group network, and the social system network—a department or the organization as a whole (Burt, 1980; Monge & Eisenberg, 1987). Analysis at the personal-network level focuses on the communication links that a focal individual has with other individuals and how these other individuals are connected to one another, as well. Analysis at the group level focuses on the patterns of communication among a set of individuals who communicate more with each other than with people in the larger network. At the system level, analysis focuses on patterns of communication among all members of the network—the identification of system components (groups and roles) and description of the overall network—using concepts like density and differentiation.

RESPONSE RATES

It is easy to collect sociometric data, "since anyone can ask sociometric questions" (Tichy, Tushman, & Fombrun, 1980, p. 378). They are difficult to analyze, however, particularly when data that describe network relationships are missing. A relationship "is not the property of an individual [but rather] a characteristic that is defined in reference to two . . . people taken together" (Monge, 1987, p. 241). Thus complete description requires information from both individuals in a relationship. To analyze a network of communication relationships, researchers "would like to collect data from all [its] members" (Monge & Contractor, 1988, p. 123). In practice, however, returned surveys often represent less than a 100% response rate, and "missing data are . . . a curse to survey network data [because] network analysis is especially sensitive to missing data" (Burt, 1987b, p. 63). Missing data pose a particularly serious problem for network analysis *at the system level* because they may create "huge holes in the who-to-whom data matrix" (Rogers & Kincaid, 1981, p. 111) that distort the system's communication structure. Yet response rates reported in the literature suggest that network researchers are often faced with having to analyze data sets with response rates between 90% and 65% (Albrecht, 1984; Dean & Brass, 1985; Moch, 1980; Monge, Edwards, & Kirste, 1983; Roberts & O'Reilly, 1978, 1979).

This article examines the problems caused by nonrespondents and describes approaches to the analysis of incomplete data sets that may lessen the impact of missing data. Suggestions are offered for the design of network studies and data-collection instruments that will improve response rates and provide the kind of information needed to justify decisions about how incomplete data sets are analyzed.

AN ILLUSTRATIVE EXAMPLE OF NONRESPONSE

Let us illustrate how many data are actually missing from the data matrix when some network members do not return their sociometric surveys. Assume that the entire network contains 60 people. If all 60 people returned their surveys and described their relationships with all other members of the network, every relationship would be described by 2 people. The data matrix would contain 3,540 (60 × 59) descriptions of 1,770 (3,540 ÷ 2) relationships.

Now, assume that only 45 network members complete their questionnaires (Table 1). Between pairs of respondents, there would be 1,980 (45 × 44) descriptions of 990 (45 × 44 / 2) relationships. There would also be descriptions of 675 (45 × 15) relationships between respondents and nonrespondents, each of which would be described by only 1 person (the respondent). There would be no information on the 105 (15 × 14 ÷ 2) relationships between pairs of nonrespondents.

Thus, with a 75% response rate, there are complete data for only 55% of the relationships in the network. There are no data on 6% of the relationships, but there are partial data for the remaining 38%. In general, if the response rate is *R*%, there will be complete information on only *R*% × *R*% of the relationships in the network.

Unfortunately, Knoke and Kuklinski (1982) are correct when they write that there is "no failsafe solution to the missing data problem" (p. 35) in network analysis. The reality, however, is that incomplete data matrices, such

TABLE 1
Linkage Information in a Network With Nonrespondents

	A 60-Person Network With 15 Nonrespondents (75% Response, 25% Nonresponse)			*A 60-Person Network With 0 Nonrespondents (100% Response)*
Who is connected?	*Respondents and respondents*	*Respondents and nonrespondents*	*Nonrespondents and nonrespondents*	*Respondents and respondents*
Descriptions present	1,980	675	0	3,540
Descriptions missing	0	675	210	0
Type of information	Complete	Partial	None	Complete
Relationships	990	675	105	1,770
Percentage of all relationships in the network	56	38	6	100

as the one illustrated in this example, are common, and therefore issues about how to analyze them are important to address. The discussion begins by identifying approaches that have been suggested in the social science literature for the analysis of nonnetwork data sets and then considers the appropriateness of these approaches to the analysis of network data sets.

HOW SOCIAL SCIENCE HANDLES MISSING DATA

When surveys are used to gather data about individual-level attributes and characteristics (e.g., age, sex, education, organizational tenure, attitudes, values), it is assumed that individuals' responses are independent of one another. Whether Person A responds (or how Person A responds) has no effect on Person B's responses. The value attached to a particular variable for one person is independent of its value for another person. In survey research of this type, matrices with missing data can be analyzed in several different ways. These include *complete-case analysis*, *available-case analysis*, and *imputation* (Little & Rubin, 1989/1990). The simplest approach – to use only complete cases – is often the default option in statistical analysis programs such as SPSS. Complete-case analysis ignores data by discarding all incomplete cases. The second approach includes both complete and incomplete cases and uses whatever data are available for a given analysis. To calculate univariate statistics, for example, the available-case method uses all cases for which data on the particular variable are available. With imputation, missing values are replaced by estimated values, and the resulting complete rectangular data matrix is then analyzed.

These three general social science approaches have been operationalized in many different ways (Armstrong & Overton, 1977; Daniel, 1975; Goudy, 1976; Hawkins, 1975; Little & Rubin, 1987, 1989/1990). Some of these methods assume that variables are independent of one another, others do not. None deals with the handling of such data sets when independence among cases (rather than variables) is an issue, as is the case in network analysis.

HOW NONRESPONDENTS IN NETWORKS CAN BE HANDLED

If a complete-case approach is used for the analysis of incomplete network data sets, all partially described links would be discarded. Only completely described links would be retained in the analysis. With a 75% response rate (as in the earlier example), this approach would use only 56% of the links in the network and would seriously weaken any analysis at the system level. To operationalize an imputation approach, researchers would have to supply linkage descriptions where none exist, that is, between pairs of nonrespondents. With no information on these relationships, imputing relationship descriptions is not reasonable.

An available-case approach applied to network analysis would use both fully described links (two descriptions) and links that are only partially described (one description). To use partially described links, the assumption is that *if* A describes a relationship with B, that, indeed, a relationship does exist between them. This assumption is operationalized by ascribing Person A's description of the A-B linkage to B as well. Although this approach, which we are calling *reconstruction*, may seem analogous to imputation, there is a difference. Reconstruction in network studies does not add links to the data set where there were none. Rather, reconstruction simply allows the description supplied by one person to be how the link between two people is described. The presence or strength of a relationship is simply determined by one description rather than two.

Ascribing respondents' descriptions of relationships that they have with nonrespondents to their nonresponding partners results in a symmetrical data set. With 15 nonrespondents in the 60-person network example, 675 (15 × 45) present and absent links from nonrespondents to respondents can be reconstructed. Because we do not know who the nonrespondents talk to, we assume they talk to people who report talking to them, and we can ascribe the link descriptions supplied by respondents to their nonresponding partners.

JUSTIFYING RECONSTRUCTION

The approach outlined above has intuitive appeal and appears to be a common approach in network studies (Alexander & Danowski, 1990; Finet & Shook, 1988; Lievrouw, Rogers, Lowe, & Nadel, 1987; Rice, Grant, Schmitz, & Torobin, 1990). However, in this section we argue that, like many other aspects of data manipulation and analysis, reconstruction needs to be justified. This discussion highlights the conditions that make reconstruction a justifiable strategy in communication network studies.

There are two criteria that should be satisfied before reconstructing missing linkage descriptions in communication network studies. The first is that respondents should not be systematically different from nonrespondents. The second is that the data available from respondents should be reliable descriptions of the relationships that they have with nonrespondents.

RESPONDENT AND NONRESPONDENT SIMILARITY

Nonrespondents and respondents should be compared in two ways—using individual-level data and using data that describe their patterns of communication. The first comparison should use variables that have been shown to influence or constrain communication in organizations. Such variables could include sex, age, race, tenure, department, professional training, physical location, and level in the organization (Allen, 1977; Klauss & Bass, 1982; Lincoln & Miller, 1979; Rogers & Kincaid, 1981; Roberts & O'Reilly, 1979; Sproull, 1981).

The communication patterns of respondents and nonrespondents should also be compared. Although not immediately obvious, it is indeed possible to compare at least some aspects of the communication patterns of respondents and nonrespondents. To analyze communication patterns, those who have provided data (i.e., respondents) are conceptualized as link senders. People with whom respondents communicate are the link receivers. Receivers would include both respondents and nonrespondents, because respondents describe the relationships that they have with both nonrespondents and respondents. Thus the data available from completed sociometric surveys may allow respondents and nonrespondents to be compared in terms of the links they receive. By combining data about received links with the individual-level attribute data, the two groups (respondents and nonrespondents) can be compared in terms of the number and strength of links that they receive and from whom they receive them (men, women, long tenure, short tenure, managers, subordinates, etc.).

RELIABILITY: CONFIRMATION

The reliability of the linkage descriptions supplied by respondents will also influence the appropriateness of reconstruction. In this context, *reliability* refers to interrater reliability, operationalized in network studies as confirmation, or the extent of agreement between people on the nature of the relationship (or relationships) between them. Confirmation can be operationalized only for pairs of respondents, so the confirmation rate in a network depends on the proportion of pairwise links described similarly by both people involved. If nonrespondents are similar to respondents and the confirmation rate is high, the assumption is that a single linkage description can reliably characterize the link between a respondent and a nonrespondent.

The distinction between undirected and directed communication is important in the operationalization of confirmation. "Converses with" or "talks with" are examples of undirected communication. "Informs" or "gives advice to" are examples of directed communication. With directed communication, the message is sent from a message sender to a message receiver (Shannon & Weaver, 1949). With undirected communication, the two communication partners are more accurately described as transceivers (de Sola Pool, 1973) in the communication process.

With undirected communication, a report from Person A of a conversation with Person B would be confirmed if Person B also reported that a conversation took place. Such confirmation would indicate a reciprocal relationship between the two. In the case of directed communication, confirmation is not the same as reciprocity, and therefore using confirmation to argue for reconstruction is more complicated. If Person A indicates that he has given advice to Person B, A's description would be confirmed if B indicates that advice had been received from A. In studies of directed communication, confirmation can be established only if both functional sides of a relationship have been measured. In an advice-exchange network, this would mean asking individuals not only from whom they get advice but also to whom they give advice.

The decision to reconstruct missing linkage descriptions should be based on an assessment of respondent and nonrespondent similarity and data reliability. There are, however, no hard and fast rules for deciding when confirmation rates are high enough or when nonrespondents and respondents are similar enough. These are judgments that researchers must make. Authors, however, should report confirmation rates and should describe how similarity was assessed when they use reconstruction to minimize the impact of missing data in a communication network.

AN EMPIRICAL NETWORK STUDY WITH NONRESPONDENTS

A study of the work communication network of a young and growing research and development organization (Stork, 1991) is used to show how respondent and nonrespondent similarity and confirmation can be operationalized and to describe some nonrespondent problems that cannot be overcome even when linkage descriptions are reconstructed. In this study, network analysis was performed using NEGOPY (Richards, 1986). This program was chosen for two reasons. The first is that NEGOPY was designed specifically for the analysis of communication networks and has been widely used for that purpose (Eisenberg et al., 1983; Lievrouw et al., 1987; Monge et al., 1983; Papa, 1990; Rice et al., 1990; Wigand, 1988). The second reason is that it has been suggested that NEGOPY is "less sensitive to missing data than other sociometric programs" (Roberts & O'Reilly, 1979, p. 49).

The site for this study of work-related communication was "Ultra," a research division of a multinational pharmaceutical company. Ultra was established at the end of 1983, as a basic and applied pharmaceutical research organization. Its initial goals were focused on the creation and expansion of knowledge and technology in a specific medical area.

The study focused on the evolution of Ultra's work communication network. It was hypothesized that over time, Ultra's work communication network would become increasingly structured, less dense, and more differentiated into groups.

Method. Ultra scientists were asked to complete sociometric questionnaires in three successive years (1984, 1985, and 1986). Each questionnaire asked them to think back over the past couple of months and to indicate how frequently they had work conversations with every other member of the scientific staff. The names of all Ultra scientists were presented below the instructions, and people were asked to respond to every name. For each name, they were instructed to place a check mark in the column that best described the frequency of their work conversations with this person. Column choices included once every 2 weeks, once a week, two or three times a week, every day, and less often than once every 2 weeks. Questionnaires were distributed to everyone, but not all were completed and returned. Response rates were approximately 80% for 1984 and 1985 and 54% for 1986. Demographic data were obtained from personnel records. Interview and observation data were also collected.

Data analysis. Although a number of different analyses were performed, this discussion focuses on using NEGOPY. It describes the program, highlights the logic used to justify reconstruction, and also shows that NEGOPY is indeed sensitive to missing data.

NEGOPY represents a relational rather than a positional approach to the analysis of networks (Burt, 1980) and, therefore, defines groups in the network on the basis of the amount of contact among nodes. In a communication network, NEGOPY identifies groups of individuals who communicate more with one another than with individuals in other groups. The program defines a group using strict criteria, that is, at least three people, all of whom must have more than one half their communication with other members of the group. On the basis of individuals' connections with others in the network, NEGOPY also assigns each person to one of several role categories, including group member, isolate, and liaison. NEGOPY does not permit people to belong to more than one group or to be assigned to more than one communication role.

NEGOPY calculates various network indices and measures. Network density is the ratio of member-to-member links divided by the maximum possible number of links. NEGOPY's structural index (SI), a measure of the amount of order or organization in a network, "is defined as a deviation from complete chaos, so that a value of zero would indicate that the system is essentially random, and a value of one would indicate total constraint or maximum order" (Richards, 1988a, p. 599).

To construct the SI, NEGOPY computes the number of triads (where A, B, and C are all connected) found in the network. NEGOPY calculates how many triads would be expected in a random network of the same size, density, and linkage distribution and the maximum possible number of triads in such a network. The observed number of triads is then compared to both the maximum number and the number expected in a random network. Higher SI values indicate less randomness, or more structure, in the network.

For input, NEGOPY requires a list of all pairwise links between members of the system. This list may also include information about the frequency of interaction.

In dealing with data sets that include nonrespondents, NEGOPY provides three ways of creating a symmetrical data matrix. At one extreme, all one-way links are dropped (a complete-case approach). At the other extreme, a single report of a link between two people is sufficient evidence for the existence of a connection between them (analogous to available case). The third approach is a compromise between the other two, in that a single description of a strong link is used to reconstruct the missing description, and single descriptions of weak links are dropped.

In the Ultra study, the first decision was whether NEGOPY should be instructed to reconstruct the missing halves of links. Therefore, respondents and nonrespondents were compared, and confirmation rates were calculated. Comparing respondents and nonrespondents in terms of their attributes and their patterns of communication meant working with two different units of analysis — people and connections between people. Although other programs could have been used for this analysis, we chose to use FATCAT (Richards, 1988b), because it was designed to combine data files describing different units of analysis and because it works with a NEGOPY data file. FATCAT uses two files of data — a file containing the pairwise linkage information and a file containing information about individuals in the network.

FATCAT was used to merge the linkage data file with the demographic data file, which included the variables sex, age, physical location, level of education, and scientific discipline. Each of these was a variable for which data were available for all scientists. Because FATCAT requires categorical descriptors, ordinal and interval data like age and educational level were coded as categories (e.g., without Ph.D. and with Ph.D.). The program sorted scientists into categories using each of the variables. Respondent status (respondents and nonrespondents) and variable categories were cross tabulated, and results showed no significant relationships between the demographic variables and respondent status.

To analyze linkage patterns, respondents and nonrespondents were compared in terms of how many links they received and from whom they received them. Communication links were operationalized as coming *from senders* and going *to receivers*. (Senders are those who described their links; receivers are those to whom links were sent. Receivers included both respondents and nonrespondents.) Respondents and nonrespondents did not differ in the number of links that they received from link senders. By categorizing link senders (respondents) using the demographic variables (sex, educational level, etc.), it was also possible to compare from whom respondents and nonrespondents received links. Chi-square analyses showed no significant differences between the expected number and the observed number of links sent from different categories of scientists to respondents and to nonrespondents. Using the available data, we concluded that respondents and nonrespondents had similar attributes and similar patterns of received links and, therefore, that reconstruction might be justified.

The second criterion for justifying the reconstruction of missing linkage descriptions is the reliability of the available descriptions, operationalized using confirmation rates. If binary data had been collected, confirmation would have been straightforward—when A reported a communication link with B, did B also report the communication link? However, in this study, frequency data were also collected. The approach taken to confirmation was similar to that used by Hammer (1984). We defined a confirmed link as one in which both persons indicated a link and assigned it to the same frequency category or adjacent frequency categories. Using this operationalization, confirmation rates for each of the 3 years was close to 90%.

Using the similarity and confirmation criteria, a decision to reconstruct missing linkage descriptions seemed justified. Both fully described links (two descriptions) and partially described links (one description) were retained in the data set, and NEGOPY was instructed to reconstruct the missing halves of partially described links.

Before the analysis could proceed, it was also necessary to tell NEGOPY how to handle the situation in which frequency estimates for a single relationship differed. In that case, NEGOPY was instructed to use the mean of the two as the measure of link frequency. All other NEGOPY parameters were left at their default values.

Results. The hypotheses tested in this study were supported by the results, some of which were based on NEGOPY analyses, others that were not (see Stork, 1991). Although it was possible to show that Ultra's work communication network became increasingly structured, more differentiated, and less dense over time, the use of NEGOPY in the generation of results was complicated because the program is, in fact, sensitive to missing data. Given the program's popularity, it is important to understand its sensitivity.

Conclusions about NEGOPY. The NEGOPY program relies on the identification of completed triads (in which Persons A, B, and C are all connected) in the calculation of the Structural Index (SI). The argument that follows shows why, with nonrespondents, a network will appear less structured than it really is.

Assume there are four people. A and D are respondents; B and C are not. Both A and D report links to B and C. If there is a link between B and C, there would be two completed triads (ABC and DBC). But, because neither B nor C is a respondent, we cannot know if this critical link exists. If the link exists and either B or C was a respondent, the completed triads could be identified. With both B and C being nonrespondents, the ABC triad and the DBC triad will be incorrectly classified as incomplete, and the calculated SI will underrepresent the true value. Missing data caused by nonrespondents appear to result in SI values that are too low.

Further simulation analyses (Stork, 1991) support the conclusion that in networks containing nonrespondents, NEGOPY will underestimate the amount of structure. These analyses provide evidence that NEGOPY's density estimates and its group-identification procedures are also affected by the presence of nonrespondents. With nonrespondents, density estimates are too low, and NEGOPY underestimates the amount of differentiation into groups.

Although reconstruction may lessen the impact of nonrespondents in the network by assigning linkage descriptions of respondents to their nonresponding partners, some links cannot be reconstructed. These are the links that connect pairs of nonrespondents. There is no information about these links, and they are completely ignored in the analysis. Thus, even if reconstruction is appropriate, researchers would like to have data from as many network members as possible.

RECOMMENDATIONS FOR DESIGNING NETWORK STUDIES

In this concluding section, we offer several suggestions for the design of communication network studies that will encourage a high response rate and provide the information needed to make informed decisions about how to analyze networks that include some nonrespondents. The goal is to highlight steps that can be taken to ensure that complete and meaningful sociometric data are collected from as many network members as possible.

The first suggestion relates to the administration of sociometric surveys. Although it is not always feasible to administer questionnaires in a group setting, this approach appears to enhance response rates. By administering sociometric questionnaires to groups, rather than to individuals, Monge et al. (1983) obtained a response rate of nearly 90%, and Albrecht and Ropp (1984) reported usable data from over 90% of network members.

Whether administered individually, with respondents completing questionnaires in their own time, or administered in a group setting, the design of the instrument may also affect the response rate and the completeness of the data that respondents provide. When the size of the network permits the use of a roster—with all network members listed—a roster should be used, and often is (Albrecht, 1984; Eisenberg et al., 1983; Papa, 1990; Wigand, 1988). In addition to making it easy for people to respond (and therefore increasing the likelihood of a high response rate), providing a roster of names lessens the likelihood that respondents will overlook certain of their relationships. Without a roster, it is not possible to tell whether A does not identify a relationship with B because there is no relationship or because A has simply forgotten about B. Using a roster approach increases the likelihood that weak links, as well as strong links (Granovetter, 1973, 1982), will be described.

To collect meaningful communication network data, the sociometric questions should clearly reflect how the communication relationship is conceptualized, particularly with respect to directionality. In studies of directed relationships, questions should be asked that capture both sides of the relationship. To analyze advice networks, for example, questions should be asked about both getting advice and giving advice. If only one half of a directed relationship is measured, it is not possible for one respondent to confirm what another says about the relationship between them. This would make it impossible to assess data reliability and would, therefore, also limit the ways in which unconfirmed links should be treated.

Whether the relationship is directed or undirected, instruments that ask for binary data only (presence or absence of links) yield weak descriptions of linkages and relationships. This makes it impossible to distinguish between links of varying degrees of significance and reduces the number of options available for handling missing and discrepant descriptions. Strength, frequency, or intensity estimates should almost always be part of the measurement strategy, for both measurement reasons and conceptual reasons. Weak links often hold the network together—by facilitating the flow of information and ideas between groups (Friedkin, 1980; Granovetter, 1973, 1982; Weimann, 1983).

As with other types of research, network studies using a triangulation approach to data collection will result in richer information and a more complete picture of the network (Albrecht & Ropp, 1982; Lievrouw et al., 1987; Rogers, 1987). In addition to sociometric surveys, interviews, observation, and other unobtrusive data-collection methods can provide useful data for analysis and can help establish the reliability of the self-report data (Bernard & Killworth, 1977; Bernard, Killworth, & Sailer, 1982).

Our final suggestion relates to the collection of demographic data that can be used to compare respondents and nonrespondents. Given their role in the reconstruction decision, these data are very important. First, such data must be available for all network members—respondents and nonrespondents. This means they must be available from sources other than individual network members. Second, respondents and nonrespondents should be compared using age, sex, physical location, tenure, and other variables that have been shown to influence interpersonal communication in organizations (Allen, 1977; Lincoln & Miller, 1979; Rogers & Kincaid, 1981).

Most often, personnel records will include the kinds of demographic data that should be used for comparing nonrespondents and respondents. Other kinds of variables may also be appropriate for these analyses, although their identification remains an empirical question.

Both researchers and consultants should find these suggestions useful in their efforts to design organizational communication network studies. Although higher response rates are obviously to be preferred over lower response rates, attempts to encourage a 100% response rate are rarely successful, and network analyses are typically performed on incomplete data sets. With this thought in mind at the design stage, efforts can be made to collect the kinds of data that will facilitate the analysis of incomplete communication network data sets.

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