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Abstract

In a previous *MCQ* article, Monge et al. overviewed the fundamental concepts and processes of evolutionary theory and their applications to key issues in organizational communication. This article extends that work by providing an overview of research tools for studying organizational ecology and evolution, including (a) the variation-selection-retention sequence, (b) the likelihood of events occurring over a period of time (event history analysis), (c) transition sequence of populations from one state to another (sequence analysis), (d) relationships among nodes in networks over time (network analysis), (e) simulation of complex relationships and interactions

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(computational modeling), (f) changes in populations' fitness for survival (NKC models), and (g) competitive interdependence among populations over time (predator-prey models). We conclude with a brief review of graphical and qualitative methods.

Keywords

research methods, organizational communication, evolutionary theory, ecology, event history analysis, sequence analysis, network analysis, simulation, NKC models, and predator-prey models

Evolutionary theory was introduced to the field of organizational scholarship more than 40 years ago. Early seminal pieces include Hannan and Freeman's (1977) article, "The Population Ecology of Organizations," Weick's (1979) *Social Psychology of Organizing* (first edition published in 1969), Aldrich's (1979) *Organizations and Environments*, and DiMaggio and Powell's (1983) treatise on neoinstitutionalism. Though once considered a counterpoint, neoinstitutionalism is now widely recognized to have much in common with evolutionary theory (Palmer & Biggart, 2002).

Early evolutionary theorizing and research focused on populations of organizations (Hannan & Freeman, 1977). These populations were defined as sets of organizations that shared the same organizational form or genre (Hsu & Hannan, 2005; McKelvey, 1982), such as newspapers (Delacroix & Carroll, 1983), credit unions (Barron, West, & Hannan, 1994), or gas stations (Usher & Evans, 1996). Although that line of research has continued, the scope of inquiry has expanded considerably. Astley (1985; Astley & Formbrun, 1987) argued that populations should be studied in the context of the other populations with which they interact, not in isolation, as was the tradition in population ecology (see also, Hawley, 1986). Thus community ecology (sometimes called organizational ecology) examines how organizational populations compete and/or cooperate with each other in their efforts to obtain resources from community environments. For example, Powell, White, Koput, and Owen-Smith (2005) showed how five different populations—dedicated biotechnology firms, venture capitalists, research and development institutions, pharmaceutical companies, and government regulators—alternatively contributed to and hindered the emergence of the biotechnology industry over a 10-year period. Thus two strands of organizational evolutionary research exist, one at the population level and the other at the community level, although both are based on the same evolutionary principles. It should also be stressed that the terms *populations* and *communities* are relative and can be used at a variety of different levels. For example, organizations, like

Tennis Channel, can be members of larger populations such as the cable networks that are in turn members of an institutional community, the media industry. Or, they can be communities that contain a variety of different populations like universities that are comprised of multiple schools or colleges. Furthermore, as Rao (2002) points out, "Populations in communities, organizations in populations, and routines within organizations comprise an ecological hierarchy (Baum & Singh, 1994)" (p. 552).

A large corpus of evolutionary and ecological theory and research exists in the organizational literature (Aldrich & Ruef, 2006; Baum, 2002) although little of this work has influenced research in organizational communication (see Dimmick, 2003, and Dimmick & Rothenbuhler, 1984, for exceptions). Recently, however, organizational communication scholars have begun to apply evolutionary theories to communication issues. For example, Bryant and Monge (2008) studied the growth, transformation, and decline of the children's television community from 1950 to 2000. Similarly, Shumate, Fulk, and Monge (2005) studied the evolution of international nongovernmental organization (INGO) community networks over time showing that preexisting links were the best predictors of future links. Weber, Fulk, and Monge (2011) examined processes of legitimation in the evolution of online communities as an organizational form.

In a previous *MCQ* article, Monge et al. (2011) described how evolutionary theory could be applied to organizational communication (see also, Monge, Heiss, & Margolin, 2008). They reviewed fundamental processes of variation, selection, and retention, as well as several other central theoretical mechanisms such as competition and cooperation, growth and decay, and inertia. Investigation of evolutionary processes involves a variety of methodological tools, some of which are specialized for this type of model. This article provides an overview of research tools that have been used to study organizational ecology. These include event history analysis, sequence analysis, computational simulations and several others. The article provides brief descriptions of major evolutionary concepts and processes followed by explications of the methods that have been developed for studying them. Sufficient references are provided to enable interested organizational communication scholars to pursue the relevant details.

Key Evolutionary Concepts and Processes

Evolutionary processes center on variation, selection, and retention mechanisms. Initially, variations are generated, which involves changes to existing structures or behaviors (Aldrich, 2007; Campbell, 1965). Variation can be "planned, unplanned, haphazard, systematic, random, predictable, or heterogeneous"

(Aldrich, 2007, p. 33). Blind variation is produced by random mutations independent of environmental conditions. On the other hand, variation can be based on conscious efforts such as management planning, hypothesis-driven trial-and-error learning, and search activities (Campbell, 1965; Romanelli, 1989). In organizational populations, variation may occur through speciation, or the creation of new organizational forms (Rao & Singh, 1999). Baum and Rao (2004) suggest that institutional changes, technological innovations, entrepreneurs, and social movements can operate as sources of variations in organizational populations or communities. An example can be found in Dimmick's (2003) analysis of communication and media industries. Dimmick explains that "radio music box" (p. 6) was a new variation in the evolutionary process of radio broadcasting, which was born out of an innovative and divergent attempt to utilize sound transmission technology to receive broadcasts of news and music.

Selection processes winnow available variations, selecting for some alternatives and against others. Selection can be conceptualized at various levels of analysis. Poole, Hollingshead, McGrath, Moreland, and Rohrbaugh (2004) note that in the realm of organizational communication, the concept of selection has been applied at the group level. According to this line of thought, humans prefer groups of people who are kin or otherwise homophilous on some dimensions over members of other groups that are less like themselves. Thus, human grouping leads people to select certain altruistic and cooperative behaviors toward members of their own ingroups but not toward members of outgroups (Boyd & Richerson, 2005; see Part 3). At the organizational level, organizational routines are selected through learning or imitation, subsequently creating a new mix of routines (Miner & Raghavan, 1999). At the population level, selection is typically operationalized as the survival or failure of organizations. Depending on the industry context, selection events can be defined in various ways including disbanding, exit to another industry, merger, or acquisition (Dobrev & Carroll, 2003). Selection events at one level can be seen as processes of adaptation and transformation at the higher level of organizational populations (Usher & Evans, 1996) or communities. It is important to emphasize that the selection process operates repeatedly and that new variations are often selected to replace previously selected variations.

Retention occurs when structural inertia is favored in the selection process (Hannan & Freeman, 1984). Under structural inertia, firms persist in organizational routines by pursuing similar sets of activities repeatedly (Gulati, 1999). Inertia is generated, in part, by retention mechanisms that keep the values of selected traits of the members of a population at the same levels

over some extended period of time. The mechanisms that produce this stability come largely “from unbiased sampling and faithful copying of models” (Richerson & Boyd, 2005, p. 68) that exist in the current or previous generations. Change is produced by variation and selection forces that overcome inertia and thus lead to further evolution. Thus, both change and stability are critical factors in the evolutionary trajectory of populations (Richerson & Boyd, 2005). It is also important to note that most evolutionary change is cumulative. As Lenski (2005) says, “both organic and sociocultural evolution may be defined as *the cumulation of heritable or transferable information within populations and its attendant consequences*” [emphasis in the original] (p. 43).

In evolutionary theory, symbiotic and commensalistic relations are theorized based on the relationships that organizations have with environmental resources. When different populations depend on similar resources in the environment, the populations are said to be in commensalistic relations with each other. However, when populations have complementary differences and rely on different resources, they form symbiotic relations (Astley, 1985; Hawley, 1986). For example, in the context of the instruments manufacturing industry, Audia, Freeman, and Reynolds (2006) conceptualized commensalistic relations as populations having similar production processes or serving similar markets. On the other hand, populations that are functionally interdependent, such as those in supplier-purchaser relations, were considered to be symbiotic to each other.

Commensalistic relations can take either of two forms: competitive or mutualistic (cooperative; Aldrich & Ruef, 2006). Barnett and Carroll (1987) distinguished between these two different types of relationships based on whether the presence of organizations of one organizational form increased (competitive) or decreased (mutualistic) the rate of death for organizations of another organizational form. Both competition and mutualism can be either direct or diffuse, depending on whether it happens between pairs of organizations (direct) or among many organizations that are largely anonymous to each other (diffuse; Barnett & Carroll, 1987; Hannan & Freeman, 1989). In the former case, direct competition and direct mutualism can be measured at the interorganizational level. For instance, Bryant and Monge (2008) studied the evolution of the children’s television community over the 50 years that comprised most of its lifespan. Industry participants identified the types of relationships between pairs of eight organizational populations in the community. On the other hand, diffuse competition is often measured by the density of the organizational population as defined by the number of organizations in a given population. Competition within a population for limited environmental

resources influences the number of organizations in a population by determining organizations' chances of survival (e.g., Dobrev & Carroll, 2003; Hannan & Freeman, 1989). Furthermore, some studies emphasize more specific diffuse measures of competition such as scale-based and/or localized competition, which incorporate organization size and/or geographic location (e.g., Hannan, Carroll, Dundon, & Torres, 1995; Ruef, 1997).

Another key concept that underlies a variety of ecological processes is niche width (Hannan & Freeman, 1977, 1989), sometimes also referred to as niche breadth (Colwell & Futuyma, 1971). Organizations, organizational populations, and communities as well as messages and message campaigns exist in niches that contain resources, some of which are abundant, others of which are scarce. Niche theory distinguishes between generalist and specialist forms (Baum & Singh, 1994; Carroll, 1985; Freeman & Hannan, 1983). Generalist organizations encompass a wide range of resources, while specialist organizations focus on a narrow set of resources. For example, major newspapers are generalists that have a broad base of readers, while blogs are specialists because they usually target a narrow set of readers. In another example, microbreweries and farm wineries are specialist organizations that produce particular types of beer and wine products (Swaminathan, 2001). Dimmick, Chen, and Li (2004) provide an example of applying niche theory to explain competition within and between media industries. For instance, the extent to which different media, such as newspapers and the Internet, overlap in their ability to satisfy users' various needs helps explain how these media are used and displaced.

The emphasis on organization–environment relations that is central to evolutionary theory is shown in the concept of imprinting as well. Organizational imprinting theory suggests that the founding context of organizations has a lasting impact on the character of the organizations (Stinchcombe, 1965). The founding environment includes various political, economic, cultural, and technological elements that influence entrepreneurs (Johnson, 2007). In an archival analysis of the Paris Opera, Johnson showed how an organization's environments at its founding is incorporated into its entrepreneurship and subsequently reproduced throughout the course of the organization. Scholars have suggested that imprinting affects various organizational outcomes such as managerial structure (Baron, Hannan, & Burton, 1999) and survival (Romanelli, 1989; Swaminathan, 1996) as well as interorganizational networks (Marquis, 2003). For example, Marquis compared local intercorporate directorship networks in 51 U.S. major cities in 1986 and 2000 and found that the technologies available at the time of founding continued to influence subsequent communication patterns.

The concept of imprinting can be extended to organizational characteristics across generations, as suggested in the studies of organizational genealogies

(Aldrich & Pfeffer, 1976). In a study based on the population of law firms in the Silicon Valley, Phillips (2005) found that gender inequality that existed in the parent firms was transferred to the progeny firms through organizational routines. The above ideas explain why organizational forms or structures persist despite environmental changes over time, therefore relating to the concepts of inertia and path dependence. Together with organizational change (e.g., Barnett & Carroll, 1995), inertia constitutes a central theme in organizational ecology. The relative inertia hypothesis suggests that “organizations are typically unable to match structural changes to their competitive environments in a timely fashion” (Ruef, 1997, p. 837). These constraints on change also affect inertia in interorganizational networks (Kim, Oh, & Swaminathan, 2006). In addition, the path dependence hypothesis specifies that the evolution of an organization to its present or future state is not only influenced by the selective pressures in the environment but is also dependent on the previous sequence of events affecting organizational growth (Carroll & Hannan, 2000). Early choices by an organization may dictate future growth because the possible paths of organizational growth are limited by these early constraints (Levinthal & Warglien, 1999).

In addition to these key concepts and processes, there are several explanatory covariates that are important in evolutionary research. These covariates will differ depending on the objects of study, such as messages, processes or organizations. For organizations, there are several important covariates. First, basic demographic variables need to be accounted for when developing an evolutionary study. These include organizational size (see Dobrev & Carroll, 2003, for a literature review), organizational age, and tenure in a particular population. In addition, some scholars suggest that the order of entry of an organization into a population is important because it can provide first-mover advantages or late-entrant advantages (Sorenson, 2000, p. 583). Second, environmental conditions should be taken into account where relevant and/or feasible. These include density, density at founding, economic conditions in particular time periods (Dobrev & Carroll, 2003), regulatory changes (Ruef, 1997), industry events (Madhavan, Koka, & Prescott, 1998), and technological cycles (Tushman & Anderson, 1986).

As the preceding review suggests, organizational researchers have used evolutionary theory to describe and explain a wide array of phenomena at multiple levels of analysis. Consequently, there is no single method or family of methods that can be applied in every research context. Thus, when thinking about methods for testing evolutionary theories, it is useful to first consider potential questions that can be developed and tested.

For instance, researchers may wish to examine how communicative decision-making processes change over time, or to study how teams within an

organization decide to adopt and use a new form of communication technology. Likewise, the diffusion of new communication technologies through organizations or groups can be addressed with evolutionary methods. Researchers studying organizational culture and change can use evolutionary theories to address transformation in organizational cultures and the effects of changes in management communication strategies. Methodologically, tools exist that allow researchers to identify patterns in changes over time, such as variation methods, event history, sequence analysis, and time series.

In addition to the above, other questions of interest may include addressing how organizational positions evolve within information and communication resource niches. For example, research could investigate how cloud computing companies have positioned themselves within the online storage industry to compete for information resources. Looking at predator-prey models (described in the next section), research could be structured to estimate cooperation and competition between different populations of media organizations such as blogs and blog aggregators. A number of methods, such as network analysis, simulation and computational models, organizational landscapes and fitness models, and predator-prey models, are available for researchers seeking to address these types of questions.

What follows is a short description of the major methods used in organizational ecology and evolutionary research. These methods provide a starting foundation for communication researchers interested in studying behaviors linked to organizational phenomena like message competition or studying communicative ecological processes that occur between individuals, groups, organizations, or industries. Despite the variety of applications for these methods, evolutionary phenomena are rarely described with statistics alone; mixed-methods research, including the use of interviews and historical records, often helps to accurately describe evolutionary processes. Table 1 illustrates the research questions above, the related theoretical mechanisms, and the methods for analysis. In addition, two broad classes of methods are presented that augment statistical techniques: graphical analysis and qualitative methods. These methods can be complementary to statistical approaches or can serve as a precursor to the selection of an appropriate statistical technique.

Research Method

Variation Methods

Communication researchers often are interested in examining how processes change over time. Studies of variation look at many phenomena, including

Table 1. Illustrative Evolutionary Research Questions, Theoretical Mechanisms, and Methods

| Illustrative research questions | Theoretical mechanisms and models | Representative methods |
|---|--|--|
| How do communicative decision-making processes change over time? | Variation in populations (variation-selection-retention processes) | Genealogy models |
| How do new communication technologies diffuse through groups or organizations? | Isomorphism; communication technologies and message genres | Event history analysis Genealogy models Entropy measures to track change in a population |
| What are the effects of changes in management communication strategies? | Diffusion of innovations; evolutionary models of change in management communication strategies | Time series analysis |
| How do companies position themselves within a communication ecosystem to compete more effectively for scarce resources? | Community ecology and fitness landscapes models | Computational models & NK(C) models |
| How do populations of organizations and messages compete and cooperate with one another? | Community ecology; commensalist and symbiotic network ties | Predator–prey models & Lotka–Volterra equations Network analysis |

whether a population of similar entities, such as the texts that comprise a discourse, are becoming more or less similar to one another over time, or how a group of individuals vary their interactions or work processes over time.

Genealogical studies of evolutionary processes are one method for studying how groups vary and develop over time. Genealogical studies trace the “births” and “deaths” of organizations or processes within a population; these events are then used as markers denoting the origination or termination of a process or an organizational generation. An organizational genealogy is a record of critical events in a community’s history with visual representation illustrating branching (the emergence of new variations) and persistence (the duration of a given variation) through a timeline graph (Van de Ven & Grazman, 1999). These transformations may occur as the result of environmental shocks or shifts; for example, a change in technology standards may drive a

company to adopt a new organizational structure. Over time, the variations created by these events may recombine into new forms, revert back to previous incarnations, or develop new unexpected variations. Van de Ven and Grazman used genealogical techniques to illustrate the development of the health care community in Minneapolis over a 140-year period. By mapping out the emergence of variations, the study showed that branching and adaptation (e.g., the adoption of prepaid health care plans) are more apt to occur during periods of resource wealth, while a focus on institutional reinforcement, such as the formation of alliances and the strengthening of senior management, is more likely during periods of scarcity.

Phillips (2005) looked at the genealogical transfer of knowledge among law firms in Silicon Valley. Rather than mapping genealogical processes, this study tracked the movement of personnel from one firm to another and showed that the transfer of tacit knowledge via people increases the chances of survival for a new firm and decreases the chances of survival for an existing firm. Kitts (2009) looked at the evolution of organizational forms of communes in the United States from 1609 to 1965. This study treated organizational forms as a template retained by organizations from generation to generation. Using the concept of template, this research suggests that organizational form have a life cycle independent of the organizational age. In Kitts' study, for instance, communes that had formed around ethnic identities had a very limited lifetime when organized solely as "ethnic communes." Some communes, however, were able to extend their lives as individual organizations by adopting new templates, such as transforming into municipalities. The genealogical framework provided a setting for studying this ongoing process and mapping out changes from generation to generation. From an organizational communication perspective, these methods hold potential for the study of communication genres. For example, Yates (1989) argued that the office memo genre grew out of the more established business letter genre in response to technological and cultural changes in the late 19th century.

In addition to mapping the specific variants that emerge along particular genealogical paths, researchers can track the overall degree of variety in a population over time. Increases in variety often signal that a population is moving toward exploration of and experimentation with new ideas. These shifts often not only increase the probability of discovering valuable, previously untried innovations but can also decrease average fitness or performance in the short term, a phenomenon described by March (1991) as the exploration-exploitation trade-off.

McDonald and Dimmick (2003) reviewed several measures of variety, which they also referred to as measures of diversity or measures of concentration

(concentration being a reversed scaled measure of variety or diversity). They found that diversity is a concept that contains two basic dimensions: the number of categories or types over which a set of observations may be distributed and the degree to which these observations are evenly distributed among these categories. While several measures are mathematically equivalent to one another, they found that there are three basic implementations for calculating this two-dimensional concept. Probability or proportional measures rely on the direct proportion of element counts for each category. The best known of these is Simpson's D. "Simpson's D reflects the probability that two elements picked at random from a population come from the same category" (p. 67). The advantage of Simpson's D is its ease of interpretability. Another category of measures reflects these proportions where one or both of the proportions are transformed into a logarithm. The best known of these is Shannon's H. The advantage of this more complex measure is the ease with which variation can be partitioned such that independent contributions to changes in the measure can be identified (McDonald & Dimmick, 2003, p. 76). They describe another set of measures as "ranking"-based measures (p. 69). These include Hall and Tideman's measure of concentration, which weights proportions by the rank of the categories, and Fager's NM, which is based on the number of moves required to transform the observed distribution into a uniform distribution. This is similar to the rationale employed in optimal string matching (described in detail below).

Each of these measures addresses a similar basic question: given the complete set of combinations of attributes that members of a population may possess, to what extent are any particular combinations observed more frequently than others? When all possible combinations are equally represented in the population, variety is high. When a few combinations are dominant and a large number of combinations are unrepresented, the population has low variety. For example, if all memos contain the "to," "from," "date," and "re" features, scores on these measures will be low, indicating the genre has low variety (Yates, 1989). If, however, many memos contain a subset of these features, but no particular subset is more common than any other, entropy will be high, indicating high variety.

These methods can be applied to track changes in the variety and co-occurrence of features in new communication technologies as well as message genres (Yates & Orlikowski, 1992). Frenken and Nuvolari (2004) use Shannon's H-based measures to track the variety and speciation in steam engine designs from 1760 to 1800. They categorized steam engines in terms of whether they possessed each of 7 design features. Under high variety, all design features would occur with roughly the same frequency. As designers

favor some features and include them more frequently than others in engine designs, variety declines. To capture speciation, Frenken and Nuvolari measured the degree of co-occurrence of features. Co-occurrence of features suggests particular forms of designs with clusters of complementary features. Frenken and Nuvolari found that variety was extremely low in the early history of the steam engine as there was only one dominant design to which all steam engines conformed (the Newcomen engine). Starting in the early 1770s, several new designs were experimented with and variety increased. Subsequently, as designers found useful, complementary design feature combinations, alternative species such as the Watt engine emerged.

In addition to variation in individual communication practices or technologies, communication researchers may be interested in the sequential variation of communication processes, such as dialogues. Pentland (2003a, 2003b) articulated a distinction between content variety and process variety. Content variety refers to variety in inputs and outputs, whereas process variety refers to variety in the steps that can be taken to turn inputs into outputs. Process variety can be further subdivided into task variety, which refers to the number of different procedures that an organization or organizational subunit deploys, and sequential variety, which refers to the number of different orders in which these procedures are deployed. An organization's response to customer complaints can serve as an example. When an organization mandates that customer complaints be submitted in a specific online form, it reduces input variety. When all complaints are compensated with a financial reward, the organization has low output variety. When all complaints are routed through a small number of procedures, the organization has low task variety. When these procedures are always performed in the same order, the organization has low sequential variety.

Pentland (2003a) tested three measures of sequential variety with simulated data: optimal string matching, algorithmic complexity, and deviation from random or "Markov variety." The simulation results indicate that both optimal string matching and Markov variety are reliable measures, while algorithmic complexity becomes unstable with even modest numbers of random deviations in the sequences.

Optimal string matching variety is calculated using sequence comparison methods (described in detail below). In this method, each observed sequence of tasks is compared to each other observed sequence of tasks such that a distance can be calculated between them. The average sequential distance across all pairs can then serve as a measure of the total sequential variety in the system. Continuing the example from above, the complaint department may have a small degree of sequential variety, but this variety may be increasing

over time, perhaps indicating that its procedures are under increasing strain or that a new, more effective sequence is more likely to be found.

Pentland (2003b) also suggested a measure of Markov variety. This measure follows a similar logic to the variety statistics described above but applies to adjacent pairs within sequences. Markov variety captures the degree to which enacting one task predicts that a particular task is highly likely to follow. For example, if complaints of a certain type are always addressed first with a letter to the complainant acknowledging receipt and then with an investigation of the merits of the complaint, Markov variety would be low. Compared to optimal matching, Markov variety looks only at pairs of actions adjacent in time (immediately preceding or following a given action) and ignores similarities or differences in prior history. The advantage of this simplifying assumption is that computation is substantially simplified and is recommended when the number of sequences is high. The ability to accurately measure variety has important implications for the assessment of the consistency of routines, such as equitable service to all of an organization's clients or the ability to innovate in response to changes in environments.

Event History Analysis

Event history analysis is a common technique for testing evolutionary hypotheses (Carroll & Hannan, 2000). In event history models, the dependent variable is the occurrence of an "event." Event history models estimate the risk or likelihood of the event occurring given a set of covariates. Many organizational phenomena can be viewed from an event history perspective, such as the members of an organizational population who start, drop out of, or complete a training program, or the sequence of events in career paths. Therefore, event history analysis is one of the most commonly used ecological analyses.

Although there are many standard techniques for the analysis of categorical variables, such as logistic regression, most of them are not well-suited for the analysis of event histories (Allison, 1984). For example, consider a study of organizational information systems. As a new internal communication system is introduced to an organization, the researcher is interested in the variables affecting people's decision to adopt the technology. With a traditional approach such as logistic regression, decisions to adopt are regressed on the explanatory variables, such as gender, educational level, and experience with technology. The model attempts to predict the relative likelihood or probability of an event occurring. This likelihood is converted to log-odds (i.e., logarithmic odds, the logarithm of the ratio of the probability of an event

occurring divided by the probability that it will not occur) thus permitting estimation in a linear model.

This logistic regression approach has limitations. One might reasonably assume that the longer it has been since the technology has been introduced to the organization, the more likely it will be adopted. Yet a study usually has a finite—and usually arbitrary—window of observation. Therefore, those people who still have not adopted the technology at the point of data collection may adopt it later, after the observation ends, but their adoption decisions are not reflected in the data analysis. In a standard logistic regression model, those late adopters are simply treated as nonadopters, adding bias to the analysis. This problem is referred to as “right censoring,” which occurs when the observation period ends before the event has occurred in a particular observation case. In a censored observation, the risk of the event occurring is eliminated by the study design rather than by any properties of the observed entity itself.

Even if the observation is not censored, another problem inherent in the standard logistic regression approach is how to incorporate time-varying explanatory variables. These are predictors that change over time, such as experience with technology and the adoption decision of one’s supervisor. In contrast, fixed covariates such as gender stay the same across the whole observation. Time-varying explanatory variables are difficult to capture with logistic regression without adding a large number of correlated predictors (e.g., adoption status of supervisor at Time 1, adoption status of supervisor at Time 2, etc.).

Event history analysis consists of a set of techniques that are developed to properly handle these two common problems—right-censoring and time-varying explanatory variables (Tuma, Hannan, & Groeneveld, 1979). The technique corrects for “censoring” of data. If data collection ends 12 months after the communication technology is introduced into the organization, the ultimate adoption decision of all the personnel that still have not adopted the technology by then is not known. In an event history model, this lack of information is accounted for by evaluating cases in terms of the time periods, called spells, during which they are “at risk” for an event. By considering the full set of time intervals, event history analysis incorporates information about how long employees resisted adoption rather than evaluates whether they adopted before the completion of an arbitrary observation window, correcting the censoring distortion. Event history analysis can also incorporate time-varying covariates over the full time range under consideration. In this way, event history analysis is well-suited for the analysis of dynamic and longitudinal processes.

The specification of event history models is determined by several important factors, including the type of outcome variables, the assumption of the temporal distribution of events, and the role of randomness, among others (Carroll & Hannan, 2000). Perhaps the most important consideration for organizational communication scholars is the ecological process of interest. If the focus of the research is the likelihood of an event occurring in a given population, such as the adoption of a communication technology within an organization, it is typical to model the “risk” or “hazard” of such an event using hazard functions. Hazard functions describe the likelihood of events occurring at any particular point in time given that the observed cases are “at risk” for the event (Allison, 1984). Most studies on organizational failure and transformation have used hazard models (e.g., Amburgey, Kelly, & Barnett, 1993). Alternatively, if the process of interest is the event not occurring, such as not adopting the technology, it is typical to model the likelihood survival functions. For example, Carroll and Delacroix (1982) estimated the survival probabilities of newly founded newspaper organizations. Finally, a modified technique is used for cases in which the research questions are related to the likelihood of an event occurring where the at-risk population cannot be observed. For example, in the case of organizational foundings or the birth of new organizational forms, the researcher can observe the occurrence of the event (organizational foundings) but not the complements to the event (foundings that could have occurred but did not). For these cases, data are typically collected in the aggregated form of event counts at different time intervals. Poisson regression and negative binomial regression models are usually used to estimate the probability of events based on aggregated count data (Carroll & Hannan, 2000). For example, Schulz (1998) examined whether bureaucratic rules generate more rules in a large organization by modeling the rule birth rate.

Sequence Methods

An important phenomenon in evolutionary analysis is the transition of populations or population members from one categorical state to another. For example, a communication researcher may be interested in changes in stages of dialogue or group argument (Seibold & Meyers, 2007). Optimal matching analysis can be used to group sequences of transitions between categorical states (Abbott & Tsay, 2000). The method has been adapted for social research from research in genetics (Stark & Vedres, 2006). In optimal matching analysis, the categorical state of each case is recorded at each point in time for which it is available. For example, Abbott and Hrycak (1990) illustrate

the method with an analysis of the careers of 18th-century German musicians. At each point in musicians' careers, their "states" were the particular jobs they held, such as organist or music director. As they changed jobs over time, their careers shifted from "state" to "state." These categorical states, arrayed over time for each musician, were the sequences or paths of their individual careers.

The next step in optimal matching analysis is to discern patterns of similar paths across decision-making sequences. This is performed by comparing each individual sequence (decision-making path) to every other individual sequence as a pair. The number of "moves" that would be required to transform the first sequence into the second sequence is then calculated. Sequences that are already similar require fewer moves. The moves can also be weighted based on theoretical assessments of their difficulty. These weights are captured by hypothetical costs of moving from one particular state to another. For example, Stark and Vedres (2006) analyzed the ego network connections that comprised ownership structures between Hungarian companies. They found that transitions from small ego networks to large ego networks required the addition of many ties and thus were considered more costly than transitions from small ego networks to isolated ego networks that required the loss of only a few ties.

Once each move is assigned a cost, a total cost for transforming one sequence into another can be calculated. This total cost serves as a measure of distance between the two sequences. That is, if two sequences require many, expensive moves in order to be made similar, they have little in common. Sequences that share long common subsequences or runs, however, may require few moves and thus require lower costs to be made equivalent. These sequences are more similar. Similar sequences can then be grouped or clustered to form more general categories of developmental paths taken by individuals or organizations in that population (Stark & Vedres, 2006).

Optimal matching analysis has been criticized for vulnerability to arbitrariness because the method makes no prescriptions regarding the appropriate setting of the transition costs (Wu, 2000). Yet previous research establishes that groups often seek to avoid transitions between states to minimize energy expenditure on discussion and conflict. This follows Poole and Roth's (1989b) Energy Conservation Model, which predicted that groups will simplify the decision-making process, when possible, to conserve energy. This criticism points to a potential complementarity with evolutionary models. Evolutionary theory may provide the conceptual tools for appropriately setting these costs by specifying the likelihood of transitions in terms of variations, selection of those variations, and their subsequent retention. For example,

according to evolutionary theory, blind, random variations can be treated as relatively “costless” because they require minimal information to produce, since there is little need for planning or design or resources to perform an evaluation or make a selection. Sequence analysis determines the number of moves required to change one sequence into another, so a transition can be evaluated in terms of its likelihood of occurrence from random variation processes where moves are drawn at random or from a prior distribution. The lower the probability that the transition was due to a blind variation process, the greater the chance that the transition was made using planning or selection processes, and thus the larger the cost of the transition. Conversely, optimal matching methods may provide researchers with relatively simple mathematical tools for capturing the complex, path dependent processes predicted by evolutionary theory.

Using another form of sequence analysis, Poole and Roth (1989a, 1989b) analyzed sequences of the decision-making paths chosen in a series of recorded conversations. Decision-making conversations were broken down into discrete time units, and at each unit the discussion was categorized based on their present phase in the decision process (i.e., problem analysis, solution development, confirmation). Using a technique developed by Pelz (1985), Poole and Roth evaluated the degree to which each phase tended to precede or follow another. Rather than relying strictly on direct transitions from one phase to another, these tendencies reflected the general order in which phases tended to occur. These tendencies were then used to form a matrix containing “precedence scores,” reflecting the degree to which a phase tends to come before other phases, and “separation scores,” the degree to which the phases tend to occur at distinct points in the sequence. The sequence of paths was used to categorize the decision-making sequence for a given group. Using the precedence and separation scores and qualitative analysis, Poole & Roth were able to identify a typology of sequence types.

Time Series Analysis

As in event history and sequence methods, time series analysis allows for the examination of changes over time. However, with the use of time series, dependent variables are not constrained to be events. And, as with event history analysis, time-varying covariates can be used to predict the dependent variables. Time series can be used to estimate and account for the trend (the extent to which the series generally increases or decreases over time) and periodicity (or cyclicity, such as daily, weekly, or annual cycles) of an underlying base model, accounting for noise in the changes over time. In

addition, the effect of either discrete events (represented by interrupted time series designs) or other time series (transfer functions) on the dependent variable series can also be estimated (Williams & Monge, 2001; Yanovitzky & VanLear, 2008). Such effects can be estimated as immediately following the predicting event or lagged to a specific time interval (Williams & Monge, 2001). In addition to being used to predict organizational foundings (Freeman & Lomi, 1994), time series have also been used to estimate ratio-level variables such as the variation in funding in an industry over time (Anderson, 1999). Time series analysis could be used to examine a variety of ecological processes involving organizations and their environment, such as how the strategic promotion of particular issue frames by an organization corresponds to news media coverage of those frames. Furthermore, time series can also be useful for estimating both instantaneous and lagged effects of environmental changes on organizational outcomes and how these effects decay over time.

A number of theoretical and methodological developments have been made to study dynamic processes in organizational communication (e.g., Monge, 1990; Monge & Kalman, 1996; Poole, Van de Ven, Dooley, & Holmes, 2000). Various analyses of management communication processes could be conducted from within the evolutionary paradigm. For example, theories of self-organizing systems (Contractor, 1994; Contractor & Grant, 1996) focus on the emergence of structure and patterned behaviors from local-level interactions. Among ways of modeling and predicting these systems, cellular automata (e.g., Corman, 1996; Lomi & Larsen, 1999; discussed more in the section Computational Models and Simulations) is a simulation method in which cells, initially assigned to a random state, interact with neighboring cells according to a simple set of rules. In the study of organizations, cellular automata have been applied to model the interaction among work units over time as well as the spread of social influence in systems. For example, these computational models can be used to predict the differing patterns of communication technology adoption over time depending on who were selected as initial targets of technology use (Hyatt, Contractor, & Jones, 1997). The focus on processes in these approaches emphasizes that temporal context is an important aspect of communication (Yanovitzky & VanLear, 2008).

Network Analysis

Both intra- and interorganizational networks have been a growing area of research in organizational communication over the past few decades (e.g.,

Barnett, 2001; Danowski & Edison-Swift, 1985; Monge & Contractor, 2003). Networks deliver resources that are unattainable within a single unit, and therefore, are one of the important forces that influence organizational capabilities, learning, and other evolutionary processes such as founding and mortality. Network analysis methods are used to model the relationships among individuals, organizations, or populations, often coupled with conventional statistical techniques to make comparisons across different time points. In a study of alliance formation, Gulati (1999) coded alliances among organizations into matrices by year and computed network measures such as centrality and cliques to capture the position of organizations in the industry. The results showed that network resources, determined by prior alliances, influenced the likelihood of new alliance formation. Organizational networks are sometimes treated as resulting from evolutionary forces. For example, Madhavan et al. (1998) compared the relationships between pairs of partners in the global steel industry before and after external events. The comparison of centrality, centralization, and interblock measures showed that industry events had structure-reinforcing or structure-loosening impact as well as provided opportunities for organizations to strategically restructure their positions.

Network techniques can be used to support the analysis of how organizational positions evolve within their niches (Podolny, Stuart, & Hannan, 1996; Stuart & Podolny, 1996). Based on patent co-citation data, Stuart and Podolny examined the technological relations among firms' inventions in the semiconductor industry. The study used multidimensional scaling (MDS) techniques to show how Japanese semiconductor producers "could be positioned and grouped according to the similarities in their innovative capabilities" (p. 21).

Another stream of research examines the longitudinal evolution of organizational communication networks (e.g., Bryant & Monge, 2008; Lee & Monge, in press). In these studies, the main goal is to examine the formation and dissolution of ties as well as the emergence of particular network structures over time. In addition, an important consideration is how these evolutionary changes influence or are influenced by external variables such as node attributes. For example, social influence on organizational adoption of information technologies is a widely studied topic in organizational communication research (Fulk, 1993; Fulk, Schmitz, & Steinfield, 1990; Rice, 1993). When longitudinal data are available, these examinations can be enriched by simultaneously estimating changes in node attributes (e.g., adoption or usage status of an employee) and relational properties (e.g., ties with coworkers or managers). Recent developments in network analytic methods such as exponential random graph modeling (ERGM) provide new methods

for these types of investigations (Robins, Snijders, Wang, Handcock, & Pattison, 2007; Wang, Robins, & Pattison, 2008). ERGM, while controlling for interdependencies present in network data, allows the detection of salient local structural properties such as reciprocity or transitivity in the observed network. A longitudinal version of ERGM, incorporated in programs such as LPNet, enables the investigation of whether there is an increased or decreased tendency for particular structural properties to occur over time (Lee & Monge, in press). SIENA is a simulation-based program that was developed to model longitudinal changes in networks, in particular, the coevolution of the overall network and nodal behavior (Snijders, 2005; Snijders, Steglich, Schweinberg, & Huisman, 2007). The program models outcome variables that consist of changing network properties and changing node behavior observed across multiple time points. By estimating parameters that specify network and behavior dynamics, conclusions about social influence (the effects of ties on behaviors) and social selection (the effects of behaviors on ties) can be drawn (see Shumate, 2011).

A recent study by Zaheer and Soda (2009) examined the processes in which structural holes emerge among the production teams in the Italian TV industry. They applied the evolutionary principle of path dependence to illustrate that past network structure provided not only opportunities but also inertial constraints on network members. Past and current measures of network structure were modeled using network analysis and subsequently estimated in a two-stage least squares regression model. This study suggested an example of studying the evolution of specific types of network structures, as opposed to the majority of studies that focused on examining single ties or an entire network.

Computational Models and Simulations

The previously described methods provide techniques for studying changes in communication processes where existing data are available; yet scholars often want to look at phenomena for which data are unavailable. Consequently, scholars often turn to computational models and computer simulations. The use of these techniques in the study of organizations is not new; model sequences were used extensively in studies of organizational decision theory (Cohen, March, & Olsen, 1972; Levinthal & March, 1981) and in studies of the evolution of repeated instances of cooperation between individuals adhering to the rules of the Prisoner's Dilemma game (Huberman & Glance, 1993; Nowak & May, 1992). However, the emergence of artificial intelligence

tools and new programming languages has accelerated the use of simulations in the study of organizations (Masuch & LaPotin, 1989).

Simulations are frequently used to predict how a system will behave under a given set of conditions and to advance the development of theory in the absence of appropriate data (Dooley, 2002). There are three primary approaches to simulation research: discrete event, system dynamics, and agent-based. Discrete event simulations model systems based on prescribed variables and events that trigger changes in the overall system but do not generally allow for interaction between variables. The system dynamics approach explicitly describes interactions across the system as a whole. Because these approaches do not generally allow for the modeling of individual interactions, or interaction across levels, they have not been used extensively in organizational ecology. On the other hand, the agent-based approach describes interactions between individual agents and the surrounding environment and is primarily used to model individual actions. Advanced models of this type further allow agents to interact with one another (Dooley, 2002). For example, a study of interorganizational network evolution used agent-based modeling to demonstrate that over time new entrants will repeatedly seek out high-status firms that have similar attributes (Van de Bunt & Groenewegen, 2007). In another study, researchers demonstrated that in social situations proximity is an early indicator of bond formation, whereas over time network position is increasingly important (Van Duijn, Zeggelink, Huisman, Stokman, & Wasseur, 2003).

The core premise of computational models and simulations is that complicated behaviors occurring within organizational systems can be recreated and tested through mathematical representations (Macy & Willer, 2002). One common paradigm of computational modeling of organizations follows the principles of cellular automata. The cellular automata model consists of entities that can have one of two states (on or off), that have connections to adjacent entities, and that must obey certain behavioral rules. Under this scheme, economic and social functions of organizations are represented by simple agents that occupy cells in a common lattice. The common lattice is simply a matrix in which entities can only interact with locally adjacent others. Building on established theory and hypothetical projections, researchers establish a set of behavioral rules that govern the actions of organizations. Furthermore, interactions between organizations are scripted by additional rules. These rules are then programmed into a simulation and tested to see if the resulting outcomes adhere to the predictions guided by theory. Successful computational models rely on presenting relatively simple mathematical idealizations of organizational interactions; the outcome of even simplistic

representations will often be both complex and varied when simulated across levels (Lomi & Larsen, 1999). Simulations combine mathematical computational models with action guidelines and replicate them over time to provide verifiable outcomes that can be tested against theory. Depending on the nature of the modeled system, agent and organizational attributes can be modeled as fixed inputs or variables. Researchers must decide the most appropriate timing mechanism to govern organizational actions. Although synchronous timing of system interactions simplifies models, asynchronous timing using mechanisms such as Poisson processes can more accurately simulate real life systems (Glance, Hogg, & Huberman, 1997).

Interactions occur in organizational ecology both within a particular level of observation and across different levels. As a result the modeling of such systems is particularly complex. Carroll and Hannan (2000) described computational models for simulating the effects of organizational size, founding rates, mortality rates, growth, and decline as well as organizational structure. They tested the computational models against data from a single population of organizations and against data from mixed populations. They found that single population data produced more accurate results. At the organizational level, Carroll and Harrison (1998) looked at the effect of tenure within organizations over time. To model interactions between individuals and the organization, six simultaneous interactions were examined including the size of the top management team, selectivity of company hiring processes, peer socialization between managers, turnover, and CEO leadership style. Computational models also have been used to study the mimetic processes of organizational learning and change (Mezias & Lant, 1994), the interaction of managerial cognition and intraindustry structure (Johnson & Hoopes, 2003), and the effects of ongoing employee turnover on organizational development (Glance, 2007).

Formal simulation systems combine a common set of assumptions with a variable level of inputs and allow researchers to manipulate conditions within a preset range. For instance, Burgelman and Mittman (1994) outlined the CORPSTRAT simulation system as a tool for modeling the interactions that occur between individuals and organizations in decision-making situations. The variables included environmental conditions, corporate context, and risk-taking behavior. The CORPSTRAT system allows researchers to use firms, projects, and managers as inputs, and then model the evolution of the organization system based on outcomes of strategy-making decisions. For instance, this type of model was used to show that managers who tend to take a moderate amount of risk in decision making have a higher survival rate over time, regardless of the overall strategic position of the firm itself (Burgelman &

Mittman, 1994). In addition to programs such as CORPSTAT, social network analysis packages increasingly accommodate simulation research. Both SIENA (Snijders et al., 2007) and PNet (Wang et al., 2008) allow for the simulation of networks overtime based on input attributes that predict network size and linking behavior.

Computational modeling, however, is not a definitive method for understanding the intricacies of organizational ecology. Most computational models function under the assumption of synchronous updating; as in the case of cellular automata, actions are structured in a lattice, and every site on that lattice is updated based on a common synchronous mechanism (Huberman & Glance, 1993), but such systems may significantly oversimplify organizational interactions. Furthermore, simulations are typically based on a broad class of rules that generally are applied to a wide array of organizations; as a result, simulations are most useful when looking at macroscopic level phenomena although increasingly complex models support simulations of micro-to macro-level relationships (Lomi & Larsen, 1999). Overall, simulations provide a complementary technique to empirical data when researchers want to examine a particular mechanism or theoretical interaction (Amburgey & Rao, 1996). As long as the research is theoretically grounded, computational models can provide valuable insights on evolutionary phenomena.

Organizational Landscapes and Fitness Models

One specific method used to model the evolution of organizational populations that primarily relies on computational models is the analysis of fitness landscapes. A fitness landscape is a multidimensional space in which each dimension represents a particular trait of the organizational population (Levinthal, 1997; Wright, 1931). In addition, an extra dimension, typically represented as the “height” of the graph, indicates how well each particular combination of traits fits the organizational environment. Within the field of biology, Kauffman (1993, 1995) and Kauffman and Johnsen (1991) applied an *NK* model to fitness landscapes to describe the ways in which species may move to various level of fitness on the landscape. In his model, *N* represents the number of genetic traits being studied in a species. For ease of interpretation, each gene is binary, which means that any given gene can be in one of two states, present or absent. The coefficient, *K*, is the number of epistatic links, which are links among traits that restrict the possible trait configurations. Thus it is a measure of the internal interdependency or complexity of the organizational population (Kauffman & Johnsen, 1991). McKelvey (1999) suggested how this model could be adapted for use with organizational

populations with N representing the number of organizational traits such as subunits, teams, or employees within a firm and K representing the “links [among the N units] that inhibit change” (p. 303). Chang and Harrington (2000) have applied the model with N being organizational practices, such as standards for inventory size or number of product lines.

Kauffman (1993) used computer simulations to model the ways in which populations can move on this fitness landscape. In a process referred to as an adaptive walk, each player takes a turn randomly mutating one trait. If the resulting fitness is improved, then that trait is selected (Kauffman & Johnsen, 1991). Organizations move to the adjacent location on the fitness landscape corresponding to the one-trait mutation. If no constraints exist between traits ($K = 0$), then each trait can be changed independently to improve fitness. In this case, the landscape includes a single global optimum across all traits (Kauffman, 1993). Hill climbing, which represents moving to successively higher fitness levels on the landscape, will consistently take organizations closer to that global optimum. As K increases, the ruggedness of the fitness landscape increases. In other words, as the number of constraints between traits increases, changing a single trait may not lead to improved fitness because of its negative impact on the fitness of the other traits. Instead of a single best fit with the environment, multiple peaks exist. Typically, organizations will hill climb to a variety of local optima. There is no guarantee that hill climbing will lead to a global optimum over time (Kauffman & Johnsen, 1991). In fact, as K increases, only a small fraction of starting genotypes have the ability to reach the global fitness optimum (Kauffman, 1993). At a maximum level of $K = N - 1$, the fitness landscape becomes completely random and uncorrelated. Any change in one trait is dependent on all of the others, and the result is that organizations cannot find any one-trait mutations that improve fitness. This situation is referred to as a complexity catastrophe (Kauffman & Johnsen, 1991; McKelvey, 1999). In this case, the value of local optima is the same as the average fitness value for the fitness landscape. As K increases relative to N , the value of the peaks becomes comparatively smaller (Kauffman, 1993). For K greater than 0 but much less than N , this complexity catastrophe can be avoided (Kauffman, 1993).

To model coevolutionary processes, Kauffman (1993) and Kauffman and Johnsen (1991) added an additional coefficient to the NK model, C . In this new $NK[C]$ model, C is the number of traits that are constrained by relationships with the other populations with which the focal population is coevolving. In other words, C is the number of interdependencies between “competing coevolving firms” (McKelvey, 1999 p. 303). In terms of the fitness landscape, the landscapes of the populations are coupled by C . As one firm moves

on its landscape, the landscape of the other firm changes. Specifically, “both the fitness and the fitness landscape of each species are a function of the other species” (Kauffman, 1993, p. 243). Kauffman and Johnsen (1991) refer to the deformations of one landscape in response to the moves made by the population on the other landscape as dancing. In their words, “either the partners keep dancing, or the coupled system attains a steady-state at which the local optimum of each partner is consistent with the local optimum of all the other partners via the ‘C’ couplings” (Kauffman & Johnsen, 1991, p. 475). This state is called a Nash equilibrium and applies to many dynamic phenomena. When a Nash equilibrium has been reached, any additional mutations by one species are constrained by the relationships with other species. This means that if one species moves on its landscape, then it will deform the landscape of the other species and constrain the overall fitness of the community. If K is less than C , then the landscapes are very rugged, and it can take a long time to reach a Nash equilibrium. In contrast, for K greater than C , Nash equilibria are reached quickly (Kauffman, 1993; Kauffman & Johnsen, 1991). Monge and Contractor (2003, p. 9) provide a number of examples applying $NK(C)$ models to communication processes.

Predator–Prey Models

Competition between different populations can be complex and delicately balanced. The underlying mechanism of predator–prey models is a pair of feedback loops between two populations, similar to that described by the C relations in the $NK(C)$ model. In bioecology, the population density of the prey supports (i.e., has a positive influence on) the density of the predator population. When there are more rabbits, more wolves can survive. By contrast, the density of the predator population has a negative influence on the density of the prey population. When there are more wolves, fewer rabbits can survive. These competitive dynamics are sensitive to the relative influence of within population versus across population factors (Hannan & Freeman, 1989). Typically, when within population density effects (such as competition or cooperation) are greater than between population influences (predators influences on prey), population densities will fluctuate mildly around stable equilibria. When between population influences are relatively dominant, densities can fluctuate chaotically, often leading to the extinction of one or both populations (Hannan & Freeman, 1989).

Predator–prey relations can be modeled with a system of differential equations called the Lotka–Volterra equations to estimate the population growth rates (Hannan & Freeman, 1989). These equations can be approximated with

simultaneous regression equations estimated with weighted generalized least squares (Carroll, 1981). In a community in which two populations (A and B) are being considered, their interdependence on each other can be estimated by coefficients α_{AB} and α_{BA} . These coefficients show the relationship between the population density of the first population and rate of change (growth or decline) of the second population. Positive values denote beneficial relationships and negative values denote damaging relationships (Hannan & Freeman, 1977; Rao, 2002).

In the organizational context, these coefficients often reflect the degree to which populations of organizations have cooperative relationships, in which case growth in one population leads to growth in the other, or a competitive one, in which growth in one population suppresses growth in the other (McPherson, 1983). Carroll (1981) used this method to estimate the simultaneous cooperative and competitive influences of organizational populations providing primary, secondary, and tertiary education. Primary education organizations provide resources, in the form of sufficiently prepared students, to higher level education organizations. Yet all three populations draw on a limited pool of general education resources, such as government funding and qualified teachers. The populations are thus involved in a complex set of positive and negative feedback loops. Growth in primary education leads to an increase in students seeking secondary and tertiary education, increasing the size of these populations as well. Yet an increase in the number of organizations engaging in secondary and tertiary education draws funding and teachers away from primary education, suppressing further growth in the primary education population. This in turn suppresses growth in the secondary and tertiary populations, and so on.

These complex interactions may lead the population levels to remain at stable equilibria or to fluctuate more extensively toward unstable conditions. As Monge (1990) demonstrates, both positive and negative feedback are capable of producing stability or instability depending on the sign and magnitude of the coefficients that comprise the feedback loop. Loop products with an absolute value greater than 1.0 lead to instability; loop products with an absolute value less than 1.0 lead to stability (Carroll & Hannan, 2000; Contractor, 1994). Approximation of the Lotka–Volterra equations provides the ability to estimate the coefficients for the conditions under which the populations will remain at or deviate from equilibrium levels (Carroll, 1981). The relationship between blogs and blog aggregators might be similarly modeled. Blog aggregators rely on smaller blogs for content while pulling readers away from them.

Graphics as Tools for Analysis

Researchers are increasingly utilizing advanced visualization techniques to illustrate evolutionary dynamics of organizations. For instance, computational lattice models utilize visual diffusion diagrams to illustrate patterns of change. As participants evolve in the model (i.e., as they change from an “off” to an “on” state), they change color. The effect of different variables can thus be observed through the visual changes in the diagram (Huberman & Glance, 1993).

In their study of gas stations in Edmonton, Canada, Usher and Evans (1996) graphically depict changes in both the diversity of organizational forms in a population and the distribution of organizations over those forms for a given period of time. Through the use of graphs that track the emergence and death of organizational forms, their results show that both Darwinian (forms change only across generations) and Lamarckian (forms can change within one generation) processes are at work within the gas station population.

In studies employing social network analysis, network diagrams provide clear illustrations of the changes in network patterns over time. Powell et al. (2005) used network diagrams to illustrate the evolution of the biotechnology industry over time. Similarly, Stark and Vedres' (2006) development of sequence analysis uses network diagrams to illustrate the change in organizational configurations in sequencing patterns. In recent years network analysis has benefited from new visualizations techniques such as animated movies and graphics that show the evolution of network structures over time and allow researchers to highlight evolutionary mechanisms visually (Bender-deMoll & McFarland, 2006; Moody, McFarland, & Bender-deMoll, 2005).

Qualitative Methods of Analysis

Although the majority of evolutionary research has been quantitative in nature, researchers also have employed a variety of qualitative methods to study different facets of evolutionary theory, including organizational transformation, imprinting, and organizational learning. Qualitative methods focus more on textual than on numerical data. The paragraphs below review some qualitative methods for data collection and analysis, with reference to both extant and potential studies in the evolutionary tradition.

In-depth, open-ended interviews. One of the most prevalent qualitative methodologies used in evolutionary and ecological research is interviews. Although closed-ended interviews can be used for obtaining data that can be

coded numerically for subsequent quantitative analysis (e.g., Miner, 1991), qualitative studies typically employ less structured interviews where responses do not necessarily fit into standardized categories for numerical analysis and which sometimes rely on the researcher's personal interpretation of patterns and phenomena. For example, Raff (2000) was interested in how firm capabilities develop and evolve over time. Raff used extensive interviews with industry participants as well as archival data to track the rise of the book retail "superstores" and their supporting infrastructure. The interview data led him to posit that there are two very different and competing models of superstore success, typified by Borders vs. Barnes & Noble, and that paths to success developed through different processes based on historical capabilities. Doz (1996) used archival data and interviews of participants at partner firms in a longitudinal case study of evolution of learning in alliances. His interpretation of the qualitative data led him to conclude that successful alliances went through a sequence of learning, reevaluation, and readjustment (p. 55), whereas less successful alliances were more inert; these processes also seemed to be linked to initial conditions.

Evolutionary researchers have also used interviews to supplement quantitative data. Carroll and Swaminathan (1992), using interviews in addition to event history analysis, found that organizational identity is central to the separation of specialist and generalist firms within the beer industry. Gulati (1999) used interviews in conjunction with network analysis to estimate the likelihood that a firm will enter into an alliance.

Case studies. The rich detail provided by this method allows researchers to obtain a deeper understanding of a variety of evolutionary phenomena. Case studies vary in their scope and degree of detail. Some take a more specific focus and examine single organizations or events (e.g., Arino & de la Torre, 1998; Tripsas, 2009). For example, based on an in-depth case study of Intel, Burgelman (1991, 1996) developed an evolutionary model of corporate strategy. In contrast, others have analyzed entire industries (e.g., Louca & Mendonca, 2002; McKelvey, 1997; McKendrick & Carroll, 2001; Nelson, 1996). McKendrick and Carroll used a case study of the disk array market to demonstrate the validity of a new, density dependence model for detecting the emergence of new organizational forms. In another macro-level case study, Feldman and Schreuder (1996) document the historical conditions that led to the geographic clustering of the U.S. pharmaceutical industry in the Mid-Atlantic region.

Historical research. Archival analysis is often a key component of case studies (e.g., Johnson, 2007; Shostak, Conrad, & Horwitz, 2008), as illustrated in previous examples. It is a main method for historical research. Through the

analysis of historical records, researchers are able to track how organizations change throughout their lifecycles. In her case study of the Paris Opera, Johnson used archival analysis to explore the role of entrepreneurship in organizational imprinting. After discussing the history of this organization, the author concluded that, as organizational ecologists would predict, no individual founder shaped the future of this organization; instead, the founder's intentions were transformed by the political context and the meaning of the opera in 17th-century France. Van de Ven and Garud (1994), in their case study of a cochlear implant manufacturer, content analyzed multiple historical data sources to track variation, selection, and retention events over time, finding that these events coevolved with the development of cochlear implants. Others have used interviews in conjunction with archival analysis (e.g., Arino & de la Torre, 1998; Doz, 1996; Raff, 2000; Tripsas, 2009; Van den Bosch, Volberda, & de Boer, 1999). For example, Tripsas used a combination of interviews and archival data in her investigation of organizational identity's role in a photography company's adoption of new technologies. She found that identity acts as an inertial force that can be a key barrier to new technology adoption, particularly when the technology challenges the existing organizational identity.

Ethnography. Ethnography has been an important method in the study of evolution in the natural sciences, with field work focusing on change process in animal communities. Ethnography has not been a mainstay of research on organizational evolution. However, it offers important advantages in providing close-hand knowledge and sufficient detail for observing evolutionary change processes in action rather than making inferences from observed changes in states without direct data on intervening processes. Ethnographies of start-up firms, for example, could provide important details on specific processes related to organizations' survival or death in fledgling industries. Relying on qualitative and quantitative analysis of ethnographic data, Leonardi (2009) revealed how users' interpretation of a new technology evolved as a result of their interactions with the material features of the technology as well as other users in the organization.

In summary, qualitative methods have been demonstrated to be highly valuable for evolutionary research, and yet they have been employed far less frequently than quantitative methodologies. This fact suggests that there is important potential for new and different insights on evolutionary processes to be gained by incorporating more qualitative methodologies into evolutionary research. For example, discourse analysis could be applied to archival data such as corporate annual reports to track how interpretations of niches and environmental resource richness become institutionalized in populations

and the conditions under which stable discursive constructions are dislodged by new sense-making regimes (Monge & Poole, 2008).

Conclusion

Organizational communication scholars recently have begun to apply evolutionary and ecological theories to communication issues. The few organizational communication studies to date form just the beginning of a research program; the opportunities abound for this exciting research area. As the preceding review suggests, organizational and communication researchers have used evolutionary theory to describe and explain a wide array of phenomena at multiple levels of analysis and have employed a host of different methods for analyzing ecological data. These methods provide a foundation for communication researchers interested in studying communication-related ecological processes that occur among individuals, groups, organizations, populations of organizations, and communities. As the examples in the previous pages suggest, a great many topics of research in organizational communication can be studied beneficially from an ecological standpoint, offering the potential for uncovering important new insights into contemporary organizational communication.

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