The Emergence of Shared Interpretations in Organizations

A Self-Organizing Systems Perspective

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The past decade has seen the emergence of an enduring interest in the study of organizational communication from an interpretive perspective. In a comprehensive critique, Putnam (1983) notes that past functionalist research treated "social phenomena as concrete, materialistic, entities—types of social facts" (p. 34) and "organizational charts as fixed, concrete structures that determine authority and task relationships" (p. 35). Functionalist research tended to "reify social processes by ignoring the creation of structures, by recasting individual actions into fixed properties as levels, departments, and boundaries, and by treating organizations as containers or entities" (p. 35). It assumed a "unitary view of organizations; that is, organizations [were] treated as cooperative systems in pursuit of common interests and goals" (p. 36). There was also a tendency for functionalist research to pursue "universal laws, that is, explanatory theories that apply to a wide range of circum-

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stances" (p. 40)—laws that were premised on a "unilateral and linear" (p. 42) conception of causality.

This chapter begins with the premise that the interpretive critique of past functionalist research, including research that claimed to be inspired by traditional systems theory, is fair in many cases. However, unlike most interpretive scholars. we argue that the response to this critique does not entail abandoning the quantitative approaches accompanying this research tradition. Instead, the critique offers a constructive opportunity to revise and redirect the focus of systems theorizing and research. This chapter presents recent developments in the field of self-organizing systems theory that are well-suited to complement and extend our understanding of social systems from an interpretive perspective. The chapter concludes with a simple, yet novel, self-organizing systems model to illustrate the emergence of shared interpretations in organizations.

Interpretive Critique of Traditional Functionalist Research

During the past two decades, several organizational communication scholars have questioned the utility of functionalist research (Hawes, 1974; Putnam, 1983; Weick, 1979). Their concerns can be broadly classified into three categories:

- Longitudinal inference from cross-sectional research
- A focus on objectively measured explanatory variables
- Predominance of linear analytic models

First, even though scholars have had a long-standing interest in theorizing about communication processes (Berlo, 1960), the overwhelming body of empirical research was cross-sectional in design (Monge et al., 1984). Less obvious, but perhaps more significant, the knowledge claims made on the basis of this cross-sectional research implicitly assumed that the systems being studied were static in character (Abell, 1971). That is, they claimed to be taking a snapshot of a still picture. Hence, there was a growing chasm between the verbal articulation of processes in communication, theory and the cross-sectional empirical research that purported to test these theories. The token

acknowledgment at the end of cross-sectional research articles calling for "future longitudinal research" has worn thin.

Second, in its enthusiasm for measurement precision, reliability and validity, traditional functionalist research, had privileged objective phenomena in organizations. This in turn led to the theoretical reification of certain material aspects of organizations that failed to recognize the fact that organizations can also be usefully conceptualized as products of their members' visions, ideas, norms, and beliefs (Pondy & Mitroff, 1979). As a result, although there was a growing intellectual movement conceptualizing organizations as cultures and meaning systems (Eisenberg & Riley, 1988; Putnam & Pacanowsky, 1983), its influence on functionalist theories and research was virtually nonexistent.

Third, although methodological advances in functionalist research were making substantial strides (Monge & Cappella, 1980), these advances were primarily concerned with the estimation of linear, unidirectional causal analysis of covariance structures. Critics (e.g., Abbott, 1988; Weick, 1983) noted that these techniques were ill equipped to capture the contemporary intellectual conceptualizations of social systems. Scholars were theorizing about communication process in terms best captured by systems' concepts such as nonlinearity, historicity, mutual causality, causal loops, time irreversibility, discontinuity, and deviation amplifying feedback (for details, see Contractor, 1994). However, with a few notable exceptions (e.g., Monge, 1977, 1982), these concepts were not in the discursive mainstream of organizational communication research. Even research that claimed to be based on a system perspective would often deploy the terminology in a ceremonial way while eschewing the precise articulation embodied by such a perspective (Berlinksi, 1976).

Disillusionment with functionalist research and, by unfair but understandable association, systems perspectives in the three areas discussed above were largely responsible for the rise of the interpretive paradigm in organizational communication research. In an attempt to organize the intellectual domains, scholars (e.g., Putnam, 1983) distinguished between the two paradigms in terms of their different ontological and epistemological assumptions (Burrell & Morgan, 1979). Functionalist research was invested with an objective ontological stance in contrast to interpretive research's interest in the subjective. Epistemologically, functionalist research sought generalizable, ordered knowledge claims, whereas interpretive research was more concerned with understanding the particular (Putnam, 1983).

Having made these distinctions, the 1980s witnessed an uneasy coexistence between scholars within these two paradigms. An examination of publications and conference papers indicate a normative wall separating functionalist research, with quantitative methods on one side and interpretive research using qualitative methods on the other side.

Extending the Interpretive Perspective

In the past few years, a few scholars (Barnett, 1988a, 1988b; Monge & Eisenberg, 1987; Poole, 1990, 1994) have advocated, and attempted to demonstrate, the utility of applying the quantitative techniques of functionalist research to interpretive questions. In their review of organizational communication networks, Monge and Eisenberg (1987) propose the operationalization of networks from a cultural tradition. They note that past functionalist research on communication networks had been justly criticized for ignoring the content of communication networks (Richards, 1985; Rogers & Kincaid, 1981). Rogers and Kincaid (1981) summarized this deficiency:

> We need to combine the research method of content analysis of communication messages with the technique of network analysis to better understand how individuals give meaning to information that is exchanged through the communication process. (p. 77)

Monge and Eisenberg (1987) proposed the use of the coorientation model (McLeod & Chaffee, 1976) to operationalize a new genre of networks—semantic networks—in which the dyadic link measures the extent to which communicators share common interpretations.

Unlike traditional communication networks that measure the amount (or duration) of communication between individuals, semantic networks tap into the shared interpretation systems by asking individuals to provide their interpretations of key terms, slogans, stories, or rituals in the workplace. A semantic network link measures the degree of overlap (or lack thereof) of organizational members' interpretations. Further, mapping the configuration of individuals in a semantic network makes it possible to deploy the techniques of network analysis to further our systemic understanding of a collective of individuals as an interpretation system. For instance, whereas communication network density

indicates the extent to which a group of individuals communicate with one another, semantic network density indicates the extent to which a group of individuals share their interpretations. Likewise, whereas communication network heterogeneity indicates the extent to which some individuals communicate with others who do not communicate with one another, semantic network heterogeneity measures the extent to which some individuals hold multiple interpretations that they share with others who do not have shared interpretations.

The operationalization of semantic networks is an example of the judicious application of quantitative research techniques to address questions that are central to an interpretive conceptualization of organizational communication. Monge and Eisenherg (1987) note that

> semantic network analysis can be used to examine the assumption held by some researchers that organizations are made up of individuals with highly similar core values and beliefs. Organizations could be compared empirically to assess the degree of homogeneity of interpretations or core values. Subcultures could he identified around semantic. . . cliques. (p. 334)

As such, semantic network analysis has the potential for advancing our understanding of organizations as shared interpretation systems beyond what is capable by purely qualitative analysis. Many of the central concepts in interpretive-critical research are richly evocative verbal descriptions that are highly inadequate both in operationalizing the concepts and articulating their interrelationships. Poole (1990, 1994) describes these inadequacies as the interpretive version of the reductionist problem associated with some functionalist research.

Although the operationalization of semantic networks is a first attempt at incorporating quantitative methods to the study of interpretations, it does not directly address a central focus of interpretive researchers: "Interpretivist research extends beyond disclosing subjective meanings to an examination of why and how shared meanings exist" (Putnam, 1983, p. 41). That is, the interpretive perspective conceptualizes the emergence of shared interpretation as a circular causal chain relating, on the one hand, the manner in which interpretations are created and altered through interaction and, on the other hand, the manner in which shared interpretations shape interaction among individuals. Typically, interpretivists describe this relationship in a verbal narrative in the context of a particular study. They prefer this ideographic explanation and dismiss functionalists' search for a nomothetic explanation

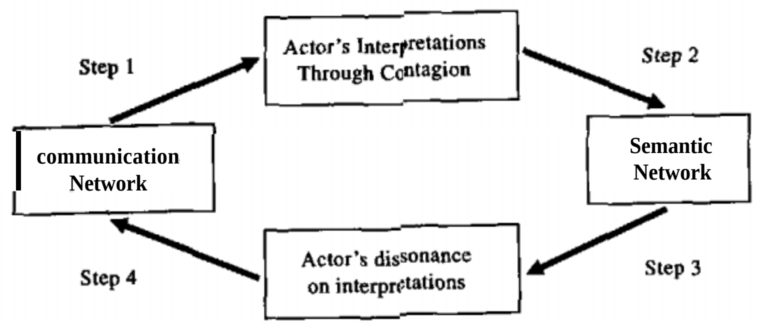

Figure 9.1. Self-organizing model for the emergence of shared interpretations.

(i.e., a universal law) that would predict the same emergent process in all organizations. The next section discusses a reconceptualization of the emergence of shared interpretations from a self-organizing systems perspective. Although this perspective offers the precision associated with functionalist research, it is also based on the premise that the observed emergence processes can vary considerably.

A Self-Organizing Model of the Emergence of Shared Interpretations

Broadly speaking, self-organizing systems theory seeks to explain the emergence of patterned behavior in systems that are initially in a State of disorganization or in a different state of organization. From the start of this century, researchers in many of the physical and life sciences had observed that systems initially in a state of disorganization (high entropy) would under certain conditions spontaneously demonstrate patterned behavior (Nicolis & Prigogine, 1977; Prigogine, 1980). Further, these systems under certain specifiable conditions would spontaneously change to a different state of organization. The theoretical requirements of self-organizing systems are described in Contractor (1994) and Contractor and Seibold (1993). The generative mechanisms, describing the dynamic interrelationship among the elements of a self-organizing system, must include a feedback loop.

In the past decade, there have been calls for the application of self-organizing perspectives in management (Malik & Probst, 1984; von Foerster, 1984), organizational change (Ford & Backoff, 1988; Gersick, 1991; Goldstein, 1988), the appropriation of new communication technologies (Contractor & Seibold, 1993), communication and societal development (Krippendorff, 1987). communication and cultural evolution (Kincaid, 1987), and mass communication technologies and society (Batra, 1990). Cellular automata models (a class of self-organizing models) have also been used to study the unintended consequences of organizational communication (see Corman, this volume),

In this chapter we offer a simplified, but illustrative, self-organizing systems model of the process by which shared interpretations emerge among organizational members. That is. we attempt to model the process by which a group of individuals who start out with some initial communication and semantic network configurations self-organize their subsequent levels of interactions (i.e., communication networks) and interpretations (i.e., semantic networks).

Figure 9.1 depicts the four generative mechanisms in this self-organizing model. The four mechanisms are labeled Steps 1 through 4. Let C_{ijt} denote the communication link between individuals i and j at time t. In addition, let I_{it} and I_{jt} indicate individuals i's and j's agreement (on a scale from 0 to 12) with a particular interpretation at time t.

In Step 1, an individual i's interpretations are given by Equation 9-1:

$$I_{it+1} = b_p I_{it} + b_s \sum_{i \neq j} C_{ijt} I_{jt} + \textit{random noise}, \qquad [9\text{-}1]$$

where the autocorrelation parameter b_p indicates the individual's interpretation inertia (i.e., the disposition for an individual to retain the same interpretation from one point in time to the next); the parameter b_s indicates the extent to which the individual is vulnerable to social influence from the communication network. The parameters b_p and b_s are scaled to sum to 1.

Equation 9-1 states that the interpretation held by individual i at time t + 1 is in part based on the individual's interpretation at the previous point in time, t. It is also based in part on the interpretations held by all other individuals in the network weighted by the extent to which individual i communicates with each of these other individuals. Finally, the effects of unaccounted variables on an individual's interpretation are assumed to vary in a nonsystematic manner and are characterized in

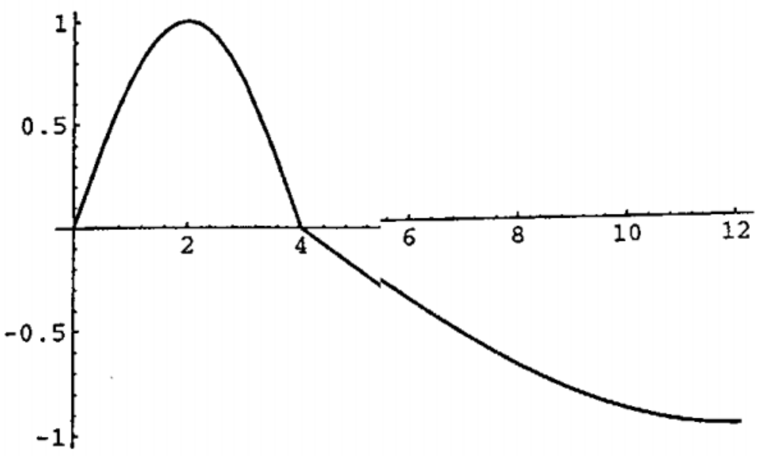

Figure 9.2. Change in communication as a function of differences in interpretations. X-axis reflects difference in interpretations; Y-axis reflects change in communication.

the equation by a random noise component. This equation has been described by Burt (1982) as the contagion model for network effects.

Step 2 describes the configuration of a semantic network based on individuals' interpretations. A semantic link, S_{ijt+1}, between two individuals i and j is given by:

$$S_{ijt+1} = 12 - |I_{it} - I_{jt}| \quad [9\text{-}2]$$

Equation 9-2 states that the semantic link between two individuals will be strongest (i.e., 12) if the two individuals have no disagreement in their interpretations. It will have a minimum value of 0 if the two individuals are in complete disagreement about the interpretation.

Step 3 maps the dissonance created as a result of differences in interpretations. Newcomb (1956) notes that differences in opinion among individuals has a curvilinear effect on their propensity to communicate. That is, in cases where there are modest differences in opinion between individuals, their need for balance (Heider, 1958) will motivate them to increase their communication with one another in order to reach agreement. However, there comes a point where substantial differences

in opinion will result in individuals withdrawing their communication with one another. Figure 9.2 maps ΔC_{ijt+1}, the change in communication between individuals i and j, as a function of $|I_{it+1} - I_{jt+1}|$, the absolute difference in their interpretations. This function is represented by the equation:

$$\Delta C_{ijt+1} = \sin\left[\frac{\pi |I_{it+1} - I_{jt+1}|}{4}\right] \quad \text{if } |I_{it+1} - I_{jt+1}| \leq 4$$

$$\Delta C_{ijt+1} = \sin\left[\frac{\pi(4 - |I_{it+1} - I_{jt+1}|)}{16}\right] \quad \text{if } |I_{it+1} - I_{jt+1}| > 4 \quad [9\text{-}3]$$

Equation **9-3** states that if two individuals share a common interpretation there will be no change in their level of communication. If their disagreement is less than or equal to **4,** they will increase their communication. If their disagreement is greater than **4,** they will decrease their communication. The number **4** was used as a cutoff value because it is the expected value of the absolute difference $|I_{it+1} - I_{jt+1}|$ if I_{it+1} and I_{jt+1} are allowed to vary randomly between 0 and 12.

Finally, Step **4** describes C_{ijt+1}, the new communication link between individuals i and j, as a function of C_{ijt}, the previous level of communication ΔC_{ijt+1}, the change in communication between individuals i and j, described above, and random noise. Hence:

$$C_{ijt+1} = C_{ijt} + \Delta C_{ijt+1} + \textit{random noise} \quad [9\text{-}4]$$

As the cycle repeats itself through several iterations, the communication and semantic networks can self-organize into stable configurations. The self-organizing process modeled above offers a simple, yet novel, approach to understanding the emergence of shared interpretations. In the model specified above, the process by which shared interpretations emerge will depend on the characteristics of the initial communication and semantic networks, the extent to which individuals' interpretations are susceptible to network influence (i.e., the relative value of b_s as Compared to b_p), and random noise. Even if these parameters are fixed at certain values, it is not possible for the human intellect to construe mentally the emergent process by inspecting the four dynamic equations. Hanneman **(1988)** advocates the use of computer simulations to gain insights into the long-term implications of a dynamic model.

Traditional Research Process	SOST Research Process
• Theory • Verbally deduce hypotheses • Empirical validation	• Theory • Formulate logics of emergence • Run dynamic simulations • Deduce hypotheses from simulation data • Empirical validation

Figure 9.3. Comparison of traditional and proposed research process.

Carley and Prietula (1994) suggest the emergence of a new field, Computational Organizational Theory, to signal the growing interest in the construction of computational models to augment theory building. It is important to emphasize that the results of a computer simulation are not a surrogate for empirical data. Rather, they indicate the emergent process implied by the model proposed above. As such, simulation data provide the researcher with an opportunity to deduce hypotheses (that are implied but not immediately obvious) about differences in the emergence of shared interpretations in varied contexts. The distinctions between traditional and proposed research process are summarized in Figure 9.3. The next section describes the deduction of hypotheses based on a series of computer simulations executed on the model described above.

Deducing Hypotheses About the Emergence of Shared Interpretations

Research Questions

As discussed above, there ate several potential influences on the emergent process specified by the self-organizing model. In this chapter we report the extent to which the emergent process is influenced by one initial communication network characteristic, communication network heterogeneity, and one initial interpretation characteristic, the initial variance in interpretations among the individuals.

Communication network heterogeneity is defined as the variation in the level of prominence among individuals in the network. An individual i is prominent to the extent that he or she receives links from other prominent individuals. The prominence, P_i, of individual i, is given by

$$P_i = \sum_{j=1}^{N} P_j C_{ij} \qquad \forall i \neq j \qquad [9\text{-}5]$$

where C_{ij} represents a communication network link between individuals i and j. Computationally, the prominence of individuals is the first eigenvcctor of the normalized communication network (Knoke & Kuklinski. 1982).

In a heterogeneous network, a few individuals will he very prominent while others would have low prominence. Conversely, a network in which all individuals are equally prominent is homogeneous, Knoke and Burt (1983) proposed the following information-theoretic measure as an operational definition of *network heterogeneity*, H,

$$H = \frac{\sum_{j=1}^{N}\left[\left(\frac{P_j}{P_m}\right) ln\left(\frac{P_j}{P_m}\right)\right]}{N\, ln(N)} \qquad [9\text{-}6]$$

where P, is the prominence of individual j, P_m is the mean prominence of all individuals in the network, N is the number of individuals in the network, and ln is the natural logarithm. Network heterogeneity, as operationalized here, is analogous to Freeman's (1979) operationalization of network centralization.

The goal of running the computer simulations is to deduce hypotheses in response to the following two research questions:

RQ1: According to the self-organizing model for the emergence of shared interpretations described above, to what extent does the initial level of communication network heterogeneity influence, in the short and long term. the subsequent communication and semantic network densities among the individuals? That is, will the emergence of shared interpretations in groups where some members start out being much more prominent in the communication network than their peers differ significantly from the emergence process in groups where all members are equally Prominent in the communication network?

RQ2: According to the self-organizing model for the emergence of shared interpretations described above, to what extent does the initial level of variance in individuals' interpretations influence, in the short and long term, the subsequent communication and semantic network densities among the individuals? That is, will the emergence of shared interpretations in groups where members vary greatly in their initial interpretations differ significantly from the emergence process in groups where all members do not vary greatly in their initial interpretations?

Data Generation

The self-organizing model described above requires initial values for .the communication network and individuals' initial interpretations.

Initial Communication Network Structure

The initial communication network structure was operationalized as a binary asymmetric communication network of 6 individuals. One hundred such networks were generated using Monte Carlo techniques (Burt, 1991). All 100 networks were specified to have a density of 0.2. That is, in each network the total number of communication links were 6, one-fifth of the total number of possible 30 links. In 50 of the networks generated, the communication network heterogeneity was specified to be high (*mean* = .61, SE < .001). In these networks, some members were significantly more prominent than others. In the remaining 50 networks, communication network heterogeneity was specified to be low (*mean* = .23, *SE* < .001). There was not much variation in individuals' prominence scores in these networks.

Individuals' Initial Interpretation

Individuals' initial interpretations were operationalized as a 6 × 1 vector. Forty vectors were generated, with each vector containing the interpretation scores for each individual in a group of 6 individuals. Each individual's interpretation was allowed to vary between 0 (no agreement) and 12 (high agreement). For each of the 40 vectors, the mean interest among the individuals was held constant at 6.0. In 20 of the vectors generated, the variance among the individuals' interpretations was held constant **at** a high value (mean = 4.0, SE < .01); for the remaining 20 vectors, the variance among individuals' interpretations was restricted to a low value (mean = 1.00, SE < .005).

The parameters b_p and b_s were fixed at 0.4 and 0.6, respectively, and were held constant through the simulation.

TABLE 9.1 Correlation Coefficients of Communication Network Densities at Each Time Period (T1 through T10), With Initial (TO) Communication Network Heterogeneity and Interpretation Variance ($N = 4{,}000$)

	TI	*T2*	*T3*	*T4*	*T5*	*Tb*	*T7*	*T8*	*T9*	*T10*
Initial communication heterogeneity	0.002	0.002	0.003	0.002	0.001	0.002	0.003	0.002	0.001	0.001
Initial interpretation variance	0.003	***0.012***	0.027	0.078	0.087	0.122	0.187	0.226	0.226	0.226

Design of the Simulation

The initial communication network matrices and initial individual interpretation vectors generated were used to examine the emergence of shared interpretations as implied by the self-organizing model described above. Combinations of the 50 communication network matrices and 20 interpretation vectors in each of the four conditions (high/low initial communication network heterogeneity, high/low variance in initial interpretation) resulted in 4,000 simulations, which were executed on a supercomputer using ***Marhematica*** (Wolfram, 1991). An inspection of a large number of random simulation runs indicated that the self-organizing process stabilized in well under 10 iterations. Hence, each simulation was allowed to progress through 10 iterations.

Results

The data from the simulations were analyzed to deduce hypotheses based on the two research questions posed earlier in this section. In Particular, at each of the 10 points in time, Communication network densities and semantic network densities were computed for each of the groups. Table 9.1 reports the correlation coefficients of the communication network densities at each time period (TI through T10) with initial (T0) communication network heterogeneity and initial (TO) interpretation variance. Table 9.2 uses the same time parameters to report the correlation coefficients of the semantic network densities.

TABLE 9.2 Correlation Coefficients of Semantic Network Densities at Each Time Period (T1 through T10), With Initial (TO) Communication Network Heterogeneity and Interpretation Variance (N = 4,000)

	T1	*T2*	*T3*	*T4*	*T5*	*T6*	*T7*	*T8*	*T9*	*T10*
Initial communication heterogeneity	0.004	0.003	**0.041**	0.132	0.172	0.188	0.043	**0.007**	**0.007**	**0.007**
Initial interpretation variance	–.781	–.657	–.637	–.174	–.135	–.056	–.008	–.003	–.003	–.003

The correlation coefficients reported in these tables suggest the following hypotheses:

H1: Initial differences in communication network heterogeneity will have no short- or long-term effect on the communication network density.

H2: A higher initial variance in individuals' interpretations will have a positive but delayed impact on communication network density.

H3: Initial differences in communication network heterogeneity will have a delayed but transient positive impact on semantic network density.

H4: A higher initial variance in individuals' interpretations will have a negative but transient impact on semantic network density.

It must he emphasized that the model presented above is intentionally simplified to serve as an illustration. A more realistic self-organizing model must remedy two serious limitations of this illustrative model. First, the above model does not permit individuals to possess multiple interpretations, some of which may be more influential than others. For instance, individual A may offer three interpretations of the organization's slogan—and may be variably committed to each of the three interpretations. Second, the above model is essentially closed, implying that communication is the only variable influencing, and being influenced by, shared interpretations. The literature on organizational socialization suggests that shared interpretations are also significantly influenced by other variables, such as similar levels in the hierarchy and tenure within the organization (Van Maanen & Schein, 1979). It must be noted that both these limitations are specific to the model illustrated above and not the self-organizing systems perspective in general. Hypotheses, deduced from a more realistic model, will be tested using longitudinal communication and semantic network data that have been collected over a six-year period among scientific research teams at a large midwestern university. Empirical support for the hypotheses would indicate that the proposed self-organizing model for the emergence of shared interpretations cannot be rejected.

Conclusion

This chapter began with a critique of traditional functionalist research. These criticisms dealt with the inappropriateness of cross-sectional validation of process theories, the reification of objective measures and concepts while shying away from more compelling but difficult to measure interpretive concepts. and the methodological primacy of linear, unidirectional causal modeling. The critical-interpretive perspectives that were launched in the wake of this dissatisfaction have offered new and useful insights into organizational communication processes. However, in their haste to dismiss and discredit the quantitative approaches associated with the traditional functionalist approaches, the interpretive perspectives have severely limited their own ability to add precision and rigor to the concepts and processes they seek to examine.

The self-organizing systems perspective described and illustrated in this chapter has accommodated three of the criticisms offered by the interpretive tradition hut not its ontological and epistemological commitments. First, its explicit focus on deducing hypotheses based on the simulation of dynamic interrelationships precludes the possibility of researchers conflating cross-sectional and dynamic knowledge claims. Second, the substantive domain of the example used in this chapter—the emergence of shared interpretations in organizations—underscores the ability of a self-organizing systems model to explain phenomena in terms that are not objective, reified, and relying on material aspects of the organization. Third, our use of computer simulations as a tool to assist theory building is offered as one strategy to deal with the methodological challenges and analytic intractability of social scientific theories that describe nonlinear processes. Simulations can also facilitate precision by being used to disambiguate theories that, in their verbal description, are amenable to more than one set of generative mechanisms. For instance, Monge and Kalman (this volume) note that many theories do not adequately distinguishbetween generative mechanisms that are sequential, simultaneous, or synchronous.

It is important to note that the self-organizing systems perspective, while attempting to extend the interpretive perspective, does not share the latter's ontological and epistemoiogical assumptions. First, ontologically, unlike interpretivists, a systems approach subscribes to the goal of nomothetic explanations. In a self-organizing systems perspective, the nomothetic explanations are articulated as the generative mechanisms, describing the interrelationship among the elements of a system. It must be pointed out that a nomothetic set of explanations at the level of generative mechanisms allows for the manifestation of seemingly ideographic emergent processes. Hence, it is possible that two groups in which the emergence of shared interpretations are manifestly different can he explained by the same set of generative mechanisms.

Second, epistemologically, unlike interpretivists, a systems approach subscribes to a deductive logic. In a self-organizing systems perspective, the hypotheses are not deduced directly from the theory. Instead, the theory is used to identify generative mechanisms. Hypotheses are deduced by dynamically modeling the generative mechanisms. It must he pointed out that the commitment to a deductive model of shared interpretations does not preclude a researcher from allowing the data in a specific organization to reveal the existence of interpretations that are unique to members in that setting.

Following the lead of a few pioneering scholars, this chapter has attempted to demonstrate the utility of employing recent intellectual developments in systems theory and new computational capabilities to extend our understanding of keyr themes within the interpretive perspective.

Predicting Television Viewing

Cycles, the Weather, and Social Events

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Television viewing is a major consumer of the leisure time, occupying over 28 hours a week per person or over 49 hours a week per household (Condry, 1989; Lodziak, 1986; Robinson, 1981). It has become a regular social habit along with sleeping, working, and various other activities (Goodhardt, Ehrenherg, & Collins, 1987).

Television constitutes a complex innovation as its adoption not only changed the everyday use of time hut also culture (Barnett, 1988a). Further, its adoption has altered the communication patterns and social habits of society's members (Barnett, Chang, Fink, & Richards, 1991; Hamblin, Miller, & Saxton, 1979; Robinson, 1972). Condry (1989) divides the effect of television into indirect and direct. The direct effects result from watching specific program content. Indirect effects arise simply from the *adoption* of television because this leads to changes in the distribution of time in daily life, This chapter focuses on the indirect effects—how the average household uses television regardless of its specific content.

Television, as a complex innovation, has changed the use of leisure time (Robinson, 1981; Sahin & Robinson, 1980). Since its beginning, several studies have described viewing patterns and suggested several