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The Complexity Paradigm for Studying Human Communication: A Summary and Integration of Two Fields

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Abstract

There are more things in heaven and earth, Horatio,
than are dreamt of in your philosophy.
Hamlet (Act 1, Scene 5)

This popular quote from Hamlet might be recast for the field of communication as "There are more things in science than are dreamt of in our philosophies". This article will review several new and strange ideas from complexity science about how the natural world is organized and how we can go about researching it. These strange ideas, (e.g., deterministic, but unpredictable systems) resonate with many communication phenomena that our field has traditionally had difficulty studying. By reviewing these areas, we hope to add a new, compelling and useful way to think about science that goes beyond the current dominant philosophy of science employed in communication. Though the concepts reviewed here are difficult and often appear at odds with the dominant paradigm; they are not. Instead, this approach will facilitate research on problems of communication process and interaction that the dominant paradigm has struggled to study. Specifically, this article explores the question of process research in communication by reviewing three major paradigms of science and then delving more deeply into the most recent: complexity science. The article provides a broad overview of many of the major ideas in complexity science and how these ideas can be used to study many of the most difficult questions in communication science. It concludes with suggestions going forward for incorporating complexity science into communication.

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Highlights

- There is a third paradigm of science, commonly referred to as complexity science.
- It provides analytic methods that will facilitate the study dynamic and interactive communication processes.
- Though the complexity science paradigm is not well-known to communication scientists, it has facilitated important discoveries in most other branches of science.
- The complexity paradigm focuses on how simple rules (e.g., basic laws of evolution) generate highly complex-appearing systems (e.g., all life on Earth).
- The characteristics of communicative interaction processes are a strong fit with criteria for complex systems.
- Communicative interaction can be modeled and tested using a computer simulation.
- Complexity will require researchers to integrate existing knowledge into a very different paradigm, slowing broad-based adoption in the field.

Content

The Complexity Paradigm for Studying Human Communication

You do not need a Ph.D. in communication to know that human communication is a complex interactive process made up of simultaneous verbal and nonverbal messages. However, the interactive process of communication has long vexed communication researchers and eluded scientific study (Berger, 2010; Burleson, 1992; Lang, 2013; Lang & Ewoldsen, 2010; Poole, 2007; Salem, 2012). Are there clear and predictable patterns to the interactive process by which individuals exchange meaning and influence one another (Miller, 1977)? Why does the communication flow effortlessly sometimes but not at other times, despite similar circumstances? How does the interactive process of communication lead to distinctive group decisions or strong group entitativity? Can we capture the interactive dynamic of communication in such a way as to gain understanding and control over persuasion or negotiation? What is the process by which communication creates the emergence of phenomena like Internet memes, flash mobs, or international fan groups for television or film franchises?

Though our field has long held that communication is a process (Berlo, 1960; Johnson & Klare, 1961), we have had great difficulty studying it as such (Miller, 1977; Poole, 2007; Watt & VanLear, 1996). As early as 1960, Berlo wrote, in *The Process of Communication*, that in order to study communication, "we must arrest the dynamic of the process, in the same way that we arrest motion when we take a still picture with a camera" (p. 25). This raises the question: what is lost from a dynamic phenomenon when we change it from what it is to a snapshot of what it is? For example, can we understand how a bird flies by looking at its still body? Well, yes and no. There is clearly much to learn about flight from bird physiology (e.g., nearly weightless hollow bones, optimal wing to body-size ratio, airfoil shape). There also remains a great deal left to know related to the rhythms of muscle movement, the positioning of feathers, and the bird's responses to varying air dynamics. Importantly, the methods used to understand static physiology (e.g., dissection) will not be particularly useful for understanding the dynamic process of flying. We could say that knowledge of static bird is necessary, but not sufficient, for understanding flight.

The current state of communication research is analogous to studying static birds. During the last four decades, our field has produced tremendous research on static communication, but little on the dynamic interactive process of communication. Just as the methods for studying static bird physiology had to give way to the methods of fluid dynamics to more fully understand the process of flight, the methods we use to study communicative interaction need to be more appropriate to interaction dynamics. In this article, we review a number of epistemological ideas currently being used in other sciences to understand similarly complex dynamic processes. Just as in the Hamlet quote, this new epistemology will require new imagination on the part of quantitative and qualitative communication researchers. We will review the current dominant paradigm in communication science; contrast and introduce the domain, concepts, and methods of complexity science; and give suggestions for topics and methods of studying the dynamics of communication from the perspective of this new paradigm. It is hoped that this article will stimulate new thinking and investigation of how complexity research can enhance the study of human communication processes.

The Dominant Paradigm in Communication Science

Communication science Ph.D. students are taught that science consists of the search for laws of communication represented as relationships among a small number of variables (e.g., Berger, Roloff & Ewoldsen, 2009; Chaffee, & Berger 1987; Shoemaker, Tankard & Lasorsa, 2004) and presented as static snapshots. For example, the popular theory of reasoned action states that the relationship between cognitions and behavioral intention are an additive function of attitudes and social norms stated as: $BI = A + SN$ (Ajzen & Fishbein, 1980). Many theories are modeled as boxes (constructs) and arrows (relationships/direction) (Shoemaker et al., 2004). This method of scientific explanation is derived from the logical-empirical paradigm primarily drawn from the work of Hempel and Oppenheim (1948) and Popper (1934/1959). The logical-empirical paradigm states that an explanation consists of logically structured theories that allow for deduction of hypotheses which can be empirically tested to falsify theoretical claims (Berger, 1977; Shoemaker, et al., 2004). As a result, scientific explanation is the search for causal laws/relationships among variables: "Causation is literally the driving force of variance theories in that causes are assumed to produce the effects in a regular manner, and knowing the values of the causal variables is sufficient to know what effects will occur." (Poole, 2007, p. 183)

Causality is held to have three components, following Cook & Campbell's (1979) formulation: covariation, time order, and elimination of alternative explanations for the cause-effect relationship. To accomplish the task of finding causal laws, scholars attempt to specify a set of relationships among predictor variables that explain the maximum amount of variance in the outcome variable. Relationships among variables are conceived in terms of covariation, where the relationship is usually algebraically linear. Statistics are used to determine the extent to which the observed relationship is consistent with the linear prediction (e.g., effect size) by assessing the amount of variance in the dependent variable that results from variance in the independent variable. Time order is typically handled methodologically by experimental manipulation or some type of quasi-experimental design (Cook & Campbell, 1979; Davis, 1985). Possible alternative explanations can be ruled out methodologically or through statistical analysis. Empirically, these theorized relationships rarely explain 100% of the variance and are instead considered probabilistic rather than strictly deterministic.

In the vast majority of cases, the research model is assumed to be linear, even if the individual terms (i.e., variable and coefficient) are nonlinear. Linear systems are those that meet the criteria for superposition: scaling and additivity. Scaling refers to systems in which the change in the dependent variable is proportional to the change in the independent variable. In other words, the relationship between independent and dependent variables is a fixed ratio (e.g., a 1:3 ratio in which every increase of one unit in the IV results in an increase of three units in the DV). In contrast, in nonlinear systems, a change of one unit in the IV might result in enormous qualitative change in the DV (Campbell, 1987). For example, a simple nonlinear function such as $y = x^2$ results in the following series of ordered pairs in which the DV is increasing at a much higher rate than the IV {(1, 1), (2, 4), (3, 9), (4, 16) …}. Additivity refers to systems where the amount of variance explained in the dependent variable is the sum of the effects of the set of independent variables, as in a multiple linear regression equation (i.e., variance explained in the criterion variable is an additive function of a set of weighted predictor variables). Whereas the terms of a linear system can be separated, solved individually, and then summed back together, the terms in a nonlinear system must be solved simultaneously (Campbell, 1987). As a result, "no general analytic[1] approach exists for solving typical nonlinear equations." (Campbell, 1987, p. 219) Instead, these systems are represented as a series of numbers to be interpreted qualitatively rather than as a single math expression.

Empirical communication research makes extensive use of inferential statistics to test theorized causal relationships. Inferential statistics are used to determine the likelihood that an effect observed in a sample is large enough to represent a real result in some larger population of humans, media or events from which the sample was drawn. Despite the stated goal that empirical work in communication be conducted by deriving hypotheses from theory, the majority of empirical work in communication employs inferential statistics to locate descriptive variable relationships (Bryant & Miron, 2007). As such, much empirical research in communication is akin to Weaver's (1948) description of research in the early life sciences: "largely concerned with the necessary preliminary stages in the application of the scientific method-- preliminary stages which chiefly involve collection, description, classification, and the observation of concurrent and apparently correlated effects." (p. 536)

Table 1. *Weaver's historical eras of science*

	Simplicity	Disorganized Complexity	Organized Complexity
Century	17th-19th	19th-20th	20th-21st
Sciences	Physical	Biological/Behavioral	Physical/Biological/ Cognitive/Social
Problem	Variables/Relationships	Probability/statistics	Organization/Process
Variables	2-3 variables	Billions of variables	Two < n < Billions
Operate on	Variables	Averages	Systems
Examples	Laws of motion	Thermodynamics	Flocking/Herding
Communication	Persuasion	Public opinion	Conversations/ Group discussions

[1] Analytical solutions are those that can be represented as a math expression consisting of numbers and operators (e.g., +, -, *, ln, roots). Analytic solutions are contrasted with numerical solutions that consist of a series of numbers.

Different Eras Use Different Approaches to Science

Communication science's focus on laws and statistical trends reflects two of the most important scientific paradigms of the last four centuries. In the past 50 years, a third major scientific paradigm has emerged. Renowned American mathematician and science advocate, Warren Weaver (1948), argues that these three great movements in the history of Western science can be distinguished by the size and complexity of problems they addressed, from relatively simple, to disorganized and complex, to organized and complex (see Table 1). The first era, which Weaver labels "problems of simplicity", are represented by the traditional two variable physics of the 17th through 19th century (e.g., Newton's laws, Maxwell's equations, Ohm's law). These problems represent comparatively simple relationships among two or three individual variables, typically stated as equations that specify how proportions among variables change over time (e.g., Newton's second law of motion states that the change in momentum of a body is directly proportional to the acting force F and inversely proportional to its mass m; $F=d(mv))/dt$). Exact solutions are analytically solvable for these problems, meaning that precise point predictions can be made for the values of missing variables or for future states[2]. This is the approach to science that Hempel and Oppenheim (1948) and Popper (1934/1959) describe in their philosophies of science and that communication Ph.D. students are taught to emulate (Shoemaker et al., 2004).

By the late 19th century, physicists became concerned with problems that had many more than two or three variables. Weaver (1948) calls these problems, best represented by the field of statistical mechanics, "problems of disorganized complexity". Disorganized complexity refers to systems displaying "helter-skelter, or unknown, behavior of all the individual variables; (although) the system as a whole possesses certain orderly and analyzable *average* properties." (Weaver, 1948, p. 537-538, emphasis added) For example, statistical mechanics uses probability theory to study average behavior (e.g., temperature, entropy) in thermodynamic or kinetic systems that have millions of variables. While there is no law for temperature or entropy at the microscopic level of molecules, temperature and entropy laws are evidenced on average at the macro level of large collections of molecules. Because of the very large number of variables involved, these systems are not analytically solvable. Instead, scientists developed techniques of statistics and probability to tackle these problems[3]. For example, insurance companies depend on trends in human behavior to predict costs and rates, although they know almost nothing about the millions of individual customers those trends summarize. Communication researchers commonly use statistical probability techniques to understand general behavior trends in large populations of individuals represented as a general trend called *public opinion*.

A third scientific era developed in the mid-20th century and continues to develop through the 21st century: problems of organized complexity. These problems exist in the space between problems of simplicity and disorganized complexity. Weaver (1948) writes that these problems are both "just too complicated to yield to the old nineteenth-century techniques which were so dramatically successful on two-, three-, or four-variable problems of simplicity" and "cannot be handled with the statistical techniques so effective in describing average behavior in problems of disorganized complexity." (p. 540) These midlevel problems focus on phenomena that display a level of self-organizational behavior that is not reducible to simple laws, such as herding and flocking behavior (Reynolds, 1987), superconductivity (Anderson, 1972), weather (Lorenz, 1963), neural processing (Beer, 2000; Sporns, 2002; van Gelder, 1998), and many types of social organization (Miller & Page, 2009). They are problems "which involve dealing simultaneously with a sizable number of factors which are interrelated into an organic whole." (Weaver, 1948 p. 541) For Weaver, these problems included problems from chemistry (e.g., how two chemicals can consist of the same atoms, yet one be poisonous and the other harmless); biology (e.g., how protein molecules know how to reproduce their own pattern), and

[2] This statement is only true under certain limited conditions.

[3] Note that statistics are unnecessary for problems of simplicity because it is possible to solve the system analytically.

social science (e.g., what are the determinants of the price of wheat?; how can we stabilize currency?; why do organized groups such as labor unions or a group of manufacturers behave the way they do?). Many of the most vexing communication problems such as conversational interaction, group dynamics, and negotiation, as well as other questions such as media choice, emergent Internet behavior trends (e.g., memes, flash mobs) or the gradual coalescing of public opinion exist at this midlevel of how systems create order and/or adapt to other systems. These problems have to do with how individuals co-organize meaning and experience in communication to accomplish higher level organization including culture, social structure, politics and economics. The remainder of the article will explore emerging third era research at the midlevel and propose some ideas about studying various types of communication interaction as an organized complexity phenomenon.

What are Complex Systems? A Brief Introduction

A half century after Weaver's observations (1948), a major thrust of scientific research continues to be the study of complex systems (e.g., Anderson, 1995; Flake, 1998; Miller & Page, 2009; Mitchell, 2009; Newman, 2005; Solé, & Goodwin, 2000; Waldrop, 1993). Beginning primarily in mathematics, physics, and computer science, complex systems research has expanded to a broad array of research disciplines including chemistry, biology, neuroscience, information science, medical science, cognitive science, economics, and public policy. The shift toward complex system research has been facilitated by increasing computational power resulting from the invention of the microchip. Digital computers provided researchers the computational power necessary to analyze very large data sets, to model iterative dynamic systems, and to uncover mathematical principles proposed, but not tested, by past generations (Pagels, 1988). In the process, scientists have begun to unlock secrets of systems that were resistant to less computationally-intensive traditional methodologies. Dramatic examples of complexity science include the use of the Lorenz attractor for weather prediction (1963); the discovery of emergent fractal properties of the Mandelbrot sets (1983); the working out of genetic algorithms to accomplish computer learning (Holland, 1995); understanding how apparently complex behavior can result from self-organization of inorganic material (e.g., autocatalytic sets, Kauffman, 1986); how very low intelligence animals evidence complex social behavior (e.g., ant behavior, Gordon, 2010; bird flocking, Reynolds, 1987); and discoveries of dynamical systems properties of the human brain (Beer, 2000; Sporns, 2003; van Gelder, 1998). These discoveries and others repeatedly demonstrate the counterintuitive, but compelling lesson of complex systems research: the apparent complexity of the world can often be explained by simple sets of rules iterated over large populations.

Definitions

Because complexity science is a relatively new and highly multi-disciplinary area with a broad array of methodologies, a consensus definition has yet to emerge (Mitchell, 2009). Ilachinski (2001) defines complexity science as the study of systems in which an "increasing number of independent variables are interacting in interdependent and unpredictable ways" (p. xxvii). Holland (2014) emphasizes that complexity is concerned with the subset of systems that display unique nonlinear and emergent behavior at different levels of hierarchy. For Holland, complex systems are typified by self-organization, chaotic and fat-tailed behavior, and adaptive interaction. Wolfram (2002) simply refers to complexity as *A New Kind of Science* in which computers are used to test and reveal that "complex behavior very much like what was seen in nature could in fact arise in a very general way from remarkably simple underlying rules" (p. 861). Page (2011), who focuses on human social behavior, writes "Complexity can be loosely thought of as interesting structures and patterns that are not easily described or predicted. Systems that produce complexity consist of *diverse* rule-following entities whose behaviors are *interdependent*. Those entities interact over a *contact structure* or *network*. In addition, the entities often *adapt*." (p. 17)

Some researchers focus on understanding general principles of complex system behavior, while others use the insights and methodologies afforded by fundamental complex system research to understand specific incidents of complex behavior. The boundaries remain fuzzy. In an attempt to provide some guidance, complex systems theorists have identified sets of characteristics common to most complex systems studied to date. Mitchell (2009) summarizes these characteristics as: 1) behavior among large collections of components/agents; 2) signaling and information processing among components/agents; and 3) adaptation in response to other components/agents and to the environment following deterministic rules. Such complex systems are typically highly organized, robust against failure, capable of flexibility, and self-organizing (there is no central actor dictating the behavior of the components). Perhaps the most familiar example of a self-organizing system is biological evolution. Absent a central guiding force, very large numbers of biological agents (organisms), with subtle individual differences (genetics), repeatedly apply evolutionary algorithms (descent with modification) informed by feedback from the environment over millions of years to realize an organism that is robust to its environment (optimally adapted).

Flake (1998) offers a similar list of six basic properties of complex systems that render these systems organized, adaptive and robust:

Collections.

Complex systems typically have a very large collections of agents/actors (e.g., humans, bees, ants, cells, genes, molecules). Large collections afford a fault tolerance in the system; the loss of any single agent or group of agents does not have a dramatic effect on the system. Redundancy is built into the system.

Multiplicity.

Agents in a complex system frequently have subtle differences that make the system even more robust against loss. If multiple agents represent different solutions to a survival problem, one of them is bound to work better than the others. Page (2011) refers to this characteristic of complex systems as diversity within a type or variation. Examples are abundant in evolved organisms such as variation in size, color, sensitivity or resistance. At higher levels of emergence, such as a human society, diversity is often found in the composition of members of the system (e.g., teachers, police officers, doctors, janitors).

Parallelism.

The large number of agents in a complex system often work simultaneously on the same task. Like billions of neurons processing human thought, parallel processing allows large tasks to be completed more efficiently. More work can be performed in a given time frame than if work were arranged serially, with one agent waiting for the other to finish and pass off the work as in an assembly line.

Iteration.

In addition to the physical redundancy of collections, multiplicity, and parallelism, systems are redundant in time. Redundancy in time is accomplished via *computation*, a broad class of information processing procedures which execute an algorithm (i.e., a sequence of instructions). Computation isn't necessarily numerical; natural processes such as cell reproduction, evolution, and neural networks are examples of computational processes as well. Iteration is a form of computation in which an algorithm is applied repeatedly in order to grow the system. For example, icicles and stalactites grow through an iterative sequence in which new layers of liquid move toward the bottom of the structure and then solidify on the end. Iteration of an adaptive algorithm provides the opportunity for a system to incorporate change from one time-state to the next. In living systems, reproduction is a form of iteration (Flake, 1998).

Recursion.

Recursion is a computational process that differs from iteration in that its function "refers back to itself through information flow, influence or cause and effect" (Flake, 1998, p. 463). Sloman (1978) provides a simple example from computer programming: "in the set of instructions defining one program *A*, there is an instruction of the form 'If condition *X* is satisfied then run program *B*', while program *B* contains a similar call of program *A*." (p. 117) The system, consisting of the combination of programs *A* and *B*, refers back to itself at each step; *A* performs an algorithm on *B* and vice versa. Flake & Pennock (2010) note that a biological ecosystem is recursive because of "the circularity of the ecosystem's dependencies." (p. 98) That is, each generation is a function of the interdependencies among individuals (e.g., competition to reproduce) and species (e.g., predators and prey) found in the generation that preceded it. They extend the ecosystem argument to the World Wide Web, whose structure and function result from recursive generational interdependencies in terms of connectedness and traffic. The greater a site's connectedness, the greater its traffic and vice versa.

Recursion accounts for self-similarity that is frequently seen in complex systems (Flake, 1998). Self-similarity refers to a set of object characteristics that show the same properties at different scales (e.g., a map of one mile of coastline looks very similar to a map of 100 miles of the same coastline). The Mandelbrot equations are mathematically recursive (the function being defined is applied within its own function) and gives rise to infinitely complex fractals that nonetheless display the so-called 'Mandelbrot bug' at every level (see example at http://www.wrongway.org/java/mandel.php). Self-similarity due to recursion is seen in many natural systems such as snowflakes, broccoli, tree branches, and crystals.

Feedback.

Feedback can be defined as the "circularity of action between the parts of a dynamic system." (Ashby, 1957, p. 53) Inherent in the concept of feedback is interaction between two parts of a system; a change in system A results in system B reacting by an increase (positive) or decrease/halting (negative) in function and vice versa. A positive feedback loop exists when system A induces an increase in system B, which subsequently induces increased change in A. For example, a positive feedback loop exists between humans and agricultural production. As the number of humans increases, they do additional farming to provide an adequate amount of food; as food production increases, there is enough food to support additional humans. Negative feedback regulates a system by reducing (i.e., reversing) or halting change. The canonical example of negative feedback is a furnace thermostat. The furnace increases room temperature until the thermostat senses the temperature has reached a designated upper value, at which point the thermostat sends a signal to the furnace to halt production of heat, (i.e., effectively reversing the increasing temperature as the room temperature begins to fall again). When the decreasing temperature reaches a designated lower value, the thermostat sends a signal to the furnace to increase the heat (i.e., reverse the decreasing temperature).

These six basic properties give rise to a vast assortment of organized, adaptive, and robust complex systems. Principles of number (i.e., large collections of redundant agents with minor differences, working in parallel) and process (i.e., recursion and iteration) provide the basis for organization in the system such that patterns of self-similarity in appearance and behavior emerge via recursive iteration of a set of rules across multiple agents in response to signals from the environment. This allows the system to grow, adapt and survive, while retaining the core mission of the system.

A frequently used example of a complex system is the behavior of ant colonies. Ants display a rich, complex, and varied social life (see Gordon, 2010). They are capable of finding all available food within a self-selected foraging area, organize armies to fight off threats, farm fungus, and build intricate homes for themselves, even constructing dams to protect the nest from flooding. Despite the appearance of complex organization, ants are neither centrally organized nor intelligent as well as functionally blind. In order to generate complex collective behavior, ants are programmed to attend to a very limited set of instructions (algorithms) repeatedly. For example, to forage, thousands of ants simultaneously travel random paths in the foraging area. When an individual ant finds food, it returns to the nest laying down a pheromone trail as it goes. When other randomly traveling ants come across the pheromone trail, the scent from the trail leads them to the food and then back to the nest. Like the first forager, each subsequent ant lays additional pheromone scent on the trail, drawing additional ants to the trail and the food. Eventually, a stream of ants emerges following the same trail, carrying food back to the nest. No single ant directs the behavior; discovery is random, and the trail is strengthened by positive feedback. The overall behavior is so rich and complex-appearing that people frequently assume there is some level of hierarchy (e.g., a queen ant giving orders).

Types of Complexity

Manson (2001) delineates three types of mechanisms found in complex systems: algorithmic, deterministic, and aggregate. Algorithmic complexity is rooted in mathematics and information theory and examines systems that organize via iteration and recursion. As an adjunct of information theory (Shannon entropy, see below), algorithmic complexity searches for the simplest algorithm that can reproduce complexity. Examples include a range of work that has been done with Shannon entropy (Berger, Della Pietra & Della Pietra, 1996). Deterministic complexity has its intellectual roots in Poincare's work on qualitative analysis of *n*-body systems and addresses topics including phase transitions, chaos, and catastrophe. It uses deterministic mathematics, along with feedback, to model qualitative change in systems. Examples include population and extinction dynamics in a wide variety of wildlife (May, 1976; Zimmer, 1999) and chaos dynamics in neural systems responsible for biological information processing (Tsuda, 2001). Aggregate complexity focuses on relationships and structure in systems that interact with an environment. Often times these aggregate systems learn from their environment and adjust as needed. The best example of such a system is Darwin's theory of descent with modification (evolution). The following section describes each type of complexity in greater detail and provides examples that could be applicable to communication research.

Algorithmic complexity.

Algorithmic complexity "contends that the complexity of a system lies in the difficulty faced in describing system characteristics." (Manson, 2001, p. 405) One subtype of algorithmic complexity is concerned with quantifying the amount of effort required to solve a mathematical system. A second subtype is more germane to the problems that communication researchers might encounter. This type of algorithmic complexity is concerned with discovering the "simplest computation algorithm that can reproduce system behavior." (Manson, 2001, p. 405) In other words, what is the simplest set of discrete rules that give rise to the behavior of interest. There are many ways that the diversity of life on Earth may have come about; the theory of evolution (descent by modification) provides a small set of rules that effectively explains the diversity of life (e.g., inheritance, fitness, random genetic modification). One of the best known examples of the second approach comes from Shannon's (1948) highly influential paper *A Mathematical Theory of Communication*.

Shannon entropy.

Shannon entropy refers to a set of mathematical procedures for determining the amount of information in a system. Following Boltzmann, Shannon conceived entropy as the amount of randomness or unpredictability in a system. Shannon's (1948) entropy quantifies information as the inverse of the amount of uncertainty in a communication system, specified as the relationship among transmission rate, reliability, bandwidth, and signal-to-noise ratio in the movement of a bit of information over a phone system. The entropy equation measures how uncertain we are of an outcome given the number of available possibilities, the probabilities associated with those possibilities and the amount of noise in the system. This allows us to understand and compare the amount of uncertainty that is present in all kinds of systems, from data compression to biological sensory processing to econometrics or communication. Information does not need to be formally encoded in a language; it can take any form that the system uses to organize itself. Broadhurst and Darnell (1965) argue that "the important thing as far as rhetoric or human communication is concerned is that information theory provides a basis for a comprehensive theory of organization" (p. 452), which may in turn provide insight into the organization of effective rhetorical messages for various contexts and individuals. Theories such as uncertainty reduction theory (Berger & Calabrese, 1975) and diffusion of innovation (Rogers, 1994) that claim communication is a process by which we reduce uncertainty about others are a natural fit for this type of complexity. Some form of Shannon's entropy could be used as a measure of the degree to which a communication process reduces uncertainty.

Deterministic complexity.

According to Manson (2001), deterministic complexity refers to a type of complexity that "has four key characteristics: (1) the use of determinist mathematics and mathematical attractors; (2) the notion of feedback; (3) sensitivity to initial conditions and bifurcation; and (4) the idea of deterministic chaos and strange attractors." (p. 407) Importantly, deterministic complexity frequently leads to abrupt and sometimes radical qualitative change in systems. The most commonly cited examples of deterministic complexity are attractors and phase transitions.

Deterministic mathematics and attractors.

Because complex systems are frequently nonlinear, they are commonly modeled by specifying relationships among variables (which can be any type of mathematical function) and the system's interaction with the environment, and then iterated some number of times. The result is not a point parameter (e.g., correlation), but a series of numbers representing patterns of behavior geometrically mapped onto a mathematical phase space. Researchers examine the resulting patterns and how they unfold and/or move to resolution. Phase space is an n-dimensional portrait of all possible states of a system, such as a two-dimensional space with an x-axis and a y-axis. The phase space has as many dimensions as there are variables in the system (Figure 1 is the phase portrait of a three-dimensional system). The initial conditions (starting values) of the system are mapped as a single point in phase space, after which the next point in the phase portrait is determined by applying the appropriate mathematical equation to each variable. As the system applies the variable's equations through successive points, the behavior of the system is mapped to create a phase portrait of system behavior. The system can be iterated any number of times. The resulting phase portrait is mathematically deterministic because the specified equations determine each successive point. However, a single equation or set of deterministic equations may evidence a variety of qualitatively different behaviors, a subset of which are known as attractors.

May's (1974; 1976) provides a relatively simple example of how varying initial conditions in a nonlinear deterministic system can result in a variety of qualitatively different system behaviors. May (1974) simulated the Verhulst (1838) population dynamics equations[4] using

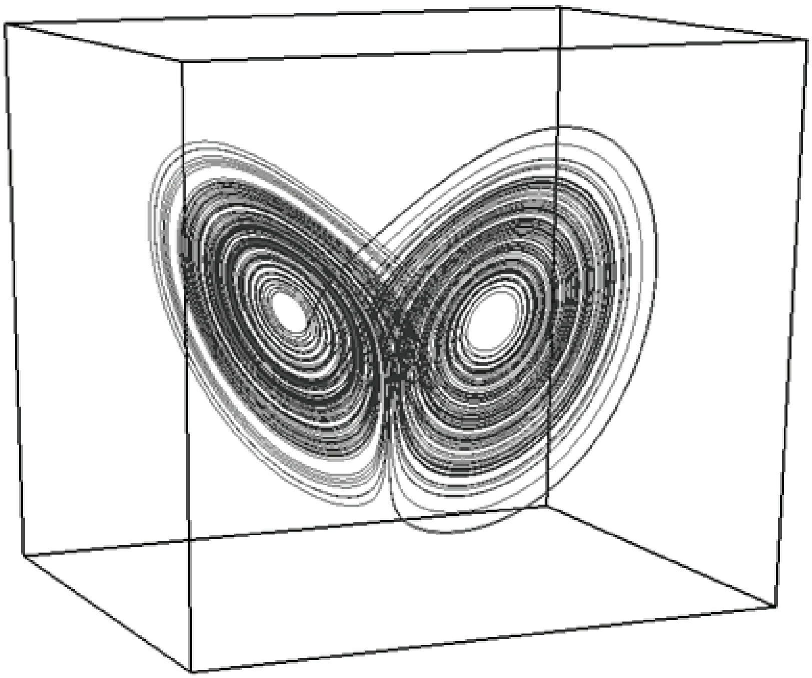

Figure 1. *The Lorenz attractor.* Created using 3D Attractor version 1.0 by Juan G. Restrepo. Downloaded April 4, 2014 at http://amath.colorado.edu/faculty/juanga/3DAttractors.html

[4] This example can be understood better by doing the computations with different initial parameters and readers are strongly encouraged to do so. Java applets are available on-line for this purpose at sites such as: https://math.la.asu.edu/~chaos/logistic.html and http://www.geom.uiuc.edu/~math5337/ds/applets/iteration/Iteration.html

a range of initial condition values. Verhulst's (1838) logistic equation (see Equation 1) specifies animal population dynamics relative to the environment's carrying capacity (see Vogels, Zoeckler, Stasiw, & Cerny, 1976). The Verhulst equation states that changes in a species population is proportional to the existing population and the amount of available resources:

$$\frac{dN}{dt} = rN\left(1 - \frac{N}{K}\right), \quad r \leq 4 \qquad (1)$$

where N = population, r is the rate of population change, and K is the carrying capacity of the environment. In this model, the population N increases at rate r until it reaches capacity K. May (1974) demonstrated that varying the initial parameters in this simple dynamic system (differential equation) will result in behavior that settles to one of three attractors: a single/equilibrium state (fixed point), a recurring behavior loop (limit cycle), or a phase portrait that does not settle to either a fixed point or a cycle (strange). An attractor is a subset of phase space representing "the long term stable sets of points of the dynamical system, that is, the location in the phase portrait towards which the system's dynamics are attracted" (Goldstein, 2011, p. 5). For population change rate values of $1.00 < r < 3.00$, the iterated logistic equation eventually settles to a single, unchanging value for the population, known as a fixed point attractor. For values of population change rate r in which $3.00 < r < 3.57$, the system is attracted to a phase space called a limit cycle attractor. In the case of a limit cycle attractor, the system will settle to a repeating set of values (hence the idea of 'cycle'). Finally, when the population change rate value is $3.57 < r < 4.00$, the system is attracted to a phase space known as a strange attractor. The phase portrait of a strange attractor displays neither a fixed point or a limit cycle attractor, but instead the system progresses through a series of values that never repeat. The best-known strange attractor, resembling a butterfly, is the three-dimensional phase portrait driven by the Lorenz equations (see Figure 1).

Phase transition.

Attractors represent different qualitative behavior in a single deterministic system. The point at which the system changes from one type of behavior/attractor to another (e.g., from a limit cycle to a strange attractor) is known as a phase transition (Solé, 2011). Phase transitions are where we see some of the most interesting and useful types of qualitative behavior of many systems (e.g., steam from boiling liquids). As such, phase transitions are an important feature of the study of attractors. The most familiar example is the transition of H_2O from its solid state to liquid state at 0 degrees °C and from the liquid state to gas state at 100 degrees °C. By understanding why and when a system will go into a phase transition, one can exercise control over the behavior of that system (Garfinkel, Spano, Ditto & Weiss, 1992; Solé, 2011). The moment of phase transition (aka: the edge of chaos) shows interesting and powerful dynamics that have proven to be useful in applied situations. Consider all the uses that humans have made of the phase transition of water from liquid to gas (e.g., steam engines, cooking, steam heat). In addition to introducing new behavior to a system, phase transitions can also mark the moment when the system completely fails, known as catastrophe (Solé, 2011).

Familiar examples from communication include the qualitative change when two people in a conversation finally "get" one another, a sudden breakdown in negotiations, or a moment of spontaneous applause during a speech. Mass communication scholars write of abrupt shifts into and out of the flow state during media use (Sherry, 2004; Weber, Tamborini, Westcott-Baker, & Kantor, 2009). Importantly, phase transitions are marked by a sudden change in the quality of behavior, rather than a gradual shift from one behavior to the next (Solé,, 2011). Because of this, phase transitions can often be located by using computer simulations of the system of interest, allowing researchers to run the system under a wide range of parameters in search of values at which system behavior changes.

Aggregate Complexity.

Aggregate complexity describes the manner by which a system self-organizes by delineating how the relationships, structure and environment of a system adapt over time to create an emergent system. Emergence is defined as the processes and mechanisms of micro-to-macro transition that result in unique, real and non-aggregatable properties that have autonomous causal powers (Sawyer, 2004). That is, "emergent properties are present at certain levels of complexity, but not at lower ones" (Minati &

Pessa, 2007, p. 90). This is not to say that the system that emerges is not reducible, but to say that the mechanism that gives rise to the emergent phenomenon is not simply the sum of parts, but a process of organizing (Bedau, 2011). In this way, organized complex systems are both emergent and reducible (Anderson, 1972). Take the behavior of foraging ants as an example. The foraging ant system is reducible to a number of ants, some ant food, pheromone signals, some territory, and a nest. Each of these items is further reducible to various components, molecules, atoms. However, foraging behavior only emerges when the ants enact the mechanistic search algorithm. Bedau (2011) argues that any conception of emergence must meet the twin hallmarks of explaining how the whole depends on its parts and how the whole is independent of its parts. Clearly, if any part of the system is absent (e.g., food, ants) foraging is not possible (what Sawyer refers to as a non-aggregatable system). On the other hand, other animals forage and communicate by scent; foraging is an activity that is not dependent on a particular set of components. Emergence in complex systems results from the dynamics of the system as it changes over time according to deterministic rules, feedback and adaptation.

Nature is replete with examples of qualitative differences in substance that are not simple functions of a lower deductive level. John Stuart Mill (1872) noted that "The chemical combination of two substances produces, as is well known, a third substance with properties different from those of either of the two substances separately, or of both of them taken together." (p. 371) As another example, a brain is a collection of a variety of cells, each of which engaging in a slightly different behavior; the most familiar of which is conducting electricity from one synapse to another. However, none of these cells can imagine a cell. It takes the collection of cells, organized in one of many possible configurations, to imagine a thing called a cell. Though cells are used for thinking, a cell cannot think. How is thought accomplished?

Self-organization.

Emergence is the result of system self-organization. Self-organization refers to a group of models in which global order arises from interactions among the components of the system. There is no internal or external force dictating the new global behavior of the system; individuals acting within the system and without knowledge of global behavior drive the system. Common examples of self-organized systems include flocking, herding, swarming, and schooling by large collections of animals. The canonical example of self-organization is a computer program called Boids (Reynolds, 1987; there are numerous examples of Boids online, but its best to start with Reynolds' web site which has reference to additional examples of self-organization: http://www.red3d.com/cwr/boids/). While trying to improve computer animation techniques, Reynolds (1987) developed a computer simulation that accurately reproduces the behavior of birds flocking using three simple rules: (1) steer toward the average heading of local flockmates (alignment); (2) steer to move toward average position of local flockmates (convergence); and (3) steer to avoid crowding local flockmates (separation). The animated computer boids show realistic and complex flocking behavior, even when confronted with obstacles (flock flies around flagpole) or when reacting to an external threat. Note that no single bird has the cognitive capacity to control the movement of the flock and that the three simple rules conform are within range of the limited cognitive ability of a bird (or fish, ant, buffalo). A well-studied example of human self-organization is the standing ovation problem (Miller & Page, 2009) in which the emergence of a standing ovation is a function of each audience member's seat location (front, back, or side of the room), neighbors (friend or stranger), and each audience member's evaluation of the quality of the performance. The dynamics of communication diffusion (e.g., a type of slang, a vocal affectation, healthcare information) could be modeled in a similar manner.

Adaptation.

Adaptation refers to intergenerational learning. Adaptation models mimic the interact-and-adjust mechanism of evolution via a series of positive feedback loops. The core idea behind adaptation comes from Darwin's idea of descent by modification, in which each generation of an organism is challenged by its environment and either survives or dies off. Those that survive create offspring that inherent traits that make the offspring more robust against the challenges in the environment than prior generations. Importantly, descent by modification occurs at the species level as a function of the survival of generations of organisms, rather than at the level of the individual. That is, the organism has no knowledge of the overall mechanism by which the species becomes robust over time. John Holland (1995) modeled this process when he created genetic algorithms: a process intended to create artificial computer learning. Genetic algorithms represent a single entity as a string of values (e.g., like a genetic code). For each generation, all the strings in a population are judged according to a preset criterion and strings that meet the criteria move to the next generation. By iterating the presentation, evaluation, and modification sequence many times, the string becomes optimized for the environment (preset criteria) via the mechanism of adaptation. Genetic algorithms are commonly used by engineers to optimize systems for a specific set of environmental challenges.

For example, one could imagine the process of educational communication as a adaptation process in which the teacher is providing successive generations of feedback to a group of students (even while receiving feedback on her own behavior). She might present information using a set of techniques that she believes will be successful in her environment (students). These techniques are judged by the students' reactions and success at learning (environmental criteria), even while the students judge their own behavior by the standards provided by the teacher (grades). She and her students can modify the next set of techniques, keeping those parts of the string that appeared to fit the environment and discarding those that do not. Over time, her teaching style and the students' learning style becomes optimized due to feedback and intergenerational learning.

Synchronization.

In addition to adapting to optimize behavior, systems also adapt to match other systems. This is a process known as synchronization. For example, two metronomes (i.e., pendulums) sharing a moving platform will eventually align so that they swing in common time (numerous video examples can be found on-line by searching "metronome synchronization", e.g., http://www.youtube.com/watch?v=W1TMZASCR-I). Synchronization is defined as the adjustment of rhythms of self-sustained periodic oscillators (a system that varies repetitively in time, such as a pendulum) due to their weak interaction (the moving platform). Synchronization is observed in a wide variety of behaviors, from the flashing of fireflies in unison to human circadian rhythms to neural processing in cardiac sinus rhythm, as well as in numerous communication situations (Burgoon, Stern, & Dillman, 1995). There are a number of types of synchrony, but they all share the same set of basic characteristics. First, synchronization can only occur between oscillating systems. The systems must oscillate (display a regular repeated pattern of change). In the case of the metronome, the oscillation occurs as the arm swings from one side to another over time. Second, synchronization happens between two or more independent systems; any individual metronome will run independently of all other metronomes. In other words, the systems must be independent, self-sustaining oscillators. Next, the systems need to weakly interact with one another (they must be coupled). The process happens in a variety of ways, including master-slave systems (slave oscillator synchronizes to the master), external forcing (an external force acts on both systems), pulse coupling (exchange of signals move each oscillator toward the other), and others. In the pendulum example, the moving platform that they share is the coupling device. Essentially, the coupling device provides the channel for communication among oscillators.

Several types of human cognition appear to result from the synchronization of neurons in the brain (an EEG is designed to detect the electrical signal generated by neural synchronization). If communication is the process by which a cognition is moved from one brain to another brain and cognitions are neural synchronization, communication is a set of behaviors used to synchronize neural systems between brains (Hasson, Ghazanfar, Galantucci, Garrod, & Keysers, 2012; Jiang et al. 2012; Nummenmaa et al. 2012). That is, in order to transfer an idea from one brain to another, the sending brain needs to generate a similar pattern of neural synchrony in the receiving brain as in the sending brain. The degree to which two systems are moving toward being in sync can be measured using the Lyapunov exponent (lambda), which measures the separation in orbits (paths of the system) in time.

Organized Complexity and Communication Science

There has been little written in the communication science literature on alternatives to variable analytic or statistical approaches to scientific research. Instead of studying communication as a process that unfolds over time, communication is studied as structural relationships among variables and functions (e.g., persuasion, social support) of those relationships (Salem, 2013). In fact, Poole (2007) estimates that less than 10% of articles in communication journals focus on process rather than structure and function of variance approaches. Often, when confronted with problems that don't conform well to static variance-based approaches, scholars have either engaged in interpretive, qualitative research or simply ignored the question. Unlike interpretive qualitative research, complexity research values objective empirical observation and logical explanation. However, those explanations take a very different form than the two-three variable laws common in communication research. Most often, explanation in complexity research consists of a description of a system, the mechanism that animates the system over time, and the possible outcomes of the system for different parameters. Analysis is not restricted to linear operation, but is most often nonlinear (or a combination of both), making point prediction inappropriate. Instead, organized complexity research focuses on the structure and process by which midlevel systems give rise to new and sometimes unpredictable behavior.

Is Communication a Complex System?

Communication scholars have long grappled with the apparent complexity of human communication, particularly as it changes over time. Miller (1977) felt the challenge was not beyond us. He wrote, "to say that a set of phenomena differ in many ways does not imply that there are no regularities which the phenomena share. The task of the communication scientist is the discovery of these regularities." (p. 7) It may be that the complex system approach is what our field has been waiting for to disentangle the complexity of human communication. First, we need to know the extent to which communication meets the characteristics of complex systems. If that is the case, it makes sense to pursue this approach in communication research.

Mitchell (2009) states that complex systems are typified by behavior among a large number of components in which there are signaling and adaptation in response to other components and the environment. From this set of characteristics, it is clear that communication plays a central role in complex system behavior (signaling among agents). However, that is not the same as stating that communication is a complex system. Flake (1998) provides six criteria for complex systems: collections, multiplicity, parallelism, iteration, recursion and feedback. To what extent does communication meet these criteria? To explore whether communication meets the criteria of a complex system, we will consider the case of an interpersonal conversation among three friends, held up against each of Flake's (1998) six criteria (see Table 2). The friends are sitting at a coffee house engaged in the type of wide-ranging conversation that frequently happens in these settings.

Collections.

Collections refer to the fact that complex systems are made up of very large sets of agents (actors). If we take the unit of analysis in conversation as the individual, a communication system does not appear to qualify as having a collection. However, the individual is the unit of analysis for psychology, not communication. Instead, the unit of analysis for communication is the set of components that make up the system of exchange. These components are a collection consisting of nonverbal display (i.e., artifactual communication), signaling (e.g., unintended physiological response such as pupil dilation, muscle twitch), verbal behaviors (e.g., words, speech acts, frames), and nonverbal behaviors (e.g., proxemics, vocalics, gestures, prosody, haptics). Imagine the number of communicative symbol components our three interactants create in the course of their conversation. Now imagine that the conversation is being held via computer-mediated communication (CMC). The loss of display, signaling and nonverbal behavior components does not prevent the conversation from occurring, but it may affect the number of components that make up the conversation system.

Table 2. *Characteristics of Communication and Complex Systems*

Complex Systems	Communication
Collections	Verbal & nonverbal symbols
Multiplicity	Number of talk turns
Parallelism	Multiple simultaneous communication channels
Iteration	Repetition of conversational forms; Cultural codes, jargon & slang
Recursion	Reference to prior utterances and building upon those utterances; Rules of talk turns; Grice's conversational maxims
Feedback	Effect of each message on subsequent messages can add to or limit communication; Communicative adjustment to conversational partner

Multiplicity.

Multiplicity refers to variation in type among the agents in a complex system. Minor variations among agents make the system robust against failure by allowing for a number of different solutions to a survival problem. This is a well-known feature of verbal and nonverbal communication systems: there is more than one way to express or interpret an idea. Communication can be seen as a process of negotiation of meaning transfer among people who have different manners of expression as well as different background knowledge and assumptions. In our example case, the three interactants are friends who likely share a common set of communication symbols and meanings. This would not be the case if the three interactants were strangers from different cultural backgrounds. Communication accommodation theory (Giles, Coupland, & Coupland, 1991) posits communication as a process of convergence or divergence among people with different cultural and linguistic backgrounds. Because each of our three interactants brings culturally different experiences, goals, and expectations to the conversation, there is an inherent multiplicity of linguistic and nonverbal expression, messages and topics for conversation. Despite the multiplicity, communication can be successful when interactants use the variety in language to negotiate common meaning.

Parallelism.

Parallelism refers to simultaneous agent behavior that allows tasks to be accomplished more efficiently. The communication system our three interactants are using consists of a high degree of parallelism in display, signaling, verbal, and nonverbal communication components. If one interactant decides to make a sarcastic remark, it is necessary for him to create simultaneous, but incongruent, verbal and nonverbal messages. Conversely, an unintended nonverbal behavior may make a particular verbal message difficult to interpret. There are often subtle and unconscious uses of parallel signals. We might observe that our three interactants move in a subtle coordinated manner as they talk. Nonverbal postural synchronization has been shown to affect a variety of communication outcomes, including facilitating mutual understanding (Richardson, Dale, & Shockley, 2008; Shockley, Richardson & Dale, 2009; Shockley, Santana, & Fowler, 2003).

Iteration.

Iteration has been found at multiple levels of conversational communication (e.g., words, phrases, prosody, nonverbal movement). A number of nonverbal scholars have identified common use or matching of nonverbals among interactants (for an excellent overview of this extensive research, see Burgoon et al. 1995). We may find that our three interactants fall into common repetitive speech patterns (e.g., playing 'the dozens', repeating funny lines from a movie). At a higher level, we may find that they are iterating a series of double interacts such as the Scheidel and Crowell (1966) cycle *act—respond—adjustment*. Linguists have identified both iteration and recursion as fundamental types of sequential semantic arrangement of language (Karlsson, 2010). Karlsson argues that the "main difference is that recursion builds structure by increasing embedding depth whereas iteration yields flat output structures, repetitive sequences on the same depth level as the first instance." (p. 45) As such, iteration is created by concatenating a series of structural elements (e.g., a series of clauses, listing a series of names) all at the same level.

Recursion.

Similarly to iteration, recursion appears to be a dominant feature of communication in that each talk turn or message point builds from and upon prior messages. In fact, Hauser, Chomsky and Fitch (2002) argue that recursion "is the only uniquely human component of the faculty of language." (p. 1569) Grice (1975) argues that any talk turn that does not somehow refer to the prior talk turn is considered odd (though conversations can be peripatetic in certain contexts). While it is difficult to predict with a great deal of certainty where our three interacts' conversation will go, we can be quite certain that each subsequent talk turn is built upon the conversational turns that went before. Recursion often gives rise to self-similarity within behaviors in the system. Communication displays high levels of self-similarity of language (cultural codes and generational slang) even as language evolves across time. Recursion patterns can be found in Grice's (1975) other maxims as well, that specify rules for responding to others in conversation. Stech (1979) outlines and tests for the presence of these rules in three sets of transcripts. Though he finds that some rules are followed more than others, his transcript analyses showed a significant and predictable rule structure guiding communication. The field of discourse analysis has located many such patterns, though they do not tend to quantitatively analyze the presence of recursion patterns.

Feedback.

Of course, feedback has long been considered an important feature of communication (see Berlo, 1960; Johnson & Klare, 1961). From a complex systems perspective, feedback is a type of communication that a system has with itself as well as between itself and the environment. Feedback provides information to the system so that it can adjust to internal and external demands. Both positive and negative feedback are evident in conversations. Positive feedback drives the conversation forward toward change and new ideas. We might think of our three friends brainstorming a solution to a problem. Each talk turn has the potential to move the conversation in a new direction. On the other hand, there are clear conversational signals that are negative feedback in that they prevent the conversation from moving in certain directions. Perhaps one of our friends is devoutly religious and another is staunchly atheistic. As the brainstorming conversation moves toward religion, the third member may exercise negative feedback control to keep the conversation from breaking down into an argument.

Given that human communication displays all the characteristics found in other complex systems, adopting ideas from complexity science has some efficacy for enhancing our understanding of human communication processes. Complexity science shows that simple rules iterated over large populations determine emergent behavior. It may be that communication follows established rules of complex systems, requiring those interested in studying human communication processes to adapt existing rules to communication (e.g., Shannon entropy, predator-prey models). Additionally, it is also possible that communication contains new, unknown rules for complexity science.

Communication Considerations of Complexity

The shifting paradigm in other sciences has not gone completely unnoticed by communication researchers. A number of overviews and theoretically oriented articles and chapters have been published over the past two decades, though there remains a lack of empirical studies. The most thorough volume on complexity and communication is Philip Salem's (2012) book *The Complexity of Human Communication*. In this broad treatment, Salem (2012) connects many of the better known concepts from complexity science (e.g., attractors, emergence, self organization/autopoiesis/autocatalytic sets, agent adaptation/evolution, and networks) with a broad range of general ideas in the communication literature such as interaction, credibility/trust, information, conflict and storytelling. In the third chapter, he proposes a model of dynamic and complex communication framed within Fisher's (1987) typology of communication research foci and drawing on the work of several communication scholars (e.g., Wieck, Burgoon, Watzlawick, Baxter). The model, which he calls the social channel, describes communication as a process of interaction that results in emergent relationship among communicators. The actors in the model are self-aware and incorporate signals from themselves and others in the process. Though he does not mathematically specify the algorithms by which his actors will create emergent relationships, he hints at future possibilities. Overall, Salem's book covers a good deal of ground in linking communication with complexity science.

There have also been several edited books in the field that include chapters on concepts from complex system research (e.g., Barnett & Houston, 2005; Contractor & Whitbred, 1997; Sherry, 2014; VanLear, 1996). In 1996, Watt and VanLear published the most extensive work on communication dynamics, which featured a few chapters on complexity. Though many of the dynamic mathematical models proposed in the volume followed traditional linear thinking, the book included introductions to cellular automata (Corman, 1996), self-organization (Contractor & Grant, 1996), and nonlinear systems (VanLear, 1996). These chapters were primarily designed to introduce concepts and didn't include specific theory or data arising from these topics. Similarly, Barnett & Houston (2005) edited a volume on self-organization that provided introductory overviews on such several concepts from complexity science including autopoiesis, catastrophe theory, fractal geometry, dissipative structures, and cellular automata. Contractor & Whitbred's (1997) chapter in an earlier volume on organizational communication edited by Barnett & Thayer (1997) proposed a generative mechanism for decision-making groups as a self-organization process. The proposed model was linear, and therefore not a direct fit with the types of models typically used in complexity research, but represents an attempt to embrace the idea of self-organization in a mathematical manner. Publishing in a different communication area, Sherry (2014) illustrated how uses and gratifications shares common assumptions with complexity and how understanding video game play and learning as a complex system will lead to more effective interventions. He proposed a phase transition model to explore the qualitatively different outcomes frequently observed in the games and learning literature.

In 1996, the *Journal of Communication* published a symposium issue on Bibb Latane's dynamic social impact theory (Fink, 1996). While Latane's theory is primarily psychological, Fink notes that it models processes that cut across many levels within the domain of communication research. Dynamic social impact theory is primarily concerned with the creation and maintenance of cognitive constructs such as attitudes, beliefs and belief systems. Because attitudes and beliefs are a function of both individual psychology and social interaction, the theory posits a cultural system with which individuals interact. Within this system, individuals interact in a recursive and stochastic (Markovian) manner. Nonlinearities exist in terms of catastrophe and emergent chaotic dynamics. Work on dynamic social impact theory is sometimes done using cellular automata and simulation. The articles that comprise the symposium are all coauthored by Latane and illustrate dynamic social impact system theory across a variety of communication phenomena including: culture, cognition, intersubjectivity, and stereotypes.

A few articles in communication journals have also provided a general introduction to ideas from complexity science and illustrated how those ideas might be applied to communication problems (e.g., Bruder, 1991; Hoffman, 2008)[5]. Following May (1976), Buder (1991) employed

[5] There are additional articles that purport to be in line with mainstream complexity research, but the ideas that they draw on are not consistent with the general principles of complex systems research as it is currently accepted (e.g., Corman, Kuhn, Mcphee & Dooley, 2002; Fisher, Glover & Ellis, 1977).

the logistic equation for population dynamics to illustrate how a variety of outcomes, in terms of attractor states, are possible in conversation. Bruder (1991) applied the equation to the communication context by modeling the effect of level of involvement (the rate term) on the ongoing communication behavior (the *N* term). Like May's (1974) initial study, Bruder's series of simulations showed that all the types of attractors are possible outcomes based on the magnitude of the rate parameter. Because he uses the same algorithm as May, this is not surprising. The usefulness of Bruder's model is dependent on whether the real world communication dynamics he is trying to model are equivalent to the animal population dynamics modeled by the Verhulst/May's equations.

Hoffman (2008) attempts to shift communication researchers' understanding of causality by asserting that complexity science shows "both coherence and novelty arise from the coupling of forces of regularity and irregularity, a coupling that characterizes interactive living activity." (p. 427) She primarily focuses on organizational communication, drawing most of her insights from the work of management professor Ralph Stacy (2001) and psychiatrist Daniel Seigel (1999), as well as organizational communication researchers Weick (1995) and Taylor (1995). Central to her argument is the idea that complexity shifts communication from a deterministic to a transformative perspective of uncertainty. Though she does not define 'transformative', she notes that communication is often paradoxical, is embodied in the communicators, can be unstable, and does not need to embrace the content-relational split in messages. The article contains many analogy-based connections between complexity and communication, but there are some misunderstandings. For example, her use of the term *determinism* appears to be incorrect (she does not offer a definition) in that she argues that a complexity approach will rid the field of determinism. However, most complex systems are deterministic. Hoffman appears to have meant to use the term *linear* rather than *deterministic* because complex systems are not analytically predictive in the long run (e.g., chaos) and the deterministic rules may realize systems that are similar, though qualitatively different from one another (e.g., fractals). Nonetheless, she offers complexity as a likely response to Craig's (1999) call for a constitutive approach to communication.

The bulk of the empirical work on communication and complexity has been conducted outside of the field of communication by researchers in neuroscience, computer science, mathematics, mathematical sociology, and cognitive psychology. For example, neuroscientists Oullier & Kelso (2009) study the self-organizing nature of social and neural mechanisms that facilitate bonds among individuals. They posit social coordination dynamics as self-organizing dynamical systems that are coupled via information exchange. In other words, synchronization of individual behavior and neural processing is used by organisms to form bonds with other organisms. Research in this area looks at spontaneous human synchronization by simultaneously looking at behavior dynamics and brain dynamics during interaction. Similarly, Shockley (2005) and colleagues (Pellecchia & Shockley, 2005; Shockley, Richardson & Dale, 2009; Shockley, Santana & Fowler, 2003) have studied postural dynamics during conversations. They track the center of pressure of individuals conversing while standing on a force platform. Using nonlinear recurrence analysis, they found evidence for synchronization of postural position among individuals in conversation.

Andras, Roberts & Lazarus (2003) created a simulation to investigate the contribution of communication to cooperation in groups. While economists have created agent-based models of the formation of cooperation groups due to altruism or indirect reciprocity, none of the previous models had allowed agents to communicate their intentions. The Andras et al. (2003) agent-based model allowed agents to signal their intention to cooperate, allowing cooperators to find each other and cheaters to potentially be ostracized. Agents chose collaborators in a simulated world in which risk is increased as a function of the time it takes to make the decision to collaborate: spending too much time confirming the intentions of a potential partner risks losing the first-mover advantage in the market, while spending too little time confirming partner intentions may result in poor collaborator choice. They found that communication creates positive feedback loops that facilitate cooperation for agents who intend to cooperate, but slow collaboration formation when a potential cheater is present.

Mastragneli, Schmidt and Lacasa (2010) were interested in the dynamics by which conversational groups schism into smaller groups (Egbert, 1997), a question that had been qualitatively studied by Goffman (1963) and

Sacks, Schegloff & Jefferson (1974). They created a simple agent-based model simulation in which 15 agents were placed around a table and allowed to form conversational groups based on each agent's individual happiness with the conversation (modeled as interest in continuing in a particular group's conversation). Though assumptions about the conversation were abstracted considerably to facilitate modeling, the iterated model showed that the initial single group of 15 members broke down to four groups of 3-5 members within the first 20-125 iterations, similar to what happens in real conversational groups. Mastrangeli et al. (2010) concluded that "characteristic time needed to reach the stationary state scales exponentially with the maximum level of happiness, and linearly with the number of participants." (p. 10) In other words, the greater the range of happiness and the number of participants, the longer it takes for groups to stabilize.

Research Methodology for Complexity Research in Communication

Complexity research presents a unique set of challenges for communication researchers who are more accustomed to variable analytic, static model testing. Salem (2012) lists these as: (1) challenges to quantitative analysis; (2) challenges to qualitative analysis; (3) challenges of mixing quantitative and qualitative analysis; and (4) additional problems related to mathematics and simulation. Quantitative scholars versed in statistics may well be intimidated by the size and breadth of datasets required to analyze complex systems over time. Interactions among several variables measured at hundreds of points in a time series could quickly overwhelm the data management and computational capacity of most statistical software. In addition, it is necessary to account for dependencies among variables over time. Qualitative researchers face the challenge of treating complexity as more than a metaphor. Many ideas from complexity science are apparent in qualitative analysis, but rigorous mathematical treatment of dynamics is typically noted for its metaphorical relationship to complexity. Commitments to qualitative analysis at all costs (e.g., Schegloff, 1993) will need to be rethought. In other words, qualitative scholars will need to become more quantitative, even as they help quantitative scholars to embrace the complexities of qualitative research. It will not be as simple as merging quantitative and qualitative analysis into complexity analysis. To do so would neglect crucial insights that make complexity research so compelling as a third scientific paradigm. Instead, researchers will need to come to terms with some highly sophisticated mathematical methods and with a proper understanding of computational simulation. We will need to solicit assistance from mathematicians and computer scientists.

A process for studying complex systems

There is no quick and easy way to solve the problems inherent in doing complexity research with communication. Instead, a large number of new ideas must be mastered, and careful thought must be put into figuring out the nature of the organized system under observation. One process by which a group of researchers might study communication as a complex system is as follows: (1) decide whether the phenomenon is a problem of organized complexity; (2) assess the type of complexity it might be; (3) determine what is the composition of the system and what is changing over time in order to realize the observed organization; (4) determine the rule for change over time; (5) formalize and test the system computationally under a variety of parameters; (6) verify those results against nature; and (7) experiment with the simulation. The goal is not to determine the degree to which the results exactly match nature (e.g., as variance explained), but whether the computational model is an accurate mechanism for recreating the process by which nature creates its diversity.

Assess fit to paradigm.

The first step is to understand that complexity approaches are not a panacea for studying all communication problems. We need to assess the phenomena we want to understand in terms of its level of complexity. The key is to match the approach to nature, rather than the other way around. Problems that fall into the area of organized complexity are ones that evidence organization, adaptation, and robustness (Miller & Page, 2009). Not all communication questions are of this ilk, but many are. When a problem of organized complexity has been identified, the next step is to determine the level at which the system is organizing, adapting, or creating robustness to environmental harm. While linguists and many communication researchers have focused on the signal level (e.g., verbal messages, nonverbal behaviors), it is also possible that important aspects of communication occur at higher emergent levels. This is the case for communication accommodation theory (Giles et al. 1991) and relational frame theory (Drake & Donohue, 1996).

Think about the type of complexity.

One of the interesting findings in complexity science is that the same organizing mechanism may be found across organic and inorganic materials at a variety of levels of organization (Mitchell, 2009). It is probable that some of the mechanisms that have been found in other complex systems may also be used in communication behavior (i.e., synchronization, adaptation, and Shannon entropy are obvious candidates for many communication problems; phase transitions are apparent). It is useful to consider whether the class of the complexity may be algorithmic, deterministic or aggregate. It is also possible that a yet-to-be-discovered organizing mechanism is at work in communication. How are components in the system are influencing each other?

Specify the system.

A dynamic system is typically defined by three elements: 1) the state, 2) a transition function, and 3) the state-space (Fuchs, 2013; Luenberger, 1979; Strogatz, 1994). The system's state is the composition of that system at any single point in time and its ambiance, or surrounding environment (Chu, Strand & Fjelland, 2003). One useful way to model a system is Bunge's (2004) CESM model of system structure: components, environment, structure and mechanism. What are the components needed to create the system's organization? How are those elements structured relative to each other? Do the elements interact with the environment in the process of organizing and in what ways? What is the mechanism by which the components interact with the environment to realize the system organization? For example, let's say we are studying the dynamics of the diffusion of a new technology in a small town. In this case, the components could consist of the members of a social system (potential adopters) change agents, opinion leaders, and the available communication channels (e.g., Internet, radio, pamphlets). These components may be structured in common groups such as family, work colleagues or neighbors. The environment consists of variables that impact on adoption (e.g., availability of electricity, access to 4G wireless signals, supply chain of products to the town, retail outlets). The mechanism for this system, from diffusion theory, is the exchange of communication that reduces uncertainty about the new technology.

Determine the rule for change over time.

The rule for change over time, or transition function, dictates how the system will evolve over time. The transition function is traditionally specified as a differential or difference equation, dependent on whether the dynamics of the system are believed to be continuous or discrete. For example, in 1969, Bass published a dynamic model of new product diffusion, based on Rogers' (1961) diffusion of innovation research (see Equation 2). The transition function states that the likelihood of adoption at any particular time [L(t)] is a linear function of both external influence (p) and internal influence (q) where the effect of internal influence (e.g., imitation, word of mouth) is proportional to the ratio of current adopters [$A(t)$] to potential (M) adopters. As adoption increases in a fixed population, the overall rate of adoption shrinks because there are fewer potential adopters relative to actual adopters. Bass (1969) compared his model to actual sales data from eleven consumer goods and found a very good fit for each.

$$L(t) = p + \frac{q}{M}\left[A(t)\right] \qquad (2)$$

The system becomes dynamic when the transition function is applied to the values of the initial conditions of the system. The trajectory of the system (phase portrait) can then be geometrically mapped onto phase space for analysis (for an interesting collection of phase portraits, see Julien C. Sprott's collection at http://sprott.physics.wisc.edu/fractals.htm).

Formalize and test the system.

When the system and the mechanism have been defined, it is time to test the system. The goal is to determine whether the defined system recreates the types of behavior seen in the real world. For our diffusion problem, we would need to begin with some reasonable initial conditions (starting values) for the presence of the new technology and some parameters for adoption behavior of individuals and network influence. We can plot our starting position, referred to as Time 0 or t_0. Next, we apply the equation (mechanism) to calculate values for adoption at the next step (time $t + 1$ or t_1). The equation can then be applied to values calculated at t_1 to determine adoption values at $t_2 \ldots. t_x$. The values that result from each application of the equation are plotted on a phase plot allowing observation of the behavior of the defined system over time. Behavior of the defined system can be compared to behavior of a real world system to determine whether the modeled system is recreating the behavior observed in the real world system. If this is the case, it can be argued that the modeled system is a valid process by which the real world behavior can be realized. The argument for the validity of the simulation must be supported by the same validity criteria used in any other empirical scientific research (i.e., Cook & Campbell, 1979).

There are two common types of computer simulations: equation-based and agent-based. Of the two, equation-based simulations were first and have been used in most sciences (Winsberg, 2013). Equation-based simulations iterate well-known equations (e.g., third law of motion) as the rule/algorithm to define change in the system state. These simulations can be used to generate analytic point solutions for a specific engineering application (e.g., determine the required tensile strength for suspension springs on a car) or can be used to generate geometric solutions to more complex systems (e.g., weather prediction). They allow scientists and engineers to perform computationally intensive calculations that were not practical before the advent of computers.

A second class of simulations, agent-based, were developed in the 1970s to study systems that are not necessarily driven by clear variable laws (Miller & Page, 2009). Agent-based simulations are typically used in the social, cognitive and behavioral sciences to study such topics as animal populations, micro-economics (e.g., altruism, trust), macro-level behavior (e.g., voting, migration, public opinion), artificial life, and political science (for more examples, see Miller & Page, 2009). Some simulations are studied specifically to determine the extent to which computers can approximate real-life behavior. For example, one type of simulation, called cellular automata, are used to study emergence. In 1970, mathematician John Horton Conway created the *Game of Life*, a cellular automata in which a two-dimensional grid consisting of *x* by *x* cells are populated by binary agents (black or white) in various patterns (see Figure 2). All cells follow a set of four rules to determine their next state as the program iterates. Any live cell (black) that has three live neighbors dies (turns white), while any dead cells (white) become live if they have three live neighbors. The simulation iterates in real time, creating emergent patterns based on very simple rules (Conway's program Golly can be downloaded at: http://www.dmoz.org/Computers/Artificial_Life/Cellular_Automata/Conway's_Game_of_Life).

A wide variety of social behavior has been studied using agent-based models (ABMs; Holland, 1995; Miller & Page, 2009). ABMs are a class of computer simulations in which autonomous virtual 'agents' interact with one another guided by a set of simple rules that are iterated in time steps. These simulations provide observable evidence for how iterating a simple set of rules can result in robust and complex-appearing behavior. Researchers specify the rules by which the agents interact and the number of agents; the program randomly seeds the world's population of agents. Parameters of each rule can be manipulated to test for variations in emergent social world behavior. Open source computer programs such as NetLogo (http://ccl.northwestern.edu/netlogo/) or Swarm (http://www.swarm.org/) allow researchers to program and run simulations of social behavior under varying parameters to uncover underlying interaction dynamics. This approach is best suited for examination of the dynamics by which people interact under assumptions of simple rules such as cooperation, diffusion, traffic patterns, and prisoner's dilemma. More complex speech interaction would be difficult to model under such simple assumptions.

While we often think of simulations as computer programs, they can also be performed in a lab (e.g., fluid dynamics simulations) or *in situ* (e.g., Gordon's ant studies) (Gilbert & Troitzsch, 2004; Richards, 1980). The

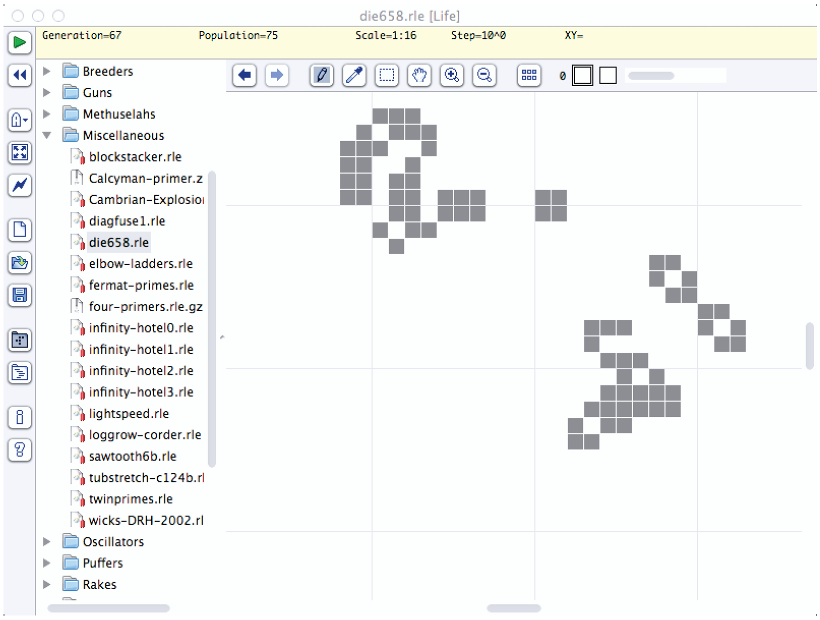

Figure 2. *Screen grab of Conway's Game of Life program Golly.* Downloaded from http://golly.sourceforge.net/

so-called 'telephone game' that is often played in introductory communication classes is a simulation of real world message degradation. In this game, a message is given to a student and then passed through all remaining students in the class. Most often, the message that the last student receives is quite different from the initial message. Lab or *in situ* studies of human communication are difficult, but possible. The biggest difficulty is controlling parameters of the model (e.g., speaker intelligence, motivation). Greater control over system behavior is possible with computer simulation. In general, a computer simulation is "a program that is run on a computer and that uses step-by-step methods to explore the approximate behavior of a mathematical model." (Winsberg, 2013, p. 1.1) The parameters of the initial system state are input into the computer, along with the rules/algorithms defining how the system changes over time, and the computer repeatedly applies the rule to the data to produce a picture of the time evolution of the system.

Verify and modify the system.

Verification of a simulation adheres to the same general principles as other types of empirical research in that it attempts to determine the extent to which the proposed model is isomorphic with reality. The primary difference lies in the nature of what is observed. In traditional variance approaches to communication research, we test the extent to which the interaction of a small number of variables results in a solution predicted by a theory. The relationship is stated as the hypothesis: if theory X is correct, we will observe the following relationship between variable A and variable B post manipulation. The theory is considered supported as long as there is a relationship between the variables in the predicted direction that is not attributable to chance. In the vast majority of cases, the relationship is a snapshot of a static moment.

In the case of organized complexity research and simulation, we test the behavior of the theory over time, rather than a static moment predicted by the theory. Therefore, the question is whether the behavior of the system is consistent with the behavior of the real world system and not simply attributable to chance. As a result, there are a number of potential measures of fit, as articulated by Cyert (1966):

1. number of turning points,
2. timing of turning points,
3. direction of turning points,
4. amplitude of the fluctuations for corresponding time segments,
5. average amplitude over the whole series,
6. simultaneity of turning points for different variables,

7. average values of variables,
8. exact matching of values of variables.

There are a number of 'goodness-of-fit' statistics proposed to test whether the values of the simulation are significantly different from real-world values including: ANOVA, chi-square, Kolmogorov-Smirnov test, factor analysis, some non-parametric tests, regression analysis and spectral analysis (Naylor & Finger, 1967). Values generated by the simulation can be compared to data on system behavior under similar conditions/parameters. These data can be collected by the research on real-world system behavior or can be generated from historical records of system behavior (e.g., economic data).

In practice, the validity of simulations is verified both via formal statistical tests and by more visual geometric observation. Whereas a formal statistical test may be incisive for the measures laid out by Cyert (1966), statistics do not allow for an assessment of more complex dynamic patterns that are apparent by visual inspection. For example, does the simulation of turbulent and laminar fluid flow *look like* real world turbulent and laminar flow? Does a simulation of traffic patterns behave like real world traffic patterns behave? This type of qualitative analysis remains important because the human brain is still the most powerful tool for assessing dynamic patterns, as long as care is taken that the brain is not systematically fooled. In addition, like other forms of empirical research, models can be subject to tests of face validity by experts in the phenomenon and can be subject to inspection of internal validity by testing the extent to which repeated runs of the simulation are consistent with one another.

Simulations can also be tested by attempting to replicate well know unique system behavior (Sargent, 2012). For example, simulations can be run under the assumptions of an extreme condition or well known event. In these cases, the output of the real-world system is known (e.g., catastrophic breakdown), and the simulation should replicate this behavior. Does the simulation boil at 100 °K? Does the automotive supply chain break down when steel becomes rare? Simulations can also output graphics representing the occurrence of particular events, such as the number of times the system takes one path versus another. Simulation graphs can be compared to graphs of real system behavior. In all cases, the process of verification is an iterative one in which breakdowns in the simulation trigger reassessment and modification of the system model.

Use of the simulation.

The successful completion of a simulation that is isomorphic with real-world systems represents both an accomplishment and an opportunity. The accomplishment is that the mechanisms that lead to real-world behavior are known at a very specific level. Rather than testing a hypothesized result arising from a theory, the simulation is an explanatory model that explains the manner by which the entire system creates the behavior of interest. In addition, the simulation also provides the opportunity to test the model under a vast combination of conditions that would be very difficult to observe in the real world. The model can be tested to determine failure points or points of transition to new qualitative behavior (Winsberg, 2013). For example, the percentage of innovators in a community can be varied to see how the adoption curve is effected. Alternatively, the level of uncertainty in the community can be adjusted up or down to see how uncertainty effects the speed of adoption. Because organized complexity problems are often nonlinear, these parameter adjustments may have unexpected qualitative outcomes (e.g., phase transition, a threshold, catastrophe).

Simulation scientists test, verify and experiment on systems by running the simulation hundreds of times under the same set of parameters. The behavior of nonlinear systems will remain consistent even though the end-point of the simulation will result in different values. By running the simulation many times, scientists are able to observe the range of possible outcomes of the system in addition to the general dynamics of the process. Occasionally, a highly unusual outcome will be generated, triggering the scientist to inspect what happened on that run and why the anomalous outcome resulted.

The Way Forward for Complexity and Communication

The opportunities for new scientific communication discovery made possible with the complexity paradigm are both accelerating and formidable. Studying communication as organized complexity phenomenon opens the opportunity to examine important processes of communication that have gone unstudied. However, the complexity approach is neither a panacea for answering all communication questions or an easy way forward. Salem (2012) points out a number of fundamental theoretical obstacles to studying communication within a complexity paradigm. First, complexity approaches will shift the questions we ask from those of structure and sequence to questions of process. Rather than asking how a bird's wing is attached to its body (ball and socket structure), we will need to ask how it is that the joint gives rise to and maintains flight. This can only be understood by looking at how the range of motion afforded by the joint interacts with airflow, the bird's body and the airfoil shape of the wing to create and maintain lift. The system can only be understood as a group of simultaneous interactions. Second, Salem (2012) argues that communication theorists will need to come to grips with a concept that they have resisted: emergence. For a group that has focused on reductionism since the early studies of Hovland and McGuire, emergence is anathema. Like complexity, emergence is an imprecisely defined idea. Finally, Salem (2012) argues that embracing complexity means abandoning the simple theoretic representations of boxes and arrows for models that move. Additionally, journals and textbooks will need to accommodate theories presented as dynamic and/or interactive systems.

There are at least three more challenges that we will need to be aware of as we move forward. These challenges will make us think about how to integrate our prior static research in new dynamic theories, how to avoid trivializing the complexity we wish to understand, and overcoming institutional bottlenecks of expanding our intellectual repertoire.

Don't forget the past

Interestingly, we have a rich tradition of ideas that lend themselves to the complexity science paradigm. Pearce and Cronen's (1980) coordinated management of meaning claims that persons-in-conversation co-construct their social reality by the ways they respond to each other via communication. In other words, people use communication to organize social experience. Similarly, constructivism (Delia, O'Keefe & O'Keefe, 1982) speaks to individual differences in people's ability to organize social reality to their own ends. Those who are cognitively complex are better able to organize social experience to their own advantage and desires than those who are less cognitively complex. In this same vein, adaptive structuration theory (Poole & DeSanctis, 1990) argues that group decisions are a function of how people organize the process via use of rules and resources in interaction. In this case, both the experience of a particular group and the outcome of that group's work is organized through communication. Focusing on a different organizing mechanism for communication, communication accommodation theory (Giles et al. 1991) conceives of intercultural communication as a process of convergence and divergence that creates understanding between people from diverse groups. Whatever understanding results is a function of how the communication organization occurs and how the individuals in the conversation organize relatively to one another (converge or diverge).

Relational interpersonal communication also has a number of perspectives that imply organized complexity in communication. Relational dialectics (Baxter & Montgomery, 1996) argues that communication in close relationships consists of the interplay of oppositional differences. The ongoing process by which oppositional tensions are negotiated and modified organize the experience of the relationship. Burgoon et al. (1995) reviewed an extensive literature on behavior in dyadic communication and found a set of commonalities that they used to derive their interaction adaptation theory. The review and theory focused on the different ways that interaction is organized over time, including convergence, entrainment, and divergence. The patterns they found in the literature could readily be used to envision a powerful organized complexity process of interaction based on existing empirical research. Scholars who are looking for ideas to study communication processes would be well advised to return to the existing interpersonal literature. Though the studies and theories are mostly linear and simple, the core ideas are a rich source for ideas for a complexity approach.

The future will be difficult

Complexity research requires a level of precision that is not the norm in the field of communication. This will not only affect how we think about our models, but also how we present them and read our literature. For example, it can take longer to read a five-page mathematical article than a 25-page communication article. As precision increases, the text tends to become denser and symbol systems (i.e., equations) are required to articulate relationships precisely. The transition function that represents the theoretical core mechanism of the system must be stated with great clarity, typically as either a set of differential equations or as a specific set of rules by with the system changes. Programming a simulation requires highly logical and unambiguous rule statements so that the program does not crash. These programs can be required as part of a manuscript submission, meaning that reviewers can readily run the simulation to test the results to check the extent to which the article accurately describes the proposed mechanism. Additionally, authors and reviewers will need to be sure that the computational model maps onto the theorized model as asserted.

The two bottlenecks

The greatest bottlenecks in any disciplinary system occur at the two most important components: graduate training and editorial review. It will be quite difficult to instantiate a new paradigm at the graduate school level because to do so requires the teaching of both the new paradigm and the traditional one. A graduate student can hardly be considered an expert in the field without a strong background in the past 60 years of communication research, including the epistemology that informs that research. Most leading programs require a core set of courses on traditional theory and methodology. However, traditional theory and methodology is limited to problems of simplicity and disorganized complexity. Extending the core to include organized complexity would require additional coursework on current systems thinking, nonlinear mathematics, and the use of computational modeling, including basic computer programming. Do we extend the time to Ph.D. or drop other important content? And who teaches these classes if they are not already a part of the discipline? The most logical course for most programs will be to leave their programs as is and allowing students to learn complexity in their limited external coursework.

The difficulties of adopting complexity in graduate programs pales in comparison to the difficulties of publishing this type of work in communication journals. How many scholars in our field understand the subtleties of computational modeling in adequate detail to be able to offer a fair and reasoned critique of a manuscript? If editors go outside for reviewers, the assessments run the risk of losing sight of communication assumptions that are informing the way the simulations are built. What about demands for statistical independence that underlie the tradition of null hypothesis significance testing? Complex models are highly dependent, just like the natural world that they attempt to explain. I have already run into difficulties with well-intentioned reviewers and editors that insist on traditional linear statistics as a basic criterion for publication. How will these reviewers deal with bizarre, but valid concepts like deterministic systems that lack predictability? My guess is that we will need to wait for current graduate students who have engaged these ideas to mature into reviewing roles, at least in our journals. We can take consolation in the fact that this type of work is frequently published in journals like Science, Nature, and PNAS.

Final thoughts

History has shown that paradigms shift very slowly. There is tremendous inertia around established ways of doing things and scientists are (correctly) cautious about new ideas. The main thrust for embracing complexity will come from graduate students who are increasingly exposed to these ideas in their outside coursework and who have time and energy to do the tremendous work to learn a new paradigm. These graduate students will increasingly work with teams from a broad array of disciplines that are already knowledgeable about complexity. Breakthrough articles will most likely not be published in communication journals, but will find an initial audience in areas that have already shifted to complexity. This is because the ideas will be too different for reviewers in our field to embrace. However, the interdisciplinary moments created by working with scholars from other fields, producing basic scientific discovery of the processes underlying human communication, and publishing those breakthroughs in broader-based journals will draw more credibility to our small field. Perhaps Hoffman

(2008) is correct—complexity will ultimately unite many of the factions in communication research around a constitutive approach to communication.

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