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Toward a Computational Model of Complex Human Systems Dynamics

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Abstract. A robust and reliable computational model of complex human systems dynamics could support advancements in theory and practice for social systems at all levels, from intrapersonal experience to global politics and economics. Models of human interactions have evolved from traditional, Newtonian systems assumptions, which served a variety of practical and theoretical needs of the past. Another class of models has been inspired and informed by models and methods from nonlinear dynamics, chaos, and complexity science. None of the existing models, however, is able to represent the open, high dimension, and nonlinear self-organizing dynamics of social systems. An effective model will represent interactions at multiple levels to generate emergent patterns of social and political life of individuals and groups. Existing models and modeling methods are considered and assessed against characteristic pattern-forming processes in observed and experienced phenomena of human systems. A conceptual model, CDE Model, based on the conditions for self-organizing in human systems, is explored as an alternative to existing models and methods. While the new model overcomes the limitations of previous models, it also provides an explanatory base and foundation for prospective analysis to inform real-time meaning making and action taking in response to complex conditions in the real world. An invitation is extended to readers to engage in developing a computational model that incorporates the assumptions, meta-variables, and relationships of this open, high dimension, and nonlinear conceptual model of the complex dynamics of human systems.

Keywords: Human Systems Dynamics, CAS, CDE, self-organizing, complex adaptive systems

1 Modeling Human Behavior

A computational model[1] that captures the nonlinear nature of the dynamics of human systems with fidelity would yield great benefits for scholars and practitioners who face emergent personal, professional, and political challenges. Scholars would use such a model to develop and test hypotheses about human behavior, institutional development, and evolution of industrial and political ecosystems. Practitioners would use a robust nonlinear model to inform decision making in real time and instructional programs to develop knowledge and skills required in complex environments. Individuals and groups would build adaptive capacity to see, understand, and influence complex and unpredictable patterns as they emerge.

Many different quantitative and qualitative, rigorous and imaginative models are currently used for all of these functions. Rational choice theory, statistical analysis, systems dynamics modeling, adaptive leadership, Myers Briggs Type Indicator, Strength Finder, Technology of Participation, and so on are just a few examples. All of these models support useful methods of research and practice in a variety of con-texts. Each one also has limitations based on its fundamental assumptions about the dynamics of human systems. The most rigorous of the existing models may apply only in narrowly defined theoretical contexts. The most imaginative, without benefit of disciplined research, may prove to be ineffective or even destructive in practice.

While these models of human interaction have served well enough in the past, their inherent weaknesses are beginning to show. They assume clear and distinct boundaries in space, time, and function, and our global economy transcends all bounds. They assume a low number of relevant variables and clear indicators of performance. The recent focus on systemic issues such as sustainability underscores the need to consider many factors at the same time, some of which are unpredictable or ambiguous. They assume linear cause and effect. Today massively complex information and resource networks contribute to nonlinear effects that cannot be ignored. As the world becomes more complex, the choices we have made to simplify our models seriously limit their reliability and usefulness.

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[1] We will use the term model throughout to refer to “a simplified description, especially a mathematical one, of a system or process to assist calculations and predictions.” (Oxford Dictionaries Online. (n.d.). Oxford Dictionaries Online. Retrieved from http://oxforddictionaries.com/.) We will characterize all systemic representations including qualitative and quantitative, positivistic and interpretive as models. We will make the distinction explicit when referring specifically to simulation, mathematical, conceptual, or computational models.

As challenges of humanity become more complex, the limitations of these models turn into fatal flaws. When individual, corporate, social, and political patterns are radically open to external influences, assumed boundaries of a model become irrelevant. As human systems at all levels are shaped by innumerable and constantly changing variables, model assumptions about a small number of dependent and independent variables are no longer valid. As our challenges involve more and faster feedback loops, model assumptions of linear cause and effect prove insufficient to capture the emergent dynamics of the system. In short, as human systems become more complex, our models—even the complicated ones—are not sufficient to inform either our research or our practice. Today's global challenges exceed the capacity of our historical models of human systems dynamics. Robust theory and effective practice demand a new generation of models and modeling techniques.

Even with all their flaws, the models of human interaction that currently exist pro-vide insights to support historical analysis, current decision making, forecasting, and planning. In the same way that Ptolemy gave a "good enough" model of celestial movement, social and economic models of the 20th century have been "good enough" to guide thinking and action across all levels of meaning making and action taking. Just as Copernicus introduced an alternative model to solve challenges that could not be solved under Ptolemy's geocentric worldview, we need a new model of human systems dynamics that will allow us to transcend the limitations of our past theory and practice to respond to uncertainty and radical emergence of our complex reality.

Today, the inherent weaknesses of the existing models are increasingly apparent. Decision makers in all sectors and industries realize the limitations of the models and methods available to inform their action. Economists acknowledge that the conditions resulting in crisis and collapse are not represented in their econometric models. In spite of sophisticated technologies, intelligence communities have insufficient power to deal with the challenges of information collection, collaboration, and interpretation in the midst of unpredictable and complex networks of insurgents. Political upheavals, social movements, violent and nonviolent conflict generate phenomena that we urgently need to understand and influence. Around the world, institutions find themselves overwhelmed and without sufficient tools to see emerging patterns, understand their implications, and generate and select options for action to influence systemic patterns of health or sustainability.

Over the past two decades, research into nonlinear dynamics has revolutionized models and methods in a variety of physical science and mathematical disciplines. Techniques emerging from the study of nonlinear physical systems, such as nonlinear time series analysis and dynamical network theory, have been applied to social systems dynamics with some success. Research and practice indicate that even those models have limited utility in shaping effective theory and practice in complex social systems.

In this paper, we will explore usefulness and limitations of some of the models of social interaction that have influenced research and practice in psychology and economics. We will also describe benefits and constraints of innovative methods that have emerged from nonlinear dynamics applied to social systems. We will explore these approaches in the contexts of the open, high dimension, and nonlinear patterns of today's complex human systems dynamics. We will introduce a conceptual model of the human systems dynamics based on a nonlinear paradigm of systemic interaction and emergent structuration. Based in both theory and practice, this conceptual model informs action while it assumes open, high dimension, and nonlinear dynamics of social systems at all scales. Finally, we will invite colleagues to engage with us to develop a computational model to quantify and test this emerging conceptual model.

Our experience is that this new conceptual model of human interaction resolves is-sues of previous models and helps individuals and groups see patterns in emergent systems, understand their implications in given contexts, and take intentional action to influence the patterns as they emerge. We speculate that this conceptual model might provide a strong theoretical grounding for a computational model to inform theory and practice, and that such a computational model would be robust enough to address our emerging challenges in complex human systems. After introducing the conceptual model and speculating about a possible computational implementation, we will propose a research agenda and invite colleagues to join us in creating a computational model that exceeds the benefits and resolves the risks of existing models of human systems dynamics and their applications in theory and practice.

2 Traditional Models of Social Interaction

"Essentially, all models are wrong, but some are useful."[1] Diverse fields in social sciences develop and apply mathematical and qualitative models and methods to represent human behavior. Each one has emerged from a specific discipline to respond to specific questions and inform certain kinds of decision making. Like any other model, each model applied to human interaction has its own inherent limitations.

2.1 Sources and Applications of Traditional Models

Models of human behavior have emerged from many different social sciences. Political science, education, arts, anthropology, industrial engineering, sociology, and a wide array of other fields focus on specific aspects of human systems and human behavior. Within each of these fields, a variety of conceptual and some computational models inform theory and practice. For the purposes of this paper, we will focus only on illustrative examples drawn from the fields of psychology and economics. Detailed analyses and critiques of even these models are beyond the scope of this paper. We intend only to acknowledge the widely accepted notion of the gap between human systems as they are experienced and as they are captured in current models.

Psychological models are based on a variety of theoretical frameworks and support diverse practical applications. For example, biological and cognitive models of time have emerged from psychological research and practice.[1] Models of mood disorders are diverse and emerge from a wide variety of theoretical frameworks.[3] Decision making is another application of psychological model making.[45] One class of psychological decision models is particularly applied to intelligence efforts and the decision making and action in the intelligence community. Judgment and Decision Making (JDM), Analysis of Competing Hypotheses (ACH), Naturalistic Decision Making (NDM), foraging, and various group decision-making models[6] are all applied to the field of intelligence collection, analysis, and action.

These and many other models emerge from psychological research, and they can be applied with good purpose to enhance theory and practice when individuals and groups seek to see, understand, and influence change in social systems. As useful as they are, these psychological models are limited to specific contexts and challenges, and they are applicable at a limited number of human systems scales. Some focus on the individual (and occasionally a small group) level of organization in human systems. Other sets of models deal with patterns at the community, institution, or nation-al scope. None of them are intended to speak simultaneously to all of the open, high dimension, and nonlinear patterns that emerge across the complex systems of human dynamics. In addition, most of these models are not amenable to computational modeling or other quantitative methods of inquiry. The lack of commensurability between qualitative and quantitative representation of dynamics fuels the on-going conflict between positivistic and interpretive epistemologies and research methodologies. The closer traditional models come to realistically describing open, high dimension, and nonlinear phenomena, the more difficult it becomes to represent their dynamics in mathematical or computational models. Simplicity and fidelity are constantly in tension in the whole range of models of psychological interaction. Where one succeeds, the other fails.

Economic models, from statistical analyses to rational choice theory and chaotic dynamics[7], have shaped individual, institutional, and market decision making for decades. The reliability and usefulness of such representations have been challenged for equally as long.[8] In spite of their acknowledged limitations, models of macroeconomic patterns of global interactions have become relatively common. They are used to influence decisions that affect global politics and commerce.[9] The reliability, robustness, and relevance of economic models can be characterized in many ways, but each model stands on its own foundation of assumptions and acceptable methods.[10]

The insufficiency of current economic models is widely understood. In January of 2011, Ban ki-Moon, Secretary General of the UN proclaimed:

> *It is easy to mouth the words "sustainable development", but to make it happen, we have to be prepared to make major changes — in our lifestyles, our economic models, our social organization and our political life. We have to connect the dots between climate change and what I might call here WEF — water, energy and food.*[11]

The systems we seek to sustain—physical, economic, social—are open, high dimension, and nonlinear. Models we use to represent those systems must be able to capture such complex dynamics. If we are to think simply and with fidelity about these systems, we must have new models that capture the complex dynamics of economic systems and their behavior. The current disconnect between micro- and macroeconomic models is one example of this challenge. Economic models isolate local action from the global patterns that capture consequences. The lack of integration also makes it difficult to incorporate emergent global patterns into local decision making. Global outcomes that depend on local action require new models for economic behavior that scale across levels of analysis and action while accounting for the massive complexity of nonlinear dynamics within every scale and among all scales. Current economic models are not able to satisfy any of these requirements.

We might add to this list of economic and psychological models ones from political science, sociology, management, organization development, education, and many other social sciences. All of these models are useful for their intended purposes, but none are robust enough to represent complex dynamics of human systems in ways that inform understanding or action in systems that exhibit complex, nonlinear, emergent phenomena. When we acknowledge that human systems are simultaneously open, high dimension and nonlinear, these models fall short in a variety of ways.

2.2 Limitations of Traditional Models

Traditional models serve many purposes, but they are not able to represent the complex dynamics of human systems as we experience them individually or in groups. Their major limitations emerge from assumptions of 1) a single level of analysis rather than massive interdependencies across scales; 2) closed boundaries rather than open interactions with emergent environmental landscapes; 3) low dimensionality rather than high and/or indeterminate number of relevant variables; 4) linear causality rather than nonlinear relationships and mutual causality; 5) random variability supporting statistical analysis rather than significant levels of ambient background correlation. While they make the problems more tractable, these assumptions also limit the usefulness of the models to address real dynamics of real problems.

Traditional models of human interaction tend to focus on a single scale of human activity. Like the disciplines from which they emerged, current models focus on one or at most two specific levels of social organization. One model might consider the state of the individual in relation to the group dynamics. Another might look at the firm in relation to a market. Yet another might consider political entities and their interactions in global patterns of behavior. None of the models support a look across levels or at the interactions among multiple levels. None capture the scale-free pat-tern-forming processes that are common in complex adaptive systems. Even though we are keenly aware that global interactions can influence and be influenced by individual or group decision making, our models continue to represent one level in a way that is incommensurable with the levels above and below it. While some techniques, like traditional systems dynamics modeling, can include models within models to represent multiple levels of underlying dynamics; still, the ability to generalize insights or actions across scales is severely limited.

This limitation of being scale-bound is neither trivial nor merely theoretical. In many fields, analysis at the micro and macro scales are totally incommensurate, so critical information is not able to flow between local and global meaning making and action. Incidents of violent conflict demonstrate the effects of missing inter-scale communication. Individual peace makers interact with individuals in communities on the ground. They may use conflict resolution models and methods to quell emerging conflict between neighbors in a neighborhood. At the same time, the economic and geopolitical analyses may capture critical contextual cues that are not visible from the ground, but miss the messages that are local and specific to a particular hotspot. As a result, model-informed insights about both the local and global patterns are incomplete, and decision making and action taking in both contexts are constrained. Increasingly, social scientists refer to macro-, meso-, and micro-levels of interaction. While moving from one or two to three levels of analysis is definitely an improvement, such a conceptualization still misses the scale-free interdependence that is critical in the dynamics of complex adaptive systems.

The second limitation of current models is that they require human systems to be bounded in space and/or time. Traditional models that represent human interaction are based on assumptions that limit the conceptual definition of a situation to make its problem space more tractable. Bounding conditions increase certainty, so limiting assumptions make it easier to manage the mathematics or theoretical descriptions. On the other hand, each assumption that limits the problem space makes it more difficult to correlate model behavior to real human behavior in the living system. Of course this is the purpose of the model—to represent the system in a simplified way. In the past, the trade-offs between bounded simplicity and real-world fidelity were manageable. Phenomena of social systems were simple enough that our finite, constrained representations were sufficient to inform theory and practice. As our local and global situations become more complex, however, it is increasingly difficult to support the delusion that our situations are as bounded as our models assume them to be. A robust and reliable model of human interaction must acknowledge and incorporate open system relationships if it is to support meaningful theory building, pragmatic decision making, and effective action.

While we know that all social systems are open to external influence, theoretical and mathematical models are seldom able to represent such open boundaries. Even the most closed examples of human institutions—prisons or fascist regimes—are subject to external influences. Many modeling methods constrain these unpredictable influences by artificially bounding the system in time or space. While such a com-promise makes the mathematics more tractable, it limits the correspondence between behavior of the model and a real human system—whatever the scale.

High dimensionality is the third complexity of real human behavior that is difficult (if not impossible) to capture in traditional conceptual or mathematical models. Per-force, our models assume that any human decision or action depends on a finite number of relevant variables; while we know even the simplest decision in real life may be driven by a large and unpredictable number of parameters. Not only is the number of variables that influence human behavior high, they also change constantly. At one time, for multiple individuals or at different times for the same individual, different considerations will influence a particular decision or action. If this is true at the level of the individual, it is even more obvious for communities, institutions, or nation states.

This radical diversity of complex human systems is a major challenge to effective modeling. One drawback of any model is the distinction between the generalized, abstracted, perfect case represented in the model and the specific, embodied, particular example that occurs in reality. In order for a model to apply to a variety of many cases, assumptions had to limit the amount of variability among the cases in the system. In so far as the variability was limited, the model would fail to represent the particular.

Some models, such as those founded on rational choice theory, simply denied local variability in order to represent a consistent general case. Other models, including all of those based in traditional statistics, assume a random distribution of phenomena across a context. Beginning with the random distribution, modelers use statistical analyses to discern and characterize patterns of interaction and intention that might emerge over time. For example, when you assume random distribution, you can focus on average behavior as representative of the whole. Again, this strategy has been "good enough," but it breaks down in the class of systems considered to be complex adaptive. These systems generate system-wide patterns, so they do not begin from a state of normal distribution. When the goal is to model how individuals are influenced by each other, it is not "good enough" to imagine that their cultural or personal patterns are random to begin with. If human beings have free will and if they influence each other, which most model makers and users would like to believe, then we cannot assume an initial random distribution. Each individual case has the freedom to vary in unpredictable ways and the assumption of zero natural correlation, which is required for statistical analysis, is no longer valid. When agent behavior is naturally and unpredictably correlated, as happens when many human beings are connected, their individual actions, driven by their free will, influence each other. As a result, we cannot assume a random distribution as a precondition for statistical analysis of overall system behavior, whether the system is a person, a group, institution, or community. We need a different way to conceptualize non-random, unpredictable differentiation that is common in our observations and experiences of human systems dynamics.

Statistical analysis has been applied in the social sciences to deal with radical variability. It allowed social scientists to analyze complex data and to see patterns as they emerged from messy, diverse, localized data. Traditional statistical methods, however, derive from fundamental assumptions about random distribution of underlying behaviors. If the normal curve represents normal distribution of behaviors, then deviation from that norm can be tested and interpreted in meaningful ways. In some situations—those that focus on closed system, low dimensionality, and linear causality—it can be valid to assume random distribution of behaviors in human systems. However, cursory observation of human beings and their institutions can quickly demonstrate that underlying dynamics are anything but random when individuals or groups make decisions or take actions. Patterns in complex social systems are simply not randomly distributed.

Narrative is one modeling method that has successfully been used to represent open, high dimension, nonlinear, and locally variable phenomena[12]. Stories are powerful ways to represent reality in its own language, including its most complex characteristics. While the uses of narrative are becoming increasingly robust and rigorous[13] the dilemma of how to generalize or abstract narrative as a model of social interaction has not been resolved. Two computer-based narrative analysis methods are able to derive complex patterns of meaning from narrative data. CRAWDAD (www.crawdadtech.com)[14] uses the linguistic technique of centering resonance analysis to detect relations among noun phrases in a natural language sample and represent those relationships as a network of meaning.[15] Quantitative analysis of the network provides rich information about the patterns encoded in a narrative selection. Sensemaker (www.sensemaker-suite.com)[16] is another software-based narrative analysis process that transforms narrative into patterns of meaning. While both products create open, high dimension, and nonlinear models of narrative text, they share limitations of other complexity-inspired models which we will discuss later.

Historical models of human behavior have understandably compromised fidelity to make models more tractable and more generalizable. They focused on a single level of analysis; they bounded systems, focused on a small number of variables, assumed linear causality, avoided free will and interdependency by assuming random distribution of behavior. While such models serve specific purposes, they do not capture the complex dynamics that are relevant to decision making and action taking in the 21st century. In efforts to adapt models to match reality, many social scientists have embraced a variety of complexity-inspired modeling methods. We will explore some of those methodologies next.

3 Complexity and Social Interaction

Traditional models of human interaction and human behavior have drawn from traditional scientific, linguistic, and mathematical models and methodologies. Since the mid-1970s, new and more complex analytical methods have emerged, and they have been applied to research and modeling of human systems.[17] These approaches break through some of the limitations of traditional approaches to modeling social systems because they deal explicitly with nonlinear causality. On the other hand, they fall prey to some of the traditional limitations while introducing some new limitations of their own. We will briefly introduce five modeling approaches that have been derived from nonlinear dynamical methods, explore how they support decision making and action taking in complex human systems, and explore their limitations as true and useful representations of complex dynamics of human systems for research and practice in complex and uncertain environments.

3.1 Sources and Applications of Complexity-Inspired Models

Beginning in the mid-1970s and continuing to the current day, models, methods, and insights of the nonlinear dynamics in physical and mathematical systems have been applied to explore human systems dynamics. Scholars and practitioners have used these approaches more and less metaphorically to create simple models of complex human system behavior at a variety of scales. Five categories of models have been particularly useful, and we will describe them briefly here:

- Catastrophe theory
- Dynamical network theory
- Nonlinear time series modeling
- Agent-based simulation modeling
- Power law dynamics

Renee Thom's catastrophe theory[18] emerged as one of the earliest quantitative models of complex dynamics. Not only did it deal with nonlinearity, but it also included ways to capture high-dimension interactions. It has been applied in many ways to social systems, including applications to error and injury rates and growth of firms[19]. While catastrophe theory showed great promise in its ability to represent the dynamics of complex human interactions, it had limited practical use for a variety of reasons. First, the mathematical sophistication of the model made it complicated and difficult for practitioners to understand. In addition, its graphical representations of systems in more than three dimensions were impossible to see and even difficult for most people to imagine. So, while the qualitative explanations of Thom's work were powerful and early interest in them was great, the quantitative applications proved too complicated to be useful for decision making and action taking. Within a few years, the promise of catastrophe theory as a definitive model of human interaction faded from most scholarly and practitioner applications.

Dynamical network theory[20] has been used extensively as a powerful modeling method to explore market potential, social cohesion, and dissemination of information[21] and innovation.[22] In the past decade, a variety of software packages[23] have come on the market to simplify the methods of collecting and analyzing network-related data. Measures of network properties such as clustering, connectedness, density, and centrality have opened new ways to see and understand the patterns of social interaction and emergent social structures. Online social network sites have helped make such models familiar to the public and have accelerated the acceptance of network-based models of social systems. Stages of network evolution, from hub and spoke to scale-free structures, have informed an understanding of the development of social and computer networks over time. While this approach solves many of the issues of pre-complexity models, it is essentially descriptive, providing a snapshot of a current state without explanation of what came before options for action to influence the future.

One of the earliest modeling methods from deterministic chaos involved a process of nonlinear time series analysis.[24] In this method, an extended time series is analyzed and plotted in phase space, looking not at change through time, but comparing the change in non-time variables from one point to the next across the entire time series. Such analysis allowed the researcher to characterize the nonlinear phenomenon as following the pattern of a random, point, periodic, or strange attractor pattern. Further analysis of the time series could reveal the dimensionality of the phenomenon by pointing to the number of key variables involved in the dynamics that shaped the pattern. In the early 90s many researchers used methods of nonlinear time series analysis, searching for strange attractors as evidence of deterministic chaotic dynamics in social systems. Three challenges emerged in using this approach either for theory or practice development. First, the analytical method required a long and reliable time series as input data, and appropriate data was not often available from the systems under examination. Second, the mathematics required for the analysis were so complicated that they were not well understood by many researchers, so they were embedded in a variety of automated analysis tools. Lack of basic understanding of the underlying method led to a variety of errors in analysis and interpretation, including misinterpretation and artifacts of the analytical methods themselves. The third challenge was embedded in practice. Even when strange attractor patterns were reliably discerned in time series data, the interpretation and meaning making based on the results were not clear or compelling. For these reasons and others, attractor pattern reconstruction as a modeling method to support decision making and action taking in human systems has been relegated to a small number of highly technical research applications.

Agent-based computer simulation modeling has become a popular research method to demonstrate processes and outcomes of self-organizing dynamics of social systems[25] in decision science[26], financial markets[27], sociology[28], information and political science[29], conflict analysis[30], and a wide variety of other social science applications[31]. Given a set of initial conditions and agent characteristics, semi-autonomous agents in the model follow local rules, learn adaptive behaviors, and contribute to formation of system-wide patterns. These models can be used to visualize data about interactions, to test hypotheses regarding conditions and paths of self-organizing processes, and to teach about dynamics of complex change in human systems. The premier institution committed to the study of agent-based modeling and its influence in both physical and social sciences is the Santa Fe Institute (http://santafe.edu/). They have used the method to model and explore a wide variety of dynamical systems and emergent phenomena. Though they demonstrate relationships between initial conditions and outcomes based on simple rules, the abstract and generalized structure of an agent-based simulation model limit its usefulness for decision making and action taking in real-world situations.

Per Bak led one group that pioneered our fifth and final method of nonlinear modeling for human systems, the power law.[32] Power law dynamics, sometimes called Pareto distributions and Zipf's Law, have been used to describe major transition phenomena of markets and market development[33]. The idea was popularized as the "long tail" of internet-driven business models[34]. Power law dynamics have also been used to describe dynamics of population migration, violent conflict, and addiction. Because of its ability to capture inter-level dynamics and to account for discontinuous change, the power law has become one of the symbols of the changing dynamics of human systems. The power law is scale-free, so it works at every level of human system, from brain dynamics to world-wide conflict. The challenge is that there is currently no robust theoretical explanation of why these mathematical relationships emerge over time in complex systems, so the model can be used to analyze data ex post facto, but it is not yet used in a rigorous way to inform prospective decision making and action.

All of these modeling methods have emerged from the study of nonlinear dynamics in physical and mathematical systems. They have been applied to human systems in an effort to develop models and methodologies that support better observation, understanding, and intentional action in all scales of social systems from intrapersonal reflections to international relations. Each one of these modeling techniques brings a special feature that helps the researcher or observant practitioner engage effectively and perform well in social systems that may be far-from-equilibrium and actively emergent. All of these models, however, share two characteristics that limit their usefulness when they are applied to real dynamics in situations of real decision making and action taking.

3.2 Limitations of Complexity-Inspired Models

Each of these models transcends some or all of the limitations of traditional methods of modeling human systems. The table below provides a brief analysis of the five modeling methods and their relationship to the five limitations of the traditional models described above. Exceptions to these simple categorizations may certainly exist. Hybrid methods and models are emerging across many fields of study, but in general, these families of approaches share the assumptions described here. Networks and power law analyses deal with multiple levels of analysis and are able to represent massive interdependencies across scales. Networks, agent-based models, and power law distributions assume the possibility of open system boundaries. All of these methods except agent-based modeling assume high dimensional dynamics, and all of the methods account for both nonlinear and non-random pattern formation.

Table 1. Limiting assumptions for complexity-inspired models of human systems dynamics.

Model Characteristics	Catastrophe Theory	Dynamical Networks	Nonlinear Time Series Analysis	Agent-Based Modeling	Power-Law Dynamics
Multi-level		X			X
Open		X		X	X
High dimension	X	X	X		X
Nonlinear	X	X	X	X	X
Non-random	X	X	X	X	X

These models share a more robust set of assumptions than previous modeling approaches, and they account for social systems' complex and nonlinear dynamics. They are far superior in representing the emergent dynamics of complex human inter-actions in the real world, but they still have two characteristics that limit application to formal and informal real-time decision making and action taking in social systems.

First, they are all inductive models, so they can only provide analysis in retrospect. None of them support effective forecasting or even anticipation of future pattern formation. All of these methods draw data from the past to describe relationships and transformations that happened in the past. Time series analysis requires a long and detailed data set extracted from previous events. Network analysis captures past and current nodes and edges, but it usually does not help anticipate or recommend action for the future. Being a node in an information network can certainly inform decision making and empower action taking, but creating a network model from empirical data does not inform options for action or risk and benefit calculation except in very limited cases. Catastrophe theory bases model characteristics on existing data and its models represent historical dynamics. Agent-based modeling and power law dynamics both start with sets of assumptions, but the findings of the models are descriptions of historical systemic behavior as opposed to anticipation of future patterns of behavior. In essence, none of these models have the power to anticipate future patterns or to provide intelligence that can inform future action for decision makers who are engaged in self-organizing dynamics in real time.

On the one hand, this reliance on historical patterns is to be expected because complex dynamical systems are sensitive to initial conditions and, by nature, are unpredictable. You would not expect a model based on emergent dynamics to be predictive. On the other hand, if a model is to be of service to real decision makers in real situations, it must provide some level of intelligence about underlying dynamics and ways to intervene to influence an emergent future. An effective model also needs to provide information about the dynamics in any given moment to inform action that might shift those dynamics for future benefit. All of these complexity-inspired models are backward looking, and none of them propose a causal mechanism, so none of them are able to meet the requirement of support for prospective decision making in real human systems.

Second, the models are descriptive rather than explanatory. A descriptive model represents the "symptoms" of dynamical self-organizing processes. These models help describe the behaviors that emerged over time in complex human systems. We can use them to determine whether the system patterns conformed to multi-dimensional manifolds (catastrophe theory); generated or broke connections (network theory); showed coherent behavior in phase space (nonlinear time series analysis); generated system-wide patterns from local interactions (agent-based simulations); or generated constant ratios between numbers and sizes of events (power law). Each of these models describes patterns that emerged among the components of a given system, but they do not capture explanations for those dynamics. An explanatory model, on the other hand, provides information about the underlying relationships that set conditions for observable behaviors to emerge. For example, the life cycle of the rhinovirus is an explanation for the common cold, while a runny nose is a true, but descriptive, symptom. Effective intervention depends on the explanation, and current complexity-inspired models of human behavior provide only descriptions.

We should note two possible exceptions to this rather radical observation. Per Bak and others who work with power law dynamics hypothesize a variety of explanatory theories.[35] Bak, himself, speculates that power law dynamics emerge from cycles of accumulation and release of tension among agents at various levels in a complex system. When enough tension accumulates in one scale of the system, structural changes take place in scales either above or below to release the tension and reach a more stable state. This mechanism is incorporated in the model we will propose shortly. The other notable possible exception is the work of June Holley regarding her network weaving approach.[36] Her work is derived from extensive experience in supporting development of entrepreneurial networks, but the connections between her practical advice and the structure of dynamical models is not always explicit. Her insights have also informed our emerging conceptual model as well as our practice in real human systems. With these slight exceptions, most models from the nonlinear array can, at best, describe the world as it has been. They cannot inform theoreticians or practitioners about why those patterns emerged or how they might be influenced.

Traditional models of physical and social dynamics provided explanations for phenomena in social systems, but they were of limited use because they drew from Newtonian mechanics, in which systems were closed, low dimensional, and linear. In those situations, the causality and explanations were clear, but not trustworthy when applied to complex human systems. In complex dynamics, where none of these limiting conditions persist, a new explanatory model is to inform human action inside emergent, complex adaptive systems.

Finally, because the complexity-inspired models are neither prospective nor explanatory, they cannot support decision making or action taking in a moment. They do represent systemic patterns of the past and can certainly support meaning making for individuals and groups who want to understand historical patterns. But if the goal is to create a computational model that informs wise forward-looking action, then it must be based on a conceptual model that provides prospective insight and explanation of self-organizing dynamics that help people see, understand, and influence patterns as they emerge in complex systems.

4 Conceptual Model of Human Systems Dynamics

The challenge is to develop a computational model and modeling methodology that 1) represents the complex and unpredictable dynamics of human systems; 2) works at all scales from intrapersonal to global; 3) provides information about the possible futures of systemic behavior, even knowing that the future of complex systems cannot be predicted or controlled; 4) provides sufficient explanation of interactions within the system to inform options for action; 5) reveals meaningful patterns even in systems that are open, high dimension, and nonlinear; 6) represents the diversity of the parts and the coherence of the whole simultaneously; and 7) provides sufficient explanatory foundation to inform wise and responsible action, even under conditions of the greatest uncertainty. The computational model must be based on a conceptual model that rigorously meets all of these criteria, as well.

Social sciences are not the only contexts in which this challenge exists. Even across the physical and mathematical sciences, no single conceptual model of complex systems dynamics has proved to be general and robust enough to be universally accepted today. Fitness landscapes[37], dissipative structures[38], power law dynamics[39], synergetics[40], and dynamical networks[41] have all proven to be useful conceptualizations of complex dynamics, but none dominate across disciplines. Even in these con-texts of physical and biological sciences (which are substantially less open, high dimension, and nonlinear than human systems), no model is accepted as a definitive representation of all complex adaptive phenomena. All accept limitations that com-promise fidelity or specificity in favor of tractability.

We propose an alternative conceptual model of human systems dynamics that is derived from patterns common to a wide variety of physical science and mathematical models of complex adaptive systems. This emerging model also draws from philosophical foundations of perception and knowledge that are unique to the functioning of human systems. It is grounded in conscious and intentional action with real groups facing real challenges in organizations and communities[42]. In both theory and practice, this conceptual model captures the dynamics of human systems at all scales, in ways that inform decision making and action taking in complex and uncertain environments.

4.1 Conditions of Self-Organizing in Complex Systems

We accept the definition of *complex adaptive system (CAS)* as a collection of semi-autonomous agents that have the freedom to act in unpredictable ways, and their interactions generate self-organized patterns across the entire collection. As patterns form in the system, they constrain the options of the agents in subsequent phases as this self-organizing process continues.[43] We use an operational definition of *pattern* as similarities, differences, and connections that have meaning across space and/or time. Examples of CAS and the patterns they form are myriad in physical systems (e.g., whirlpools, heart rate variability, embryonic development, crystal formation), but we will focus here on such processes as they influence human systems. In the context of human experience, intrapersonal reflection and emotional and cognitive experiences generate self-organizing patterns for individuals[44]. (Some even argue that consciousness itself is self-organizing processes of a complex adaptive system[45], but that conversation is outside the scope of our current exploration.) Two or more people who form a coherent group for learning, work, or play function as agents in the complex adaptive system[46] of a group. Neighborhoods can be seen as CASs as well as agents that contribute to the patterns of an urban landscape. Firms self-organize from within and participate in emergent patterns of markets and industries. Provinces, nations, national allies all are examples of CASs in the realm of human systems.

It is one thing simply to say that human systems self-organize. It is another to track self-organizing processes in retrospect through case study narratives, nonlinear analysis of time series, construction of network maps, and so on. Existing conceptual and computational models, as described above, are sufficient for such descriptive investigations. Analysis that supports proactive decision making in a complex human system, however, requires more. It requires an understanding of the conditions that influence the speed, path, and outcomes of self-organizing processes.

Examination of diverse models of self-organizing processes in non-human complex systems revealed that self-organizing patterns only emerged under certain conditions. Any complex adaptive system only generates patterns when it is constrained in some way. The Belousov–Zhabotinsky reaction requires a containing vessel, a certain temperature threshold, and very particular chemical gradients. An ecosystem will be bounded in space and requires predator, prey, and reproductive interactions among organisms. Fractals require a nonlinear equation to act as a seed and the context of the complex number plane. A fitness landscape requires specific parameters that define fitness and feedback loops to determine survival on the landscape over time. A laser beam depends on both control and order parameters. A scale-free network has nodes and hubs with specified characteristics and criteria for connection. Without any constraints, regardless of the system or its substrata, no pattern self-organizes.

The same realization about the necessity of constraint in pattern formation came from personal and professional experience in social systems. Self-organizing processes in complex human systems, such as large group meetings or team performance, required some constraining conditions for patterns to emerge. Depending on those conditions, pattern formation was sometimes fast, direct, and clear. In other circumstances, the process of pattern formation was slow, wandering, and messy. Within a particular self-organizing process, the patterns were sometimes coherent and distinct, and sometimes they were distorted or ambiguous. Sometimes the emergent patterns were healthy or fit to purpose, and sometimes they were dysfunctional. Sometimes the self-organizing process moved quickly through exploratory stages and into exploitation. At other times the process got stuck in exploration and productive patterns emerged slowly, if at all. Patterns at the individual scale were sometimes in conflict with those at intrapersonal or group scales, and patterns in two separate parts of the system often contradicted each other.

These variations on the process of human systems emergence were not random. They were influenced by the context, and the context was formed by other self-organizing processes in other places and times. As one pattern emerged, it influenced the conditions that informed the speed, path, and outcomes of other patterns in the vicinity. This interdependency among patterns held whether the patterns were in scales above or below, or in remote parts of the system at the same scale. This mechanism of constraints influencing emergence of shifting, interdependent patterns held across environments, contexts, and levels of analysis.

The question emerged for us: Would it be possible to identify parameters that influenced the variability of self-organizing processes, while acknowledging the open, high dimension, and nonlinear nature of self-organizing in human systems? If so, those parameters could be used to see self-organizing patterns in the moment, under-stand their potential for future pattern formation, and influence the conditions to nudge the emerging pattern toward desired outcomes.

These conditions that result from one self-organizing process and influence other self-organizing processes were the focus of our investigation and the foundations for the CDE Model for the conditions for self-organizing in human systems. CDE stands for the three fundamental, necessary and sufficient clusters of constraining conditions: container, difference, and exchange. The CDE Model is grounded in a multi-disciplinary study of nonlinear dynamics in a wide range of physical and mathematical sciences as well as action research in diverse human systems settings[47]. We will first introduce the model, then articulate ways in which it meets all of the criteria earlier defined for a conceptual model to inform theory and practice in complex human systems.

4.2 CDE Model for Conditions of Self-Organizing in Human Systems

The CDE Model of conditions for self-organizing in human systems is a qualitative conceptual model of a set of meta-variables that represent a wide variety of constraints that influence the speed, direction, and outcomes of self-organizing processes in human systems. The characteristics of these meta-variables and the nonlinear interdependencies among them form the foundation of a model of human systems dynamics that meets all of our criteria for a useful way to support seeing, understanding, and influencing the complex dynamics of social systems at all scales.

Container

Boundaries and boundary conditions have always been an integral concern of systems theory.[48] Open, high dimension, nonlinear conditions that are common in human systems challenge traditional understandings of system boundaries. Especially in complex human systems, practitioners and theoreticians challenge the traditional ways that systems are defined and system boundaries are represented. Boundaries of human systems much account for multiple, massively entangled levels of pattern formation, from personal insight to mob behavior. At the same time, human system boundaries have to account for the fact that "inside" and "outside" have diverse meanings, and that those meanings change over time depending on perspective. To meet the needs of both flexibility and fidelity to a human system, the CDE Model must account for system boundaries that can be simultaneously open and closed, unitary and multiple, local and global.

In response to this need, the first meta-variable in the CDE Model highlights the boundaries of the focal system. This set is called *container* and is represented by "C". A container, (C), of any self-organizing process includes any condition, or collection of parameters, that hold the agents of the CAS close enough together that they can interact and form patterns. A particular container may be physical, like a room or a mountain range. It may be conceptual, like a national identity, a stated purpose, or religious belief. It may be social, like an invitation to a party or an artistic performance. As these examples demonstrate, a container can be a bounding condition (fence), an attractive condition (magnet), or a combination of multiple mutual attractions (network).

In any real human system, there are innumerable containers at play simultaneously, and usually, the containers are massively entangled. Containers can be simply nested within each other, for example, a child is in a classroom, a classroom is in a building, a building in a district, and a district in an educational system. More often, however, the relevant containers are overlapping and interdependent. For example, the child is a member of a family, a scout troop, a baseball team, a cultural community, a gender group, a gang, and so on. Standing within all these boundaries simultaneously, the child is a participant in many different self-organizing complex adaptive systems. At every moment, the child both influences and is influenced by patterns emerging in any of these diverse containers.

C, in the CDE Model, is the meta-variable that encompasses all conditions that influence any particular complex adaptive system at any given point in time. Any particular emergent pattern of a CAS involves some subset of all possible Cs, and within a pattern, some Cs will be more and others will be less relevant to a particular purpose. For example, the child's elementary school class container may be irrelevant when he or she is playing first base, though it does not cease to exist. As intentional agents who see, understand, and influence patterns in self-organizing processes, we recognize the most relevant containers and focus our attention and action on them. At the same time, we understand that innumerable other containers exist and might become relevant at any moment. The simultaneous reality of one configuration of containers and the potential of another configuration of them allows us to deal with the system as if it were simultaneously bounded (to support computation and decision making) and unbounded (to represent the openness of observed social reality).

Containers manifest the self-organizing patterns at a specific point in time, but they also influence the potential for change in the pattern in the future by increasing or decreasing the degrees of freedom for all of the agents contained in the system. Larger or weaker containers reduce the pressure of constraint and increase the degrees of freedom for the agents to establish relations and to organize, so the process of pattern formation is likely to be slower and less articulated. Smaller or tighter containers, on the other hand, tend to increase constraints, decrease degrees of freedom, and so increase the likelihood of collision and the speed and clarity of the self-organizing process.

The correlation between container size and the speed and clarity of the self-organizing process serves as an explanation to support decision making and action taking by individuals and groups. It is significant to note, however, that the relation-ship is not simply causal. A particular change in the size of a container does not necessarily determine the effect on the pattern as a whole. The precise relationship be-tween the container and the emergent pattern is not predictable in any given self-organizing situation because the influence of the container is mediated by the other two conditions for self-organizing—D (difference) and E (exchange).

Difference

Difference has also historically been an important factor in the ontology and epistemology of systems, and it is the second condition for self-organizing in the CDE Model. Even the ancients recognized the power of difference for causing change and making meaning.[49] Traditional physics considered difference as the key to all kinds of potential energy, and more recently, complexity scholars have explored the power of difference in understanding[50] and influencing systemic patterns.[51] The challenge is that in our open, high dimension, nonlinear human systems, we must deal with the fact that potential is embedded in many differences simultaneously, and that the relevance of a particular difference, and its influence on system-wide patterns, can shift without warning.

As a result, the CDE includes "D" as the second meta-variable to capture the myriad differences that influence change in a human system. A *difference* is any gradient or distinction that exists within any given container that bounds the complex adaptive system of focus. At a given moment, in any given human system, at any given scale, an indeterminate number of differences articulate the systemic pattern and hold the potential of the system to change.

In the system dynamics as captured in the CDE Model, relevant differences serve two functions. First, difference articulates a pattern as it emerges out of self-organizing interaction. Difference allows the pattern to be observed, analyzed, and influenced. Differences can be physical, emotional, social, political, financial, or any other dimension you can imagine. They may be subjective, objective, or normative. Regardless of the substantive manifestation of the difference, as agents interact, the interactions among their different characteristics manifest a pattern across the system. At any point in time or location in space, the pattern of a CAS consists of variation in one or another characteristic among the agents bounded by a given system container. For example, in a team, differences in expertise might contribute to the pattern of high performance. In a neighborhood, differences in household income might contribute to the architectural design for the whole. In a nation, differences in political assumptions and values shape the pattern of decision making and action for the government. Differences are relevant in different ways in different containers. For example, height can be a difference that makes a difference on a basketball team, but it might be irrelevant in an academic learning environment. Difference may refer to the degree of variation (more or less tall, more or less happy) or to the kind of variation (height or attitude). Discrete and large differences build clear patterns, and continuous differences or small ones contribute to fuzzy or ambiguous patterns.

The second function served by difference is to establish potential for change. Potential energy in physical systems is an example of the motive power of difference. Difference in height, spring tension, and heat are all examples of the ways in which potential for change is "stored" in differentiation between or among system-wide parameters. In human systems, the tensions created across differences also motivate action. The teacher knows more, and the student wants to learn. The racist is moved to violence. Platforms of political parties motivate voters. Gender, values, expertise, wealth, curiosity, expectations, age, power, faith commitments are just a few examples of differences that can hold the potential energy of a human system at any point in time. Any of these differences may shift a relevant pattern and result in new patterns self-organizing across a single human scale or between scales. For example, my level of confusion results from a difference within my own cognitive frame. It may cause me to bother my neighbor, and together we may interrupt the flow of an otherwise orderly class. A difference at one place or scale of a system motivates the local pattern to shift, and a shift in local pattern may result in shifts at a more global level.

Difference is such a powerful influence on change because it, too, represents levels of constraint (degrees of freedom). Large differences increase degrees of freedom and tend to motivate rapid or more turbulent change, while small differences constrain degrees of freedom and, therefore, convert more slowly. A system with few relevant differences (lower degrees of freedom, more constraint) will manifest a clear and coherent pattern, while one with many relevant differences (higher degrees of freedom, less constraint) may appear random and be stuck in an entropy trough.

Conversion of the potential energy of difference to the kinetic energy of change in a human system is not simply a causal process. At any moment, differences in multiple containers are influencing each other. For example, a social definition of political correctness, and my desire to make a good impression on my boss, may damp my action in regard to my political or racial bias. Even within the same container, multiple differences vie for dominance in the self-organizing process. For example, I love chocolate, and I am committed to weight control. Sometimes one difference sets the potential for action, sometimes the other does, and sometimes two differences are balanced, and the result is stasis.

The meta-variable of difference, both as demonstration of current pattern and motivation for change in the future, establishes another link in an explanatory pattern that can inform observation, meaning making, and action for people engaged in social systems. As long as any one difference or small set of differences is relevant at a given instant, the system may be manipulated as if it were simply a low dimensional phenomenon. Because "D" is a meta-variable, the CDE problem space is tractable enough for individuals to see (and groups to discuss) coherent mental models of a self-organizing social system. On the other hand, because an unlimited number of differences can be represented by "C" in the CDE, the system as a whole can be understood simultaneously to function in high dimension problem. In this way, the model matches both the need for tractable representation and infinite variety of real experience.

While changes in "D" shift patterns in a system, they do not allow for total prediction or control. Multiple interacting differences influence a given pattern at a given moment, so an intentional change in one may be distorted or damped by any other. Even if differences are constrained to a small and manageable number, a change in the complex human system cannot be controlled. By itself, or even in tandem with defined containers, difference can influence direction but not pre-determine outcome of a self-organizing process. The final set of meta-variables that simultaneously influence the emergent self-organizing patterns involves the connections across the system that allow difference to accumulate or dissipate.

Exchange

From feedback in traditional systems dynamics modeling[52] to the theory of constraints[53] and complex responsive processes[54] the idea of flow has been essential to conceptual and computational models of human systems. In the past decade, nonlinear relationships and feedback loops have been accommodated in models of human interaction, but they have usually been conceptualized in the context of low dimension and/or closed systems. When a nonlinear relationship is embedded in a quasi-bounded, high dimension space, it quickly becomes intractable. When coupled with high dimension and open boundaries, feedback has resulted in system patterns that are either disordered or radically subjective. These are critical modeling challenges because it is just such exchanges, in open and high dimension space, that are critical to understanding and action in human systems.

To meet this requirement, the final meta-variable in the CDE connects across the system to realize the potential stored in any of its differences. We call this meta-variable *exchange* and represent it by "E". Exchange includes any transfer of information, energy, force, signal, material, or anything else between or among agents. It appears as flow from one part of the system to another and it establishes relationships that are observed before, during, and after self-organizing processes in human systems.

While many kinds of exchanges influence pattern formation in human systems, the easiest to visualize is the flow of information during a conversation. Two people hold different views or expectations (D). When they come together for a particular purpose (C), they exchange (E) information, and if everything goes well, a coherent pattern of the whole emerges. The emergent pattern is not predictable. It may be increasing anger, distrust, frustration, and separation, or it may be shared mental models and harmonious friendship. The presence of the exchange cannot pre-determine the nature of the emergent pattern, but the absence of exchange will result in no shared pattern at all.

Exchanges are taking place in many different containers and across many different relevant differences simultaneously. An individual is thinking about one thing, her team is focusing a conversation on another, senior management is assessing the team's performance against others, and other firms in the industry are seeking competitive intelligence. All of these Es are simultaneously influencing the emergent patterns at all scales of the system. A change resulting from one may well influence the efficacy of another. Exchanges that are invisible to one system participant may be quite powerful for another, and those that are global and formal are often less powerful than those that are local and informal.

Like containers and differences, exchange derives its influence on systemic behavior from increasing or decreasing degrees of freedom. The power of a given exchange is denoted by limiting degrees of freedom by the tightness of the connection it establishes across differences in a system. Tightness is determined by a variety of factors, including speed (time required to complete the connection), width (number of differences considered), strength (size of differences traversed). Tighter exchanges (increasing constraint and reducing degrees of freedom) tend to speed up self-organizing processes, and weaker ones (lower constraint, more degrees of freedom) slow it down. When exchanges are absent, no self-organizing change will occur at all.

Again, the "E" meta-variable can be used to assess and influence self-organizing patterns as they emerge. One might tighten exchanges to increase the speed and influence the outcomes of a self-organizing process, but the results of that intervention are unpredictable. The relationship is not simply causal. The variability of competing exchanges and the indeterminacy of containers and differences in the system at large make the future unknowable, even while exchanges can be manipulated with the intention of influencing the speed, path, or outcomes of a self-organizing process.

Interdependencies among C, D, E

The indeterminacy of the meta-variables of C, D, and E help capture the open, high dimension, and nonlinear nature of human systems. The relationships among the sets of meta-variables account for the emergent, self-organizing dynamics of those systems. Variability of the speed, direction, and outcome of a self-organizing process is influenced by the dynamic relationships among members of the same variable class within each of the meta-variables (C_1 to C_2, D_1 to D_2, or E_1 to E_2). The process is also influenced by the nonlinear relationships among the three collections of meta-variables (C_n to D_n to E_n). These interdependencies generate a variety of interesting consequences that increase the fidelity of the CDE Model to the lived reality of self-organizing processes in human systems. A shift in one difference begins a self-organizing shift in other differences, as well as in multiple exchanges within the same container and in related containers as well. For example, I observe an anomaly (D_1), this causes me to question (E_1) other observations (D_2) in the current experiment (C_1) as well as to challenge a protocol (E_2) that might be used by others on my team (C_2). Given the number of variables represented with each meta-variable and the interconnections among the meta-variables in any system moment, it is easy to understand how complex adaptive systems are sensitive to initial conditions. This complex interdependency among system conditions helps explain why complex adaptive systems can be unpredictable at the local and patterned at global scales.

Any feature of a social system that might influence a self-organizing pattern can be accounted for in this conceptual model. Even system features that would otherwise be seen as extraneous can be incorporated into the CDE portrait of any systemic pattern. The only adjustment that is required is to recognize the larger, relevant container that encompasses both what was originally "outside" with what was "inside." And, because the three conditions do not depend on time or distance, a CDE portrait is necessarily scale-free. For example, when we work with teachers in the throes of school reform, they focus primarily on their classrooms (C_1) and their students (C_2). When they perceive the requirement for high-stakes testing (E_1), they see it as an external force (C_3) that is being imposed on them and their students from the outside. Instead, we encourage the teachers to see high stakes testing as a difference that makes a difference (D) in their classrooms. By recognizing the test as a part of a classroom pattern, rather than an external imposition, new options for teaching and learning (E_2) emerge.

The three conditions (C, D, and E) are mutually determined, so changes in any one spontaneously result in changes in the other two conditions. It is possible that the broader universe of conditions holds a particular pattern (C or D or E) in place, so an adjustment may not be immediate or predictable. Ultimately, as the related conditions shift, more and more energy is required to resist the tendency of the system to adapt internally. For example, a corporate focus on profits (D_1) as a sole difference that makes a difference can pre-determine (E_1) policies and procedures (C_1) that contradict (D_2) individuals' (C_2) personal values (D_3). If exchanges are established that allow employees who share values to talk (E_2) with each other, they may amplify the values difference between them and their boss and, ultimately undermine profit-dominated patterns of behavior.

Difference and container have a special relationship in the context of complex adaptive systems. Within a container, a difference can denote a pattern and set conditions for self-organizing change. At the same time, if that difference is great enough, it may overwhelm exchanges that mediate the difference within the whole, until the system bifurcates along the fault lines formed by the difference. When this happens, the characteristic that functioned as a difference previously is transformed into a container, which bounds a new and somewhat autonomous system. In an opposite process, two containers may be connected by an exchange that is strong enough to elicit a shared pattern. In that case, the previous containers become mere differences that make a difference within a new emergent whole. Examples of both of these situations abound in real human systems. A team includes people of both genders, so gender is a difference that may or may not make a difference. A sexist joke or a harassing behavior can turn that difference into a container in which the men and the women face off against each other. At the same time, race and experience, which were also differences within the original container, may be invisible and equally distributed across the system, waiting for circumstances that transform them into features that contain rather than just differentiate an emerging pattern.

Recognizing the features that contain, differentiate, and connect across self-organizing patterns allows a conscious agent to observe the process of change as it occurs. Understanding the relationships among the conditions for self-organizing and seeing the pattern from a variety of perspectives allows the conscious agent to make meaning of social change as it emerges. Acknowledging options for action and anticipating the nonlinear consequences of a change allows the conscious agent to take intentional action to shift patterns in the course of self-organizing. Finally, continuing to observe the system patterns in formation allows the conscious agent to take adaptive action to amplify opportunity and mitigate risk in real time.[55] These three iterative problem solving steps—observe, understand, influence—engage the ac-tor/observer with patterns as they emerge. They are the foundation of adaptive action and adaptive capacity for individuals, communities, and organizations.

4.3 Implications of the CDE Model

The CDE Model addresses and resolves many of the limitations of models of human systems that were informed by Newtonian and previous applications of complexity science, but it also introduces some challenges of its own as a foundation for either a conceptual or a computational model.

Like other complexity-inspired models, the CDE is able to address phenomena across levels of organization. As we stated before, none of the meta-variables necessarily includes either time or distance, so they are applicable on any scale of human system, as well as across scales in the same system at the same time. For example, one might map the containers, differences, and exchanges involved in the self-organizing process of one person (C) falling (E) in love (D). At the same time, a single container might include the other lover (CDE), a balcony (C) and a dialogue (E) about the moon (D), a CDE of families in conflict for generations, and a city containing both a crypt and a bottle of poison. Shakespeare's portrait of such tragic self-organizing has persisted for 400 years[56].

The CDE Model represents human systems as simultaneously open and closed. While one might focus on a single configuration of C, D, and E at one moment, it is done with the consciousness that an infinite number of other containers, differences, and exchanges might become relevant at any moment. For example, a particular orphaned boy might live in a shack (C) with his mean (D) sister and ineffectual (D) brother-in-law who cared (E) for and ridiculed (E) him. A chance encounter (E) with an escaped (D) convict in a river (C), can transform his life into one of *Great Expectations*, thanks to Charles Dickens[57].

CDE as a conceptual model also opens the space for a system to be both high and low dimension at the same time. Differences that make a difference at one moment may be supplanted by any one of a slew of other differences, all of which fit into the category of conditions represented by the meta-variable, D. In the touching short story of de Maupassant called *The Necklace*[58], an eager and aspiring young woman was destroyed when she borrowed elegance to impress others and discovered too late that a life invested in diamonds purchased only cheap paste.

The CDE Model matches the nonlinear causality that is so familiar in human systems. The massive and mutual interdependency among the meta-variables reflects the massive interdependency among the conditions that shape the speed, direction, and outcomes of real self-organizing processes in the real world. For example, Tolstoy's *War and Peace*[59] demonstrates over and over the powerful interdependencies with and among nation, family, community, identity, and class (Cs) with wealth, role, status, location, personal loyalties (Ds), and love, speech, violent conflict, and exchange of money (Es). These same meta-patterns have repeated throughout history, while the particular conditions have changed with the decade and the continent.

The dynamics of CDE are not predictable, but they are not random either. Changes in one condition or pattern are highly correlated to changes in others, both local and distant. On the other hand, CDE can account for random behavior when the conditions are under-constraining. Low constraint happens when the C is large, the Ds are many, and/or the Es are weak. In these situations, the coupling and correlations among the conditions for pattern formation are so low that system behaviors may be indistinguishable from randomness. It is hard even to imagine an example of a human system that is loosely enough constrained to appear random. In the past, in all cultures, literature, folk tales, and history take what may appear to be random and give it structure and meaning. Even the experience on a battlefield in Homer's *Iliad*[60] is full of examples of people making meaning by naming families (Cs), recognizing insignia (Ds), and shaking the hands (Es) of enemies before engagement (E).

In addition to resolving the limitations of traditional models of social interaction, the CDE Model also resolves challenges unmet by other complexity-inspired models. The CDE captures the underlying dynamics of self-organizing processes by naming the categories of constraint that initiate and influence the shape of emerging patterns as well as the process of emergence. Because it explains underlying interrelationships, it can be used to inform intentional action to shift the conditions and, one can hope, influence the future path and outcomes. The causality is not absolute, and results are not predictable. The complex interactions among self-organizing conditions, both seen and unseen, make unintended consequences not just common but expected. Ancient Greek tragedy captured these dynamics in compelling ways. Oedipus saw, understood, and took action to influence a pattern when he defended (E) himself (C) and his honor (D) against a stranger (D). It was a lifetime (C) later when he realized he must pay (E) the price of a fratricide (D)[61].

Finally, the CDE Model allows an observant actor to anticipate the future consequences of current action. In this way, the CDE allows a conscious actor to construct a conceptual model of an ethical dilemma. We can consider multiple options for action and imagine possible consequences, risks, and benefits for each option. When a choice is made, the consequences may or may not be as anticipated, but each cycle of adaptive action informs the next, so individuals and groups can learn and improve their capacity to adapt and influence patterns over time. The *Count of Monte Cristo*[62] schemed a whole lifetime to influence the patterns of jealousy and corruption that plagued his life. He understood enough about the people and their culture to set conditions and influence the pattern that gave him vengeance against his enemies.

The CDE Model, as a conceptual representation of the complex dynamics of human systems, meets the challenges set out at the beginning of this paper. The CDE Model of the conditions for self-organizing in human systems 1) represents the complex and unpredictable dynamics of human systems; 2) works at all scales from intrapersonal to global; 3) provides information about future systemic behavior, even knowing that the future of complex systems cannot be predicted or controlled; 4) provides sufficient explanation of interactions within the system to inform options for action and anticipated possible outcomes; 5) reveals meaningful patterns even in systems that are open, high dimension, and nonlinear; 6) represents the diversity of the parts and the coherence of the whole simultaneously; 7) provides sufficient explanatory foundation to inform wise and responsible action, even under conditions of the greatest uncertainty.

As a conceptual model the CDE has been tested in a variety of contexts and under a wide range of conditions. It is currently informing theory and practice in education, school reform, program evaluation, occupational therapy, conflict resolution, organization development, management, leadership, team building, advocacy, public health, public policy advocacy and implementation at all levels of governance, human resource development, facilitation, diversity, ethics, and community development[63]. As a qualitative tool, it supports individuals and groups as they engage in adaptive action to see, understand, and influence the self-organizing patterns of complex human systems. The outstanding question is if and how the CDE Model might also form the foundation for a computational model of individual and collective human behavior.

5 Computational Model of Human Systems Dynamics

Over the years, we have experimented with a variety of computational models to represent the complex dynamics represented in the CDE Model. The most successful efforts at inductive model building and testing have focused on qualitative descriptions drawn from narrative or shared dialogue. In a few failed efforts, we have tried a variety of inductive and deductive mathematical models, including time series analysis, fuzzy logic, genetic algorithms, and dynamical networks. It is not possible for us to know whether these failures were a result of an incomplete conceptual model, the lack of model specification, misfit of method to model, or lack of sufficient sophistication with the various modeling approaches. It is possible that anyone or a combination of all of these problems limited our success.

We continue to search, however, for a computational model that represents systemic patterns of human systems dynamics that are open, high dimension, and nonlinear, like those represented conceptually by the CDE Model.

The model we propose will represent the C, D, and E as meta-variables that de-scribe functional clusters of conditions that constrain and inform systemic patterns. At the most macroscopic level the three conditions are co-active collections of parameters that exist in the particular situation. A collection of "containing" characteristics holds the system together without generating an impermeable boundary. A collection of "differentiating" characteristics articulates the pattern and provides the energy and directionality for change to occur in the future. A collection of "exchanging" characteristics moves information, material, and energy around the system to release tension of difference in one physical or conceptual place and contribute to accumulating tension in another.

The model will make it possible for relevant Cs, Ds, and Es to be unique in any given situation and at any given time. Over time, even if the context remains constant, different Cs, Ds, and Es can increase or decrease in relevance to shift the pattern into self-organizing change and transform the potential energy stored in the pattern into actual systemic change.

In a robust computational model, a single feature might serve the function of container, difference, or exchange, depending on the context and the perspective of the system observer and the intention of the system analysis. In practice this happens often. I belong to a team (C). My team behavior is different from my other professional behavior (D). When I am in meetings, my team communications (E) are clear and effective. The computational model will need to acknowledge and incorporate this local specificity and global ambiguity.

The computational model would support nonlinear interactions among individual parameters as well as clusters of meta-variables representing the Cs, Ds, and Es, so that a change in one generates a change in the other where the tendency or direction of change can be anticipated, though the specific outcome is indeterminate. For ex-ample, I expect for the noise level (D_1) to decrease when I move a party to a larger space (C), but perhaps the guests will simply talk louder (E), and the overall volume (D_2) will remain unchanged.

An adequate model would support manipulation of a complex combination of constraints—of the three conditions on each other or of particular conditions on others of its same kind. A combination of conditions might influence the emergent patterns within the system and provide options for action for individuals and groups interacting with the system. In this way, it should be possible to model changes in multiple Cs, Ds, and Es either in series or in parallel. For example, if we simultaneously moved to the larger room (C) and encouraged people to dance (E), what would happen to the volume in the room (D)? What other conditions, perhaps not observed previously, would emerge as relevant to the pattern?

A model that met these criteria would represent human systems dynamics in a way that would be simultaneously flexible enough to match lived experience and elegant enough to support realistic processing and interpretation.

6 An Invitation

In this document, we have summarized and critiqued a variety of models designed to represent the dynamics of human systems. Some are based on traditional understanding of mathematical, physical, and social relationships. Others are based on nonlinear dynamics and principles of emergence in complex adaptive systems. All of these models have proven useful in specific applications in a variety of social science inquiries, but they all fall short of capturing the open, high dimension, nonlinear interaction of human systems dynamics or of providing sufficient explanation to support prospective understanding and action.

While the CDE Model has proven to be a robust and useful interpretive conceptual model, its value to both research and practice in social sciences will be immeasurably enhanced when it can inform a computational model. Such a model will capture the nonlinear nature of the dynamics of human systems to inform the work of scholars and practitioners who face complex and emergent personal, professional, and political challenges. Scholars would use such a model to develop and test hypotheses about self-organizing dynamics at all scales of human interaction. Practitioners would use the model to inform decision making in real time and to develop individual and group capacity through training and instruction. Individuals and groups would build adaptive capacity to see, understand, and influence complex and unpredictable patterns as they emerge.

The network of Human Systems Dynamics scholar-practitioners invites you to engage with us in an inquiry that moves the CDE Model from the realm of conceptual and into the realm of computational modeling. Together we might create a model to help scholars and practitioners explore and develop adaptive capacity to leverage the emergent potential in our social systems today and into the unknowable future.

References

[1] G. E. P. Box and N. R. Draper, *Empirical Model-building and Response Surfaces*, New York: Wiley, p.424, (1987)

[2] J. E. Roeckelein, *Elsevier's dictionary of psychological theories*. Amsterdam: Elsevier, (2006)

[3] R. Morriss, *Psychiatry*, Volume 8, Issue 3, 82-86 (2009).

[4] Q. Miao and L Liu, *Social Behavior and Personality: An International Journal*, 38(3), 357-363 (2010)

[5] M.K. Dhami, *Psychological Science*, 14(2), 175-180 (2003)

[6] B. J. Puvathingal and D. A. Hantula, *American Psychologist*, 67(3), 199-210 (2012)

[7] L. Chen and G. Chen, *Physica A: Statistical Mechanics and Its Applications*, 374(1), 349-358 (2007)

[8] A. Gibbard and H.R. Varian, *The Journal of Philosophy*, Vol. 75, No. 11, 664-677 (1978)

[9] P. R. Mitchell, J. E. Sault, P. N. Smith, K.F. Wallis, *Economic Modeling*, Volume 15, Issue 1, 1-48 (1998)

[10] G. M. Lady, *Journal of Economic Dynamics and Control*, 19(3), 481-501 (1995)

[11] Twentieth-Century Model ‘A Global Suicide Pact’, Secretary-General Tells World Eco-nomic Forum Session on Redefining Sustainable Development. (2011, January 28). *UN News Center*. Retrieved from http://www.un.org/News/Press/docs/2011/sgsm13372.doc.htm

[12] C. Moraru, *Cosmodernism: American narrative, late globalization, and the new cultural imaginary.* Ann Arbor: University of Michigan Press, 2011

[13] A. Bontea, The year's work in critical and cultural theory. Oxford: Published for the Eng-lish Association by Oxford Journals pp. 348-366, (2009)

[14] www.crawdadtech.com

[15] T. Y. Choi and Kevin J. Dooley. *Journal of Supply Chain Management*. 45.3 p25, (2009)

[16] www.sensemaker.com

[17] M. S. Poole, Organizational change and innovation processes: Theory and methods for research. New York: Oxford University Press, (2000)

[18] R. Rosen, *Bulletin of Mathematical Biology*, 39(5), 629-632 (1977)

[19] J. Kaldasch, *Physica A: Statistical Mechanics and its Applications*, Volume 391, Issue 14, 15, 3751-3769 (2012)

[20] S. H. Strogatz. Nature. 410.6825 268 (2001)

[21] A. Krifa, M. Mendonca, R. Bin, N. Rao, C, Barakat, T, Turletti, and K. Obraczka. *ACM SIGCOMM Computer Communication Review*, Volume 41, Issue 4, 480 (2011)

[22] X. H. Xiao, G. W. Ye, G.W, B. Wang, M. F. He, *Physica A: Statistical Mechanics and its Applications*, Volume 388, Issue 5, 775 – 779 (2009)
[23] R, Toivonen, J. Onnela, J. Saramäki, J. Hyvönen, K. Kaski, *Physica A: Statistical Mechanics and its Applications*, Volume 371, Issue 2, 15, 851-860 (2006)
[24] S. J. Guastello and R. A. Gregson, *Nonlinear dynamical systems analysis for the behav-ioral sciences using real data*. Boca Raton, FL: CRC Press, (2011)
25 J. M. Epstein, *Generative social science: Studies in agent-based computational modeling*. Princeton: Princeton University Press, (2006)
[26] W.I. Sellers, R. A. Hill, and B. S. Logan, B. S, *Philosophical Transactions: Biological Sciences*, Volume 362, Issue 1485, 1699 – 1710 (2007)
[27] E. Samanidou, E. Zschischang, D. Stauffer, and T. Lux, Reports on Progress in Physics, Volume 70, Issue 3, 409 – 450 (2007)
[28] R. K. Sawyer, *Social emergence: Societies as complex systems*. Cambridge: Cambridge University Press, (2005)
[29] S. Rodriguez, V. Julián, J. Bajo, C. Carrascosa, V. Botti, and J. M. Corchado, *Engineering Applications of Artificial Intelligence*, Volume 24, Issue 5, 895 – 910, (2011)
[30] G. T. Jones, and R. Hagtvedt, R. *Journal of Business Ethics*, 77(1), 85-97 (2007)
[31] J. H. Miller, and S. E. Page, *Complex adaptive systems: An introduction to computational models of social life*. Princeton, NJ: Princeton University Press, (2007)
[32] P. Bak, *How nature works: The science of self-organized criticality*. New York, NY, USA: Copernicus, (1996)
[33] A. T. Stephen and O. Toubia, *Social Networks*, 31(4), 262-270 (2009)
[34] C Anderson, *The long tail: Why the future of business is selling less of more*. New York: Hyperion. (2006)
[35] M. J. Newman, *Contemporary Physics*, 46:5, 323-351, (2005)
[36] J. Holley, *Network Weaving Handbook*, http://www.networkweaver.com, (2011)
[37] S. A. Kauffman, *The origins of order: Self-organization and selection in evolution*. New York: Oxford University Press, (1993)
[38] I. Prigogine and I. Stengers, *The end of certainty: Time, chaos, and the new laws of nature*. New York: Free Press, (1997)
[39] P. Bak, *How nature works: The science of self-organized criticality*. New York, NY, USA: Copernicus, (1996)
[40] G. Hertel, *Journal of Managerial Psychology*, 26(3), 176-184, (2011)
[41] J. P. Bagrow, D. Wang, and A-L Barabási, PLoS ONE 6(3): e17680 (2011)
[42] G. H. Eoyang, "Conditions for Self-Organizing in Human Systems", Ph.D. Thesis, The Union Institute and University, (2001)
[43] K. Dooley and A. Van de Ven, A. *Organization Science*, 10(3): 358-372 (1999)
[44] O. Gomes, *Fractals*, Volume 42, Issue 2, 1206-1213 (2009).
[45] J. Neisser, *Consciousness and Cognition*, Volume 21, Issue 2, 681-690 (2012).
[46] S. Mennin, *Teaching and Teacher Education*, Volume 23, Issue 3, 303-313 (2007).
[47] G. H. Eoyang, *Voices from the field: An introduction to human systems dynamics*. Circle Pines: Human Systems Dynamics Institute Press, (2003)
[48] L. V. Bertalanffy, *General system theory; foundations, development, applications*. New York: G. Braziller, (1969)

[49] Plato, *The Sophist: The Professor of Wisdom*. (Translated by: E. Brann, P. Kalkavage and E Salem), Newburyport, MA: The Focus Philosophical Library (1996)
[50] J. Kelso and D. Engstrøm, *The complementary nature*. Cambridge, MA: MIT Press, (2006)
[51] S. E. Page, *The difference: How the power of diversity creates better groups, firms, schools, and societies*. Princeton: Princeton University Press, (2007)
[52] D. H. Meadows and D. Wright, *Thinking in systems: A primer*. London: Earthscan, (2009)
[53] E. Goldratt. *What is this Thing Called Theory of Constraints*. Croton-on-Hudson, NY: North River Press, (1990)
[54] R. Stacey, *Complex responsive processes in organizations: Learning and knowledge creation*. London: Routledge, (2001)
[55] G. H. Eoyang and R. Holladay. *Adaptive Action: Leveraging uncertainty in your organization*. San Francisco: Stanford University Press (in press).
[56] W. Greenhill, *Romeo and Juliet*. Chicago: Heinemann Library, (2000)
[57] C. Dickens, *Great expectations*. New York: Dodd, Mead, (1942)
[58] G. D. Maupassant, *The great short stories of de Maupassant*. New York: Pocket Books, (1958)
[59] L. Tolstoy, Tolstoy: *War and Peace*, Great Books of the Western World, Chicago: Encyclopedia Britannica, (1952)
[60] Homer. *The Illiad*. NY: Doubleday, (1974)
[61] Sophocles and P. Roche, *Sophocles: The complete plays*, New York: Signet Classics, (2001)
[62] A. Dumas, *The Count of Monte Cristo*. New York: Modern Library, (1996)
[63] HSD Institute. (2012, May 1). Directory of HSD Associates. Retrieved May 25, 2012, from http://www.hsdinstitute.org/community/associates.html.