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Problem Solving About Complex Systems: Differences Between Experts and Novices

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Abstract: This paper reports on a study of problem solving differences between scientific experts in the field of complex systems and novice undergraduate students. Significant differences were found both at the conceptual level and at the level of basic epistemological and ontological presuppositions and beliefs. It is suggested that helping students understand and use complex systems knowledge will require helping students construct a richer conceptual ecology which embraces both non-reductive and decentralized thinking, multiple causality, non-linearity, randomness, and so on. It is hoped that this research might contribute to efforts that are exploring ways for students to acquire a powerful conceptual toolkit based on emerging scientific and social science research into the dynamics of complex systems.

Keywords: Cognitive science, modeling/models, science education, student beliefs.

How does the immune system respond to constantly changing bacterial and viral invaders? How do birds achieve their flocking formations? Why do we have highly skewed wealth distribution patterns? How do galaxies form? Despite the diversity of these questions, each has been the focus of research at the frontiers of science, and each involves phenomena that may be regarded as *complex systems*. The central concepts of complex systems, including new ways of doing science involving computer explorations and computational modeling, have been found to apply in many different areas. Yaneer Bar-Yam has written, "The study of the dynamics of complex systems creates a host of new interdisciplinary fields. It not only breaks down barriers between physics, chemistry and biology, but also between these disciplines and the so-called soft sciences of psychology, sociology, economics, and anthropology" (Bar-Yam, 1997). Thus the concepts related to complex systems may function as *unifying cross-disciplinary scientific themes* which are essential to understanding emerging interdisciplinary perspectives in the natural and social sciences. Unfortunately, considerable research has documented the difficulties that students have learning scientific ideas from the past 300 years (e.g., Newtonian physics, Darwinian evolution). Helping students to learn emerging scientific knowledge and the unifying cross-disciplinary themes related to complexity and complex systems will no doubt prove even more challenging.

Complex Systems and Learning Issues

Briefly, complex systems may be characterized by the interactions of numerous individual elements or agents (often relatively simple), which self-organize at a higher hierarchical level of the system that in turn show emergent and complex properties not exhibited by the individual elements. There are also ways that living (or artificial life) agents in complex systems take in data from their environments, find regularities in the data, and compress these perceived regularities into internal models that are used to describe and predict its future (Gell-Mann, 1994). Complex systems exhibit evolutionary processes in that an agent’s internal models are subjected to selection pressures in the context of specific environmental conditions and mutations resulting in changes to the internal models over time. Finally, the emergent characteristics of a particular complex system frequently form an individual agent at a higher hierarchical level of the system. For example, the immune system antibodies continuously self-organize and evolve while being a part of the many “organism agents” of a bird, and that bird is in turn an agent in the formation of a flock of birds, and the flock of birds is in turn an agent that is part of a particular ecosystem niche, and so on. Central concepts related to complex systems that are frequently referenced in the literature include: multiple agents, agent internal models determine actions, sensitivity to initial conditions and chaos, fitness landscapes, self-organization, selection, positive feedback, emergence characteristics, hierarchical levels, local activation - distant inhibition, and homeostasis.

Unfortunately, there is reason to believe that many of the core concepts associated with these new scientific ways of thinking may be counter-intuitive or conflict with commonly held beliefs (Casti, 1994). For example, *order* is regarded from a complex systems perspective as a dynamic and emergent characteristic of self-organizing complex systems (e.g., a "flock" of flying birds), a view which challenges a common belief that order can only occur through centralized control imposed from within or outside a system (Feltovich, Spiro, & Coulson, 1989; Resnick, 1994). Also, learning ideas concerning *randomness* or *stochastic processes* are often difficult for students, possibly because these ideas conflict with teleological beliefs that ascribe purposefulness to events in the world. Resnick has proposed that there is a "centralized bias" which is a mindset that favors explanations assuming central control and single causality (Resnick, 1994; Resnick, 1996). Further, another centrally important process of complex systems--evolution by natural selection--has proven extremely difficult for learners to understand, even high ability students at high school and university levels (Bishop & Anderson, 1990; Brumby, 1984; Greene, 1990; Jacobson & Archodidou, 2000; Settlage, 1994).

Complex Systems Problem Solving Research

A consistent recommendation in recent socio-cognitive learning theory and research is to involve students, either individually or in groups, in actively working on challenging problems. If knowledge about complex systems does pose a special learning challenge for students, it seems likely that students would experience difficulties when given problem solving tasks involving complex systems phenomena. To date, there have been few qualitative or observational reports on students solving problems dealing with complex systems (e.g., Resnick, 1996; Resnick & Wilensky, 1998; Wilensky, 1996). Further, there has been no reported research that has examined complex systems problem solving in a manner intended to identify differences between experts (i.e., complex systems scientists) and novices (e.g., university students). A study was conducted to investigate expert and novice differences related to complex systems problem solving. This research examined problem-solving responses given by individuals who were professionally active in the field of complex systems (i.e., experts) and undergraduate college students (i.e., complex systems novices). The main experimental hypotheses were that there would be different complex systems problem solving profiles between the experts and the novices. The experts were hypothesized to solve the problems with not only more complex systems concepts (e.g., self-organization, emergence, evolution and selection), but also with statements reflecting epistemological and ontological beliefs about the world that were non-reductive, viewed control as being decentralized, described causality in terms of the interaction of multiple variables, described system changes as being non-teleological, nonlinear, or stochastic. (See Figure 1.) In contrast, the university students were hypothesized to use fewer complex systems concepts in their problem solutions and to use statements that reflected beliefs that were reductive, viewed control from a central source, described causality as being linear and related to a single source, and described the changes in a system as being deterministic, purposeful, or teleological.[1]

Method

The subjects for this study were from two different groups who were assumed to have relatively low and high levels of expertise related to complexity and complex systems. The novice subjects were seven undergraduate university students at a public research university who were paid for their participation. These students were working on degrees in the social sciences or humanities (e.g., English, education, pre-law); none were majoring in science or mathematics. The subjects met individually with the experimenter and an assistant for a single session of approximately two hours. The expert subjects consisted of a national and international group of scientists and advanced graduate students who responded to a request for participation posting to an electronic discussion list moderated by a non-profit educational and research organization in Boston, the *New England Complex Systems Institute* (NECSI). Nine subjects with academic or research credentials that suggested professional competence in the area of complex systems were selected to participate in the study.

There were two slightly different versions of the instruments administered to the two groups. Both instruments requested general background and demographic information (e.g., major area, gender), and included nine identical problem questions dealing with complex systems, such as: How do ants find and collect their food? How would you design a city so that there will be goods and services but minimal shortages or surpluses? How did cheetahs evolve to run so fast? Is it possible for a butterfly in Brazil to cause a snowstorm in Alaska? How do traffic jams form? These problems were based on issues or examples described in books or papers dealing with complex and dynamic systems (Bar-Yam, 1997; Casti, 1994; Gell-Mann, 1994; Holland, 1995; Kauffman, 1995; Resnick, 1994), and from prior research on evolution problem solving (Jacobson & Archodidou, 2000). These problems were written such that they could be answered in a qualitative manner appropriate for both complex systems experts and for individuals who had not received formal or informal (i.e., self-educated) training in areas dealing with complex and dynamical systems.

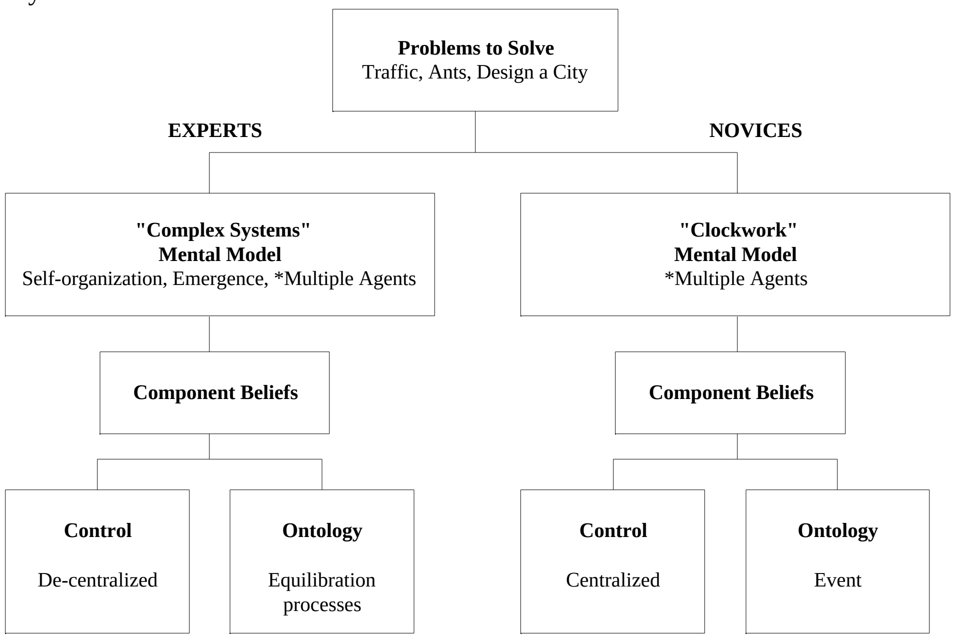

Figure 1. Diagram of hypothesized knowledge structure differences related to expert and novice complex systems problem solving. The “*” next to “multiple agents” highlights that some component beliefs might be used in either mental model.

For the novice subjects, a cognitive verbal protocol methodology was used in which the subjects were read the questions and then verbally reported all ideas they had as they solved the problems (Chi, 1997; Ericsson & Simon, 1993). Also, an experiment monitor asked clarifying or probing questions to better understand the subjects’ responses. All responses were audio taped and transcribed. The expert group was sent the written version of the instrument by electronic mail. The written responses were read and questions were asked via e-mail of several individuals in the expert group in order to clarify or better understand specific responses.

The data analysis for this study focused on the epistemological and ontological “component beliefs”[2] and the models constructed by the experts and students when solving complex systems problems. In order to analyze the responses, a *complex systems mental models framework* (CSMM) was developed to code the problem solving responses. The CSMM was based on previous research conducted in the domain of evolutionary biology (Jacobson & Archodidou, 2000), and on the Vosniadou and Brewer mental model analysis methodology originally used in the domain of astronomy (Vosniadou & Brewer, 1992; Vosniadou & Brewer, 1994). The CSMM framework consists of eight component beliefs that are hypothesized to be associated with complex systems concepts (see Table 1). These component beliefs were derived from an analysis of papers and books by various researchers working in the area of complex systems (Casti, 1994; Casti, 1994; Dennett, 1995; Gell-Mann, 1994; Holland, 1995; Kauffman, 1993; Kauffman, 1995; Mitchell, 1996; Pagels, 1988; Prigogine & Stengers, 1984; Resnick, 1994; Waldrop, 1992). For example, Resnick has proposed many people have a bias favoring centralized over decentralized explanations, and Casti has suggested there are common “intuitions” held by people such as “small effects cause small actions.” It is important to note that many of these component beliefs are accurate for certain classes of phenomena (e.g., "small effects cause small actions is appropriate for linear phenomena such as Newtonian mechanics), but may be inappropriate with respect to complex, dynamical systems such as the weather (e.g., small actions have large effects).

The problem solutions in this study were coded on the component beliefs level (i.e., see Table 1). The higher order models were initially determined from the composition of the component beliefs used based on the theory of complex systems problem solving (i.e., Clockwork, Complex Systems) (Jacobson, 1999). In the present study, only the component beliefs were coded, and statistical tests were conducted for correlations with hypothesized high order models (see Results). It was hypothesized that complex systems novices would tend to answer the questions with statements similar to or consistent with component beliefs in the Clockwork Set column of Table 1, while experts would tend to employ statements consistent with the component beliefs in the Complex Systems Set column of Table 1. A second level of coding examined the responses for the use of concepts associated with complex systems theory and research, such as *emergence, self-organization, or multiple agents*. It was expected that complex systems experts would use more complex systems concepts than the novices, even though the novices would have been exposed to several of those concepts as part of general high school and college level science courses (e.g., evolution and selection, homeostasis). One trained rater coded all of the responses, and a second rater coded a subset of the responses (approximately 15%), with the few differences discussed until a consensus was achieved.

Table 1. Complex Systems Mental Models Framework.

Categories of Component Beliefs	**Types of Component Beliefs**	
	Clockwork Set	**Complex Systems Set**
1. Understanding phenomena	*Reductive (e.g., step-wise sequences, isolated parts)*	*Non-reductive: whole-is-greater-than-the-parts*
2. Control	*Centralized (within system)* *External agent (external to system)*	*De-centralized (system interactions)*
3. Causes	*Single*	*Multiple*
4. Actions effects	Small actions --> small effects	Small action --> big effect
5. Agent actions	*Completely predictable*	*Not completely predictable / stochastic / random*
6. Complex actions	From complex rules	From simple rules
7. Final causes or purposefulness of natural phenomena	Teleological	Non-teleological or stochastic
8. Ontology	*Static structures* *Events*	*Equilibration processes*

Results

The problem solving score means, standard deviations, and F-tests are shown in Table 2. The reliability of Clockwork and Complex Systems scales in terms of their respective component beliefs was evaluated with the Cronbach alpha test. The eight Clockwork component beliefs were found to have a moderately high alpha = .72 and the reliability for the Complex Systems component beliefs scale was .76. Next, the correlation matrix and the inter-item statistics for each of the scales were examined to determine if certain component belief variables had low correlations with the overall scale. For the scale of Clockwork component beliefs, five items were found to have low Item – Total Correlations values ($r < .4$): *single causes, event ontology, complex rules explain complex phenomena, teleology*. These component belief variables were removed, leaving a revised Clockwork scale of *reductive, centralized, small actions – small effects, and predictable* as the items with the highest Item – Total Correlations (.45 - .87), and yielding a reasonably high reliability alpha of .81. Inspection of the Complex Systems correlation matrix and Item – Total Correlations for the eight variables lead to removing the items *small actions lead to big effects*, *simple rules explain complex phenomena,* and *non-teleology*. The revised Complex Systems Component Beliefs scale consisted of *non-reductive*, *de-centralized*, *multiple causes*, *randomness*, and *equilibration processes.* These variables had Item – Total Correlations between .55 and .79, and an overall reliability of .85. As expected, there was a negative and significant correlation between the revised Clockwork and Complex Systems component belief scales ($r = -.57$, $p = .02$). Significant negative correlations were also found between the two component beliefs scales and Complex Systems Concepts: Clockwork Component Beliefs and Complex Systems Concepts, $r = -.64$, $p = .008$; Complex Systems Component Beliefs and Complex Systems concepts, $r = .94$, $p = .000$.

Significant differences ($p < .05$) were found between the two groups in terms of the individual component beliefs *understanding phenomena: reductive, control: centralized, control: de-centralized,* and *complex systems* *concepts*. Significant differences between the two groups were also found for the revised Clockwork and Complex systems component beliefs scales. A near significant difference (p = .09) was found for the *Agent Actions: Random* component belief. However, given the relatively small sample size for this exploratory study, the cell sizes for some of the variables were too small to allow for calculation of certain ANOVAs (e.g., none of the experts were found to solve a problem with the *Small actions – small effects* component belief).

Table 2. Means, SD, and ANOVA for main variables.

Dependent Measures	**Novices**	**Experts**	**F**	**Sig.**
Understanding phenomena: Reductive	3.14 (1.35)	0.89 (1.27)	11.79	.004
Understanding phenomena: Non-reductive	1.14 (1.07)	2.22 (1.48)	2.63	.127
Control: Centralized	1.57 (0.98)	0.55 (0.53)	7.17	.018
Control: De-centralized	1.86 (0.90)	4 .00 (1.00)	19.69	.001
Causes: Single	0.71 (1.11)	0.78 (.67)	.02	.889
Causes: Multiple	3.86 (1.35)	4.67 (1.80)	.98	.339
Small actions – small effects	1.00 (0.00)	0.22 (.44)	N/A	N/A
Small actions – large effects	0.14 (0.38)	0.44 (0.53)	N/A	N/A
Agent actions: Predictable	1.57 (0.98)	1.33 (1.66)	.113	.712
Agent Actions: Random	1.00 (1.53)	2.56 (1.81)	3.316	.090
Complex actions: From complex rules	.14 (.38)	0.0 (0.0)	N/A	N/A
Complex actions: From simple rules	.29 (.76)	.11 (.33)	.39	.543
Final causes: Teleological or purposeful	.14 (.38)	0.0 (0.0)	N/A	N/A
Final causes: Non-teleological	.43 (1.13)	0.0 (0.0)	N/A	N/A
Ontology: Static structures	0.14 (.38)	0.0 (0.0)	N/A	N/A
Ontology: Equilibration Process	0.0 (0.0)	2.11 (1.90)	N/A	N/A
Clockwork Component Beliefs Subscale	8.42 (3.26)	3.78 (3.99)	6.23	.026
Complex Systems Component Beliefs Subscale	6.86 (2.85)	13.0 (5.10)	14.15	.002
Complex Systems Concepts	8.87 (3.45)	17.33 (5.22)	5.10	.040

Discussion

It is important to note that this was an exploratory study into the differences in solving problems about complex systems phenomena that might exist between novices and experts. Consequently, the results reported here are provisional and future research is needed with a greater number of subjects and a wider range of age and grade levels. Also, although the overall number of subjects was small (N = 16), the total number of problem solving responses (16 x 8 = 128) represents a sufficiently large pool of items from which to establish the internal validity of the instrument used to assess the component beliefs and models of the subjects. The findings of this study suggest that there was in fact a differential conceptual structure to the responses constructed by the university students and the complex systems experts to solve problems dealing with complex and dynamical systems. The experts used technical complex systems concepts that the students rarely used. This finding was expected, as the scientists who participated in this study should have had a much greater background knowledge in this area based on their advanced graduate training and research experiences where they learned complex systems concepts and methodologies. In contrast, there would typically be little opportunity for undergraduate students to learn complex systems concepts such as self-organization, emergence, and so on as these perspectives are not currently part of K – 16 curricula. However, concepts such as evolutionary selection or homeostasis *are* part of the college and precollege curricula, yet there was little evidence of these concepts in the student problem solving protocols. This finding is consistent with a considerable body of research that has documented the "inert knowledge" problem and the difficulties students have with transferring their acquired knowledge to new problems and new situations (Bereiter & Scardamalia, 1985; Cognition and Technology Group at Vanderbilt, 1997; Feltovich, Coulson, Spiro, & Dawson-Saunders, 1992; Gick & Holyoak, 1983; Gick & Holyoak, 1987; Lave, 1988; Perkins, 1992; Salomon & Globerson, 1987; Voss, 1987; Whitehead, 1929).

Another research hypothesis was that there would be a significant difference in the component beliefs used by the undergraduate students who were complex systems novices and the complex systems experts. As expected, the undergraduate novices had a higher mean score on Clockwork Component Beliefs scale while the experts had a higher mean score on the Complex Systems Component Beliefs scale. These differences were in the expected directions, and analysis of variance indicated these were significant differences. The third hypothesis, which was also confirmed, was that there would be a significant positive correlation between the higher order complex systems concepts and the Complex Systems Component Beliefs scale (r = .94) and a negative correlation with the Clockwork Component Beliefs scale (r = -.64). In particular, the correlation between the Complex Systems Component Beliefs and the Complex Systems Concepts was quite high, and the significant negative correlation between the Clockwork Component Beliefs and Complex Systems Concepts was in the anticipated direction. Taken together, these findings suggest there was a consistent pattern to the component beliefs used by the university novices and experts when solving problems involving complex systems, but the component beliefs and the higher order mental models used by these two groups were significantly different.

Implications

Although this study focused on the characteristics of complex systems problem solving, there are potentially important implications for teaching and learning as well. We are beginning to see interest in infusing concepts related to complex and dynamical systems into K – 16 curricula. However, the results of this study, and the theory and related research that have informed it, suggest that students (and many adults) may have difficulty learning about complex systems if the focus is only on the conceptual level. From the perspective of recent socio-cognitive theory and research on conceptual change (Chi, 1992; Chi, Slotta, & de Leeuw, 1994; Ferrari & Chi, 1998; Slotta & Chi, 1996; Vosniadou & Brewer, 1992; Vosniadou & Brewer, 1994), an individual's particular epistemological and ontological component beliefs may support or constrain the construction of higher order mental models that are characteristic of individuals who are competent and experienced in a domain. It follows that that the learner must have a *conceptual ecology* or a *cognitive complex system* that consists of an appropriate set of epistemological and ontological component beliefs from which to construct the higher order mental models associated with expertise in a domain. Lacking such conceptual primitives would make it difficult for the learner to construct new mental models that are qualitatively similar to expert models. This study suggests that the conceptual ecology employed by the university novices and by the complex systems experts were quite different. As such, a critical educational challenge for helping students learn about complex systems will be to *enrich* (not necessarily replace) the conceptual ecology that learners have available to use when dealing with problems and constructive learning activities involving complex systems.[3] Further research is needed to explore this hypothesis.

Finally, a more general issue relates to *why* it might be valuable to learn knowledge about complex systems. An underlying assumption of this program of research has been a vision of the importance of complex systems concepts and approaches as a means to help foster what might become a new and principled type of scientific literacy that would help students and adults to understand and to use emerging scientific knowledge to address issues and problems. The cross-disciplinary concepts and new ways of doing science related to complexity and complex systems provide an opportunity to present important dimensions of the increasing quantity of scientific knowledge in an interconnected and coherent manner that is grounded in the natural and social sciences and cognitive manageable. The applicability of complex systems concepts such as self-organization and selection, and methodologies such as multi-agent modeling, to a wide range of natural and social phenomena offers a rich palette for educators to both reach students and to help them learn important scientific knowledge and skills.

In conclusion, this paper has reported on a study of problem solving differences between scientific experts in the field of complex systems and novice undergraduate students. Significant differences were found both at the conceptual level and at the level of basic epistemological and ontological presuppositions and beliefs. It was suggested that helping students understand and use complex systems knowledge will require attention to issues of conceptual change and to helping students construct a richer conceptual ecology which embraces both non-reductive and decentralized thinking, multiple causality, non-linearity, randomness, and so on. It is hoped that this research might contribute to efforts that are exploring ways for students to acquire a powerful conceptual toolkit based on emerging scientific and social science research that is robust with respect to analyzing a wide range of problems from physics and biology to economics and political science. The challenges of the 21st century will certainly require a citizenry with such skills.

Endnotes

(1) Further a more complete discussion of the theoretical rational for these hypotheses, see Jacobson (1999).

(2) The phrase "component beliefs" is used to refer collectively to epistemological and ontological beliefs in order to highlight the function of these beliefs as components of higher order mental models a learner constructs in problem-solving contexts.

(3) There are additional implications of this study that relate to conceptual change and to the nature of knowledge transfer demonstrated by the experts and how these findings might be used to inform the design of learning materials and activities intended to help students learn complex systems knowledge. For a discussion, see Jacobson (1999).

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