An Ontological Approach to Conceptual Change: The role that complex systems thinking may play in providing the explanatory framework needed for studying contemporary sciences

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ABSTRACT

An Ontological Approach to Conceptual Change:
The role that complex systems thinking may play in providing the explanatory framework needed for studying contemporary sciences

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The inability to acquire a good understanding of certain scientific concepts, apparently because other concepts have become firmly habituated, has plagued many novice and seasoned science students. Chi, Slotta, and deLeeuw (1994), Strike and Posner, (1992), and Vosniadou (1994) categorize this problem of robust misconceptions as stemming from fundamental beliefs or "theories" held about the properties of the concept. One approach to overcoming such limiting habits may involve the reassignment of concepts from the clockwork explanation of causality (often held by novice learners) to a scientifically correct emergent causal explanation (Chi et al, 1994; Chi & Roscoe, 2002). Another approach to learning these less familiar causal processes has explored computer generated multi-agent representations and programming using StarLogoT (e.g., Resnick, 1994; Wilensky, 1999; 2001). However, the literature on complex systems thinking reveals that students have great difficulties acquiring an understanding of "emergent causal processes" (e.g., Duit, 1998; Jacobson, 2000; Penner, 2000).

Based on these identified concerns, this dissertation comprises a two-part longitudinal inquiry of complex systems thinking as a means of facilitating conceptual change. Study 1 employed a "posttest only control group" random assignment experimental design. Changes in ontological frameworks were assessed using an ontological coding taxonomy (OMMT) adopted from two sources (Ferrari & Chi, 1998; and, Jacobson, 2000) and refined for this study. The hypothesis was that first year Cegep science students receiving a complex systems intervention using StarLogoT would employ more emergent causal explanations and fewer clockwork explanations as a general explanatory framework for problem solving. By contrast, students in the control group would not. The 25 students in the experimental group generated significantly more emergent framework explanations on both near and moderate far transfer questions than

did the 20 students in the control group. Furthermore, they generated significantly fewer clockwork framework explanations on near transfer questions but not on moderate or far transfer questions than did the control students.

Study 2 was a mixed method qualitative case study of nine students selected from the participants in Study 1 using a purposeful sampling procedure. Students' acquisition of an emergent causal framework was assessed using an ontological measure referred to as the Complex Systems Taxonomy (CST) adopted from Jacobson (2000) and refined for this research. The two central research questions were the following:

- What aspects of students' ontological and epistemological beliefs facilitated or constrained their acquisition of an emergent causal framework?
- What experiences with StarLogoT facilitated or constrained this learning process?

The findings were as follows: (1) Although students experienced gains in four of the six component features of emergent causal processes, their difficulty with the concepts of "random actions" of agents and "nonlinear effects" of agents constrained their deeper understanding of emergent causal processes. (2) Although StarLogoT facilitated the acquisition of certain aspects of this knowledge, it provided no affordance for learning the concept of "nonlinearity". Furthermore, aspects of these multi-agents representations generated conflicting ontological explanations for the concept of "randomness". (3) Although the selected StarLogoT simulations demonstrated emergent causal processes, they represented different types of complex systems (i.e., tightly coupled and dissipative loosely coupled). Although most students had difficulty with the representations of dissipative systems, those who had a more advanced understanding of science concepts gained an understanding of emergent causal processes from dissipative representations. (4) Conceptual change required metacognitive scaffolding and ongoing metaconceptual prompts during the instructional phase. However, once students acquired synthetic mental models, maturation over time and experience with complementary domain curricula was sufficient for them to elaborate their understanding of emergent causal processes.

Dedication

To my husband (Lorne Woods), children (Leslie and Lindsay),
and mother (Celestine Josefita Charles).
Thanks for giving me the encouragement to grow,
and always believing that it was possible.

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It is said that the longest journey begins with a single step. What is not mentioned is that along the way one encounters many individuals: some provide important guidance at the signposts; others extend a helping hand in a "just in time" manner; and then there are those who enable you to complete the journey by walking by your side as a fellow traveler. As I look back now from the other side of this metaphorical journey, I wish to thank all the individuals who played a part in helping me complete this study with such quality.

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CHAPTER 1
INTRODUCTION

One of the current trends in science education is to look at the generalities that are present across disciplines. When scientific theories are investigated at the philosophical level it is possible to abstract a general conceptual framework from the specifics that differentiate them (Auyang, 1998). These general concepts may also be referred to as explanatory frameworks (the components as characteristics of ontological categories, Chi, Slotta, & deLeeuw, 1994). We use these general concepts such as thing, event, process, causality, relation, part and whole, space and time, to interpret and explain the world. These general concepts allow us to share ideas and build theories. Auyang states:

> The categorical framework is general and not biased toward any theory. It abstracts from scientific theories, which in turn abstract from the specifics of wide ranges of phenomena. The shared categorical framework of different theories reveals both the general way of our thinking and a general commonality among the topics of the theories thus our consideration must include the phenomena the sciences try to understand. (p. 9)

But what happens when we do not share similar explanations for a major class of phenomena? Or worst yet, we do not even "see" similar categorical frameworks extending across various phenomena? It is theorized that this is precisely why many science concepts are difficult for the novice to grasp. In science, many underlying structural and process attributes are not consistent with the surface features of the phenomena. Novice learners tend to build explanations (mental models) based on surface features and their intuitive, naïve interpretations therefore lead to incorrect conclusions and misconceptions (Glynn & Duit, 1995; Chi, Feltovich, & Glaser, 1981; Chi, Slotta, & deLeeuw, 1994; Vosniadou, 1994).

If this is the case, what if we were to take a different approach: identify common underlying structural and process attributes and teach these instead? Would that facilitate deeper level understanding? These are the fundamental questions of this present study. I will argue that teaching students (novice learners) certain principles of complex systems thinking was possible and that these students were then able to change certain aspects of the explanatory frameworks they used in both near to the model and far from the model problem-solving tasks. I will also argue that the behaviors of complex systems, as demonstrated in the multi-agent modeling language, StarLogoT, are consistent with identified dimensions of the category of "emergence" type ontological beliefs (referred to as "component beliefs" in Jacobson, 2000) and therefore offer affordances for learning about underlying emergent causal processes.

Before continuing let me first define a few important terms. To begin, the term "emergent processes" or "emergence" is used primarily to describe the behavior that arises from a collective (meta-agent) composed of a large number of smaller parts (the agents) that do not themselves exhibit behavior at all like that of the whole. Emergence is also described as the ability to generate complex behavior (complexity) from a small set of laws or rules. To illustrate this description, patterns generated by birds flocking, ant trails, the "human wave', are all examples of emergent processes. Another less visual example of emergence is a board game. Although there are many built-in constraints imposed by the rules, the outcomes are too numerous to describe (Holland, 1998). Thus emergence, as defined in this study, is a phenomenon which relies on the interactions of multiple agents, all operating under the same constraints (rules) without centralized control, yet affected by probabilistic causes and feedback loops that generate nonlinear effects creating dynamic self-organizing systems behaviors.

Many but not all complex systems exhibit emergent behaviors. It should be noted that in this study I was primarily interested in complex systems thinking that relates to the understanding of emergent causal processes. Therefore, only references to emergent causal behaviors were identified and analyzed from the students' interactions with the StarLogoT models.

The definition of the term ontological category used here is that it is a personally held "theory" or "belief" associated with what the world is and what it contains (Flood & Carson, 1993). It can be said that it is "our way of explaining the world"; hence it contains basic axioms, and a set of causal predicates that can be judged as true or false (Keil, 1979).

In this study, I will use the term "emergent causal framework" ontology to refer to the ontological category that offers an explanation for the behaviors of the particular types of phenomena that exhibit the behaviors described above (i.e., aggregating, decentralized control, nonlinear effects, random actions, probabilistic causes, and dynamic self-organizing nature). Although there may be other less liberal definitions of the emergent causal ontological category (see Perkins & Grotzer, 2000), I will argue that this more inclusive definition allows us to bring greater consistency between conceptual change research (Chi 2000b) and the expanding literature of complexity research (e.g., Holland, 1995; 1998; Jacobson, 2000; Wilensky 1999). Later in this dissertation I will discuss at length the development of the ontological category related to emergent causal explanations and the mental representations that I assert are evidence of these internally held explanatory frameworks.

A final point of clarification: the term "emergent processes" or "emergence" should not be confused with everyday usage or with the usage in qualitative data analyses where categories and themes "emerge" from the data. Because qualitative techniques are employed in this study, this latter use of the term will also arise. I will attempt to keep the context visible so that the intended distinction in meaning will be apparent to the reader.

1.1 The Problem

The literature of schema-based learning theories describes three types of learning: accretion, tuning and cognitive restructuring (Rumelhart & Norman, 1976). Research conducted in the area of cognitive restructuring generally is assembled under the heading of conceptual change. Growing interest in this field led to the identification of difficulties in learning key science topics such as electricity in physics (Chi, Feltovich, & Glaser, 1981; White, 1993), gas laws and equilibrium in chemistry (Wilson, 1998), and in the biological sciences such concepts as diffusion, osmosis (Odom, 1995; Settlage, 1994), and evolution (Anderson & Bishop 1986; Brumby, 1984; Jacobson & Archodidou, 2000).

It is very difficult to achieve cognitive restructuring. Thus far, research has shown that the presentation of anomalous data – information that contradicts the pre-instructional beliefs and theories — is generally met with resistance from the learner and seldom leads to conceptual change (Chinn & Brewer, 1993; Chinn & Brewer, 1998). There are several researchers who have followed this route and achieved differential levels of success (Tao & Gunstone, 1999; Chan, Burtis & Bereiter, 1997; Windschitl & Andre, 1998). They have combined constructivist instructional strategies, such as collaborative learning, computer-based instruction, knowledge building activities, metacognitive prompts, multiple analogies, in order to facilitate the acceptance of the anomalous data. However, these studies have not attempted to build a theory of conceptual change. Further, they have not addressed the underlying cause of the misconceptions. Chinn and Brewer (1993) propose that the crux of the problem is the learner's efforts to coordinate theory and data. These authors offer four characteristics that may account for the different responses to anomalous data. They are as follows:

- Entrenchment of prior theory
- Ontological beliefs
- Epistemological commitments
- Background knowledge

Chinn and Brewer (1993) also tell us that in the case of robust misconceptions, these four characteristics may not play an equal role. It may be that intuitive "naïve" beliefs about the nature of existence and the fundamental categories and properties of the world (ontological beliefs), and beliefs about knowledge and how it is acquired (epistemological beliefs), are deeply intertwined with who we are, as well as how and what we can learn. If we accept their argument, then these beliefs are likely associated with hopes and fears and therefore are rigorously defended and very resistant to change.

Conceptual change models fall into two primary groups, the more conventional view known as an accommodation model, posited by Piaget, and elaborated on by Strike and Posner (1985, 1992) who consider the conceptual ecology of the learner but assert that, through reason, the more fruitful explanation will be adopted. The other camp takes a more structural approach, positing that it is the very nature of the explanation, the underlying beliefs of causation that need to be addressed. Within these models are: (1) Vosniadou's "framework theories" (e.g., Vosniadou & Brewer, 1994), (2) diSessa's "causal net" (diSessa & Sherin, 1998), and (3) Chi's "ontological beliefs" (Chi et al. 1994). Although these researchers disagree on several fundamental points related to how coherent or fragmented these naïve "theories" or beliefs are, they agree that these beliefs need to be altered in order to repair and/or remove misconceptions.

I argue that the problem of robust misconceptions is an important problem to be solved. I further argue that a general theory of conceptual change is required. In order to move the debate forward, it is necessary to empirically as well as theoretically explore the assertions of these models. This present study addresses this need.

1.2 Theoretical Foundation

This study took as its starting point the conceptual change theory proposed by Chi and her colleagues (Chi, 1993; Chi & Slotta, 1996; Chi et al., 1994; Ferrari & Chi, 1998; Slotta & Chi, 1996, 1999; Slotta, Chi & Joram, 1995). The basic assumption of their theory is that all conceptions are classified into ontological categories — ordered hierarchical trees of super-ordinate and subordinate systems — based on attributes that are perceived or suggested to the learner. These schema-like associations act as facilitators or inhibitors of future transfer of knowledge and are part of general accretion and tuning.

Chi's theory is intended to explain concepts that, in the case of science education, fall within the ontological category of "processes". Within this category there are "event-type" processes and "emergent-type" processes. It is hypothesized that most of the misconceptions occur when concepts (e.g., electricity, osmosis, diffusion, equilibrium, evolution), which scientifically speaking, belong to the emergent process ontology, are assigned to other ontological categories (e.g., heat, electricity to the category of "material substances"; or evolution and diffusion to the category of "events"). Thus it is hypothesized that novices, unlike experts, assign concepts to ontological categories that are unable to support explanations of the phenomena, thereby acquiring robust misconceptions and flawed knowledge acquisition. Slotta and Chi (1999) state, "once an ontological commitment is made with respect to a concept, it is difficult for this to be undone" (p.8). The basic assumptions of Chi's conceptual change theory may thus be summarized as follows:

1. Concepts acquire membership in ontological categories through common language (predicates).
2. Concepts are assigned to an ontological tree in a hierarchical structure — therefore the structure of knowledge in categories is hierarchical.
3. The teaching of a new ontological category is possible.
4. The reassignment of an entity to another ontological category is necessary and possible for conceptual change and understanding.
5. Ontological attributes are distinct for members of each ontological tree. There are differences in the attributes of entities that belong to different trees.
6. Novices, more often than not, place entities into ontological categories based on surface level features.
7. Several concepts display contradictions between their surface features and their deep level features. On the surface, the attributes of these concepts resemble one type of ontological category while their veridical attributes belong to another ontological category. Chi et al. (1994) suggest that many scientific concepts require conceptual change across trees and that is why they are difficult to learn.

The actual mechanisms of assignment to ontological categories are a very important part of the discussion and understanding of Chi's conceptual change theory. It is postulated that explanatory frameworks are used to organize and express the ontological commitments present in the learner's cognitive structure (Slotta & Chi, 1999). These authors argue that explanatory frameworks are the key to operationalizing the capture of ontological commitments. Therefore it will be by identifying the ontological boundaries between two explanatory frameworks that the assessment of conceptual change will be made. Reassignment of concepts from one ontological category to another is taken to entail learning a new explanatory framework. This may require learning new terminology, acquiring new mental models through expository and discovery learning, and may even demand new attitudes and values (e.g., epistemological beliefs, control beliefs, emotional loadings, and changed motivation).

1.2.1 Complex Systems as a Way of Thinking

Mitchel Resnick, Uri Wilensky, and Walter Stroup have championed research pertaining to the use of complex systems as a better way of thinking about science. These authors have used the computer environment and the power of multi-agent modeling language (MAML) programming to create simulations that demonstrate characteristics of complex systems that challenge naïve ontological beliefs about centralized versus decentralized control, randomness versus determinacy, order versus chaos. "In the minds of many, the study of complexity is not just a new science, but a new way of thinking about all science, a fundamental shift from the paradigms that have dominated scientific thinking for the past 300 years" (Resnick & Wilensky, 1997, p. 4). Initial studies conducted by Resnick (1994) and Wilensky (1995) tell us that the use of particular types of simulations can afford understanding of specific aspects of complexity – knowledge of the process of emergence and the subsequent development of non-isomorphic levels of organization. They have demonstrated that the use of Starlogo simulations is a powerful means of destabilizing simplistic entrenched conceptions and of facilitating multi-level thinking. Their work has focused mainly on young learners and there have been few other empirical studies to date.

Jacobson's (2000) most recent work has further explored the relationship between complex systems concepts and conceptual beliefs. He has demonstrated that novice learners', when solving specific types of problems, use "component beliefs" (ontological and epistemological) that are correlated with what he calls "clockwork" theories which are reductive and influenced by a Newtonian view of science. On the other hand, experts, in solving the same problems, used component beliefs that were correlated with "emergent" theories, equated to complex systems concepts. Results from Jacobson's study were obtained from a small sample and are non-parametric provisional findings; however, they indicate a significant qualitative difference between expert and novice thinking when solving emergent framework questions. Hence, this dissertation study aspires to contribute to the body of literature that contends there is a relationship between component beliefs and conceptual change, and complex systems thinking.

In addition, there is a body of literature that argues for the use of elements of complexity theory in the classroom. Boyd (1999) suggests that it is possible to introduce elements of "cybersystemics" into the regular curriculum. Others such as Auyang (1997), Bar-Yam (1997), Kaput, Bar-Yam, and Jacobson (1999) contend that complex systems may function as a unifying and cross-disciplinary theme. In fact, at the most recent New England Complex Systems Institute annual conference, Jacobson, Jakobsson, Lemke, and Wilensky (2002) challenged the science education community to explore the potential of using complex systems ideas in the classroom. They stated: "the conceptual basis of complex systems ideas reflects a change in perspective about our world that is important for students to develop, as it corresponds to the scientific environment that will exist when they graduate. This perspective emphasizes both the limits of predictability as well as the possibility of understanding indirect consequences of actions taken, both positive and negative, through modeling the independence of our world" (p.2).

1.3 Purpose and Significance of the Study

There were two primary objectives of this research, first to investigate several assertions made in Chi's conceptual change model. Specifically, I intended to explore three of the seven assumptions put forward in the model described above (see assertions three, four, and five). In essence, the research question was: Does Chi's theory of conceptual change hold merit and therefore is it worth pursuing? At present, only one empirical study has tested this theory in a limited study on the concept of electrical circuits (Slotta & Chi, 1999). Their results were very promising, however, many questions still remained unanswered. The significance of this current study's exploration was the extension of Chi's theory of conceptual change.

The second purpose was to explore the question raised by Jacobson (2000) concerning the development of a cognitive theory of complex systems and how complex systems thinking can be used to acquire other cognitive skills. Specifically, does a certain kind of complex systems instruction provide sufficient knowledge of an emergent causal explanatory framework to enable students to transfer these explanations to unfamiliar but ontologically analogous problems (i.e., conceptual change)? The significance of the second aspect of my exploration was the extension of Jacobson's complex systems mental models taxonomy. This adaptation and refinement led to the development of an ontological mental model taxonomy (OMMT) that reflects both Jacobson's and Chi's perspectives on the ontological categories and subcategories.

1.4 Summary of Introduction

In summary, many science misconceptions tend to be robust and difficult to remove or repair. There are several theoretical models that posit explanations and related prescriptions for conceptual change. The model developed by Chi and her colleagues is most promising but needs to be further tested. Chi's theory postulates that learning of the ontological category of "emergent" processes will permit the re-assignment of concepts from the wrong category to better ones. At the same time, developments in computer programming languages, specifically multi-agent modeling languages (e.g., StarLogo) allow for the simulation of systems that exhibit emergent behaviors (i.e., complex systems). These two lines of research are drawn together by Jacobson's proposition that explicit instruction of complex systems thinking may provide knowledge of emergent causal processes and therefore build mental models that reflect the analogous component beliefs (ontological and epistemological beliefs).

In chapter two, I will summarize the literature in more detail. Chapter three will describe the theoretical and practical issues related to the development and use of the coding instruments that play a major role in this study: (1) the Ontological Mental Models Taxonomy (OMMT); and (2) the Complex Systems Taxonomy (CST). Chapter four explains the methodology for Study1. Research results for that first phase will be presented in chapter five. Chapter six describes the methodology for Study 2, a mixed method case study design. Chapter seven is divided into nine large sections and displays the analysis of the different types of data collected from the different activities and measures designed to generate qualitative data. In chapter eight I will discuss the three main findings of my research.

CHAPTER 2

LITERATURE REVIEW

> Concepts are construed as intrinsically relational sorts of things. They are not isolated entities connected only in the service of propositions. No individual concept can be understood without some understanding of how it relates to other concepts. Concepts are not mere probabilistic distributions of features or properties, or passive reflections of feature frequencies and correlations in the world; nor are they simple lists of necessary and sufficient features. They are mostly about things in the world, however, and bear nonarbitrary relations to features frequencies and correlations, as well as providing explanations of those frequencies and correlations. If it is the nature of concepts to provide such explanations, they can be considered to embody systematic sets of beliefs – beliefs that may be largely causal in nature. (Keil, 1989, p.1).

Our ability to evaluate the relative merit of different theoretical positions on conceptual change requires that we gain an awareness of what is known about concepts and concept formation. I contend that any principled study of conceptual change requires some background knowledge of this body of literature.

What are 'natural' concepts, how are they structured, what is the process involved in their acquisition (formation), how do they function, how are they changed, can we truly share them with others? These questions, and others like them, are the subject of countless volumes. Spanning the decades, philosophers such as Plato, Locke, Kant, Frege, Carnap, Wittgenstein, Kuhn, Quine, and Fodor to name but a few, have discussed the concept of concepts. In the latter half of the twentieth century, the disciplines of cognitive science, linguistics, and psychology have contributed extensively to the empirical exploration of these topics, positing theories and explanatory models in the hope of answering some of these important questions. Although a comprehensive discussion of this topic is outside the scope of the current study, I will provide a simple sketch of the key features of the three classes of theories of concepts (see Table 2.1) that relate to varying degrees to the literature on learners' conceptual change and therefore are relevant to this current study.

Table 2.1 Comparison of concept formation theories.

Main Theories	Specific models	Key Authors	Structure of concepts	Definitions of concepts	Criticisms
Classical Theory *Intended to explain formal logic, mathematics and physics concepts.*		Plato*; Rudolf Carnap; Kant; Russell * intended as prescriptive model except for Plato	Formally defined	<u>Prescriptive models.</u> Concepts are structured mental representations that encode a set of necessary and sufficient conditions for inclusion. Supports physics and mathematical reasoning.	Problems (when used to represent ordinary reasoning): - cannot account for typicality effect. (Rosch, 1973) - empiricist strictures (not every concept can be broken down to sensory components). - data did not support suppositions.
Prototype/ probabilistic Theories *Intended to explains 'normal' thinking and cognition.*	- Prototype - Exemplar	Wittgenstein (1953); Rosch & Mervis (1975) Hintzman & Ludlam (1980); Smith & Medin (1981)	Inference model Hierarchical	<u>Descriptive models.</u> Concepts are complex representations whose structures encode a statistical analysis/ probabilistic suppositions of the properties their members tend to have. Typicality of the instances with respect to categorization.	Problems: - does not account for typicality judgments. (i.e., typicality differs based on goal, context, cognitive effort – Barsalou, 1989; Rips, 1989). - problem accounting for compositionality when concepts combine to form new concepts. Differences from Classical view: - concepts do not have definitional structures. - do not have single set of necessary features. - emphasis on non-demonstrative inference.
	Dual Theories Selective Modification model Idealized Cognitive model (ICM)	Barsalou, (1989) Smith, Osherson, Rips & Keane (1988) Lakoff (1987)		(similar to above)	(similar to above)

Table 2.1 Continued.

Main Theories	Specific models	Key Authors	Structure of concepts	Definitions of concepts	Criticisms
Associative Theory-based Theories		Medin & Ortony (1989); Gelman & Wellman (1991); Murphy & Medin (1985)	Inferential model Networks of concepts	Concepts are structured mental representations and their structure consists in their relations to other concepts specified by their embedding theories. Role of prior knowledge. Concepts are mini-theories about the nature of categories.	Problems: - content stability. Concept does not remain invariant across changes in mental theories.
Conceptual change theories	Naïve theory Developmental Ontological shift Coordination Class	Piaget & Inhelder (1941) Carey (1985); Vosniadou (1994) Chi, Slotta, deLeeuw (1994) diSessa & Sherin (1998)	Coherent personal "theories" or beliefs. Fragmented structure	As above but both descriptive and prescriptive in nature.	
Neo-Classical Theory		Pinker (1989); Jackendoff (1983)	Inferential model	Concepts have "partial definitions" in that their structure evokes a set of necessary conditions. Linguistic investigation of the meaning of words.	
Atomism Theory		Fodor (1980); Garrett-Millikan (1998)	No structure	"Lexical" concepts are primitives. Rejects the assumption that concepts have structure.	Problems: - cannot explain compositionality of concepts. - cannot explain categorization. - radical Nativism.

Definitions compiled from Laurence & Margolis (1999).

2.1 General Background of Theories of Concepts

2.1.1 The Classical Logical Definitional School of Thought

The purpose of the Classical theories of concepts was to enable the construction of logical and scientific reasoning. They describe concepts as structured mental representations that encode a set of necessary and sufficient conditions for their own application; that is, concepts are a list of necessary and sufficient features that a concept must possess – and must not possess – in order to be classified as belonging together.

This description of concept formation had several weaknesses when used to represent ordinary everyday thinking particularly as it relates to explanations of *typicality* of category features. For instance, classification of concepts such as 'robin' compared to 'ostrich', are problematic because the supordinate concept of 'bird' could not easily be explained because ostrich was not typical of the category; in fact, it does not satisfy some of the necessary and sufficient criteria (Rosch, 1978). Representational shortcomings such as this lead to the positing of other theories championed by the cognitive school of concept research.

2.1.2 The Prototype View

The purpose of this school of thought was to represent 'normal' thinking and cognition. Prototype theories form a collection of models that describe most concepts, including lexical concepts, as complex representations whose structure encodes a probabilistic supposition of the properties their members tend to have. Features are not necessary, but rather weighted; therefore, some features are more important in satisfying the requirement of sufficiency in the determination of concept membership. Under this heading, concept acquisition takes on a statistical dimension and is described as the construction of categories based on the likelihood that certain features occur. Hence, categorization is a heuristic process based on *typicality* and probability.

Empirical studies of the 'typicality' characteristic drew attention to one of the major weaknesses of this theory, the instability of category membership. Studies conducted by Barsalou (1989) and Rips (1989) suggested that typicality was highly dependent on context; hence the continued search to unravel the mystery of conception formation.

2.1.3 The Associative Theory-based View

Primary contributions in the advancement of associative theory-based theory of concepts grew out of the empirical research in developmental psychology (e.g., Carey, 1985); as well as the study of expertise (e.g., Chi, Feltovich, & Glaser, 1981). Attempting to explain the differences between children's and adults' (novice/expert) conceptions, it identified the constraints and expectations that prior knowledge plays in limiting or facilitating the acquisition of new information.

Network structure of concepts. According to this model, it is argued that concepts are structured mental representations that are understood in relation to other concepts that are embedded in a network. These networks represent complex causal explanations that may be described as personal 'theories'[1] that mediate judgments of similarity; hence, explaining why we pay attention to some features and not others, as well as why we assign certain concepts to one category rather than another. Murphy and Medin (1985) point out that "similarity may be a by-product of conceptual coherence rather than its determinant – having a theory that relates objects may make them seem similar" (p. 428). They propose that causal mechanisms contained within theory-like mental structures may be the means by which feature correlations (i.e., similarities) are represented. In fact, Murphy (2000) suggests that causal relationships may be critical in categorization of concepts; more so than theme-based or other types of relationships.

> In some sense, then, these explanations are a bit circular. One cannot just explain why birds have wings. One must explain why they have wings, given that they fly, live in nest, and so on. Furthermore, one can explain why they live in nests,

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[1] There has been much debate concerning use of the term theory as well as the status of these personal theories. For more information on this issue, I direct the reader to discussion in Laurence and Margolis (1999, p.43) relating to theory-theory of concepts.

> given that they have winds, fly, lay eggs, and so on. And the explanation for flying is based on having wings, living in nests, and so on. Rather than a logical chain of one property or fact explaining another, which in turn explains another, the properties of many concepts are closely intertwined (Murphy, 2000, p. 364).

Critiques of the associative theory-based theories have identified the lack of concept stability as its major weakness. Concepts tend to vary from context to context depending on the personal theory to which they are attached. Laurence and Margolis, (1999) suggest that, "changes in a small number of the beliefs that make up a given theory needn't undermine stability, so long as the subsequent theory is associated with the very same formally identified symbol" (p.50).

2.1.4 Summary of Literature Review on Theories of Concepts

Conceptual structure as posited by the theory-based view pose three major concerns that impact on conceptual change research. First, because of the principle assumption that concepts are embedded in a network, the implications are that change to one component may involve a change to other components and possibly the entire system. I propose that it is reasonable to posit that the resulting cognitive behavior is likely to exhibit nonlinear (defined as non-additive) and possibly emergent characteristics; a view that appears to be supported by Limón (2001). Second, and more importantly perhaps, is that causal explanations (theories) will be a focal determinant of change in concept formation and categorization process.

I therefore argue that conceptual change theories that focus on multiple causal mechanisms are the most promising as explanations of the process of change. Supporting this conjecture, Ahn (1998) claims that there is reason to believe that self-explanations of causes are considerably more important than explaining effects in the process of categorization. While Keil (1989) makes an even stronger case for the role of causation, suggesting that explanations of causal relationships generate beliefs. Addressing the differences between novice and experts, he states that: "it seems almost certain that a host of interconnected beliefs about the mechanisms of objects underlies and constrains the novice's choice of problem groups... [While experts] have probably shifted away from attempting to characterize the problem space in terms of definitions-like rules and instead have incorporated a far more complex set of intricate [co-] causal relationships more along the lines of the homeostasis model [e.g., the feedback control]" (p. 261).

In the following section, I will attempt to link this argument to the conceptual change models of Chi and her colleagues (Chi et al., 1994; Chi, 2000b; Chi & Roscoe, 2002), and diSessa and Sherin (1998) in describing conceptual change as a process that addresses the learners' beliefs about causal relationships between concepts.

2.2 Conceptual Change Theories

A primary concern of this current study is the development of conceptual change theory. In reviewing the literature I selected three of the premier models I believe hold the most promise for a genuine theory of conceptual change. Although these models differ on several major assumptions, there are equally several specific dimensions where they support each other in a principled manner (see Table 2.2). Hence I will discuss these features and describe how they relate to this current research.

General Background

The foundations of most conceptual change theories include a Piagetian motivational theory of cognitive development. Piaget (1975) proposed that disequilibrium, dissatisfaction, or discord must be created within the child between their initial conception and the to-be-learnt one. The attempt to resolve this cognitive conflict results in the processes of "assimilation" or "accommodation"[2] of the new idea. This notion of dissatisfaction is at the base of several early models of conceptual change. However, some studies in the field have moved away from theories of cognitive conflict to theories of knowledge restructuring (e.g., Chi et al., 1994; Vosniadou, 1994).

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[2] Assimilation refers to situations in which the learners' existing theories allow them to explain new situations; whereas accommodation describes situations in which the learners' theories cannot account for or explain the new phenomena therefore must be revised, reorganized, or replaced.

Table 2.2 Comparisons of Conceptual Change Models

Model	Intuitive theories	Misconceptions created by	Conceptual change occurs when	Techniques for conceptual change	Process
Strike & Posner 1985; 1992; Thagard 1987?	Many factors conceptual ecology some have explanatory coherence.	(Does not state specifically)	Confrontation or competition between two incompatible but equally well organized theories. Knowledge replacement models (other example is Thagard, 1992) Other factors: conceptual ecology including motivation and goals.	1. Instruction of alternative information. 2. Cognitive artifacts used to achieve change: - analogies - metaphors 3. Extensive use of constructivist techniques.	Four stage process: 1. Minimal understanding of new conception 2. Dissatisfaction with existing conceptions 3. Plausibility of new conception 4. Fruitfulness of new conception
Vosniadou 1994; 1998	Coherent theories: a) Framework theory b) Specific subject dependent theory	The synthetic stage where new information is added to existing initial model. 1. Initial stage 2. Synthetic stage 3. Scientific stage	Realization that new information is inconsistent with specific theories or framework theories. Restructuring is therefore a continuous gradual enrichment.	Instruction of scientific information.	Two phased process: 1. requires metaconceptual awareness. 2. change in specific beliefs and framework Two types of Concept Change: 1) spontaneous, without need of instruction. 2) instructionally based. This process is a slow revision and gradual incorporation of science explanation.
diSessa 1993; 1998	Fragmented knowledge structures in the form of p-prims.	(Does not state specifically)	Slow refinement & restructuring of intuitive knowledge structures, p-prims, to formal principles of science. Shift in way of "seeing" which is a separate change in *readout* strategies and *causal net*.	Instruction of alternative causal net and readout strategies.	Iterative process of changes in: 1. Readout strategies 2. Causal net
Chi 1993; 1994; 1997; 1999; 2000	Coherent knowledge structures but not at the level of theory, rather organized as a schema or frame.	Assignment of concept to the incorrect ontological tree.	Reassignment of concept to different ontological tree. Change in preexisting conception.	Instruction of alternative ontological process category – specifically "emergent" processes.	Shift in reassignment to correct ontological category.

2.2.1 Dissatisfaction and Knowledge Replacement Theories

Strike and Posner's (1985) model of conceptual change expanded on Piaget's ideas of conceptual change through accommodation and assimilation. These authors contended that accommodation requires taking into account the alternative conception and comparing it to the existing conception; if the plausibility status of the alternative conception reaches a level that exceeds that of the original conception, then there will be a change. Four stages were identified: (1) dissatisfaction with original conception, (2) intelligible replacement conception, (3) plausibility of new conception, and finally (4) fruitfulness of new conception leading to replacement. A central claim of the conceptual change theory proposed by Strike and Posner (1985) is that new conceptions are understood, judged, acquired, or rejected in a conceptual context – a conceptual ecology. Hence, old and new concepts coexist. Cautioning that there were many factors other than the conceptions themselves that may affect status, they suggested that the learner would experience stops, starts, and even retreats along the road to change.

In their revised discussion of conceptual change, Strike and Posner (1992) extended the role of the conceptual ecology. Proposing that misconceptions are not the product of clearly articulated beliefs, rather, they are artifacts of deeply entrenched problems in the conceptual 'ecology'. Raising the issue of stability, they suggested that misconceptions may be weakly formed, temporal and not consistent; in fact, they may be influenced by the conceptual ecology. Addressing the issue of conceptual structure they draw attention to the systemic nature of the conceptual network.

Importance of this model. The importance of Strike and Posner's model is twofold: (1) its attention to factors such as motives and goals that influence the learners' conceptual ecology, and (2) its applicability to classroom instruction. It has been the cornerstone of most conceptual change instructional interventions, however these studies have produced some equivocal results (e.g., Chan, Burtis & Bereiter, 1997; Champagne, Gunstone & Klopfer, 1985; Jensen & Finley, 1996; Limón & Carretero, 1997). Because this model does not adequately address how to build an alternative conception, I am setting it aside here. Perhaps, however, one should return to it for answers regarding issues of ecological accommodation once a theory of conceptual change processes and mechanisms has been articulated.

2.2.2 Knowledge Restructuring Theories

If concepts are indeed embedded in stable complex networks of other concepts that represent naïve or personal theories, then conceptual change will be a formable task. If in addition, these theories are held together by causal self-explanations composed of the most basic units of our thinking – ontological and/or epistemological beliefs – then how do we start to unravel the problem of deeply held misconceptions that are ubiquitous in science learning (see, for example, Driver, 1995 or Pfundt & Duit, 1994)? Consider the following theories as steps toward clarifying a possible integrated causal approach to conceptual change.

Vosniadou – Framework and Specific Theories

Vosniadou (1994) argues that concepts are entrenched and constrained within a larger theoretical structure. This author identifies two levels of theories that control the learners' beliefs, naïve *framework theories* and various *specific theories*. Vosniadou proposes that the learner's framework theory is not available to his conscious awareness; nonetheless, this theory constrains the process of acquiring veridical knowledge about the physical world. These theories are a function of ontological and epistemological presuppositions. Specific theories on the other hand, are consciously accessible, exist within a domain and consist of a set of interrelated propositions that describe the observed behavior of physical objects. That is, the specific theory is based on the individual's observations, as well as the instructional information, and it is developed within the constraints of the presuppositions of their framework theory. These two classes of theories come together to create the mental model, the lens, through which the learner builds causal explanations of the world (I will elaborate on Vosniadou's description of the role played by mental models in the mental models section of the literature review).

Definition of conceptual change. Vosniadou (1994) identifies two kinds of conceptual change: *enrichment* and *revision*. The former is described as the simple addition of new information to existing knowledge, and achieved through the process of accretion. The latter is considered conceptual change and viewed as a substantial change that is realized by the learner when new information is inconsistent with specific theories or framework theories. She posits that inconsistencies between new information and framework theories are more difficult to resolve than inconsistencies with specific theories.

Difficulties in removing misconceptions. Vosniadou suggests that conceptual change is difficult because framework theories are coherent systems of explanations that are based on everyday experiences and grounded in years of confirmation. Additionally, because these are ontologically and epistemologically based, a shift in any of these beliefs will create a shift in the entire system of the framework theory and all the other knowledge built upon it. This assertion is similar to implications of Strike and Posner's conceptual ecology.

Failure to learn certain concepts has been attributed to inconsistencies between the to-be-learnt knowledge and framework theories. These occur when children attempt to add information to the false existing mental structure. The author describes inert knowledge as the product of inconsistent information being stored in separate microstructures and used only in particular situations. Whereas, misconceptions are the result of learners trying to reconcile the inconsistent pieces of information and in the process produce *synthetic mental models*[3]. I contend that this attempt to account for

[3] According to Vosniadou and Brewer (1994), *synthetic mental models* are likely to be formed when the knowledge acquisition process requires revision of framework theories based thus are part of the presuppositions constructed on our interpretations of everyday experiences. Synthetic models function as intermediary steps in the conceptual change process from an initial intuitive model to the scientifically culturally accepted one.

anomalous data draws this part of Vosniadou's model closer to the cognitive conflict approach. Therefore, her model may be viewed as a bridge between Strike and Posner's model and those that will be described next.

Importance of the model. Vosniadou and Brewer's (1994) empirical findings suggest: (1) there is a sequence in which concepts are acquired in a conceptual domain; and, (2) that the importance of mental models is a constraint on the knowledge acquisition process. These findings have given rise to their theoretical supposition that conceptual change is gradual and will give rise to misconceptions. They also suggest that there are developmentally distinct stages in conceptual change: (1) initial mental model, (2) synthetic mental model – learner attempts to reconcile the science model with initial model, and (3) scientific mental model. Another group of researchers, Jacobson and Archodidou (2000), have successfully identified these developmental stages in their study of conceptual change instruction on the topic of evolution.

Recently, Vosniadou and Ioannides (1998) have made two major refinements to the original model. firstly they have identified distinctions between types of conceptual change suggesting that conceptual change can be: (1) spontaneous, or (2) instructionally based. The former type is a change resulting from enriched observations in social learning context without formal science instruction. Examples of this would be language learning as a result of socialization with adults and older children as a child matures. The latter is a result of formal instruction that requires the building of synthetic models in an effort to reconcile science instruction into existing theories (e.g., understanding of astronomical processes).

Secondly, they have elaborated on Vosniadou's (1994) original assertions regarding the refinement process. The role played by *metaconceptual awareness* has been strengthened and refinement is viewed as the development of "theoretical frameworks with greater systematicity, coherence, and explanatory power [i.e., more scientific]" (Vosniadou & Ioannides, 1998, p. 1222). This feature is an important contribution to the development of the prescriptive side of the conceptual change debate. Additionally as will be shown, it is also a consistent theme between models, although it may be argued that Vosniadou makes the biggest commitment to its importance.

DiSessa's and Sherin's Model

Along the continuum of conceptual change models, the work of diSessa and Sherin (1998) is positioned closer to that of Chi and her colleagues. Similar to Chi, they too focus on the deeper issues of process and mechanism of concept formation and concept change. In fact, it may even be argued that theirs is a fuller model of concept formation. I will briefly describe this model with a focus on its assertions regarding the processes of what they call the *coordination classes*, a major structural component in concept change.

The basic assumptions of the model. Based on the research supporting the supposition that naïve learners possess impoverished causal models for understanding physics concepts (Gentner & Stevens, 1983), diSessa (1993b) developed his model of concept formation. He identified this attribution as the "naïve sense of mechanism", suggesting that this belief of causality is composed of *phenomenological primitives* (here forward referred to as *p-prims*) which are abstracted from common experiences. P-prims are the smallest unit of particular knowledge elements[4] and indeed may generate their own self-explanations. In these cases, diSessa (1993b) states that p-prims are the intuitive equivalent of physical laws and form the bases upon which one sees and explains the world. Hence, p-prims account for structures that diSessa calls *causal nets*. However, p-prims are not concepts themselves, and multiple p-prims are involved in the creation of causal nets.

Causal nets may be described as approximately corresponding to what people intuitively expect of causality, which is logical given their status as composites of p-prims. In addition, in some instances, they can be interpreted to mean the reasoning strategies used to explain how some observations are related to the information at hand. In their words: "Causal nets are, roughly, our replacement for the 'theories that lie behind

[4] Not unlike "Conversation theory" concepts as described by Gordon Pasks (Boyd, 1997).

observations'. Or the theories implicated in theory-based notions of categories" (diSessa & Sherin, 1998, p. 1174). Hence, causal nets may be described as the inference-based explanations used to make sense of the world, which in turn form the basis of our theories. These authors link this explanatory mechanism to concept acquisition through a structural component called a *coordination class*. In order to understand this sophisticated interwoven play of components requires some background information.

Background on coordination classes. DiSessa and Sherin (1998) first suggest that concepts are not all the same. In fact, concepts such as 'robin' are different from those such as 'velocity' or 'force' and require different cognitive processing. While the former requires sorting into the category-like concept of bird, the latter two fall into a special class of concepts that they refer to as *coordination classes*. These coordination classes are made of structural components that perform two distinct activities: (1) centered on gathering information through selecting what to 'see' (referred to as "readout strategies"), and the other, (2) based on the already mentioned causal net activity.

Part one, the *readout strategy*, or information gathering, is equated to a metaphorical 'seeing', and the shift in the means of seeing is considered to be the core problem of conceptual change. They state: "In many instances this seeing is a substantial accomplishment of learning and will depend only very partially on basic perceptual capabilities. In addition, these forms of seeing sometimes involve explicit strategies and extended reasoning" (diSessa& Sherin, 1998, p. 1171). I will return to this point shortly.

Elaborating on the *readout strategies* they identify two subcomponents of this phase: (1) *integration*, which refers to the fact that multiple observations or aspects may need to be coordinated so as to determine the requisite information; and (2) *invariance* (I would suggest that it could be considered a type of concept stability), which refers to the knowledge that accomplishes the readout of information from different instances and situations must consistently and reliably determine the same information.

Part two of the *coordination classes* process takes us back to the important explanatory mechanism, *causal nets*. Learning new science concepts therefore becomes an interlocking cognitive 'see-saw' where both *readout strategies* and the *causal net* are said to co-evolve. These authors suggest: "There should be episodes of 'conceptual bootstrapping', where causal assumptions drive the learning of new readout strategies. On other occasions, 'noticings' - for example, that something surprisingly affects something else - may drive reformulations in the causal net. In general, characteristics of one will have important influences on how the other behaves and develops" (p. 1177).

Definition of conceptual change. Hence diSessa and Sherin (1998) define conceptual change as involving both the separate changes in readout strategies and in the causal net. They clarify by showing an example, that it is possible that no new readout strategies are necessary in learning a new coordination class, rather existing ones come to be organized and used differently. On the causal net side, maybe the construction of a whole new causal net may be required, or an existing one may need to be developed and reorganized.

Importance of the model. The detail provided relating to the activity of the coordination classes is an important feature of this model. The suggestion that conceptual change is a two-part process in which conscious attending to evidence (e.g., data) followed by conscious attending to the explanations related to causation (e.g., personal theories) is a development and clarification on Vosniadou's concerns with "metaconceptual awareness". In fact, these authors propose that the causal net is the source of difficulty in learning school physics. Their recommendation is thus, "among other things, it [the causal net] needs to become more systematically organized. The notions of invariance and integration may play a role in the organization and selection of causal net to be used" (diSessa & Sherin, 1998, p. 1178).

I argue that missing from this model is the answer to the question: What kinds of changes occur in the causal net? In other words, if we are to attend to new causation what is needed to fill in this gap? I contend that we must turn to Chi's views on a theory of conceptual change for an answer.

2.3 Chi's Ontological Reassignment Theory

A brief introduction to Chi et al's (1994) theory was presented in the last chapter, hence the basic assertions of their model should already be familiar; therefore I will take this opportunity to elaborate upon the elements specific to this current study. Additionally, in a later chapter, I will detail the developments of Chi's ontologically-based coding schema.

2.3.1 Evolution of Ontologically-based Conceptual Change Theory

The original model. Chi et al., (1994) define conceptual change as learning that changes a preexisting conception. This definition holds a basic assumption that the learner has some prior idea on knowledge of the concept, which in turn may mean that it has already been classified into a category. Therefore the meaning of a concept is determined by its category assignment and conceptual change is defined as a change in category assignment. On the other hand, the simpler process of "belief revision", according to Chi (1992, 1997), occurs when the concept just needs an adjustment to the category (an addition or deletion of information). Accordingly, the most important aspect of Chi's theory of conceptual change is this notion of re-assignment of concept from the initial category in the ontological tree to the veridical category of the tree. The way the categories in one tree differ from categories in another is embedded in their ontological attributes.

Chi's theory of conceptual change (Chi et al., 1994; Chi & Slotta, 1993) rests on three assumptions: (1) an epistemological assumption concerning the ontological assignment and beliefs about the nature of entities in the world[5], thereby defining the

[5] There is a long tradition of theorizing about ontological categories based on predictability or use of predicates in natural languages. Keil (1979) describes the term predictability as follows: "it determines which classes of predicates can be sensibly combined with which classes of terms, and it appears to involve hierarchical organization in that a predicate P1 may be sensibly combined with a superset of the set of terms that can be sensibly combined with a predicate P2" (p. 11). Therefore an ontological category would be defined by the set of terms for which a particular set of predicates could be applied to and the statements judged to be true or false. Predicates used in such a manner that the statements cannot be judged to be veridical or fallacious, suggest that the terms do not belong to the same ontological category. An examples that are often cited would be that of colour. The predicate "is green" may apply to "the frog" (natural kind) or to "the table" (artifact) or to "the girl"

criterion of "different"; (2) a metaphysical assumption concerning the nature of certain scientific concepts (a position that I contend sets Chi apart from other theorists inasmuch as she takes an outside-looking-in approach that perhaps is related to her research on expertise); and, (3) a psychological assumption concerning the learner's naïve conceptions and miscategorization of concepts that are revealed in a propositional context (i.e., mental models).

2.3.2 Recent Refinements to the Theory

Two major changes have appeared in Chi's description of this conceptual change theory. The first relates to the difficulty in removing misconceptions, the second to the structure of the categories.

Reconceptualization on removing of misconceptions. In her most recent publications (e.g., Chi & Roscoe, 2002), Chi clarifies her stance on the structures of concepts as embedded in naïve theories. Furthermore, she explicitly acknowledges the assumptions that naïve theories and scientific theories are often incommensurate; a statement similar to diSessa and Sherin (1998). Her most important conjecture, however, is that the major challenge in conceptual change comes from the fact that "students may lack awareness of when they need to shift [to an alternative ontological category], and may lack an alternative category to shift to" (Chi & Roscoe, 2002, p. 18). These authors postulate that in fact the lack of the scientifically appropriate category (emergent processes) prevents students from requisite recategorization: "students cannot repair

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(natural kind). Because these can be proven true or false, however, "is green" cannot be with "an hour" in any sensible way except metaphorically. Keil states, "a predicate spans a term if and only if that predicate-term combination makes sense and can be assigned a truth value, which can be either true or false (p. 11).

This paper will not delve further into the discussion of predictability and the assumption that it can identify different ontological categories. It will suffice to say that the study of this topic is covered by Sommer's theory of the relation between predicates and terms, which represent a class of terms leading to differential ontological categories membership (Sommer, 1963; cited in Keil, 1979, p. 15 see figure).

Thus, a primary assumption of this study is that natural kinds and artifacts belong to distinct different ontological categories, which can be identified through a term-predicate relationship. However, it would be difficult to suggest the same rigid test could hold true for the ontological category of processes, which Chi has identified. This should not negate the fact that processes fall under different rules of operation and therefore can be considered to belong to different ways of understanding the world, hence, different ontological categories. Since there is little literature in this domain, I will base this statement on the work in complexity that uses a different mode of operation for certain phenomena (referring to statements made by Jim Kaput, Uri Wilensky, and others at symposium on Complex Systems in Education, presentation at AERA, April 2002).

misconceptions if conceptual shift is not possible. This is what makes certain misconceptions more difficult to repair than others" (p.19).

How then does one gain awareness of or access to these new categories? This is the major question posed by Chi (2000b), and Chi and Roscoe (2002); and, this is the major question that I have focused on in this dissertation.

As described earlier, empirical studies using the anomalous data confrontation models have produced equivocal results relying on constructivist instructional strategies to bolster the potency of the treatment. Limón, (2001) states:

> Despite the positive effects we have reported, perhaps the most outstanding result of the studies using the cognitive conflict strategy is the lack of efficacy for students to achieve a strong restructuring and, consequently, a deep understanding of the new information. Sometimes, partial changes are achieved, but in some cases they disappear in a short period of time after the instructional intervention. Why are students so resistant to change even when they are aware of contradiction? Why are students able to partially modify their beliefs and theories but keep the core of their initial theory? (p. 364).

This shortcoming of confrontation is exactly what Chi and Roscoe (2002) believe is averted when conceptual change is approached from the perspective of reassignment. I suggest that they indicate an answer to Limón's first question, and maybe even the second, in their statement: "The problem is that unless students have an alternate category to reassign the concept to, such instruction [presentation of anomalous data] will not be effective" (Chi & Roscoe, 2002, p. 19).

<u>The problems addressed in this dissertation research</u>. Therefore, where do we start? Initial questions are: Do novice science students possess the suitable alternative ontological categories? If they already possess the needed alternative category: Does a shift in explanation require mere facilitation or is it difficult process? If this category does not already exist, then can we teach them about this category? How can this be

accomplished, what do they learn, and how long does it take? Finally, if there is a change, is it long lasting? These are the primary questions that this dissertation elects to address.

2.3.3 Summary of the Ontological Reassignment Theory

In 1993 Chi and Slotta compared their model of conceptual change to diSessa's (1993b) model of concept formation. They concurred then that there were several points of reconciliation between the two models. For instances, the role played by p-prims could be viewed as low-level instantiation of the category reasoning process. Continuing, they point to several specific points of agreement such as: (1) intuitive knowledge is phenomenological in the sense of it being personal empirical knowledge; (2) retrieval of intuitive knowledge is driven largely by surface features; and (3) while intuitive knowledge is primitive and requires no explanation, it forms the basis of high-level reasoning about physical processes. However, there were and still are irreconcilable differences between diSessa and others regarding the structure of intuitive knowledge[6]. For example, Chi and Vosniadou view intuitive knowledge as coherent "theories", while diSessa's view is that intuitive knowledge is fragmented, "knowledge in pieces".

Although this difference is significant, I will observe that the Chi's recent focus on causation draws the two models closer. I therefore put forward the proposition that the "coordination class" may be a representation of an ontological category since it acts as the control mechanism regulating the two phases of concept acquisition – readout strategies (what we unconsciously choose to 'see' of the world) and causal nets (how consciously we explain what we 'see'). Furthermore, the ontological frame required to explain many scientific concepts is really an explanation or attribution of different types of "causation". The bringing together of the two theories was not the focus of my research, however I will revisit this argument in the discussion section of this dissertation. Finally, I propose that Vosniadou's model, although not focused on causation, suggests that some types of

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[6] Observed in a verbal debate between Andrea diSessa and Stella Vosniadou (AERA Annual Meeting, New Orleans, 2002).

conceptual change may be intentional and call for effortful attending to metacognitive processes in the form of metaconceptual awareness. This possible connection between intentional learning (e.g., metacognitive and metaconceptual awareness, motivation, and epistemological beliefs) and conceptual change is a primary focus of the recent publication edited by Sinatra and Pintrich (2002). Although this aspect of conceptual change is not directly manipulated in this dissertation study the important role of intentional reflection in the form of metacognitive activities and metaconceptual awareness was observed in the learners' behaviors in Study 2, the longitudinal case study.

2.4 Ontologically-based Misconceptions

Before proceeding, it is important to evaluate Chi's assertion that many important misconceptions are ontologically based. Hence a question to be answered was: Is there empirical evidence from the literature of ontological category-like misconceptions?

There are hundreds of reported cases of different types of scientific misconceptions (Driver, 1995; Pfundt & Duit, 1994). Some are trivial in that they require simple restructuring of information, however, the ones that are discussed in conceptual change literature tend to fit with and support Chi's ontological supposition. To illustrate my point, I present a sample of studies in the following section from a variety of disciplines and sources.

2.4.1 Misconceptions on the Topic of Evolution

There is a substantial body of literature describing the difficulties involved in changing students' misconceptions in the learning of evolution (Ferrari & Chi, 1998; Jacobson & Archodidou, 2000). The problems range from the understanding of the time frames (e.g., Renner, Brumby, & Shepherd, 1981), to the genetics (e.g., Demastes, Good, & Peebles, 1995; Jensen & Finley, 1996), to the distinctions between species and individuals (e.g., Hallden, 1988), the origin and survival of new traits, the role of variation within a population, and evolution as the changing proportion of individuals with distinct traits in a population (Bishop & Anderson, 1990;), to the explanation of spontaneous genetic mutation (Settlage, 1994), the evolutionary changes supposedly occurring as a result of need (Brumby, 1984), and finally failure to recognize that many aspects of evolution exhibit "equilibration-type" processes as opposed to "event-type" processes (Ferrari & Chi, 1998). Therefore a host of attributions ranging from those about teleological beliefs to those about isomorphic behaviors between levels is represented in these studies of difficulties in conceptualization.

2.4.2 Chemical Equilibrium, Diffusion, and Osmosis Misconceptions

The literature concerned with the instruction of chemistry has identified a persistent misconception about chemical equilibrium (e.g., Suits, 2000; Coll, R.K. & Treagust, D.F., 2002). These misconceptions appear to stem from misunderstanding of the differential levels of operations, as well as the different symbolic representations, that are discussed in the course of a normal chemistry lecture (Barnerjee, 1995). On the related topic of osmosis and diffusion, there is also evidence that similar misconceptions exist (e.g., Odom, A.L., 1995; Sanger, M. J., Brecheisen, D.M., & Hynek, B.M., 2001). Again the attributions of isomorphic behaviors between levels as well as assumed static behaviors once equilibrium is achieved are common themes. These empirical studies lend support to Chi's conjecture that there is an ontological base to this class of science misconception.

2.4.3 Deterministic Causality Misconceptions

From the literature on judgment and decision-making, evidence suggests that both adults and children exhibit difficulty reasoning about uncertainty with greater tendencies to attribute deterministic outcomes in problem solving (e.g., Shaughnessy, 1992; Tversky & Kahneman, 1974). It is arguable that the findings from studies relating to mathematics and statistics may not cross over to problems encountered in other domains of science;

however, I contend that this is not the case with attributions of determinism. According to Metz (1998): "Without an understanding of randomness and probability, formal study in statistics can have little meaning, and informal [mis]interpretations of patterns and variability in the world around us will frequently result in spurious causal attributions" (p. 286). The latter assertion is precisely the one that I propose supports this dimension to the ontological category of emergent phenomena.

Another interpretation of randomness and probability. In this study I use the terms randomness and probability in ways that may be unfamiliar to the lay person. For instances, randomness is an important behavior that accounts for much of the variety and requisite error observed an emergent phenomena (see Bar Yam, 1997). With regard to probabilistic behaviors, they occur as the interactions of the multiple agents, and systems, producing stochastic outcomes thereby making causal mechanisms more complex.

Even using these descriptions of randomness and probability there is evidence of misconceptions (Wilensky, 1993; 1995; 1997). The early work from the MIT labs (Wilensky & Resnick, 1995; Wilensky & Resnick, 1999) suggested that conceptions of randomness as being destructive are prevalent in non-scientific reasoning. Furthermore, there is abundant evidence that people have difficulty reasoning about parallelism and probability. Resnick and Wilensky have thus argued, together and independently, that these misconceptions be considered the "deterministic/centralized mindset"(further elaboration to follow).

2.4.4 A Global Perspective on Ontologically-based Misconception

Spiro and his colleagues (Feltovich, Coulsen, Spiro, & Adami, 1992; Spiro, Coulson, Feltovich and Anderson, 1988; Spiro, Feltovich, Jacobson, & Coulson, 1992) have identified a range of misconceptions exhibited by medical students. One of the common attributions they identified in learners, even in advance stages of learning, was the tendency to adopt a reductive approach to problem solving; in addition to oversimplification of the subject matter. They identified three biases: "[1] *additivity bias*, in which parts of complex entities that have been studied in isolation are assumed to retain their characteristics when the parts are reintegrated into the whole from which they were drawn; [2] *discreteness bias*, in which continuously dimensioned attributes (like length) are bifurcated to their poles and continuous processes are instead segmented into discrete steps; and [3] *compartmentalization bias*, in which conceptual elements that are in reality highly interdependent are instead treated in isolation, missing important aspects of their interaction" (Spiro et al., 1992, p. 26).

If we examine the biases individually, they can be matched to the naïve attributions listed above. Hence, the "additivity bias" may also be described as attributions of isomorphic behaviors between levels (reductive or non-emergent behaviors). While the "discreteness bias" shows signs of attributions of static outcomes or beginning end processes. Finally the "compartmentalization bias" may be related to the global lack of awareness of emergent properties.

Latest developments. Jacobson's (2000) research identified specific categories of attributions that differentiate expert and novice reasoning about emergent phenomena. These categories will be described in greater detail in the following chapter, however, for the moment it is sufficient to state that these categories support the data described above as well as Chi's ontological dimensions.

2.4.5 Summary of Ontologically-based Misconceptions

In summary, I argue that these studies provide some reasonable confirmation of the articulated interpretation of the ontological categories described by Chi (2000). Furthermore, although Spiro et al. (1992) research (i.e., Cognitive Flexibility Theory, CFT) addressed difficulties associated with advanced knowledge acquisition, I contend that CFT may also apply to challenges faced in the removal of robust science misconceptions. For these reasons, I borrowed from the recommendations made by that theory to design the instructional intervention used in this current study.

2.5 The Alternative Causal Ontological Category

If a possible solution to the removal of robust misconceptions is the reassignment to an alternative ontological category, then what are the problems associated with the learning of such categories? Before we attempt to answer this question, however, we must first define what is meant by the ontological category of emergent causal processes, and describe why they constitute a 'different' causal explanation.

Chi and her colleagues have spent the past decade describing this category using a variety of terms: "events" (Chi, 1992), "acausal interactions" Chi and Slotta (1993), "constraint-based interactions" (Chi, Slotta & deLeeuw, 1994; Slotta, Chi & Joram, 1995; Slotta & Chi, 1996), "equilibration" processes (Chi, 1997; Ferrari & Chi, 1998; Slotta & Chi, 1999), "CDS" (Chi, 2000b), and currently "emergent" processes (Chi & Roscoe, 2002). I contend that this latest naming is the most parsimonious and consistent with the existing literature on the processes that Chi has described for years using those varied terms. Although Chi has not acknowledged the body of literature from the field of complex systems, and indeed even distances herself from it (Chi, 2000b), I would assert that her latest writing (Chi & Roscoe, 2002) brings her closer than ever before to affirming a reasonable connection. I will dwell no further on this detail since I believe it is just a matter of time for the obvious similarity of descriptions that I will describe below to be recognized by Chi and others.

2.5.1 Emergent Processes

In order to describe the emergent processes ontological category I first turn to the literature that describes it best: that is, complexity and complex systems theory (see definitions in Appendix B). Born out of disciplines such as biology, cybernetics, mathematics, statistical mechanics, and quantum physics, the theories related to the phenomena of complexity are undeniably daunting. Nonetheless, the ability of these theories to explain the behaviors of countless biological, chemical, physical and social interactions requires that we take a serious look at their potency as representational structures in our curricula.

Genesis of Interest in the Topic

Kauffman (1995) identifies complexity as the state at which a system of many coupled components is "orderly enough to ensure stability, yet full of flexibility and surprise" (p. 87). He continues to describe this state as one which is just near phase transition and referred to as the "edge of chaos". One might assume from these beginnings that the study of complexity should be reserved for biologists and mathematicians; however, there is another side to this area of study. It is the conceptual side of complexity where the behaviors of countless phenomena, including social, economic, cognitive, and scientific, can be explained using the global structural features of complex systems.

Waldrop (1992), a science writer, confirms in his book entitled Complexity that at present the field is still poorly defined as researchers grapple with questions that cut across the traditional categories. This observation may also apply to the terms used to define the field. Some researchers refer to it as the study of complex systems, or complex adaptive systems, while others identify it as the study of self-organizing systems, and some as emergent systems. These differences should not be viewed as weaknesses, rather, as a sign of the newness of the area. Indeed, it is difficult to describe individual behaviors of complex systems because of their interconnected nature. In an attempt to keep the different terminology to a minimum, in this current study I will define the term "complex systems"[7] to refer to both complex adaptive systems as well as complex non-adaptive systems unless the adaptive nature is essential to describing the system. I will also use

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[7] Definition of complex systems: A system is a hierarchically organized collection of a large number of coupled components defined by stated boundaries. The smallest unit of a system is referred to as an agent. Complex systems are a category of systems characterized by highly interacting individual agents operating under specified rules resulting in emergence of meta-agents and/or systems that exhibit differential behaviors to their component agents. Complex systems may be of the adaptive type (e.g., human beings, the immune system, viruses, etc.), which form internal models that learn and evolve over time or the nonadaptive type, which does not exhibit adaptive qualities (e.g., molecules, galaxies, etc.).

the term *emergence* or *emergent properties/behaviors* of systems, as the exemplification of the characteristic displayed by some types of complex systems as well as the product of *self-organization*.

What is emergence ? A simple explanation of emergence is a phenomenon wherein the interaction of a system's parts results in a higher order organization which behaves differently from what one could predict from knowledge of the parts alone. Hence, the commonly known cliché "the whole is greater than the sum of the parts" is an apt description.

Emergence, however, is anything but simple to describe or to understand. In an effort to explain the phenomenon, I turn to two authors, John Holland and Yaneer Bar-Yam, who each have written extensively on the subject. Holland (1998) describes emergence as patterns of interactions that persist despite a continual turnover in the constituents of the patterns. In an effort to make the concept more accessible, Holland uses a metaphor of a checkers game where the rules are invariant but the outcome of the interactions are varied and never dull, particularly in the hands of skilled players. Accordingly, it is difficult to make predictions about behaviors of emergent systems even when the rules and initial states are specified. A difficulty that is compounded when the system is composed of mechanisms that allow for adaptation and learning; that is, overt internal models with *lookahead* protocols (these well be discussed more fully later on). Nonetheless, over time both adaptive and nonadaptive emergent systems exhibit recurring patterns that are discerned by attending to specific details. Therefore, such patterns are an important property of emergent systems and can be used to characterize them without reference to underlying strata.

Bar Yam (1997) describes emergence as the behavior that arises in the collective that is not exhibited in the behavior of the parts (nor would arise from a simple summation of behaviors). He is quick to point out that although the collective behavior is not readily understood from the behavior of the parts, this should not be taken to mean that the collective behavior is not "contained in the behavior of the parts if they are studied in the context in which they are found" (p.10). This subtlety leads to a distinction between two types of emergent behaviors, local emergence and global emergence. Local emergence implies that taking a small part out of a large system would result in little change to the properties of the small part or the properties of the larger system. Examples of this would be water droplets that contain the properties of water regardless of how small a quantity of water we look at (e.g., one molecule of H_20 has no fluidity). In contrast, global emergent properties invest greater interdependence of parts. For instance, an emergent traffic jam that propagates backwards despite the forward motion of the individual cars; or the parts of the brain, or a corporation that are different *in situ* compared to their isolated parts. Hence, a small part cannot be studied outside of the larger system and still exhibit the properties it has when embedded in the whole system.

Operationally defining emergence. Although Bar-Yam (1997) points to important distinctions in the phenomenon of emergence as part of the study of complexity, for the purpose of this discussion, I selected the more general description that views a system's emergent properties as patterns or recurring structures resulting from non-linear interactions, of lower level parts (agents), governed by specific rules and relationships. These rules and relationships are the mechanisms that afford emergence, which is the resultant state of coupling all the lesser processes of self-organization/aggregation, nonlinearity, stochastic behavior, tagging/selection, flows of information. Consequently, emergence is the topmost attribute of the selected system that uses the mechanisms of self-organization[8] to produce the emergent outcome.

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[8] Self-organization (as well as the process of selection) is so pervasive in nature that Kauffman (1995), one of the first scholars to write about the subject, likened it to universal laws. In his book At Home in the Universe, he builds an argument to explain how these processes made "the emergence of life well-nigh inevitable" (p.43). Waldrop (1993) describes self-organization as a process wherein "groups of agents seeking mutual accommodation and self-consistency somehow manage to transcend themselves, acquiring collective properties such as life, thought, and purpose that they might never have possessed individually" (p.11). Does this mean that self-organization is part of emergence? Yes, as agents go through the process of self-organization, there is an emergent meta-agent created as described in the previous paragraphs.

In explaining principles of self-organization particularly in developmental biology, Bar Yam touches on an essential quality in understanding the beauty of this process, that is, its economy. Self-organization is a process in which the representation describes the developmental process of formation rather than the final system itself. It is thus the creation of an algorithm from which the system is to arise. Another parsimonious property is that randomness or noise acts as a bonus to the unfolding of the algorithm in that it adds the element of chance variation without breaking the reproduction value. For further information I direct the reader to BarYam's book.

2.6 Challenges of Teaching and Learning Emergent Causal Processes

Why do concepts related to the emergent processes category prove challenging to learners? Chi (2000) suggests three possible challenges to the removal of misconceptions: (1) the nature of human cognition, (2) nature of instruction, and (3) students' lack of awareness about the nature of emergent processes.

Nature of Human Cognition

To support this conjecture, Chi cites two separate sources. First, she turns to Wilson and Keil (2000) who posit that humans are predisposed to think simplistically in causal terms (see p.5 this document, as well as diSessa's explanation of the role of causal nets, for other support of this argument). Second, she suggests that in normal cognitive development and learning, rarely are ontological shifts required. In fact, our naive theories do not often fail to explain the world. This claim is supported by the ontological category formation literature (Keil, 1979; Sommers, 1963). Furthermore, concept formation theorists such as Margolis (1999) suggest that we may mistake a paper bag (nominal kind/artifact) for an animal (natural kind) at a distance but it is soon rectified when given a second look or more time to process the information. We may also need to shift within ontological categories such as reassigning the concept 'whale' from the category of 'fish' to the category of 'mammal'. It is argued that we already possess the category of 'mammal', therefore the shift is a smooth one. The same may even be said of Vosniadou's study of children who eventually shift the concept of Earth from that of a flat object to one that is spherical and rotates around the sun (Vosniadou & Brewer, 1994). Although interesting, these sorts of category shifts are outside the scope of this current study.

The Nature of Instruction

The second challenge involved with this category is identified as the problems of textbook structuring of science content. Chi (2000) identified the following weaknesses:

(1) too much emphasis on macro level processes, therefore micro level actions are described in terms of classes of individuals rather than interactions and collective effects; (2) lack of emphasis on how macro level patterns emerge from micro level interactions; (3) insufficient emphasis on emergent processes; finally, (4) inadequate attention and direction concerning when differential strategies are required for problem solving. These problems too are outside the scope of this current study. However, the instructional intervention developed for this current study was sensitive to these concerns and therefore I will refer back to these in the discussion chapter. Unfortunately, the fashion among intellectuals to decry reductionism has meant that discussions of emergence as connections among levels has been sidelined (Boyd, submitted).

2.6.1 Overcoming Lack of Awareness of Emergent Processes

This is the one concern that is central to this current study. Chi (2000) argues that emergent processes are difficult to pinpoint because they are intertwined with [linear] causal processes. She also suggests that it is difficult because for everyday practical purposes the world is seen as functioning in a [linear] causal fashion. "Thus, the adequacy of operating at the phenomena level in an everyday world, coupled with the absence of any conflicting feedback from such an operation (such as closing the window to keep the heat out), prevents the students from being aware that their interpretation is limited at some deeper level. Without such knowledge and feedback, there is no motivation for students to seek an alternative [nonlinear] explanation" (Chi, 2000b, p.24).

Further support of this conjecture comes from Resnick and Wilensky who have argued, together and independently, that such misconceptions be considered to constitute the "deterministic/centralized mindset" (Resnick, 1994; Resnick & Wilensky, 1995; Wilensky & Resnick, 1999). They posit that attending to a single level of description, rather than the connections among levels, leads to constraints on our ability to correctly explain emergent patterns of behavior in both physical, chemical, and human organizational processes (e.g., birds flocking, gas equilibration, traffic jams). They assert that a possible explanation for this predilection is our commanding but myopic human experience as "active planning and designing agents in the world. Yet most of the natural world is composed of agents with much smaller capacities – agents that do not have enough neuronal capacity to conceive of a plan or enough bandwidth to communicate it to conspecifics." (Wilensky, 2001, p. 3). I add to the argument that we tend to anthropomorphize these behaviors, perhaps because of our limited experience with these types of agents, or perhaps because of an innate psychological behavior left over from childhood where human traits are used to explain inanimate objects (Vosniadou, 1989).

Yet another weakness of human cognition is proposed, that is, our inability to reason about multiple operations of very large numbers of entities. Wilensky (2001) states: "Because of our experience as agents and our inability to attend to large numbers of factors or long periods of time, we do not usually have significant opportunities to develop robust intuitions about how emergent phenomena arise and maintain themselves" (p.3).

2.6.2 Summary of Identified Challenges to Learning About Emergent Processes

To summarize, Chi (2000) identifies three inter-related barriers to understanding the ontological category of emergence. First, novice learners treat macro level behavior as the linear sum of causal events (lack of nonlinearity understanding). Second, learners fail to consider the interactions between agents at the micro level (lack of local interactions understanding). Third, learners fail to understand that the macro level emergent behavior is the result of the *collective* interaction of agents *and environment* - "interactions in dynamic collections" (lack of emergent process).

Resnick's and Wilensky's work, together and independently, have echoed these three common lacks of understanding as well added the observation of the deterministic and centralized mindset that guides our thinking and reasoning about emergent phenomena (Resnick, 1994; Wilensky & Resnick, 1995; Wilensky, 1993; 1995; 1997; Wilensky &

Resnick, 1999). Additionally, recent work by Wilensky's team (Stieff & Wilensky, 2002) supports that there is an over-attribution of static properties to emergent processes.

I argue that these studies, along with Jacobson's (2000) expert-novice categorization, support the contention that non-scientific attributions may be articulated into the following six categories of habitual assumptions, and studied as such:

- Isomorphic behavior at both macro and micro levels (i.e., reductive bias or non-awareness of emergence);
- Centralized control assumption;
- Single causal explanation of macro-level behavior from micro-level interactions (i.e., additive, linear);
- Determinacy assumption;
- Intentionality (i.e., teleological, anthropomorphic); and,
- Static outcomes to processes assumption (e.g., beginning-end processes).

2.7 The Status of Research on the Teaching of Emergence and Complexity

At least two major questions rise out of the body of literature described above. One is explicitly theoretically based and relates to the practical efficacy of Chi's model of conceptual change. The second is related to the mechanisms and instructional strategies that may lead to the development of understanding emergent causation. In essence, the two practical questions may be posed: First, can experiential training related to the emergent ontological category facilitate conceptual change (conceptual change defined as a shift in causal explanations)? Second, how else can we come to learn and think about complex systems emergence?

To date, only one known study has attempted to answer the first question, while the second has drawn attention from a handful of researchers exploring the possibility of using modelling and simulation with varying levels of affordances to learn about emergence (Azevedo, Seibert, Guthrie, Cromley, Wang, & Tron, 2002; Bloom, 2001; Colella, 2001; Hmelo, Holton, & Kolodner, 2000; Klopfer & Colella, 2000; Klopfer & Um, 2002; Penner, 2000; Wilensky & Resnick, 1999; Stieff & Wilensky, 2002; Wilensky, 1999; Wilensky & Reisman, in press; Wilensky & Stroup, 2000). In oder to situate this current study, I will briefly describe the revelant studies.

2.7.1 An Empirical Study on Teaching Emergence

So far, the only empirical study which supports of Chi's theoretical account of conceptual change was conducted by Slotta and Chi (1999). Slotta examined the effects of a training unit composed of a self-designed computer simulation of dynamic systems related to the diffusion of gases. Using a pretest and posttest experimental design, Slotta randomly assigned 24 university undergraduates with no science background to one of two treatment conditions (experimental and control). There were two sessions of approximately two hours each. The first session presented the ontological training module while the second was intended to provide the science content, transfer material. The training module consisted of computer simulation and text covering four attributes of air expansion and liquid diffusion considered to be an example of "equilibration processes": (1) no clear cause and effect explanations, (2) system of interacting components moving towards equilibrium, (3) combined effects of many smaller processes occuring simulataneously and independently, and (4) no beginning or ending of the process. During the training sessions prompts were used to ensure that students were paying attention to the important parts of the text.

After the training session the subjects were administered both near (air expansion and diffusion questions) and far transfer (predator-prey populations) questions to determine their comprehension of the text and asked to apply the four newly learned attributes to these questions. The test items were muliple choice "problems" on the subject of electric current based on previous work by Slotta et al. (1995).This distinguished between those who could transfer concepts of the text and those who did not.

The control group received the same content on diffusion but no ontological training. The next phase of the experiment provided the students with specially prepared text on electricity based on a conventional physics textbook but with the water analogies removed. The experimental group was cued to transfer by being told: "they would be reading about another example of an equilibration process" (p. 21).

Results from the experimental group showed significant pretest and posttest gains $F(1,22) = 6.8$, $p = 0.02$. In order to tease out the differences between those who understood the material from those who did not, the experimental group was split into high and low scorers on the training posttest. The interaction of test scores with this group was also significant, $F(2, 21) = 13.8$, $p = 0.00$. Further sorting of the data provided better explanations of the findings, which revealed that students' improvement in problem solving was directly dependent on their understanding of the training.

Slotta also collected verbal protocol data, which was analyzed using the predicate analysis technique developed in Slotta et al. (1995). Novice explanations included the following substance predicates: moves, supplied, qualified, rest, absorbed, consumed. He also identified six expert predicates: system-wide, movement process, uniform state, equilibrium state, simultaneity, independence. These coding and scoring techniques are described more fully in chapter 3 of this dissertation. The comparison of pretest posttest use of predicates also supported a change due to the training. There was a significant increase in the process predicates $F(1,10) = 31.04$, $p = 0.000$ with a decrease in the substance predicates $F(1,10) = 20.17$, $p = 0.001$. A further refinement in the analysis revealed the same clarification between those who understood the training material and their shift of explanation to the process based ontology. Slotta concluded by stating that:

> Thus, a seemingly tangential training about an ontological category has yielded dramatic results in terms of qualitative reasoning (problem solving and explanations) in another domain (in electricity concepts) that reflects 'far transfer' or deep conceptual change (Slotta & Chi, 1999, p. 29).

2.7.2 Using Models to Teach about Emergent Causation

Papert (1980) asserts that our culture is rich in pairs, couples, and one-to-one relationships, however, it is poor in publicized models of systemic procedures. In fact, he states: "Anything is easy if you can assimilate it to your collection of models. If you can't, anything can be painfully difficult" (Papert, 1980, p. vii). Models, specially computer-based models (e.g., exploratory modeling at described by Wilensky & Resnick, 1999) have proven to be powerful at reifying certain concepts and thereby supporting certain types of learning. Details of three such studies are presented below.

2.7.3 Using Physical Models to Teach About Complex Systems

Hmelo et al. (2000) studied 6th grade students understanding of the respiratory system using a design approach and building partial working models of the lungs. This study shed light on the many *affordances* for promoting deep learning of systems. They adopted a Structure Behavior Function model to both describe the system as well as code the learners' mental models (based on SBF theory - posited by Goel & Chandrasekaran, 1989). Their results provided evidence that students in the experimental group had a small but significant increase in their attending to structural relationships. Their understanding also became more rich, demonstrated by the number of relationships mentioned and their thinking of how the system worked. However, the students did not mention function as frequently and mentioned behavior least of all. These results were not unexpected, in fact, these researchers anticipated that the causal behaviors would be more difficult to observe because they happen at an invisible level and involved the understanding of dynamic relationships.

The significance of their research is providing evidence that supports my contention that understanding of complex systems' behavior is possible, in that case by 6th graders. However, it confirms the value of instructional tools with greater affordances for demonstrating emergent processes.

2.7.4 Computer Based Modeling Environments

As previously stated, the research teams of Wilensky and Resnick have conducted many qualitative studies of the affordances realized by different versions of their multi-agent modeling languages (StarLogo, Resnick, 1994; StarLogoT, Wilensky 1997; and the subsequent simulation models of NetLogo, Wilensky, 1999; and, currently ChemLogo). Although the study described below took place after my research was in progress, I present it as an example of one of the few structured inquiries of this particular modeling tool.

Stieff and Wilensky (2002) examined six undergraduate science majors' understanding of the process of chemical equilibrium when using a modeling and simulation package called ChemLogo. This modeling environment is embedded in NetLogo, which may be considered the next generation derivative of StarLogo. The intervention consisted of a three-part 90-minute interview during which the students were asked to first explain their understanding of the Le Chatelier's Principle in chemistry, then during their observations and interactions with the simulation explain the behavior of the molecules that were realizing the behaviors described by this principle; followed by the opportunity to reflect on their reasoning.

Observations reported describe a shift from formulaic problem-solving approaches and rote memorization (which were exhibited in part one of the 90-minute interview), to attempts at conceptual reasoning and justification of answers during and after using ChemLogo. The authors identified four distinct categories of observed changes: (1) defining equilibrium for a chemical system, (2) characterizing factors affecting equilibrium, (3) transitioning between submicro-, micro-, and macro- levels during problem solving, and (4) fluidly moving between various forms of symbolic representation at all three phenomenal levels. The report featured one student's (Andrew) experience and identified a change in his ability to explain and correct his predictions. He was able to deduce correctly how the micro-level events result in phenomena at the macro-level, a change that provided him with greater confidence to deduce other more accurate and reasonable answers.

2.7.5 Emergent Process Models – *Life*[9]

Penner's (2000) study looked at the development of four 6th graders engaged in a nine week after-school instruction investigating emergent properties using the computer simulation *Life* and 'talus slope'. Using a case study approach allowed him to closely investigate the changes in the students reasoning. He focused on three issues related to how these students come to develop ways of thinking about emergent systems: (1) How did they achieve an understanding of the patterns that develop? (2) Did they recognize that no primary causal factor was necessary? (3) Did they come to distinguish between micro- and macro-levels of descriptions? (4) How did they explain the effects of small changes on the resulting development? Resnick's (1994) framework related to issues of centralized versus distributed control (i.e., "lead" or "seed") were used to code the verbal protocols.

The importance of Penner's study was the confirmation that a formal taxonomy based on causal mechanisms could be used to code verbal protocols effectively (Penner (2001) used Resnick's conjecture of a "lead" or "seed" attribution). Secondly some of his participants did begin to experience a shift toward emergent causal explanations.

2.8 Research Questions Pursued in this Study

There is reasonable evidence to support the proposition that appropriate dynamic models afford better opportunities for certain types of scientific learning . Specifically, there is some evidence that computer models such as those made with StarLogoT support the construction of an understanding of emergent processes. To date, inquires about the effectiveness of models of emergent phenomena have been limited in scale (i.e., small numbers) and time (short duration). Moreover, with the exception of Slotta and Chi (1999) researchers have not used a global approach to coding, nor have they specifically

[9] As a classical example of emergent processes from simple automaton programming, Life could be played both as a paper and pencil game or on the computer.

linked the affordances of the models to subsequent of conceptual change. I argue that this current study therefore is addressing and closing some of these gaps in the literature by focusing on the following questions related to these issues.

2.8.1 Research Question – Study 1

Does complex systems instruction facilitate the construction of emergent framework mental models as demonstrated by problem-solving abilities (use of expert-like emergent explanations) applied to questions that are representative of phenomena with emergent characteristics?

2.8.2 Research Question – Study 2

1. Based on the results of Study 1, the questions arising were:

   a) Does a longer duration ontologically-based intervention support a different learning experience as demonstrated by more elaborated emergent framework mental models?

   b) Does this intervention increase the transfer of the emergent causal framework to a wider range of ontologically analogous problems?

   c) What are the effects of time on this content knowledge and the students' ability to perform these transfer tasks (i.e., ecological validity)?

2. The literature above tells us that there are barriers to understanding phenomena belonging to the ontological category of emergent causal processes. Therefore, if provided with appropriate content and learning environments, what do students' experiences tell us about acquisition of this content knowledge?

a) Which of the ontologically-based concepts are more susceptible to change, as demonstrated by changes in vocabulary, explanations, and heuristic model employed (i.e., evidence of a shift in ontological framework)? For example:

- Isomorphic behavior of both micro and macro levels behaviors (i.e., reductive ontology) *to* non-reductive ontology (emergent self-organizing ontology);
- Centralized control *to* distributed or decentralized control (decentralized control);
- Linear causal explanation of macro-level behavior from micro-level interactions (i.e., additive, linear) *to* multiple nonlinear causal explanations (nonlinear effects).
- Determinate causality *to* indeterminate causality (random actions);
- Intentionality (i.e., teleological) *to* stochastic causes (i.e., probabilistic causes);
- Static processes (i.e., beginning-end processes) *to* dynamic homeostatic behaviors (dynamic nature).

b) What are the affordances of StarLogoT (and possibly other multi-agent modeling language generated simulations) for promoting the learning of emergent causal processes?

c) What role do cognitive scaffolding and other metacognitive support play in this learning process?

3. What are the practical considerations related to using an ontologically-based intervention to facilitate conceptual change? Specifically, what does this tell us about the usefulness or limitations of these types of models as tools for acquiring emergent framework mental models?

CHAPTER 3
MENTAL MODEL CODING TAXONOMIES

Mental models are internal mental representations that allow human beings to apprehend the world. They are believed to be the mechanisms used to support problem solving, reasoning, and prediction (Johnson-Laird, 1983). In turn, researchers attempt to understand and make public internal processes, particularly higher-order thinking, problem-solving, transfer of learning, and conceptual change, by drawing inferences from the learners' words and deeds, and by describing the products of these activities as representations of learners' mental models (e.g., Azevedo, Seibert, Guthrie, Cromley, Wang & Tron, 2002; Cavallo, 1991; Chi et al, 1994; Gentner and Stevens, 1983; Jacobson & Archodidou, 2000; Mason, 1994; Monaghan & Clement, 2000; Taber, 2001; Vosniadou & Brewer, 1994). The mental representations as used by these researchers (as well as this current study) should not be confused with the actual internal mental model employed by the learner (i.e., Johnson-Laird's perspective).

Once mental representations are elicited, the researcher is faced with the task of inferring meaning and learning through identified changes in the representations. This is accomplished through the process of coding the data collected according to some *a priori*, or otherwise generated, coding schema. The intention of this chapter is to describe the development of the specialized coding taxonomy employed in this study as well as the procedure used to code and analyze the data.

3.1 Issues Related to Mental Models Coding and Analysis

3.1.1 Overview of Mental Models

There is still controversy over whether mental models are temporary structures constructed as needed, manipulated, then discarded when a conclusion is reached (Johnson-Laird, 1983; Norman, 1983); or, whether mental models are partly or wholly stored in long term memory and therefore are relatively stable structures that can be modified, elaborated and changed (in Gentner & Stevens, 1983; Vosniadou & Brewer, 1994). This present study takes the latter perspective. Addressing this position, the major assumptions are: (1) that mental models can be incomplete (i.e., are constructed differently by novices and experts), and (2) that mental models are evolving, (i.e., can be changed).

Linking Mental Models to Expert-Novice Research

The claim that learners' mental models are qualitative and exhibit levels of completeness is supported by the expert-novice literature (several citations in Chi & Glaser, 1988). Chi, Feltovich and Glaser's (1981) seminal study of expert-novice problem representations (mental models) in physics established particular characteristics of expert models not found in novice problem solvers. In essence, their study reported several findings: (1) that mental models are contextual and constructed within the constraints of the activated schema, therefore they are shaped by the initial categorization process and, (2) the completion of the model constructed is based on the content knowledge available to the problem solver. Hence, experts are individuals who correctly categorize problems and have a wealth of content knowledge with which to build their problem representation (mental models). DiSessa (1983b) also discusses the difference between experts and novices as the difference between using "common sense and scientific reasoning" - not so much the "content in knowledge, but rather its organization" (p. 32).

Idealized mental models. Voss, Vesonder and Spilich (1980) conducted groundbreaking research pertaining to an idealized mental model. By first establishing a set of necessary "tokens" to describe a half-inning of baseball (expert models), these authors determined students' grasp of the game (naïve models) through the models generated. More importantly, Voss et al. (1980) had constructed an expert model that could be used to describe any sports activity. This general application mental model was a significant development, one that is sought after in other disciplines such as science education. In essence, the assumption of this area of research is that there is an objective scientific explanation of natural phenomena (i.e., veridical scientific explanations) and that an expert is someone whose mental model, created to explain those phenomena, is nearly isomorphic to the consensus of accepted theories of the scientific community.

Evolving Mental Models

Mental models identified in Borges' and Gilbert's (1999) study appeared to evolve over time. Several dimensions to this pattern of change were identified that included: (1) change in the scope and limitation of the models; (2) change in the definition of basic notion; (3) adoption of a richer vocabulary; and (4) a move toward use of more abstract notions and the parsimonious introduction of new entities. Therefore, the development of the mental model goes toward greater consistency and completeness and becomes less context-dependent. In fact, the experienced practitioner masters the specific vocabulary of the domain, and construct less differentiated concepts.

This is in keeping with Vosniadou's position on development of mental models (Vosniadou, 1994; Vosniadou & Brewer, 1994). Her work in the field of conceptual change is predicated upon the assertion that there are three stages: (1) no formal knowledge (i.e., initial mental model), (2) misconception when models interact (i.e., *synthetic* mental model), and finally (3) true understanding (i.e., scientific mental model). Jacobson and Archodidou's (2000) research also identified several distinct stages of mental model development over the course of a two-part study on the topic of evolution. The empirical data supported the position that mental models were not only characterized as stages but also show evidence of change as a result of instruction and not merely maturation.

The mechanism of change. Although we do not yet know how, there are several speculations as to how mental models are modified. Borges and Gilbert (1999) posit that there is a change in the individuals' reasoning and explanatory capabilities. Learners move from focusing on the unproblematic and salient objects, to considering the interactions between these objects and the internal structures that arise from the interactions. "It appears that only with deliberate instruction can learners come to adopt more sophisticated models" (Borges & Gilbert, 1999, p.111). This statement may be too broad to be without challenge; however, Borges and Gilbert are not alone in the contention the certain categories of concepts require greater cognitive attention. Hence, this is in line with Vosniadou's metaconceptual awareness principle (Vosniadou, 1994), diSessa and Sherin's adjustments in readout strategies (diSessa & Sherin, 1998), and Chi and Slotta's purposeful shifts in ontological assignment (Chi 2000; Slotta & Chi, 1999). This current study therefore assessed the mental models of the participants based on those identified criteria.

Constraints on Changing Mental Models

Vosniadou (1994) defines mental models as an analog representation generated during cognitive functioning, while preserving the characteristic structure of the thing it is to represent. The unique feature of Vosniadou's description is found in her description of how mental models are generated. She asserts that mental models are drawn from the underlying knowledge structures of "specific theories" and "framework theories". In fact, "understanding the generic mental models individuals use to answer a variety of different questions related to a given concept can provide important information regarding the framework theories and specific theories that constrain the knowledge acquisition process" (p. 48). As these framework theories are refined, it allows for the generation of new mental models that are better mediators of incoming and outgoing information. As powers of observation improve, so too does the explanatory capacity, and this feedback process continues to refine the mental model until the learner develops a scientific mental model stage. She proposes an iterative process in which mental models interacting with each other can constrain the knowledge acquisition process in much the same way as beliefs and presuppositions.

The idea of constraints is also outlined in diSessa's work (1993b). He introduces the notion of phenomenological primitives, p-prims, which I assert can be viewed as low-level mental models that can provide emergent qualities when they interact. Unfortunately, if the novice does not consciously work toward a reorganization of these explanatory components, these dynamic interactions create explanations that are scientifically incorrect (see conceptual change section for more detail). Both these authors assert that mental models can be changed. This link between conceptual change theories and mental models is an important one for this present research, particularly since evidence of conceptual change was predicated on being determined by the examination of externalizations of mental models developed over the course of the treatment.

Conceptual Models

Mental models should not be confused with conceptual models. Although the literature has many ways of describing mental models (e.g., "problem representations" in Chi, et. al., 1982; "conceptual explanations" in Slotta, Chi & Joram, 1995) there is only one accepted definition of the term conceptual model. Conceptual models are external representations of internal theories. According to Norman (1983) conceptual models are more or less precise and complete representations of the phenomena represented. They are such things as scientific analogies (e.g., electric currents as being like hydraulic circuits), mathematical formulas (e.g., Lotka-Volterra equation: $dn_1/dt = n_1$ ($b-k_1n_2$ and $dn_2/dt = n_2$ (k_2n_1-d) used in predator prey interactions), and computer models (e.g., microworlds such as *Thinker Tools*, icon-based models such as *STELLA* (examples cited in Penner, 2001), to name a few). They are external representations that are shared by a community of practitioners. They are coherent with the accepted practices and knowledge of the community they represent. Indeed, conceptual models may be said to represent scientific knowledge.

Methods of Accessing Mental Models

Although we do not yet know the underlying neuro-physiology of internal mental representations, there are established methods of eliciting and analyzing them. Methods of gaining access to mental models include verbal protocols, pencil and paper problem-solving, audit trails, trouble shooting performance, information retention over time, and observational protocols (e.g., procedural mapping, Royer, Cisero, & Carlo, 1993). Each method has limitations and all are subject to some level of controversy regarding their use of inferential methodologies. In the following passage, I will describe the two methods used in this study.

Verbal protocols. Verbal protocols such as "think-alouds" (Ericsson & Simon, 1984) are used to engage learners in realistic activities then elicit their problem solving reasoning. These methods were used extensively in the research described in Gentner and Stevens (1983). The main drawback with think-aloud methods is that they are highly demanding of both human resources and time, therefore, suited to small case studies but not to large empirical ones or classroom settings (Royer et al., 1993). Another difficulty with verbal protocols is the inability of learners to verbalize all thought processes, their tendency to rationalize behavior, and the potential of unintentional prompting through nonverbal clues from the experimenter (Royer et al., 1993). Another difficulty is that they divide the learners' attention part of the time taking away from the task at hand (Ericsson & Simon, 1984).

Concept mapping. Cognitive mapping is a way of evoking explicitly representations of cognitive structure that are in memory (Shavelson, 1972). Measures of knowledge organization are based on schema theories of learning (Ausubel, 1963; Rumelhart, & Norman, 1976). These theories of associative memory suggest that concepts have conceptual similarity are stored in associative networks. A further assumption of these techniques is that knowledge can be represented as networks of relationships. Royer, et al. (1993) suggest that main weakness of associative knowledge network methods is the subjective nature of their interpretations, therefore their results must be validated through triangulation with other assessment tools.

Ways of Analyzing Externalizations of Mental Models.

There are issues surrounding analysis of mental models that are related to coding methods. One method used most frequently is "content analysis" (e.g., Berelson, 1952; Krippendoff, 1980). It is best described as a frequency count that attempts to generalize from the frequency of words used. The benefits of this method is that it can be generalized across individuals and groups and can be highly automated, particularly with recent software developments such as *NUD*IST* (Non-numerical Unstructured Data * Indexing Searching and Theorizing, trademarks of QSR International Pty Ltd., 2000). The main drawback is its insensitivity to context (Carley & Palquist, 1992). Although this weakness may be offset by a follow up inspection which increases the time spent in total but facilitates the sensitivity to context. This latter method was used to start the coding of transcript data because of the enormous volume of material.

Other methods that are more appropriate but more time consuming are propositional analysis techniques. For instance, Cavallo (1991) used a parsing technique (adapted from Mosenthal & Kinstch, 1992) involving several procedural and explicit steps. First, all written work is transcribe word for word, then all verbs in each proposition were identified, then the remainder of the proposition would be parsed and place on a grid containing "agent", "object", "action", "reference point", and "result". This method parsed the propositions according to both the macro-structure (procedural knowledge) and micro-structure (conceptual knowledge). This technique produced grids of varying degrees of complexity and they were sorted in order of increasing number of different microstructures categories filled in (see Cavallo, 1991, pp. 115-153, for more detail).

Another propositional coding method was developed specifically for ontological coding by Slotta, Chi, and Joram (1995). This technique first establishes taxonomies based on the ontological assertions of "matter" and "processes" (or in Ferrari & Chi 1998, on "events" and "equilibrations"). It then segments explanation protocols into unit sizes of single ideas (generally at the phrase to sentence level). The units are then coded for predicates (verb phrases). Next, the raw frequency of occurrence is counted; these raw scores are later normalized in order to reflect the relative frequency of one predicate over the other.

Both these methods of analyzing mental models data are typical of the systematic and complex considerations that go into this methodology. The threats to reliability are controlled through the employment of multiple raters and by imposing a requirement of consensus among them. Because of the additional mediating factor of human error, the reliability of this additional layer of inference is a valid concern. Consequently, many studies using such methods of analysis have been subjected to severe criticism. In this present study I made multiple efforts to ensure reliability through the use of multiple raters as well as other methods of triangulation.

3.2 Development of the Ontological Mental Model Taxonomy (OMMT)

> The idea of emergence is often contrasted with a reductionist perspective. The reductionist perspective thinks about parts in isolation. It is the often vilified "anti-complex systems" view of the world. However, even the idea of a system is based upon a partial reductionism. To understand this, one should carefully understand the notion of approximation or "partial-truth" which is essential for the study of complex systems.
> Yaneer Bar-Yam (2000)

Bar-Yam's statement identifies one of the many difficulties in understanding, teaching, and assessing the acquisition of complex systems concepts. Such understanding requires both the taking apart of the learners' mental model (i.e., coding into taxonomy categories) to investigate these components, yet also holding them together to appreciate how they interact to produce the emergent quality of learning. In some sense we engage in a partial reductive process when we begin to explore how the study of complex systems can be used for general learning goals such as conceptual change. But we must keep in mind that both the learning process, as well as the subject matter to be learned (complex systems), exhibits emergent properties.

3.2.1 Chi and Colleagues' Coding Taxonomy

Starting with their seminal article, Chi, Slotta, and deLeeuw (1994) identified two major categories to which concepts may be assigned: (1) "Matter", and (2) "Processes" (see Appendix A). The assertion was that the contents of these categories are orthogonal therefore each potentially contains discreet concepts. In this orthogonal arrangement, they described a particular subcategory called "Constraint-Based Interaction", which is identified as having attributes associated with many scientific concepts. In the course of articulating the attributes, Chi et al. (1994) established the beginnings of a coding schema. Based on their theory of conceptual change as ontological reassignment, they enumerated the attributes of the two categories into a taxonomy of predicates (described in Slotta et al., 1995). To test this taxonomy, these authors coded explanations for physics problems obtained from experts and novices. The assumption was that experts, when solving physics problems (heat, light, electrical current), would make greater use of predicates belonging to the Constraint-Based Interaction category, while novices would make greater use of predicates belonging to the Matter category. The results of this original study, as well as several since (e.g., Slotta et al., 1995; Reiner, Slotta, Chi, & Resnick, 2000), supported their contention and confirmed the dichotomy between the two categories as well as the predisposition of novices to miscategorize concepts.

Working toward a theory of conceptual change, Chi (1997), and Ferrari and Chi (1998), refocused on ontological distinctions in the Process category ("Events" processes versus "Equilibration" processes) and articulated six features that differentiate these categories (see Table 3.1). Although the categories were refined and the headings changed (Matter →Events, to Constraint-Based Interactions → Equilibration), the essence remained the same.

Table 3.1 Chi's ontologically based categories (adapted from Ferrari & Chi, 1998).

Events	**Equilibration**
1. Distinct actions	1. Uniform actions
2. Bounded by beginning and end	2. Unbounded, ongoing
3. Sequential	3. Simultaneous
4. Contingent and causal	4. Independent and random
5. Goal-directed	5. Net effect
6. Terminates	6. Continuous

Under the new rubric, features of the events category are best depicted using the metaphor of a baseball game, while equilibrations are described using the process of gaseous diffusion. Ferrari and Chi (1998) suggest that like a game, event processes have distinct parts, the players that perform distinct functions, the different innings, and so on. On the other hand, equilibrations have uniform actions; using the diffusion example, all molecules move according to the same physical laws. Next, events have an obvious beginning and end; the first inning begins the game while the ninth is the expected end (the record is 24 innings). This is contrasted against equilibrations where actions are ongoing; molecules continuously move even when in equilibrium. Next, events occur in sequential order, therefore one thing follows another; first the pitcher throws the ball, then the player attempts to hit the ball, and so on. In equilibration processes this is not the case, in fact, things occur simultaneously; all molecules move at the same time, and have the potential to collide. Another feature is the contingent or causal nature of the events category. For instance, runners advance to home plate only if they cross the other three. Equilibration processes, however, are independent and random; diffusion cannot be attributed to a particular molecule moving in a particular direction. The penultimate feature is goal-directedness, that is, event processes have a purpose, a goal; the objective of the game is to win. Equilibration processes are not goal-oriented; they are instead a product of the net effect of random movement (i.e., the molecules don't aim to achieve equilibrium). The final feature is that events are complete, they terminate when the goal is achieved. The process of diffusion is continuous and dynamic, the molecules do not stop moving even when in a state of equilibrium.

3.2.2 Jacobson's Coding Taxonomy

Jacobson (1999), working on a cognitive theory of complex systems problem solving, developed what he calls a "complex systems mental models framework" to code the responses from participants. His prior research (Jacobson & Archodidou, 2000; Jacobson, Sugimoto & Archodidou, 1996), as well as Vosniadou and Brewer's mental model analysis methodology (Vosniadou & Brewer, 1992; Vosniadou & Brewer, 1994), formed the basis of this coding schema.

Similar to Chi's coding, Jacobson's taxonomy places knowledge representations into two categories identified by differential and diametrically opposite ontological and epistemological characteristics, referred to as "component beliefs", 'Clockwork Set', and 'Complex Systems Set'. In so doing, he first articulates the categories in terms of eight component beliefs: (1) understanding phenomena, (2) control, (3) causes, (4) actions effects, (5) agent actions, (6) complex actions, (7) 'final causes' or purposeful natural phenomena, and (8) ontology. He then describes how these eight beliefs would be played out dependent on which of the two component beliefs is held as normal by the respondent (see Table 3.2). Therefore, someone holding component beliefs identified as clockwork would possess a reductive understanding of phenomena (e.g., step-wise sequences, with isolatable parts); while, a complex systems belief would understand phenomena in a non-reductive manner: the whole-is-greater-than-the-parts.

Turning to the category of "Control", the clockwork view of control is that it is centralized (within the system) and/or externally controlled by another agent (external to the system). The complex system view of control sees it as de-centralized (system interactions). When it comes to assigning causation, the clockwork view identifies single causes, while the complex systems view assigns multiple and recursive causes.

In terms of "Actions' Effects", the clockwork view assumes that small actions produce only small effects, while the complex systems view understands that small actions may produce big effects. The category of agents' actions is described as completely predictable by the clockwork view, and not completely predictable (i.e., stochastic or even random) by the complex systems view. Under the clockwork framework, complex actions are the result of complex rules, while the complex systems framework suggest that complex actions may result from cumulative effects of simple rules.

When it comes to "Underlying Causes", the clockwork view assigns teleological explanations whereas the complex systems view assigns non-teleological or stochastic explanations. Finally, the ontological perspective of the clockwork framework is of static structures and discrete events, while the complex systems framework is of equilibration and self-organized and highly dissipative processes.

Table 3.2 Jacobson's "component beliefs" categories (adapted from Jacobson, 2000).

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) or external agent.	De-centralized (system interactions).
3. Causes	Single	Multiple
4. Actions' effects	Small actions → small effect	Small action→big effect
5. Agents' actions	Completely predictable.	Not completely predictable/ stochastic/random.
6. Complex actions	From complex rules.	From simple rules.
7. Final causes	Teleological	Non-teleological or stochastic
8. Ontology	Static structures/events	Equilibration processes

3.2.3 Comparisons of These Two Taxonomies

A comparison of the two coding schema reveals many similarities although they arise from somewhat different perspectives, one from an effort to build a theory of conceptual change and, the other from an effort to develop a cognitive theory of complex systems. It is reasonable to suggest that because these two schemas both attempt, in part, to reflect the ontological beliefs of the problem solver they would exhibit similarities. What is not so apparent is that many of Chi's category descriptions are similar to items on Jacobson's code, but not in an isomorphic manner. For instance, the description of "distinct actions" is identical in meaning to the definition of "reductive", that is, the component are treated in isolation; however, the description of "uniform actions" and "non-reductive" are not the same. In fact, the description of "uniform action" (as well as the "independent" half of the category "independent and random") is closer to what Jacobson describes as "de-centralized" control. Where the descriptions are isomorphic are for the items "simultaneous" (Chi), which matches that of "small action → big effect" (Jacobson), and "net effect" (Chi), which again is the same as the definition for "non-teleological" (Jacobson). Where the similarity becomes more muddled is for Chi's category items of "unbounded, ongoing" and "continuous", both of which are defined by terms that appear to say the same thing as Jacobson's category of "equilibration processes". To make this point I turn to Ferrari and Chi's (1998) description of both processes: (1) ongoing – "without beginning or end, although an initiating agent external to the concept of diffusion may upset an existing equilibrium (e.g., placing a sugar cube in water)" (p.10), and (2) continuous dynamic – " continuous dynamic interaction and never terminate, even when there is no visible motion. Thus, at the molecular level, molecules are continually moving in turn they the process of diffusion" (p.10).

In summary, I contend that Jacobson's coding was a major advance in clarifying the ontologically based category items identified by Chi and her colleagues. Furthermore, by attaching these category items to the concepts of complex systems his code is grounded in a theoretical framework that has room for expansion. Both these perspectives have guided my efforts in refining this coding schema.

3.2.4 Phases in Developing the Ontological Mental Model Taxonomy (OMMT)

First Phase in OMMT Development

Using a process-based method of iterative stages, I refined Jacobson's Complex Systems Component Beliefs scale (henceforth referred to as ontologically-based to distinguish it from the other coding schema based on complex systems components). Starting with his data analysis results[10], which tested the reliability of the coding schema

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[10] Jacobson's (2000) used the statistical test of Cronbach alpha to evaluate the reliability of this CSMM taxonomy. He reported a reliability alpha of .76 and .72, for the clockwork category and complex systems category respectively. The correlation matrix and the inter-item statistics for each scale were examined. The reliability alpha for the complex systems scale was improved when several items were removed resulting in a scale made up of five variables: non-reductive, decentralized, multiple causes, randomness, and equilibration processes. These variables produced item-total correlations between .55 and .79, and an overall reliability of .85. The clockwork scale was also revised to include the following variables: reductive, centralized, small actions-small effects, and predictable. These variables produced an item-total correlation between .45 and .87, with a reliability alpha of .81. When compared statically, the two scales produced a significant negative correlation of $r = -0.57$ ($p = 0.02$). Significant correlations were also found between the two component beliefs scales and complex systems concepts. Complex systems component beliefs and complex systems concepts, $r = 0.94$, $p = 0.000$; and, clockwork component beliefs and complex systems concepts, $r = 0.64$, $p = 0.008$.

as an assessment taxonomy, I modified the original grid by removing the items that produced non-significant results. From eight items the grid was reduced to five: (1) Understanding Phenomena (reductive – non-reductive), (2) Control (centralized – de-centralized), (3) Causes (single cause – multiple causes), (4) Agents' Actions (completely predictable – not completely predictable), and (5) Ontology (static structures – equilibration processes). With data collected for the "ant" question I coded[11] the responses using the five-item grid. After the first round of coding I immediately uncovered the need to replace the item "Actions' Effects", thereby bringing the number of items up to six. Jacobson's statistical correlations had yielded a reasonably high reliability for the item "small actions →small effect" on the clockwork scale therefore this replacement was reasonably supported by the testing. Based solely on these piloted data, I decided to also reintroduce the category items of "Final Causes" (but changed the word 'final' to 'underlying') to make a seven-item coding taxonomy.

Using the OMMT taxonomy. Using the seven-item coding taxonomy I engaged in training another rater to code the pretest and immediate posttest data collected for the Ant question (Study 1). A subset of responses was coded (70 out of the 280 responses – pretest = 25 experimental group only, plus posttest = 25 experimental group + 20 control group). The inter-rater reliability yielded a reliability coefficient of .75. Inconsistencies were resolved through discussion between the raters. However, this low reliability coefficient and the subsequent discussion revealed some limitations to the taxonomy. The major difficulties were the overlapping category descriptions, as evidenced in the discussion above relating to Chi's categories exemplars. These category items needed further refinement that would take place in the second study when more detailed answers were provided to the questions.

Second Phase of OMMT Development

The second round of development used a slightly different approach. Informed by the qualitative literature on coding methods, my aim was to construct a coding taxonomy that would enable explanation of all the data. To accomplish this task I returned to the

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[11] This testing of coding was conducted on data collected from a pilot run of questions (June 2000).

complex systems literature, particularly Holland (1995) and using responses from experts for the same four complex systems questions, I began the development process by first expanding the coding grid (Table 3.3). The category headings were also modified in an effort to reflect this wider perspective on representing ontological beliefs held by experts on emergent behaviors (i.e., those behaviors exhibited by complex systems) thereby producing a coding grid based on the following identifying behaviors: Agent's behavior, Agents' interactions, and Agents' – System interactions, and Systems behaviors. This coding was comprehensive and enabled explanation of all the data, however there was a great deal of redundancy. For example, the independent/competitive behavior of the individual agent, at the system's level can also be described as decentralized control of the system. What appeared to be a problem in clarity was in reality a feature of complex systems called the complexity profile, which relates to the mathematical notion of information needed to describe the system. However, it is an apt metaphor to explain the difficulty of building a taxonomy to code for the concepts of complex systems. Bar-Yam (1997) describes this conundrum in the statement: "The complexity profile must be a monotonically falling function of the scale. This is because the information needed to describe the system on a large scale must be a subset of the information needed to describe the system on a smaller scale – any complete finer-scale description contains the coarser-scale description" (p. 14).

Thinking that perhaps the ontological categories identified were insufficient, I tested this hypothesis using the data. Indeed there were more categories but there was more difficulty with consistency in coding. The more I moved toward a complex systems coding grid the further away one got from the initial ontological beliefs. After consultation with the subject matter expert, I made the decision to separate the coding taxonomy into two separate rubrics. One related to ontological beliefs (Ontological Mental Models Taxonomy) and the other related to understanding of complex systems concepts (Complex Systems Taxonomy). This move put me back on track. Hence the final assessments of mental models were made using these two conceptually distinct, although related, coding taxonomies.

Table 3.3 Second phase developments in OMMT coding schema.

Adapted from Jacobson 2000 & Chi 1999	QUESTION: *How would you explain how ants find and collect their food? What rules do you believe they follow?*	
Component Beliefs explaining the behavior of phenomena	*Response Types*	*Coded Response*
Outcome behavior of system resulting from the agents behavior	*Deterministic behavior*	
	Probabilistic/Interdeterministic behavior	
Behavior of agents with the system	*Reductive behavior*	
	Emergent – self organizing behavior	
Organizational Mechanisms of Agents *How do agents organize themselves?*	*Follow complex rules*	
	Follow simple rules: internal models/ building blocks	
Attributes of Agents' Actions *How do agents behave?*	*Actions occur in sequence* (one thing at a time)	
	*Actions occur simultaneous (*in parallel)	
	Actions always predetermined	
	Actions can be random	
Control of System *Where is the control?*	*Centralized*: external to agents (dependence of agents)	
	De-centralized: internal to agents (independence of agents)	
Behavior of System	*Completely predictable*	
	Partly random: (probabilistic/stochastic)	
Properties of System *What is the collective effect of individual agents' actions?*	*Linear*: small actions - small effects	
	Non-linearity small actions –big effects	
Ontological processes of system	*Static structures/ Event processes* (beginning and end)	
	Dynamic equilibrium /homeostatic processes (on-going)	
Developmental Mechanisms of Systems *Role of history? Role of time?*	*Teleological* (purposefully driven by external force)	
	Selection & Adaptation processes (Natural selection/tagging.)	
Complex System Properties	*Flows:* role of feedback (multiplier effect)	
	Diversity: need for variety	

(N.B., Shaded rows represent clockwork mental models - CWMM).

3.2.5 Final Version of OMMT Used in Both Study 1 and 2

The final ontologically-based coding rubric returned to using the five categories identified by Jacobson (2000) as producing a reasonably high reliability alpha ($\alpha = 0.81$). Using the results of the preliminary coding exercise I reintroduced the category of "Final causes" because there were a substantial number of data that "fit" this category and would have been unaccounted for without its presence. The final taxonomy therefore held six categories and represented all the data generated by the outcome measures used in both studies (see Table 3.4).

Table 3.4 Final OMMT schema used to the analyze data produced in Study 1 & 2.

Component Beliefs explaining the behavior of phenomena	**Response Types**	Coded Response
1. Ontological perspective (*understanding phenomena)*	**a. reductive: step-wise sequences - isolated parts, no mention of interaction.**	
Emergent Self-organization	b. non-reductive/emergent: interaction of parts (agents) resulting in patterns or recurring structures at a higher level (system).	
2. Control of System	**a. centralized control (within system) - Each player is given specific and potentially unique rules.**	
Decentralized Control	b. decentralized control (within system): Rules are invariant - All players are given same rules but the interactions change the results.	
3. Actions effects	**a. linear explanations: small actions --> small effects**	
Nonlinear Effect	b. non-linear explanations: small action --> big effect. Inputs and outputs are not proportional and results cannot be assumed to be repeatable.	
4. Agents' actions	**a. completely predictable**	
Random Actions	b. not completely predictable / random / chance. Noise within the system may affect the agent's actions.	
5. Underlying Causes	**a. teleological - purposeful, goal-directed. The end point is determined a priori.**	
Probabilistic Causes	b. stochastic - probabilistic, not goal-directed rather affected by principles of self-organization. The end point is Indeterministic.	
6. Systems' Nature	**a. static structures or event processes: Not dynamic - elements are discreet in time and space.**	
Dynamic homeostatic nature	b. on-going dynamic process that self organize thru flows of information & feedback resulting in a state of equilibrium.	

(N.B., Grey coloured rows represent clockwork mental models - CWMM).

Individual Coding Taxonomies to Code the Specific Questions

The generic coding taxonomy provided structure to guide the coding of any ontologically-based related question. However, the raters being trained to code the material required greater guidance. I therefore developed specific models of both clockwork mental models (CWMMs) and emergent framework mental models (EFMMs), which were used in the final process (see Table 3.5 and Table 3.6)[12].

Table 3.5 Specific taxonomy used to code Clockwork Mental Models (CWMMs).

Clockwork Mental Model (CWMM)	**Components of coding**
Ontological perspective – *Reductive*	1) Agents act in isolation. 2) Simple stepwise description.
Control of system – *Centralized*	1) Orders/controls come from outside. Or is within the system but not attributed to the individual agents within. (e.g., different agents have different rules; mention of hierarchy).
Action effects – *Linear*	1) one thing leads to another. E.g. direct link between controller and controllee. (e.g., action→reaction)
Agents' actions – *Deterministic (i.e., Predictable)*	1) agents' actions are predictable. e.g., they (it) will perform the action. There is no mention of randomness or chance in their actions.
Underlying causes – *Teleologic*	1) the system knows the end point: e.g., it knows it has to survive.
Systems' Nature – *Static*	1) Explicit descriptions of non-changing system.

12 Prototype of emergent and clockwork answers were developed for each question. For examples see Appendix C.

Table 3.6 Specific taxonomy used to code Emergent Framework Mental Models.

Emergent Framework Mental Models (EFMM)	**Components of coding**
Ontological perspective – *Emergent Self-organization ontology* *Question: 1.Does a pattern emerging? 2. Is there a difference between agents and system? 3. What draws the system together?*	1) Local interactions among agents, 2) leads to the creation of something that exhibits a differential behavior than those of the component agents; 3) this interaction is made possible due to some type of identification (tagging device /organizing agent), 4) and, communication (flows of information and/or resources).
Control of system -*Decentralized control* *Question: Who or what initiates the formation of the system?*	1) The individual agents are independent of each other, yet they all operate under the same rules;
Action effects – *Nonlinear effects* *Question: Are there feedback loops within the system? Do they amplify or control the outcome?*	1) Positive feedback is a feature of these systems therefore small actions can exhibit exponential results.
Agents' actions – *Random action (indeterminacy)* *Question: How do the agents behave before they are part of the system?*	1) Agents appear to act in random independent fashion, *Also possibly present in the answer:* 2) Randomness allows for variability and variety within the system.
Underlying causes – *Probabilistic causes (Stochastic)* *Question: Is the same outcome guaranteed each time the system forms?*	1) The system organizes itself based on the interactions of the agents as described above, therefore the resulting structure is never certain, rather it is stochastic which implies that there is a probability based emergent pattern. *Also possibly present in the answer:* 2) Like other probabilistic processes, larger numbers over longer time periods are more likely to result in the formation of normal distributions.
Systems' Nature – *Dynamic homeostatic nature* *Question: Is there movement of the agents within the system?*	Agents may move through, and in and out, of the system, however the system persists in a self-organizing fashion. 1) Once the system, the recurring structure, emerges it exhibits a more stable quality; yet all the component agents have the potential to be replaced by other similar independently operating agents.

3.3 Development of Complex Systems Taxonomy (CST)

The complex systems coding taxonomy expanded on Jacobson's CSMM coding rubric using the complexity literature, particularly Holland's definitions and descriptions of complex adaptive systems. Adapting the qualitative coding process allowed for adding and testing the "fit" of category items on the scale. The final product, although a little lengthy, provided a starting point for future refinement exercises (see Table 3.7. For definitions of terms see p.133).

Table 3.7 Complex Systems Taxonomy (CST).

The theoretical framework for this coding schema is adapted from the study of complexity (i.e., complex systems) and reflects concepts presented by Holland (1995, 1998), Bar-Yam (1997), Kauffman, (1995), and others. It is intended to provide a "Fine Grain" description of the behaviors that emergent phenomena exhibits, therefore most of the overlapping of concepts has been removed.
Basic Understanding and Use of Complex Systems Concepts
1. Local interactions of many individual agents.
2. Simple rules produce complex results.
3. Decentralized control - all players have the same rules therefore absence of centralized controlling agent (I.e., no leader).
4. Random / unpredictable behavior of agents.
5. Tags - allow the agents to select among agents or objects. An organizing mechanism. (e.g., internet header on a message; immune system operation).
6. Flows of information/resources throughout the system using feedback.
7. Internal models - (schemas) gives the agent the power to anticipate - *tacit internal models* simply prescribes a current action/ *overt internal models* uses lookahead protocols.
8. Diversity/ variability - of agents within the system.
9. Modularity (i.e., building blocks).
10. Pattern formation - spontaneous order out of chaos (e.g., Turing patterns, and the work of Prigogine).
11. Systems' nature - generally open systems but can be closed (e.g. gas pressure).
12. Multiple levels of organization
13. Probabilistic/ non-deterministic outcomes - (population size affects the results).
14. Nonlinear effects - (e.g., butterfly effect).
15. Criticality - lever points wherein small amounts of input produce large directed change; threshold effect (e.g., phase changes).
16. Homeostatic - on-going (e.g., dynamic).
17. Adaptation - agent and environment interactions ("*Fitness landscape*").
18. Selection - suitability of the particular trait an agent has for surviving long enough to reproduce in a particular environment.
19. Time scale & history are critical features in development of system.
20. Multiple causality

Purpose and Use of Complex Systems Taxonomy (CST)

The complex systems taxonomy (CST) was used only in Study 2. Specifically, it was used as an *a priori* schema to code the transcript data obtained from the five instructional sessions designed for that study. The CST was used to code the transcripts because it provided the broadest list of categories that could be identified from these data. However, this also meant that once coded, this data set would not be an identical match with the outcome measure data, which was coded to the OMMT.

Comparing the CST categories to the OMMT was accomplished through creation of a temporary equivalence. For instance, by combining the categories “multiple levels”, “local interactions”, “flows” and “tags” these could be compared to the OMMT category of “emergent self-organization”. I contend that the CST was a better tool for coding transcripts because of the fine grain level and better understanding it provided in the exploratory phase of the research. Examining the student’s focus of attention or explanation of the observed behaviors tells us more about how understanding of concepts may have occurred. In essence, it tells us: (1) which concepts may be easily understood, in the process helping to explain the results of this as well as other similar studies; (2) which concepts may be strongly entrenched in component beliefs; and (3) which may not be well represented by the intervention.

3.4 Using the OMMT Coding Schema

3.4.1 Overview of Coding Required in Studies 1 & 2

Data collection measures and methods used in Study 1 and Study 2 generated three different types of data that required different coding measures and techniques. The first data set was produced from outcome measures that enabled assessment of ontologically based conceptual change (i.e., the pretest and immediate posttest from Study 1; and, the delayed and final posttest from Study 2). This analysis necessitated the adaptation and refinement of a specialized ontologically-based mental model taxonomy, OMMT, (Chi et al, 1994; Jacobson, 2000; Ferrari & Chi, 1998; Slotta & Chi, 1999); as well as the modification of a complex systems taxonomy, CST (Jacobson, 2000). Development of the OMMT involved several iterations of the taxonomy. The data were coded with an early version of the taxonomy and later recoded using the final version of the OMMT. Only the results of the final coding are used in this report.

The second data set generated in this study was obtained from the transcripts collected during Study 2 instructional sessions. They called for a qualitative approach to analysis and coding. This method involved the identification of categories emerging from the data themselves, rather than imposing categories on the data. The third data set to be analyzed was the students' concept maps that were scored according to a combined scoring method described in Ruiz-Primo and Shavelson (1996).

In the remainder of this chapter I will describe the issues and processes related to the development and application of the ontological coding schema (OMMT) and the complex systems schema (CST). The two other coding procedures will be discussed in later chapters. Table 3.8 provides an inventory of the data collected in these two studies as well as the coding procedures used.

Table 3.8 List of data collected, data analysis technique, and coding taxonomy used.

Data Collected	When	Data Analysis Technique	Coding Taxonomy Used
Pretest	Study 1	Mental model coding	1. Original Ontological - 2000 2. Revised Ontological - 2002
Immediate Posttest	Study 1	Mental model coding	1. Original Ontological - 2000 2. Revised Ontological - 2002
Delayed Posttest	Study 2	Mental model coding	1. Revised Ontological - 2002 2. Complex Systems - 2002
Final Transfer Test	Post Intervention	Mental model coding	1. Revised Ontological - 2002 2. Complex Systems - 2002
Transcripts sessions	Study 2	Qualitative coding methods (categories, themes)	Categories emerged from the data.
Concept Maps	Study 2	Qualitative coding methods	Combined method (Ruiz-Primo & Shavelson, 1996).

(N.B. Examples of all these questionnaires are found in Appendix F).

3.4.2 Coding and Scoring Procedure Using OMMT

Coding Procedure for Outcome Measures

Informed by the literature, I determined that the most beneficial unit (grain level) to begin the analysis of these data was at the phrase or sentence level[13] (often the entire answer for the pretest was made up of one long sentence). Therefore the raters started first by reading the entire answer, but parsed at the sentence(s) using the following procedure adapted from Mosenthal and Kintsch (1992a, 1992b): identify the verb (action), the noun (agent), and the object (agent effect). Next, using the mental model taxonomy, each parsed statement was coded into one of three possible categories

[13] Chi (2000) found that "because the main interest here lies within knowledge inferences, coding at the grain size of the phrase seems to be more at the knowledge level, and the inference is more sensible" (p. 168).

(EFMM, CWMM, or NM) according to how it answered the following five questions that related to five of the six possible subcategories: (1) who or what is controlling the system – "Control of System"; (2) how do the agents' behave at the start of the process – "Action Effect"; (3) what are the effects of the agent's actions – "Agents' Actions"; (4) what is the underlying cause of the system's behavior – "Underlying Cause"; and (5) how does the system behave – "Systems' Nature"? (see generic coding Tables 3.5; specific coding Tables 3.6, CWMM, and Table 3.7, EFMM; and Appendix C).

The final and sixth category, "Ontological Perspective", was coded somewhat differently. Because of the more global nature of this category, it was the only category to be coded at a large grain level (it was also scored differently, as will be discussed below), that is, the total answer was taken into account, not just each parsed statement. The questioning strategy for this category was composed of four components that required responding to the following: Was there mention of (1) local interaction between agents, (2) identification of some mechanism that would draw the agents together (tags), (3) recognition of a flow of information or resources which creates the system out of independent agents (flows), and, (4) identification of some type of pattern formation as the agents come together to form a system? If there were answers to any of these four questions the appropriate letter was entered. If, however, the students' response did not address these questions, but instead there was evidence of a stepwise (reductive) approach to the explanation, coupled with descriptions of the agents as isolated entities (i.e., no interaction among agents) the answer was coded as CWMM. As before, if neither mental mode applied, then the NM column was coded.

From the initial testing of the coding scales, it was determined that it was easier to code each question twice: once to identify evidence of one mental model (e.g., CWMM), then again to identify evidence of the other mental model (e.g., EFMM). This method produced greater consistency from the raters. To clarify by way of example, rater #1 started coding all 25 pretest responses for evidence of emergent framework mental models (EFMM). He would then repeat the process a second time, coding all 25 pretest answers for evidence of clockwork mental models (CWMM). Rater #2 would by contrast, start coding all 25 pretest responses for evidence of CWMMs, then repeating the process, code for evidence of EFMMs. This method addressed possible threats of an "order effect" from the coding procedure.

Scoring Procedure

All the data derived from the ontologically-based mental model coding were scored according to a binary method (1 or 0) thereby indicating evidence (1) or no evidence (0) of a particular mental model. Although Slotta et al. (1995) discuss the resulting loss of sensitivity[14] due to the inability of this method to distinguish the relative frequency of a predicate (mental model), in this study, it was not a major consideration due to the small number of idea units elicited from the written protocols (pretest and immediate posttest, Study1). However, clarity was of utmost importance in coding and determining what was sufficient evidence of a particular mental model, hence, the decision to use binary coding to distinguish among one of three possible states of mental models: (1) EFMM, (2) CWMM, or (3) NM. Scoring of the "Ontological Perspective" category was somewhat different. Each of the four subcomponents in the EFMM category earned 1 point if present. Therefore this category had a maximum score of 4 points[15].

3.4.3 Inter-Rater Reliability

The question of reliability was addressed by having three raters (rater #1 = a biology graduate student, the primary rater for the final coding, rater #2 = the biology subject mater expert, and rater #3 = myself). All raters coded the delayed posttest responses, however, only raters #1 and #3 coded the pretest and immediate posttest. Additionally, only raters #2 and #3 coded the final posttest, post intervention questions.

The training of the raters took approximately 60 minutes and they were provided with a coding key (see Table 3.6, and 3.7). The inter-rater reliability was established by comparing the individual coding of two raters for the pretest and immediate posttest data.

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[14] Slotta, et al. (1995) in reference to the loss of sensitivity state: "this measure, although still yielding the same basic results, robbed the analysis of any sensitivity to differences between or patterns within the use of different predicates" (p. 386).

[15] The exception to this scoring was the final posttest questions, which were not broken down into subcomponents for the "Ontological Perspective" category, therefore the maximum score was "1".

The number of total responses (25 pretest, 45 immediate posttest) was multiplied by the number of categories to be coded, then by the number of possible mental model stated (EFMM, CWMM, NM). Differences between raters were counted as the raw number of cells that were different. Therefore, if one coded a category as EFMM while the other coded the same category as CWMM this was counted as 2 changes.

On the pretest scores there was agreement on 418 out of 450 scores yielding an inter-rater reliability coefficient of 0.93. On the posttest scores there was agreement on 806 out of 846 scores, yielding an inter-rater reliability coefficient of 0.95. The delayed posttest for the case study (on the ontological mental model taxonomy) produced agreement on 140 out of 162 scores, yielding an inter-rater reliability of 0.86. Inconsistencies were resolved through discussion between raters until consensus was reached.

PART I – STUDY 1

Too often, for practical purposes and as well as to maintain control of experimental conditions, the designs of many educational and cognitive science studies have been pretest posttest studies; metaphorically equivalent to a cognitive "snapshot". However, recent literature tells us that the trajectory for cognitive competencies such as transfer, scientific reasoning, and most likely conceptual change, require considerable time (e.g., Bransford, Brown & Cocking, 1999; Hmelo-Silver & Nagarajan, 2002; Kolodner, 1983; Vosniadou, Ioannides, Dimitrakopoulou & Papdemetriou, 2001). This perspective informs my epistemological view on learning, therefore it was important to select a research design that allowed for both assessment of change (i.e., the snapshot) as well as conduct an extended observation of the learning process (i.e., a two year longitudinal study). In this chapter I will describe study one – the short-term assessment of change – that was the first phase of this two part mixed method inquiry.

Overall Research Design

Creswell (2002) describes three models of mixed method designs, two of which were used in this study: (1) the "explanatory mixed method design", and (2) the "exploratory mixed method design". The former – also referred to as a two-phase model (Creswell, 1994) – relies on collecting quantitative data followed by qualitative data to explain findings from a phase one study. The exploratory design model, on the other hand, collects qualitative data to explore a phenomenon and then proceeds to explain identified relationships through quantitative hypothesis testing.

Using Creswell's description, it may appear that this dissertation study more closely follows the explanatory mixed method design. However, given the relative state of the literature I needed to first address an issue that confronts all forays into less charted territory – is it worth the journey? Consequently I began the inquiry with an experimental research design – referred to as *Study 1*. The data from this study was analyzed using a mental model coding taxonomy adapted from the literature (e.g., Ferrari & Chi, 1998, and Jacobson, 2000). Armed with this knowledge I constructed the intervention and research design for *Study 2*, a longitudinal qualitative case study (see Figure 4.1).

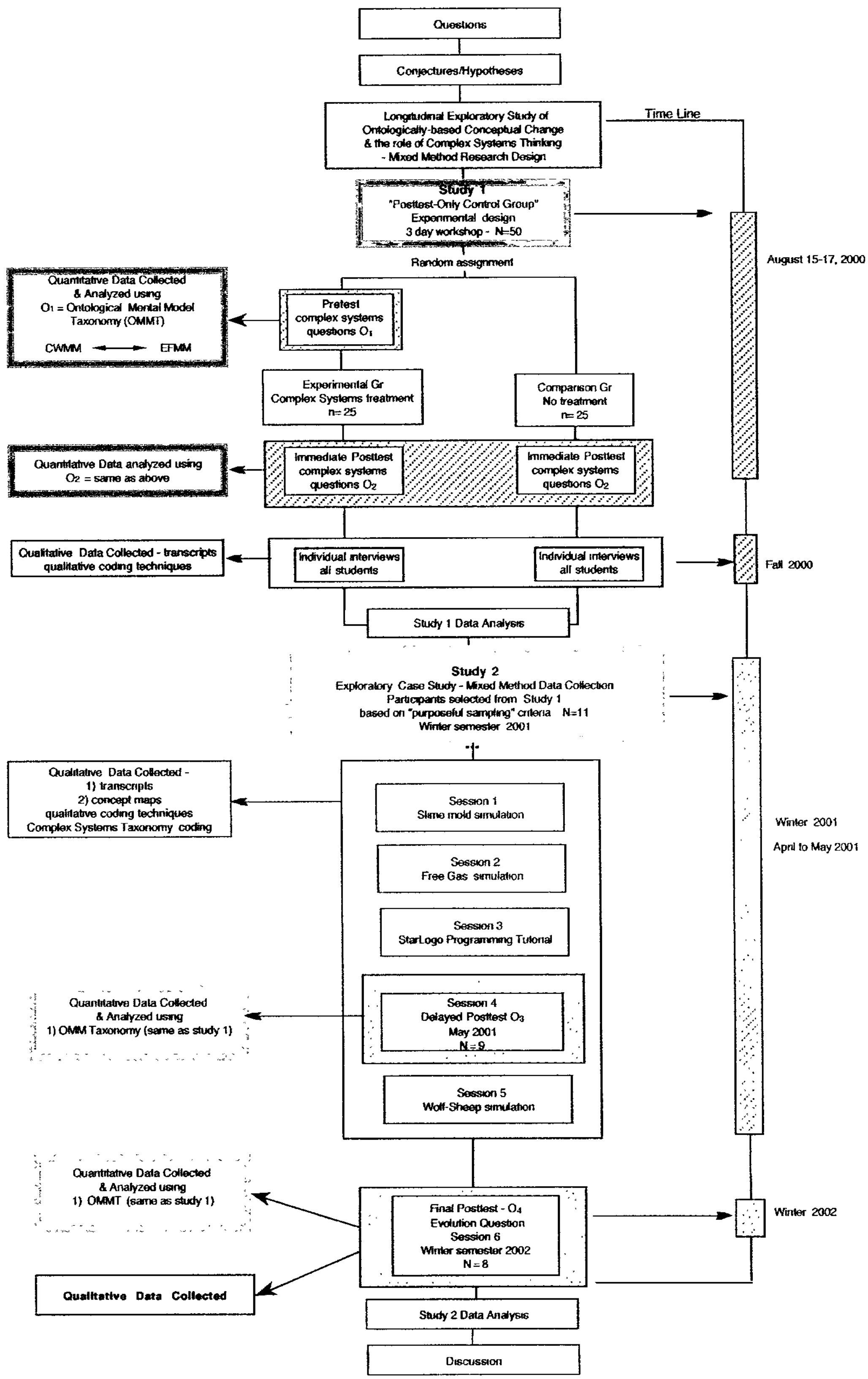

Figure 4.1 Overall view of the research design for studies 1 and 2.

CHAPTER 4
RESEARCH METHODOLOGY

4.1 Research Question and Hypotheses Being Tested in Study 1

Research Question: Does complex systems instruction facilitate the construction of emergent framework mental models as demonstrated by problem solving abilities (use of expert-like emergent explanations) applied to questions that are representative of phenomena with emergent characteristics?

Hypothesis 1: Students in the Complex Systems treatment condition [IV] would outperform students in the comparison condition by constructing a greater number of explanations, categorized as emergent framework mental models (EFMMs) [DV], when solving the near transfer problem of "emergent organization" (Ant colony food collection). By contrast, students in the comparison condition (i.e., no treatment) would outperform students in the Complex Systems treatment condition by constructing a greater number of explanations, categorized as clockwork mental models (CWMMs), used to solve the same problem.

Hypothesis 2: Students in the Complex Systems treatment condition would outperform students in the comparison condition by constructing a greater number of EFMM explanations to solve the far transfer question (Robot mining). By contrast, students in the comparison condition would construct a greater number of CWMM explanations to solve the far transfer question (Robot question) compared to students in the Complex Systems treatment condition.

Hypothesis 3: After treatment, posttest students in the Complex Systems condition would use more emergent explanations (EFMMs) to solve problems that are categorized as "emergent" phenomena than before treatment. On the other hand, after treatment, they would reduce the number of clockwork explanations (CWMM) used to solve the same problem.

4.2 Research Design

Study 1 used a "Posttest-Only Control Group Design" (see Figure 4.2). This design was selected based on its controls for confounding effects of a pretest on the control group data (Campbell & Stanley, 1966). The dependent measures for this study were Emergent Framework Mental Models (DV1) and Clockwork Mental Models (DV2). These two dependent variables are most often referred to by their acronyms EFMMs and CWMMs respectively. Although not a dependent measure, the category created to accommodate the lack of codeable evidence, No Model (NM), is described as a characteristic of the participants' performance (or lack of performance).

Experimental Design Study 1				
Experimental	R	O_1	X_1	O_2
Comparison	R			O_2

(R= random assignment; O = observations; X = treatment).

Figure 4.2 Research design for Study 1.

4.3.Participants

The final number of participants (after attrition) was 45 students[16] (N=45; 26 women and 19 men) entering their freshman year in the Science Program at a Quebec College CEGEP (equivalent to grade XII). Ages ranged from 16 to 18 years. Recruitment was accomplished through an announcement flyer added to the orientation package sent out to all 500 incoming Science Program students (see Appendix E). Participants were not paid, however, the incentives were (1) catered lunches during the three-day

[16] Attrition: Sixty-six students responded to the request for volunteers. Attendance was confirmed through mail-back portions of the recruitment letter or email. Fifty-two confirmed and attended the first day session. Seven did not complete the study, and five did not hand in the consent form. They are not reported in the number of participants.

workshop, and (2) opportunity to win over 20 small raffle style prizes drawn periodically throughout the course of the study.

Twenty-three of the participants (51%) were registered in the Health Science program and 22 (49%) were registered in the Pure and Applied Science program. The program that was followed was significant only in that it determined the semester in which the participant was eligible to take Biology NYA (the general biology course that introduces most students to the topic of evolution). Thirty participants (66%) had taken biology in high school, while the other fifteen (34%) had not. All participants had some experience using a computer prior to the start of the study. In a self-report from the demographic questionnaire (see Appendix F), based on the three levels of high, medium and low computer skills, 13 students (28%) classified themselves as having a high level of computer skills, 24 (53%) as having a medium level, and 9 (19%) as having a low level. On the question of language of instruction, 31 students (69%) had attended high schools in which English was the primary language of instruction, while 14 students (31%) had attended high schools with French as the primary language of instruction.

Participants were randomly assigned to one of two treatment groups, the complex systems group (n =26, 12 Health Science, 14 Pure & Applied Science) and the comparison group (henceforth called the control group) that received no treatment, a placebo, (n =26, 15 Health Science, 11 Pure & Applied Science). Students who dropped out or did not return the consent forms were not included in the results. No attempt was made to equalize the group sizes after attrition therefore final group sizes were experimental group (n=25), comparison group (n=20).

4.4 Instructional Materials

The instructional materials developed for this study combined both lecture and computer lab activities. The experimental condition required the development of a "Complex Systems" teaching module, while the comparison condition developed "An Introduction to College Science" module using existing materials. The main considerations for the development of these measures were: (1) establishing selection criteria to ensure appropriateness of content for both conditions (even though the comparison group received a placebo, material selection was crucial), and (2) delivery of instruction. In the following section I will discuss how I dealt with both of these as well as describe the instructional materials.

4.4.1 Instructional Design and Materials for Experimental Group

Conceptual change literature tells us that constructivist inspired learning environments offer the greatest support for the restructuring of knowledge (e.g., Duit, Roth, Komorek & Wilbers, 1998; Limón, 2001; Mason, 1994; 2001). Constructivist literature informs us that methods such as computer-based modeling (e.g., Penner, 2001; Resnick & Wilensky, 1997) and case-based instruction (e.g., Hmelo, Holton & Kolodner, 2000; Kolodner, 1993: Spiro, Feltovich, Jacobson, & Coulson, 1992) are powerful tools for knowledge acquisition. Schwartz and Bransford (1998) remind us, however, that lectures should not be considered anathema to a constructivist approach. In fact, they contend that: "the question for constructivists focuses on the kinds of activities needed to help people best construct new knowledge for themselves. Often, the act of listening to a lecture or reading a text is not the best way to help students construct new knowledge. At other times, this may be exactly what students need" (p. 476).

Guided by this literature, and in concert with two subject matter experts (i.e., one from the field of Cybernetics and the other from Biology), I designed the instructional intervention for this phase of the research. Day one was composed of practical information on the conferencing software used for this study as well as that used by the College's science program – First Class Client. Day two was a lecture on the following four topics: (1) human embryonic development, (2) slime mould colony formation (specifically the StarLogo T2000 model), (3) requisite variety, and (4) mathematical modeling of the behavior of gases (see Appendix D). Day three was a computer lab during which the students explored simulations that are described in the section below.

In addition to the theoretical perspective, there was an ethical side to the choice of content. All materials were deemed relevant to the College's science program curriculum and within the "normal" range of requirements related to comprehension.

Computer Models Used as Simulations

StarLogo[17] was selected as the model and simulation software because of its history as a unique multi-agent modeling computer language (also known as object-based parallel modeling language or agent-based modeling language) designed explicitly for exploring systems with multiple interaction agents (Wilensky, 2000; Wilensky & Resnick, 1999). For the sake of simplicity, I will refer to all versions of this programming language (the original StarLogo, StarLogoT, StarLogoT2000, etc.) as "StarLogo".

StarLogo is a computer language extending the capabilities of "Logo" which was developed by Seymour Papert (1980) to teach children simple computer programming (Resnick, 1994). Like Logo, StarLogo uses the "turtle" as one of its two basic programmable elements; however, StarLogo is capable of programming hundreds or even thousands of turtles with commands that control their interaction with each other and their environment. Turtles are located on a finite two-dimensional grid, the squares of which are called "patches" and these patches are the other programmable elements. As described by Wilensky and Resnick (1999), "in computer-science terms, StarLogo can be viewed as a collection of agents moving on top of (and interacting with) a two-dimensional cellular automaton". Because of the parallel processing features of the language, it is capable of demonstrating emergent behaviors that are characteristic of complex systems. StarLogo makes it possible to create simulations that explore the operations of hundreds or even thousands of the individual entities that make up the aggregate and discover the emergent probabilistic phenomena of multiple simultaneously interacting agents. Before the advent of parallel processing computer languages, this type of modeling was unavailable to the school population. Programs like StarLogo have therefore opened a new area of study and explanatory potential (Wilensky & Resnick, 1999).

The MIT research group (headed by Mitchel Resnick), along with the Northwestern University research team (headed by Uri Wilensky and allied with Walter Stroup's team at the University of Utah), has explored the potential of StarLogo as a teaching tool (Wilensky 2000; Wilensky & Resnick, 1999; Wilensky & Stroup, 1999).

[17] StarLogoT2000 was the actual version of the computer modeling language used. Permission to use the application was obtained from Dr. Mitchel Resnick via electronic communication, January 15th, 2000.

Primarily, these researcher/developers have used the construction of models as the measure of learning. They have, however, also engaged students in the use of pre-built StarLogo models and followed the knowledge construction from that vantage point. This current research adopted the latter strategy. The question of which models best demonstrated the instructional objectives of teaching the concept of emergent processes as exhibited by complex systems was addressed by creating selection criteria (discussed fully in an upcoming section)[18].

Reasons for the selection of the StarLogo models. The StarLogo models were judged on the criteria that they explicitly demonstrated complex systems behaviors. Four other science faculty members were convened to rate ten StarLogo models for the criteria identified on the scoring sheet (see Figure 4.3). Their cumulative scores were averaged, however there was over 90% agreement among faculty. StarLogo models earning a rating of 11 or higher were considered for inclusion in the instruction. The presentation order was also based on the rating scores; hence, "GasLab: Atmosphere", which is slower paced allowing for more interaction, and is highly relevant to the first-year Science Program, was selected as the introductory model.

Four StarLogo (Wilensky & Resnick, 1999) models were used in this workshop: (1) GasLab: Atmosphere, (2) Termites, (3) Ants, and (4) Traffic Basic. They were installed on 15 Macintosh, G3, 300 MHz computers equipped with dual monitors. These four models were used as simulations; that is, the programming code was not changed; students merely entered different parameter values. The StarLogo materials did not require any modification.

[18] As will be shown in Study 2, the issue of the StarLogo model's affordances for supporting learning of emergent processes proved to be a very important question.

Complex System Characteristic – Rating Sheet		StarLogo Models			
		1	2	3	4
		GasLab: Atmosphere	Termites	Ants	Traffic
Do these StarLogo models/simulations represent the identified characteristic? If yes to what level? Use the scale below to indicate your opinion. • 0 = construct not found • 1 = construct found but not explicit • 3 = construct found and explicit • -1 = construct is present but at an abstract level	**Are the characteristic below demonstrated?**				
	Emergence of different levels of behavior	1	3	-1	3
	De-centralized behavior (each agent is operating under the same rules)	3	3	3	1
	Randomness (agents' actions are not predictable)	1	3	3	1
	Dynamic process – ongoing (agents continue to move even after system is formed)	3	3	1	3
	Probabilistic behavior (behavior of the system is dependent on variables such as numbers of agents, an other variables controlled by the sliders)	3	1	3	-1
	Non-linear behavior (small actions can create big effects)	-1	-1	-1	1
Other considerations:	**Does the action occur slowly enough for the student to observe the behaviors of the agents?** **1 = fast** **2 = ideal** **-1 = slow**	2	1	1	2
	Relevance of simulation to the First Year Science Program? **1 = not relevant** **3 = relevant to science but not 1st year** **5 = very relevant to 1st year**	5	3	3	1
Scorer's name:	**Total Score:**	17	16	12	11

Figure 4.3 StarLogo selection scoring criteria form – Study 1.

4.4.2 Instructional Design and Materials for Control Group

The control group received a placebo treatment that consisted of a two-part presentation: (1) wave function including formulas, and (2) the steps in the "scientific method" of analysis. Both content areas were presented and prepared by expert teachers using similar constructivist methods of presentation and group discussion. The presentation of wave function used filmstrip materials that are part of the regular audio-visual materials used in Physics NYA. The presentation of the scientific method used a CD-Rom that comes with the biology textbook used in the Biology NYA course.

To ensure that standards of content validity were met, three members of the College's science program vetted the materials. All materials were judged acceptable.

4.5 Data Collection Measures

4.5.1 Measures of Ontological Frameworks

I selected four complex systems questions from a bank of a possible eight questions developed by Jacobson (2000) in his seminal study documenting expert-novice complex systems problem solving capabilities. These questions were developed from the literature of complex systems (Bar-Yam, 1997), complexity theory (Casti, 1994; Gell-Mann, 1994; Kauffman, 1995), complex adaptive systems theory (Holland, 1995, 1998) and others. He also drew on his own research on the learning of biological evolution (Jacobson & Archodidou, 2000) to build this bank of representative complex systems questions.

The decision of which questions to use was based on three criteria developed from Jacobson's results. Firstly, the questions' ability to elicit sufficiently large numbers of complex systems responses as identified through that study's coding grid. Using his scoring results from his expert participants, I selected questions that generated a score of 15 or more on the complex systems component belief scale (calculated by adding all the complex system component beliefs and subtracting the clockwork beliefs scores). This method identified the following questions: ants (24 points), butterfly (26 points), traffic (17 points).

Secondly, I gave each question a score of five points if they were general knowledge and therefore could be answered without knowledge of a specific content area. It was important that the questions be reasonably unfamiliar so as to assess reasoning abilities and not content knowledge. I made the assertion that such questions would elicit more of the learners' intuitions thereby providing a clearer picture of their pre-instruction mental model. This brought in the questions of city planning (17 points) and increased the question of traffic to (21 points).

Finally, I examined the questions based on their potential for isomorphic pairings that could be used as a near transfer, far transfer complements and assigned a score of five points. This score added to the others produced a final roster of questions: butterfly (31 points), ants (29 points), traffic (27 points), city planning (22 points), mining (19 points), and slime (18 points). These questions were therefore selected as possible candidates for the dependent measure. The decision of the final four used in the pretest, immediate posttest was made in consultation with the subject matter experts (they are referred to as "Brain Teasers", see Appendix F.1). Although the robot question was low on the list, it was viewed as a good compliment to the ant question since they both evaluated similar emergent organizational processes (the town question was used in later testing, as well, two additional questions were developed and used in "Study 2"). Once the choice was made, I used Bar-Yam's table of complex systems characteristics (see Appendix B) to expand on the concepts before collecting my own experts' answers.

Construct Validity of Complex Systems Questions

No formal test of construct validity was conducted on the complex systems questions used. However, based on the complexity literature, as well as Jacobson's (2000) research, it was reasonable to suggest that the proposed questions belong to the category of emergent processes; accordingly, they should elicit responses from experts that would be categorized as emergent. This basic assumption was tested using responses from four experts[19] in the following disciplines: cybernetics, biology, and artificial intelligence/cognitive modeling. I purposefully chose not to instruct the experts as to the manner in which they should answer the questions. This decision was based on the contention that without instruction as to how to approach these questions, the "native" mental models would be elicited. The data supported the assertion. In the discussion chapter I will return again to this issue based upon the results of Study 2 that adds some additional support to this conclusion.

4.5.2 Other Data Collection Measures Used

Demographic information was collected using a questionnaire designed for this study (see Appendix F.2). The main items were intended to determine the participants' science background and interest. On the practical side, it provided a picture of how

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[19] Another use of the experts' responses was to add to the refinement of the ontological coding taxonomy. From their answers, I was able to create prototypical expert response for each of the questions. To do this I selected portions of answers that had been coded to the six dimensions of the emergent category. This proved useful in training the raters since the categories could now be viewed as a finished product.

familiar the student might be with computers and what type of learning curve I might expect during their work with the simulations.

Another data source was the Learning Approach Questionnaire (LAQ) measure. The LAQ was developed by Donn (1989) and based on the work of Biggs and Collis (1982), Entwistle (1981) and Entwistle and Ramsden (1983). It is a 50-item five point likert scale instrument designed to measure students' tendency to engage in meaningful or rote learning as well as assess students' epistemological view of science (e.g., Donn, 1989; also for a copy of the instrument see this author). A study conducted by BouJaoude (1992) on high school chemistry students determined that the internal consistency coefficient for this instrument was determined as a Cronbach alpha = 0.77. Although this questionnaire was administered and analyzed in Study 1, it was used only in the purposeful sampling procedure that selected participants for Study 2. Therefore, the manner in which it was used will not be discussed here but in Chapter 6.

Lastly, other data sources included the students' College records such as their scores on the Nelson-Denny Reading Test (Brown, Bennett & Hanna, 1981), which is a standardized testing instrument. This test is composed of two parts. The first part is a vocabulary section of 100 items each with five answer choices and is limited to 15 minutes. The second part is a comprehension section consisting of eight reading passages and a total of 36 questions. The time limit for this section is 20 minutes. The reliability coefficient of the vocabulary score is determined to be 0.92, whereas the comprehension reliability coefficient is reported at 0.77 (for examples of the test and more detail see Brown, Bennett & Hanna, 1981). The records provided both "raw" scores for the students as well as the grade equivalent of these. For example a raw score of 70+ for vocabulary are considered at grade 16 (above average), while scores of 55+ on the reading comprehension are at grade 16 (above average). These data were collect for all students in Study 1 but only used in Study 2 to explain observed differences.

4.6 Procedure

Day One

During day one, the students were randomly assigned to one of two groups: the complex systems group (n=26) and the comparison group (n=26). The consent form (see Appendix E.2) was handed out, since all, but two, participants were under the age of 18 years, the forms required the signature of a parent or guardian. Hence consent forms were collected only on the second day. The demographic questionnaire was distributed in individual folders containing notepaper. The students were informed that they were to use it to record lecture notes, as well as for reflections on the day's events. The folder was collected at the end of phase 1. Next the LAQ questionnaire was handed out and the participants were given 30 minutes to complete the 50 questions. Both groups were then taken to separate computer labs where they received a demonstration of the conference software, First Class Client (FCC). The day concluded with a complementary lunch.

Day Two

Experimental group. For the experimental group, the second day began with the distribution of the written pretest questionnaire, entitled "Brain Teasers" (see Appendix F.1). It was considered unlikely that the participants would know the scientific explanations to these questions, therefore, verbal instructions were given reassuring them to use their "best guess" intuitive responses. The time provided to complete this task was approximately 20 - 30 minutes.

Once the answers were collected, the lecture portion of the day commenced with a brief introduction to the objectives of the study and an encouragement to take notes. The instruction portion began with the presentation from the biologist (the "emergent organization" material) and lasted for approximately 40 minutes. There was a 10 minutes coffee break with refreshments served. The presentations by the cybernetics expert (the "requisite variety" material) lasted 30 minutes, followed by the 15 minute Slime mould computer model presentation. This was followed by the gas law formula derivation demonstration. This was intended as a way to set the stage for the StarLogo models used on the third and final day of the workshop. This presentation was videotaped as a record of the activity. As a final activity for the day, participants were asked to write in their folders a brief summary of what they had learned from the day's lectures.

Control group. The control group met in a separate but similarly equipped classroom (i.e., electronic overheads, computers, etc.) with different teachers. The lecture portion of the day commenced with a brief introduction to the purpose of the condition portion of the study. The participants were also encouraged to take notes. The presentations lasted approximately the same amount of time with staggered coffee breaks to reduce the contact between groups.

Both groups. Upon completion of the day's events, all students were respectfully requested not to discuss the content of the lectures with members of the other group, if they should encounter them. The pretext used was that of friendly competition between groups for raffle prizes. They were both provided with coupons redeemable for a free pizza lunch. Due to the prescribed staggering of lecture times, the lunchtime for the two groups did not coincide thereby reducing the threat of diffusion of treatment.

Day Three

Experimental group. On the third day of the workshop, the experimental group was directed to a computer lab with 15 Macintosh G3 computers. They were assigned two to a computer, no particular criteria for group assignment was used. The room was small therefore no significance was placed on the differences between groups since discussion and on-screen activity was easily shared by all.

The first simulation was preceded by a brief lecture by a member of the physics department explaining rudimentary information required to understand the first simulation entitled "GasLab Atmosphere", which lasted 15 – 20 minutes. The participants, already seated in front of computer screens, were instructed to turn on their computers, open the StarLogo application, and go to that simulation. They were asked to access the "Window" menu and go to the "Info Window". They were informed that they should browse through the instructions since the lecture presented the factual information they would need to understand the simulation. They were instructed to explore the default setting before experimenting with the available variables: number of molecules, gravity, initial speed, initial mass. Twenty minutes was allocated for engagement with this simulation. When time expired, they were requested to stop and discuss their conclusions. A ten-minute discussion ensued centered on the behavior of the gas molecules and the science behind the phenomena. A 15-minute break followed.

Upon return, the students began the next simulation (Termites) repeating the established protocol. Twenty minutes of experimentation was followed by 15 minutes of discussion during which prizes were given out for the active participation. They were instructed to follow the same procedure for two more simulation, “Ants” and “Traffic Basic”. Thirty-minutes was allocated to this activity. When time expired they were asked to stop and close down the program. Discussion of their findings ensued for 10 minutes at the end of which the students were asked to write down, in the workshop folders, their thoughts relating to the activities of the three days. They were informed that these folders would be collected immediately. Once the folders were collected, the immediate posttest questionnaires were distributed “Brain Teaser 2” (see Appendix F.1). The students were given all the time they needed to complete the questions. Once collected, they were escorted to a classroom where the special celebratory lunch was served.

<u>The control group</u>. The control group was taken to a separate computer lab set up with PC computers with Internet access. The instruction and experience presented them with opportunities to explore simulations from both on-line Java Applets as well as some simulations on CD-Rom. Group discussion and prizes were the same as for the experimental group. At the end of the session they were asked to write down, in their workshop folders, their impressions of the three days. The procedure for distribution and collection of all data, such as the posttests, was the same as the experimental group. They were provided with similar, but non-simultaneous, breaks and a special celebratory lunch.

4.7 Threats to Internal Validity

<u>Mortality</u>. The final number of participants was 45: experimental group (25), control group (20). The experimental group decreased by one (4%), whereas the control group saw decrease of six participants (20%). The control group’s larger attrition was

adjusted for in the statistical analyses. The experimental group's low attrition was ascribed to interest in the topic and not the "novelty effect" since both groups received similar types of technology-based instruction (i.e., simulations, conferencing software, etc.).

Instrumentation. The threat of instrumentation was addressed by ensuring that there were two raters to code all answers. Efforts were made to temper the pace, and duration of the coding activity. Whenever possible, the data to coded was delivered in reverse order when given to the independent rater. Finally, inter-rater reliability checks were made.

4.8 Summary of Methods – Study 1

The experimental design described above provided the basis on which I gathered data from Study 1. Once collected, these data were analyzed using the ontologically based mental models coding taxonomy (OMMT) that was modified from the research independently conducted by Chi and colleagues, (e.g., Ferrari & Chi, 1998; Slotta & Chi, 1999) and Jacobson (Jacobson 2000) as described in chapter three.

CHAPTER 5

RESULTS & DISCUSSION STUDY 1

Overview

Two studies were conducted in the course of this research. Study 1 began the process of looking at the question of whether or not conceptual change is plausibly interpreted as the acquisition and transfer of an ontologically-based emergent framework mental model (EFMMs). The second phase of the project, Study 2, followed up that inquiry by using a qualitative exploratory case study approach to examine the process of change in more detail (i.e., what changed, and how it changed). In this chapter I will present the results and analysis of the data for Study one (see Figure 5.1).

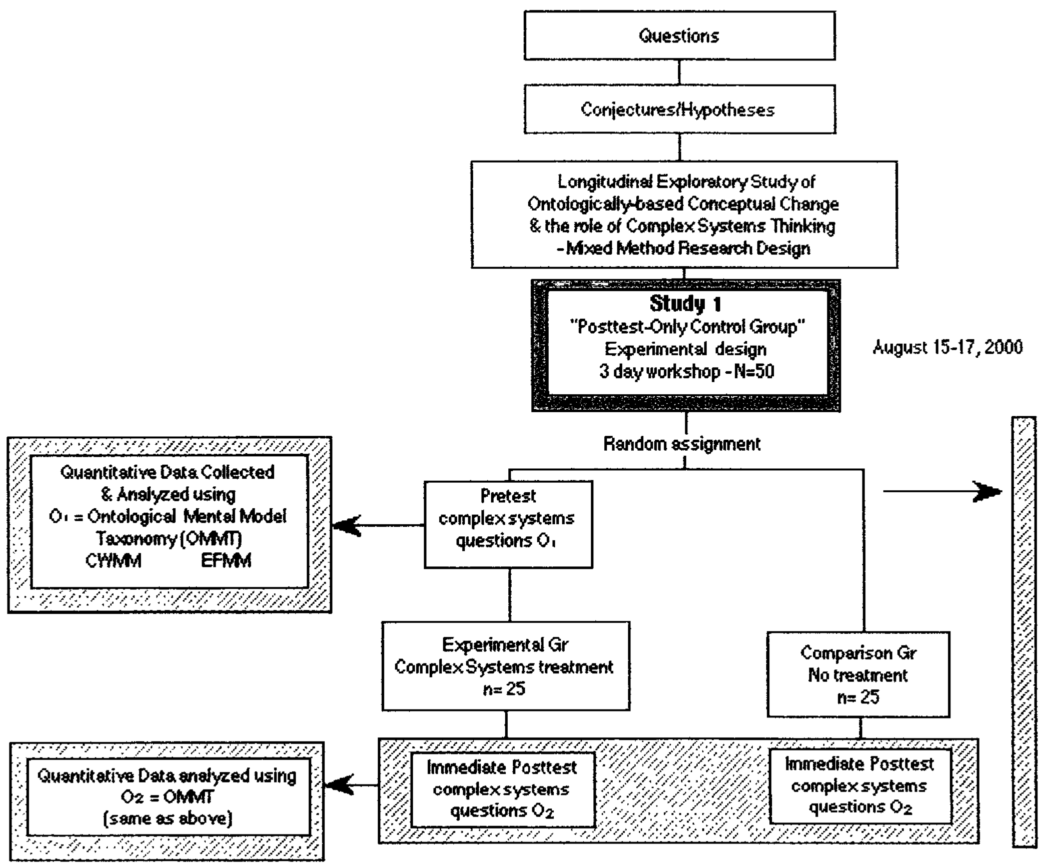

Figure 5.1 Overview of research design for Study 1.

5.1 Results of Research Question 1

Research Question 1: Can complex systems instruction facilitate the construction of emergent framework mental models (EFMMs) as demonstrated by problem solving reasoning (i.e., use of more scientifically correct explanations) applied to questions that are representative of appropriate phenomena?

Hypothesis 1: Students in the Complex Systems treatment condition [IV] would outperform students in the comparison condition by constructing a greater number of explanations, categorized as emergent framework mental models (EFMMs) [DV], when solving the near transfer problem of "emergent organization" (Ant colony food collection).

By contrast, students in the comparison condition (i.e., no treatment) would outperform students in the Complex Systems treatment condition by constructing a greater number of explanations, categorized as clockwork mental models (CWMMs), used to solve the same problem.

5.1.1 Comparison of Immediate Posttest – Near Transfer Question

To test the main hypothesis that students in the complex systems group would outperform the control group by constructing a greater number of explanations categorized as EFMMs [DV1], and conversely be out performed by the control group in the number of explanations categorized as CWMMs [DV2], to solve the near transfer question, a *t* test was used. Table 5.1 demonstrates that as hypothesized, the experimental group had significantly higher scores for EFMMs ($M = 2.96$, $SD = 2.24$) compared to the control group ($M = 0.70$, $SD = 1.22$), $t\,(38.4) = +4.303$, $p = 0.000$ (one-tailed)[20]. By contrast, the students in the experimental group ($M = 1.24$, $SD = 1.23$) had

[20] Variances were unequal and tested accordingly.

significantly lower scores on the clockwork mental models (CWMM) than did the students in the control group (M = 2.90, SD = 1.45), t(43) = -4.152, p = 0.000 (one-tailed). On the other hand, there was no difference between the experimental group (M = 2.72, SD = 1.34) and the control group (M = 2.55, SD = 1.61), t(43) = +.387, p = 0.70 (one-tailed) on the number of categories that could not be coded due to insufficient references to one or the other mental model. This evidence of no codeable mental model was characterized as No Model (NMs).

Table 5.1 Comparison of scores on immediate posttest near transfer question.

	Treatment					
Scores on	Experimental			Control		
	n	M	SD	n	M	SD
Emergent Framework Mental Models (EFMM)	25	2.96*	2.24	20	0.70	1.22
Clockwork Mental Models (CWMM)	25	1.24*	1.23	20	2.90	1.45
No model	25	2.72	1.34	20	2.55	1.61

* Significance at $\alpha = 0.05$ on one-tailed *t*-test.

(N.B. Effect size calculated: EFMM = 1.31, CWMM = -1.24, NM = 0.11)

Figure 5.2 illustrates the near transfer results and the results of the *t* test. As expected, students in the complex systems treatment condition (experimental group) out performed students in the control condition by using a greater number of emergent framework mental models (EFMMs) to solve the near transfer problem. It is important to note that the results reveal that both groups produced statistically the same number of non-codeable mental models (NMs).

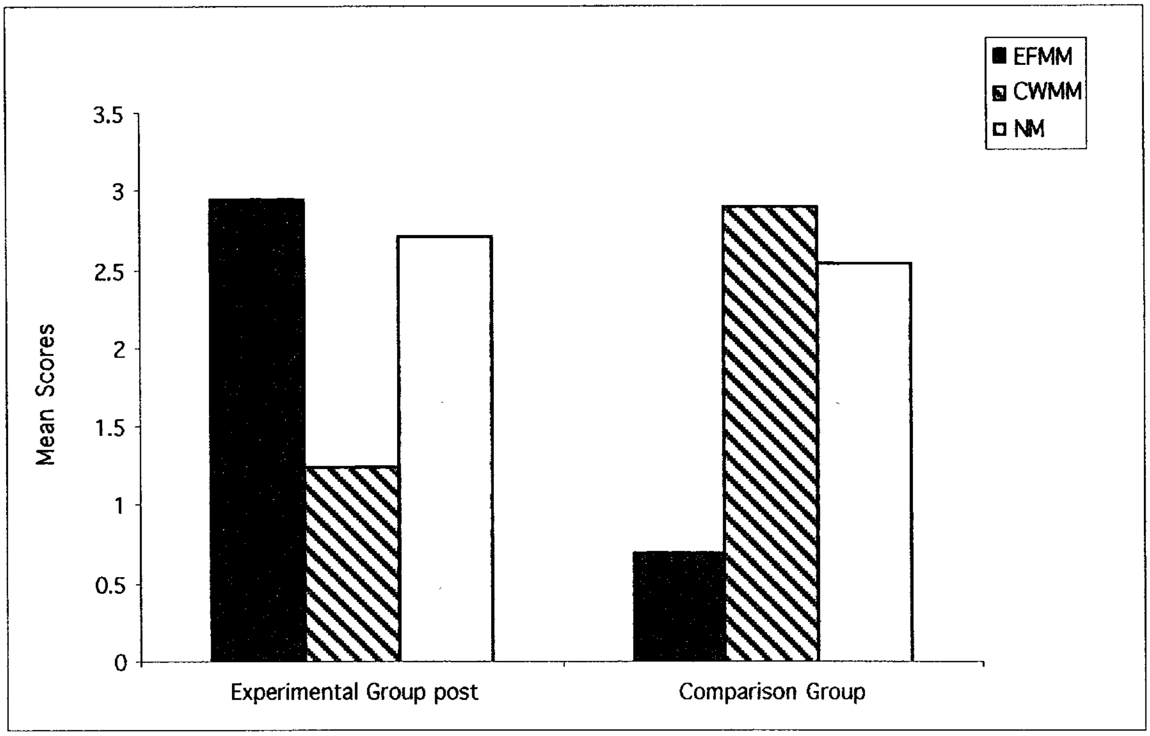

Figure 5.2 Comparison of the immediate posttest scores for the near transfer question.

5.1.2 Changes in Mental Models of Experimental Group

To compare pretest and posttest scores on the dependent variables (EFMM, CWMM), within the experimental treatment group, paired samples *t* tests were used. The gains in the students' EFMMs are indicated in Table 5.2 as means and standard deviations scores (n=25). The results of the *t* tests also indicated that the students' references to EFMMs were significantly increased between the pretest (M = 1.24, SD = 1.48) and immediate posttest scores (M = 2.96, SD = 2.24), t (24) = +3.862, p = 0.0005 (one-tailed). In addition, it indicated that the students' references to CWMMs were significantly reduced between the pretest (M = 2.28, SD = 1.40) and posttest scores (M

= 1.24, SD = 1.23), t(24) = -2.797, p = 0.005 (one-tailed). Finally, the results indicated that the students did not change the number of propositional statements that could not be coded to either model (NM) between the pretest (M = 2.68, SD = 1.25) and posttest scores (M = 2.72, SD = 1.34), t(24) = +.115, p = 0.455 (one-tailed).

Table 5.2 Changes in students' mental models on near transfer question (n = 25).

Scores on	Pretest		Posttest	
	M	SD	M	SD
Emergent Framework Mental Models (EFMMs)	1.24	1.48	2.96*	2.24
Clockwork Mental Model (CWMMs)	2.28	1.40	1.24*	1.23
No Model (NM)	2.68	1.25	2.72	1.34

* Significance at α 0.05 on one-tailed *t* test.

(N.B. Effect size calculated: EFMM = 0.92, CWMM = -0.78, NM = 0.03)

In conclusion Figure 5.3 describes the results of the within group pretest and immediate posttest comparison by illustrating the increase in emergent framework mental models (EFMMs), while there was a decrease in the number of clockwork mental models (CWMMs). Once again the number of none-codeable mental models (NMs) did not change significantly between times.

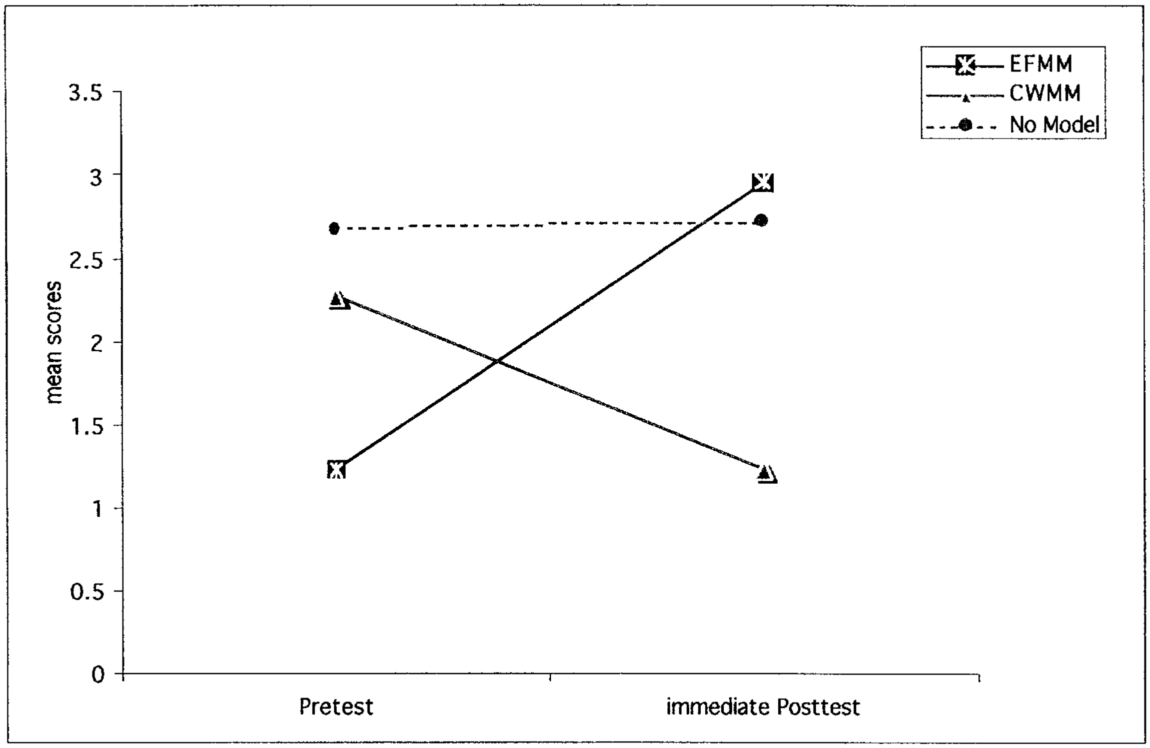

Figure 5.3 Changes over time between pretest-immediate posttest scores for near transfer question.

Hypothesis 2: Students in the Complex Systems treatment condition would out perform students in the comparison condition by constructing a greater number of EFMM explanations to solve the far transfer "Robot Mining" question[21]. By contrast, students in the comparison condition would construct a greater number of CWMM explanations to solve this far transfer question compared to students in the Complex Systems treatment condition.

5.1.3 Comparison of Immediate Posttest – Far Transfer Question

To test the second hypothesis that students in the complex systems group would out perform the control group by constructing a greater number of explanations

[21] This question was considered an assessment of far transfer compared to the near transfer "Ant" question. Although the robots' surface features are very different from the ants' features, both their deep structure behaviors could be explained as emergent causal processes.

categorized as EFMMs, and conversely be out performed by the control group in the number of explanations categorized as CWMMs, in order to solve the far transfer question, I used a *t*-test. Table 5.3 demonstrates that as hypothesized, the experimental group had significantly higher scores for EFMMs (M = 0.96, SD = 1.1) compared to the control group (M = 0.35, SD = 0.75), p = 0.021 (one-tailed). On the other hand, the students in the experimental group (M = 1.92, SD = 1.3) had slightly higher but statistically non-significant scores on the clockwork mental models (CWMM) than did the students in the control group (M = 1.7, SD = 0.92), p = 0.258 (one-tailed). By contrast, there was a small difference between the experimental group (M = 3.12, SD = 1.45) and the control group (M = 3.95, SD = 1.23), p = 0.022 (one-tailed), producing a statistical significance on NM variable.

Table 5.3 Comparison of scores on immediate posttest far transfer question.

	Treatment					
Scores on	Experimental			Control		
	n	M	SD	n	M	SD
Emergent Framework Mental Models (EFMM)	25	0.96*	1.1	20	0.35	0.75
Clockwork Mental Models (CWMM)	25	1.92	1.3	20	1.7	0.92
No model (NM)	25	3.12*	1.45	20	3.95	1.23

* Significance at $\alpha = 0.05$ on one-tailed *t*-test.

(N.B. Effect size calculated: EFMM = 0.66, CWMM = 0.20, NM = -0.62)

Figure 5.4 illustrates the far transfer results and the results of the *t* test on them. As described, students in the complex systems treatment condition (experimental group) out performed students in the control condition by using a greater number of emergent framework mental models (EFMMs) to solve the near transfer problem. It is important to note that the results reveal that both groups produced statistically the same number of none-codeable mental models (NMs). Compared to the near transfer results (Table 5.1), these far transfer results (Table 5.3) show a substantial difference between EFMMs produced by the experimental group. Possible explanations for these results will be discussed later in the chapter.

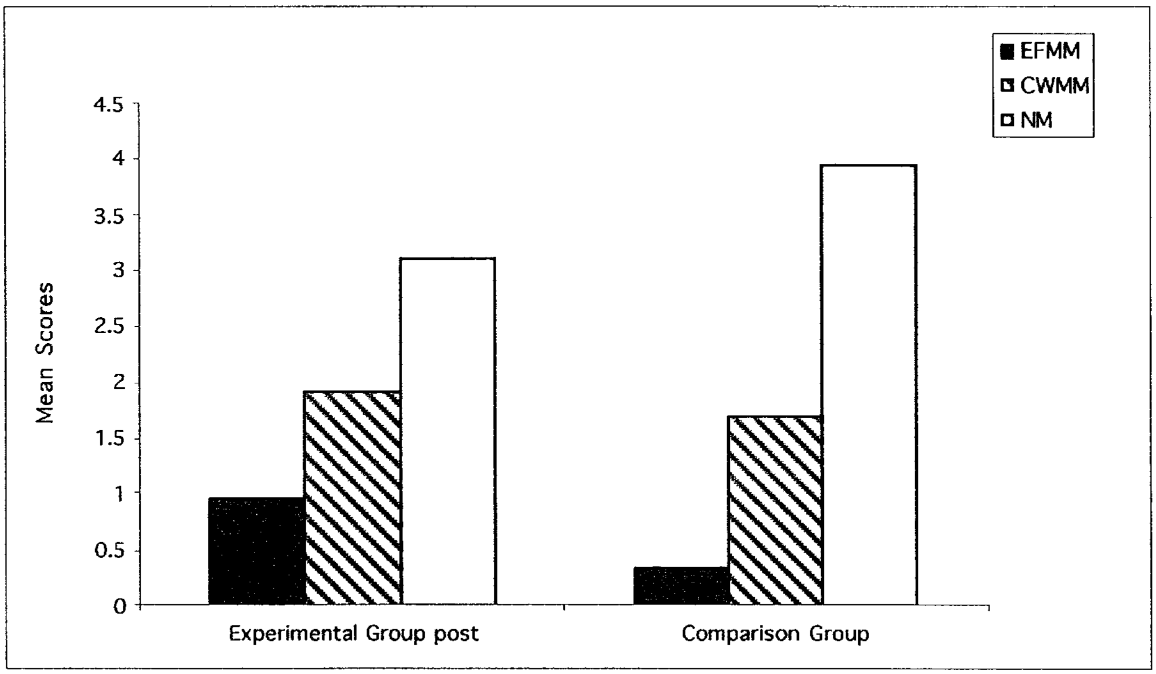

Figure 5.4 Comparison of the immediate posttest scores for the far transfer question.

5.1.4 Changes in Mental Models of Experimental Group for Far Transfer Question

To compare pretest and posttest scores on the dependent variables (EFMM, CWMM), within the experimental treatment group, paired samples *t* tests were used. The gains in the students' EFMMs are indicated in Table 5.4 as means and standard deviations scores (n=25). The results of the *t* tests also indicated that the students' references to EFMMs were significantly increased between the pretest (M = 0.68, SD =

0.85) and immediate posttest scores (M = 0.96, SD = 1.1), p = 0.024 (one-tailed). In addition, it indicated that the students' references to CWMMs no significant difference between the pretest (M = 2, SD = 1.5) and posttest scores (M = 1.92, SD = 1.3), p = 0.245 (one-tailed). Finally, the results indicated that the students did not change the number of propositional statements that could not be coded to either model (NM) between the pretest (M = 3.32, SD = 1.5) and posttest scores (M = 3.12, SD = 1.45), p = 0.067 (one-tailed).

Table 5.4. Changes in students' mental models for far transfer question (n = 25).

Scores on	Pretest		Posttest	
	M	SD	M	SD
Emergent Framework Mental Models (EFMMs)	0.68	0.85	0.96*	1.1
Clockwork Mental Model (CWMMs)	2	1.5	1.92	1.3
No Model (NM)	3.32	1.5	3.12	1.45

* Significance at $\alpha = 0.05$ on one-tailed *t* test.

(N.B. Effect size calculated: EFMM = 0.29, CWMM = -0.06, NM = -0.14)

In conclusion Figure 5.5 describes the results of the within group pretest and posttest comparison by illustrating a small increase in emergent framework mental models (EFMMs), while there was a small and statistically non-significant decrease in the number of clockwork mental models (CWMMs). There was also a small but non-significant decrease in the number of none-codeable mental models (NMs).

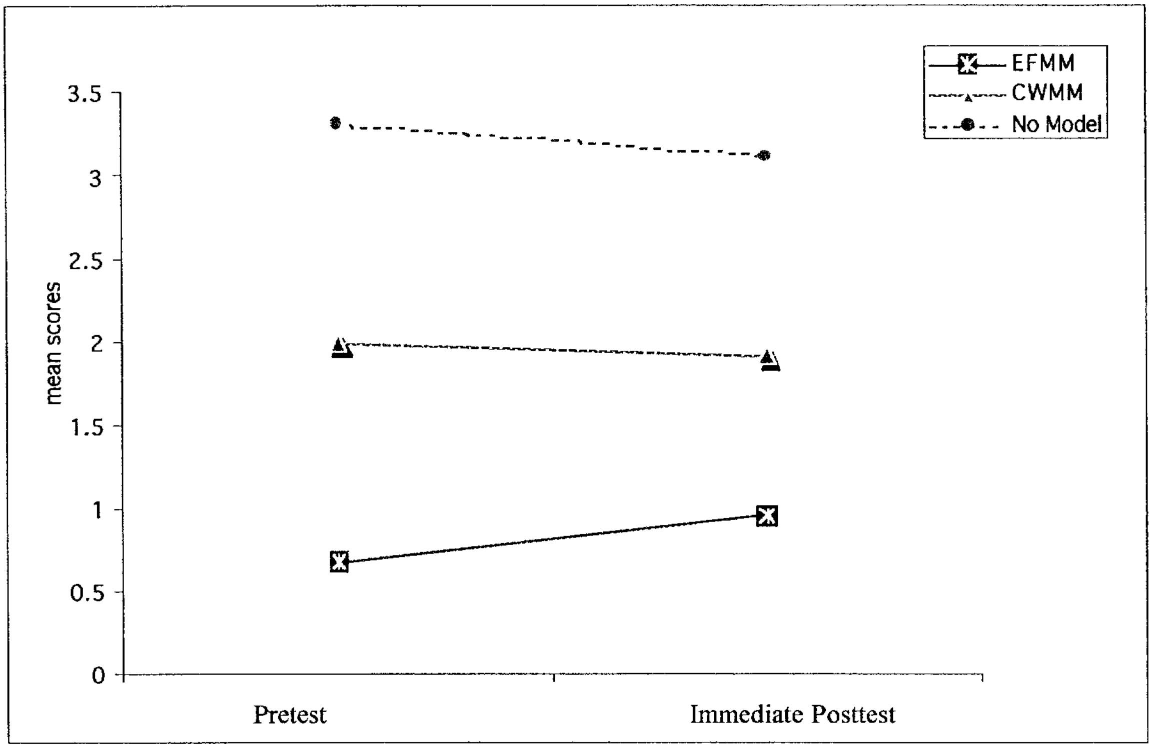

Figure 5.5 Changes over time between pretest and immediate posttest scores for far transfer question.

5.2 Discussion of Results for Study 1

The single most important purpose of Study 1 was to address empirically the question: Did complex systems instruction facilitate the construction of emergent framework mental models as demonstrated by problem solving abilities applied to questions that are representative of phenomena with emergent characteristic?

Between Group Results

Based on the "posttest only control group" random assignment experimental design no test of group equivalence was necessary. The findings of the between group immediate posttest (see Table 5.1) supported the hypothesis that students in the complex systems intervention would exhibit superior performances on the near transfer task compared to students in the control condition, by constructing a greater number of emergent framework mental models (EFMMs). The second hypothesis that the control group would out perform the treatment group on the variable of clockwork mental models (CWMMs), by producing a larger number of these mental models, was also upheld. The results showed that both groups performed equally in relation to the number of responses that did not generate sufficient evidence of students' mental models (NMs) on specific dimensions of the coding taxonomy.

The results of the immediate posttest far transfer task (see Table 5.3), also upheld the hypothesis that students in the treatment group would outperform students in the control condition on the predictive variable of emergent framework mental models (EFMMs). However, both groups performed equally well on the clockwork mental models (CWMMs) variable, therefore this hypothesis was not supported. The results also showed that the control group produced a larger number of no models (NMs), compared to the treatment group.

5.3 Conclusions Drawn from the Results

5.3.1 Emergent Framework Mental Models (EFMM) Results

Before adopting the conclusion that the complex systems intervention facilitated the creation of alternative explanatory frameworks as measured by emergent framework mental models (EFMM), let us explore another interpretation of the results. What if the increase in EFMMs was merely a change in vocabulary and not the application of an alternative explanatory framework?

This explanation was ruled out because of the few occasions in which new terminology was used. In fact, only two cases out of 25 employed any of the terms that may be directly linked to the complex systems lecture (e.g., requisite variety, and self-organizing). Moreover, the number of no models (NMs) coded did not change significantly in either near or far transfer, suggesting that it was not merely learning of some new words. In fact, the NM results support that it was equally difficult to generate explanations for these questions before and after the intervention.

Therefore, the demonstrated increase in the students' ability to use emergent explanatory frameworks (EFMMs) appears to be more likely attributed to a new way of explaining phenomena. Hence suggesting that the complex systems thinking can facilitate the generation of emergent framework mental models, and therefore the creation of a qualitatively different representation (i.e., conceptual change). Furthermore, these findings support previous research conducted by Slotta and Chi (1999) in which students were provided with a training module that presented ontologically-based content and later tested on a different content area to determine far transfer of the ontological model and what they refer to as, "deep conceptual change". Further support for Slotta and Chi's (1999) results was also garnered from the change in predicates used by the students in this study. Although these predicate data were not used to code the identified mental models, I contend that this evidence can be developed for future research through the development of larger banks of questions, and the collection of more answers that produce more novice-expert predicate differences. This will provide other means of triangulating results between coding taxonomies.

5.3.2 Clockwork Mental Models (CWMM) Results

The results for the clockwork variable (CWMM), on the other hand, were equivocal for both the between groups and within group comparisons. The explanations associated with them lead to more profound issues related to conceptual change theories. For instances, the near transfer results supported the interpretation that the treatment facilitated the replacement of clockwork mental models, whereas the far transfer results suggested that both mental models co-exist.

This is an important issue to clarify because the conceptual change literature has varying opinions on the topic of what happens to misconceptions, are they removed, replaced, restructured (also described as accommodation in some literature,) versus the position of concept reassignment (or assignment) to an intentionally acquired explanatory framework that is more scientifically accurate (e.g., Chi et al, 1994; aspects of which are supported by Vosniadou et al., 2001). The latter view, however, does not rule out the possibility of a conceptual change process that includes the learner holding two explanatory frameworks, which may be categorized as "synthetic" mental models with varying degrees of naïve to expert beliefs (e.g., elements of clockwork components beliefs – CWMMs – and emergent framework component beliefs – EFMMs). The results of Study 1 could not clarify this question of what could we expect to see from learners' mental models to suggest that conceptual change had occurred using the definition of assignment to the scientifically accepted emergent causal explanatory framework. Because the evidence from Study 1 did not sufficiently clarify this question, it was deemed necessary to conduct a follow up inquiry (i.e., Study 2).

5.3.3 Summary of Conclusions and Contributions of Study 1

This study's results were similar to Slotta's and Chi's (1999) in that it, too, reported changes to the students' emergent framework mental models, what those authors call "process based predicates". It is distinct from that study in as much as its focuses equally on the changes to both ontological frameworks. Additionally, the refinement of the ontologically-based taxonomy and the complex systems instructional measure brings this research closer to those studying the learning of complexity (Duit et al, 1998; 2001; Jacobson, 2000; Penner, 2001; Perkins & Grotzer, 2000; Resnick, 1999; Stieff & Wilensky, 2002). I contend that this is a benefit for future cross study comparisons and the increased understanding of the cognitive processes involve in learning emergent causal frameworks.

The main contribution of this first study is therefore a clarification of the dimensions of the ontological category, thereby making the coding of change more precise. The main finding from this study is that it appears that not all novice learners hold naïve clockwork mental models when answering emergent ontology questions. It is possible that this finding is population and age related; that is, science students in post-secondary educational institutions. In fact, a handful of students held more than one of the sub-category dimensions of the emergent framework ontological taxonomy. This evidence supports that it is possible to acquire emergent framework mental models without explicit instruction. In the discussion, chapter 8, will discuss the further conditions that appear to correlate with acquisition of this knowledge observed during Study 2.

PART II – STUDY 2

ACQUISITION OF EMERGENT CAUSAL FRAMEWORKS FROM MODELS AND COGNITIVE COACHING

There were two main concerns for Study 2: (1) to explore in detail if and how students acquired specific emergent causal concepts from complex systems thinking; and (2) to determine if and how these concepts provided opportunities to construct "generally applicable" representations, that facilitated transfer of the emergent causal explanatory framework (Kolodner, 1983; Bransford, Brown, & Cocking, 1999). Both these concerns were addressed by focusing on the affordances[22] for learning provided by the intervention, both the computer simulations and the cognitive coaching (scaffold).

The multi-agent modeling literature tells us that specific types of computer representations are powerful tools for learning complex systems thinking (e.g., Penner, 2001; Resnick, 1994; Wilensky & Resnick, 1999). However, this literature does not systematically detail studies of which of the many types of simulations offer better affordances for learning of these concepts. Secondly, although the literature addresses some of the issues related to which concepts may be more difficult to acquire for reasons of conflicting ontological beliefs or other deeply held attributions (e.g., Duit, et. al. 1998; 2001; Resnick, 1994; Wilensky & Resnick, 1999), it does not tell us which concepts – among the six identified thus far in this current study – are easier or more difficult to learn. Finally, the literature does not tell us if and how the conceptual knowledge acquired through engagement with these models may provide the general application representations (i.e., emergent framework mental models), which support a shift in the

[22] Jacobson and Archodidou (2000) describe *affordances* as "opportunities for action" (terminology articulated by Gibson 1979). Gibson's notion of *representational affordances* may be illustrated by examples such as digital video, or high-resolution images that engage the human visual-perceptual system in substantially different ways than text alone (in effect, reinventing Marshall McLuhan, 'the medium is the message'). In Hmelo, Holton, and Kolodner (2000), the authors investigate the affordances of promoting deep learning provided by a design approach using the construction of physical models. In this current study, the multi-agent model simulations' affordances for promoting learning of specific aspects of emergent causal explanatory frameworks are explored. I will be focusing on three issues related to the affordances of these models: (1) to facilitate and support the construction of specific complex systems concepts; (2) to challenge naïve beliefs possibly viewed as anomalous data; and (3) the constraints of these affordances resulting from the multi-agent models chosen.

novice learners' choice of ontological explanatory framework (i.e., ontological conceptual change). I argue that these gaps in the literature a partly addressed by this phase of the dissertation research.

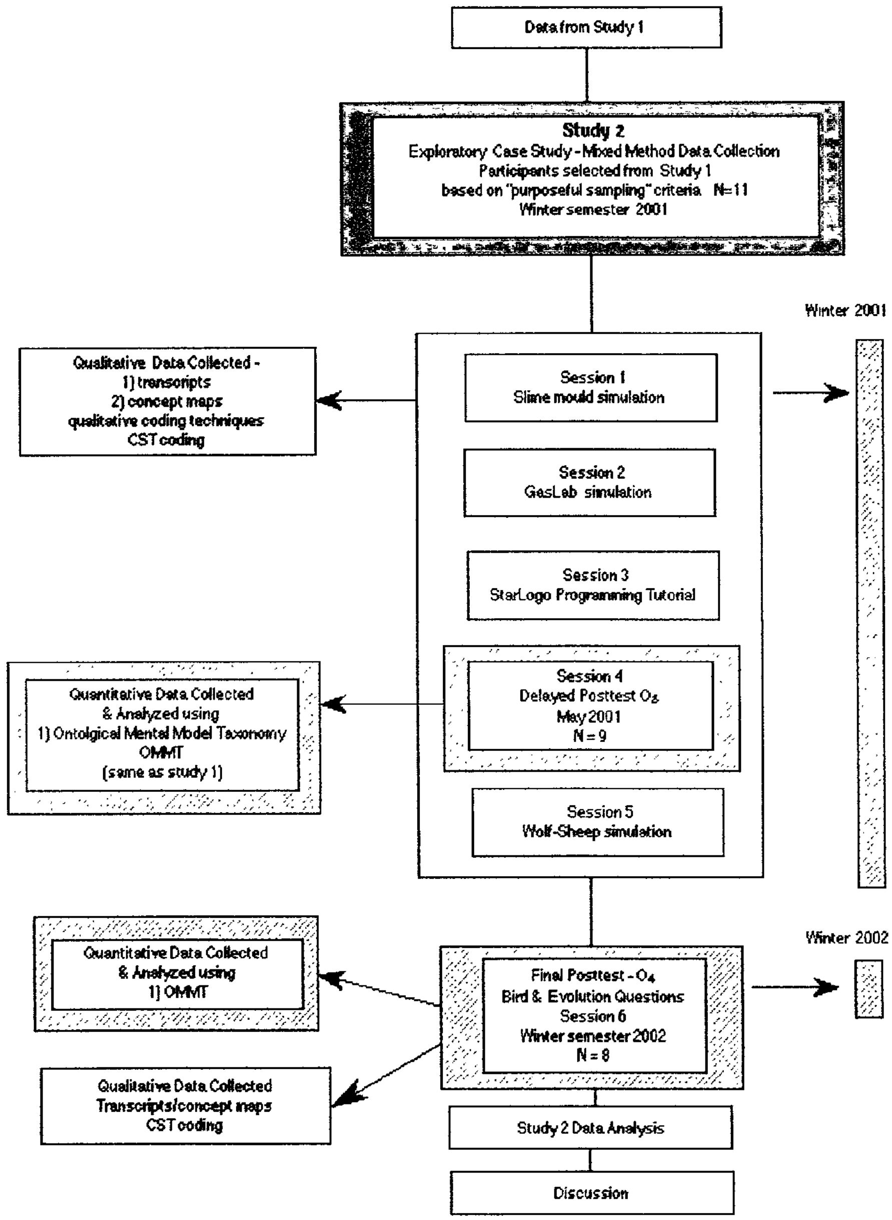

Figure 6.1 Overview of research design Study 2.

CHAPTER 6
RESEARCH DESIGN & DATA ANALYSIS METHODS – STUDY 2

6.1 Qualitative Case Study Design

This study employed a qualitative case study design. Case study research is particularistic, descriptive, and heuristic (Merriam, 1998): Particularistic, because case studies focus on a specific instance, event, program or phenomenon; descriptive, because it results in "thick" and rich descriptions of the phenomenon; and, heuristic, because it sheds light on a particular phenomenon thereby leading on toward new meaning and relationships. I contend that it was important to select this design because it allowed me to focus closely on how students reason about the behaviors of a computer driven multi-agent modeling environment portraying different types of complex systems all of which display emergent causal processes. Furthermore, the inductive nature of the design leaned toward theoretical explanations, not limiting itself solely to straightforward description. Finally, multiple cases were used to strengthen, validate and stabilize the findings (Miles and Huberman, 1984).

Recommendations for collecting qualitative data are: in-depth open-ended interviews, direct observation, and written documents (Patton, 1990). This research collected data from both pre and post intervention interviews. All interventions were audio and videotaped in order to permit the researcher to closely observe the interactions and reactions of the subjects to the intervention. Several written documents were produced by the subjects as another data set in the qualitative case study: (1) delayed posttest results from emergent framework questions; (2) final posttest results from emergent framework question including one on evolution; (3) concept maps of complex systems concepts; and (4) student records including Nelson-Denny Reading test, and course grades (see Appendix F for audit of data sources).

One of the key limitations of case study design is the sensitivity and integrity of the investigator (Merriam, 1998). Because of limited opportunities for training, and the close proximity of observer and observed, there may be unintentional bias and loss of perspective. Merriam (1998) reminds us that the researcher is both the primary instrument of data collection as well as the primary data analysts therefore attention and accounting for bias is important. Lastly, but not least, in all such research designs ethical considerations must be addressed. Guba and Lincoln (1981, cited in Merriam, 1998) tell us that case writers can make the data say anything they may want. Therefore, both the reader and the authors must be wary of these biases and look for alternative explanations and possible externally imposed agendas; particularly, in policy making, socially and politically driven case study research. I will address these issues of threats to credibility later in this chapter.

6.2 Theoretical Framework for the Development of the Intervention

6.2.1 Approach to Instruction

Study 2 employed an *inquiry-based* learning methodology for the instructional intervention. Edelson, Gordin and Pea's (1999) research tells us that this approach is particularly suited to the development and understanding of science concepts through direct exploration and confrontation with ones' knowledge boundaries. They prescribe the use of modeling tools (e.g., *ThinkerTools*, White, 1993) to facilitate the task of cognitive challenge and the recognition for knowledge reorganization. In this study, as in Study 1, students worked with StarLogoT as the chief instructional tool.

6.2.2 Importance of Cognitive Coaching as an Instructional Strategy

Metacognition is the ability to think explicitly about one's ideas or conceptions compared to merely thinking with the conceptions. Furthermore, it is knowledge about thinking that can be shared and reported to others. In this way, future performance may be analyzed and assisted through external supports – cognitive scaffolds – or it may be self-directed as one learns to manage one's own decision-making and problem-solving processes (Paris & Winograd, 1990). On the other hand, *metaconceptual awareness* is the ability to be aware of the explanatory frameworks one has constructed and the presuppositions that constrain these explanations (e.g., Vosniadou & Brewer, 1994;

Vosniadou et al., 2001). Therefore, it may be viewed as a higher level metacognitive activity aimed at the questioning and evaluating of prior beliefs. Vosniadou and colleagues suggests that the metaconceptual awareness may facilitate assimilation of new information into existing structures thereby resulting in conceptual change.

Studies in the field of science education suggest that metacognition is a vital part of scientific reasoning (e.g., Kuhn, Amsel & O'Loughlin, 1988; Hennessey & Beeth, 1993). In fact, Hennessey and Beeth (1993) suggest that learning scientific knowledge of a conceptual nature requires examination of one's conceptual understanding and the cognitive processes that produce that understanding. Any instructional strategy aimed at teaching scientific concepts such as emergent causal processes should ensure that metacognition is facilitated.

Research furthermore informs us that metacognition is facilitated in learning environments that provide cognitive scaffolds. These forms of support fall under the heading of scaffolded instruction and build on the work of the cognitive psychologist Ivan Vygotsky who posited a "zone of proximal development" in which learner and teacher/coach engage in the co-construction of knowledge (Wood, Bruner & Ross, 1976). Additionally, research findings suggest that cognitive support in the form of dialog, structured questions, and other meta-level strategies can facilitate conceptual change (e.g., Mason, 1994; Palinscar, 1986); an added benefit of this method is the development of self-directed learning skills.

In this second study, I operationalized this support by borrowing from a technique referred to in the literature as "cognitive coaching". References to this mode of instruction are found under a variety of headings ranging from computer-based instruction to educational administration (e.g., Barnett, 1995; Costa & Garmston, 1994; Lepper, Drake, O'Donnell-Johnson, 1997; Paris & Winograd, 1990). Regardless of the source, the single ubiquitous feature appears to be the use of human coaches, tutors, or mentors performing the mediating role of cognitive scaffolding thereby supporting the acquisition of higher-level reasoning skills such as problem solving and transfer.

The literature describes three aspects to this technique of cognitive coaching: (1) the cognitive, (2) metacognitive, and (3) affective. Under the heading of cognitive, there is reference to the cognitive support provided by modeling of expert problem solving strategies and shared cognition such as probing questions and self-explanation. Under the label of metacognition, there are reports of reflective learning and self-regulation that is promoted with this type of instructional environment. Lastly, the literature refers to the role of the affective domain in motivating and nurturing learning (e.g., Costa & Garmston, 1994; Lepper, Drake, & O'Donnell-Johnson, 1997). Empirical evidence from Paris and colleagues' studies (reported in Paris & Winograd, 1990) support the contention that subjects experienced significant improvement in cognitive abilities when provided with coaching as a cognitive scaffolded. Summarizing the technique they state: "cognitive coaching combines assessments of learning with sensitive instruction; it integrates cognitive explanations and motivational encouragement" (Paris & Winograd, 1990, p. 38).

In respect to the role of the coach/tutor, the literature points to the interplay between the affective and cognitive factors. Lepper et al. (1997) suggest that successful tutors "seek to both inform and inspire students; they give roughly equal attention and weight to motivational and to informational factors during the tutoring sessions; and their decisions as tutors are based on concurrent ongoing assessments or models of the tutee's affective and cognitive states" (p. 126). In describing the role of the coach/tutor, four types of motivational goals are identified: (1) confidence, which boost the student's feelings of self-esteem; (2) challenge, presented in the form of meaningful learning materials; (3) curiosity, which enjoins the students in the excitement of the subject matter; and (4) control, good tutoring fosters a sense of self-efficacy and control (Lepper et al., 1997).

This research turned to these aspects of the literature to inform the instructional design of Study 2 for two reasons: (1) because of the benefit as a general technique to support the development of both cognitive and metacognitive awareness while offering an emotionally supportive environment; and (2) probably more importantly, because of the growing body of research that suggests the need for cognitive scaffolding in facilitating conceptual change and other high level cognitive development (e.g., Mason, 1994; Vosniadou et al., 2001).

6.3 Case Study Research Methodology

6.3.1 Purposeful Sampling Procedure

According to Creswell (2002) the selection of a sample for qualitative research is based upon how well participants help the researcher understand the central phenomenon; this is called purposeful sampling. The criterion for selection is how "information rich" (Creswell citing Patton, 1990) are the individuals who are selected. This study employed the purposeful sampling strategy of "theory" sampling. That is, the participants were selected because it was thought that they could help the researcher discover specific concepts within the theory of conceptual change learning. The Learning Approach Questionnaire (LAQ, Donn, 1989) is reported to have a high predictor of performance factor (BouJaoude, 1992) therefore it was chosen as the criteria for selecting the sample for the case study. It was important that the participant have a high degree of internal motivation in order to complete the scheduled sessions. In addition, it was hypothesized that possessing a deep approach to learning and a relating style would facilitate the acquisition of the concepts and transfer. All students selected scored between 3 to 5, which according to Cavallo (1991) places them in the top half the population on this measure. Therefore they could be identified as high meaningful learning.

Sample Size

Creswell (2002) suggests three to five cases in a case study. This research started with 11 students[23] and ended with a "near complete" data sets on nine students. Although one of these nine students did not complete session 5 and the final interview because of health problems, I choose to retain her data because it contributed to demonstrating the different types of student experiences.

Participants and Settings

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[23] Eleven students began the case study project but only eight completed all five sessions plus the final interview. Two of the eleven completed two sessions but fell behind because of scheduling conflicts resulting in missed sessions. It was determined that although they were willing to continue that the data would be too difficult to compare with the other students; therefore they were politely released from their commitment. One other student, Monique, fell ill after session 4. Her data was included in the analyses because it was determined that because of the amount of data collected from her, it was a substantial contribution to the study thereby adding a dimension that would be beneficial to understanding how emergent framework mental models are constructed.

The participants in this study were drawn from the sample of students who participated in Study 1, therefore they were familiar with the researcher and with aspects of the intervention. As a reminder, all the participants were between the ages of 17 –18, they were all[24] enrolled in the second semester of the science program in a Quebec college, CEGEP (equivalent to grade XII). All participants signed a Study 2 consent form, unless they were under the age of majority, in which case their parents sign (see Appendix E.3).

Data Collected

The applicable data from the first study was rolled forward and provided background information such as demographics details, college grades, LAQ scores and Nelson-Denny scores. Additionally, this phase of the study collected transcript data, concept map drawings and outcome measures, all of which have been described in detail elsewhere.

6.3.2 Procedure

The treatment consisted of five, 60 minute one-on-one constructivist learning sessions (see Figure 6.2 for summary of sessions). Each session was comprised of two major components: (1) three models (simulations – see Appendix D.4) programmed in StarLogo T2000 computer language (see Figure 6.3 for summary of simulations' affordances for teaching emergent causal concepts as estimated by four independent experts); and (2) the cognitive scaffolding provided by a human coach. The objectives of the coaching were to scaffold the cognitive load of learning the particular aspects and behaviors of these models. Great effort was made to limit any direct instruction unless the participant showed a substantial lack of understanding or frustration; defined as periods of over 10 to 15 minutes without describing or explaining anything new, or taking the discussion in a completely unrelated direction. Therefore students' developed awareness and learning of emergent causal processes should be viewed as the outcome of self-directed discovery rather than direct instruction.

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[24] All but one participant was still enrolled in the second semester of the science program. However he was taking a comparable course on the topic of evolution.

Session	Simulation	Emergent Causal Concept Featured
Session 1	Slime	Demonstrates the process of aggregation and pattern formation. It is also a good illustration of micro-level behavior versus macro-level behavior. That is, at the micro-level, the behavior of the agents appear erratic and random, while at the macro-level, there is a sense of stability. All the while both levels exhibit a dynamic behavior, which, at the macro-level, is best described as homeostatic. At a more abstract level of description, one could identify the phenomenon of emergence as the micro-level agents interact to create a macro-level entity, the two levels exhibiting differential behaviors.
Session 2	GasLab Free Gas	Because of the graphs, this model was particularly good at describing the normal frequency distribution observed in large populations. Therefore, it was the probabilistic nature of certain types of complex systems. It also was excellent at describing the effects of large numbers in producing normal distributions. By the same process it demonstrated the extreme effects of the individual when in system defined by small numbers. Therefore, the effect of the individual on the system is dependent on the size of the population. It also demonstrated the equilibration effects of the system. That is, all systems work toward a state of equilibrium regardless of the starting conditions. This was well demonstrated by the speed counts graph. On a more abstract level, it also demonstrated the phenomenon of levels, with the micro-level molecules in constant motion while the on the macro-level, the gas attained a stable distribution (i.e., pressure, speed).
Session 3	Tutorial	It was not intended as a how to program in StarLogo lesson, rather, as an opportunity to see the simple rules behind the complex behaviors of the StarLogo models. Engaging in this activity allowed for greater sense of control and involvement in the models. The students felt that, if necessary, they could easily construct or alter the parameters of the models.
Session 4	*Testing*	
Session 5	Wolf-Sheep Predation	This is an example of a probabilistic model. It demonstrates equilibration processes with its patterns on the graphs over time as the populations rise and fall. It demonstrates flows as the energy moves from one part of the system to another. In so doing there is an element of non-linearity as the system draws near to "chaos" or extinction and then recovers in a nonlinear fashion. It also demonstrates the concepts of time (and maybe history) if we are to allow the simulation to run for a long time and also interact with it on the fly. That is, to see how a change in one of the variables affects an existing system. As a matter of fact, all the simulations operate in much the same way when it comes to the potential of adding history into the equation. In this research, this variable was not focused on and the subjects were encouraged to restart the system to isolate and ensure that they understood the effects of the variable that was been explored. It would be interesting to see how once the subject is familiar with the simulations, how they would react to working with the concept of history and adaptation of the system over time. It was the first model that involved more than one variable. There were three variable interacting with each other. Two of the variables were directly dependent on each other. In addition to demonstrating the predator prey relationship it displayed the effect of pattern and equilibrium. It demonstrated how fragile the system could be when certain parameters are not met. Therefore the notion of edge of chaos was well demonstrated in this model and equilibrium is a little harder to achieve in this system particularly when the sliders were adjusted "on the fly". On an abstract level there was the effects of history. On levels there was the level of the individual that was always dynamic while the system could develop into a stable one. The oscillation of elements. The effects of time on systems with these types of variability.

Figure 6.2 Summary of the five inquiry-based sessions used in Study 2.

	Complex System's characteristic Emergent Causal Processes	Sessions							
		1	2	3	4		5	6	
		Slime	GasLab	Tutorial	Text Part A	Brain Teaser Part B	Wolf Sheep Predation	Post- Case Interview	Comments
Initial Process	Pattern formation (development of levels)	√√√	√√√	√√			√√		
Outcomes of system behavior	**Emergence – self organizing**	√√√	√√√	√			√√√		
	Probabilistic nature - Stochastic	√√	√√√				√√√		
	Dynamic equilibrium – homeostatic	√√	√√√				√√		
	Edge of Chaos – effect of environment/ lack of predictability						√√√		
	Role of time – history						√√√		
Relationship between agents and system Characteristics of interactions between agents, or between system and environment	**De-centralized control (independence of agents - internal models)**	√√√	√√√	√√√			√√√		
	Partly random actions (random actions of agents)	√√√	√√√	√√√			√√√		
	Effect of numbers of agents on system (effect of individuals on population)	√√	√√√				√√		
	Ongoing process – agents and system are dynamical interacting	√√√	√√√				√√		
	Non-linear effects (small actions – big effects)	√√	√√				√√√		
	Flows of information – feedback "multiplier" effect	√ (AB)	√ (AB)				√√√		
	Selection & Adaptation (Tagging)	√√√ (AB)	√				√√		
	Diversity (requisite variety)	√√ (AB)					√√√		
	Interaction of environment						√√√		

(The √ marks indicate the degree to which a group of experts agreed that the models displayed these characteristics. One √ indicates somewhat illustrative of the named characteristic, two √√ indicates moderately illustrative, and three √√√ indicates highly illustrative. For concepts that are highly illustrated however are quite abstract, the notation of "AB" was added).
NB. Items shaded in blue are also represented on the ontological mental model taxonomy (OMMT).

Figure 6.3 Four experts' assessment of StarLogo models' affordances for teaching emergent causal concepts – Study 2.

Session 1

Before engaging in the first session, the student was asked to sign a consent form alerting him or her to the fact that they would be audio or videotaped during the five sessions (same as mentioned above). Furthermore, the student was informed that she would be asked repeatedly to discuss aloud her decisions and reasoning. For some students it was easy to engage in this "think aloud" protocol while for others, it required continual prompting through questioning and verbal descriptions of their actions, or the effects of their action as demonstrated by changes in the simulation.

During this first session each student in this one-on-one format was reintroduced (or introduced) to the Starlogo simulation software. Because six of the nine participants had used the simulations in Study 1 their learning curve was not steep as the three who took a little longer to become familiar with its features. No student found it impossible or too difficult to use the simulations, although some simulations were more challenging, as will be discussed in the results section.

To start the student was asked to open the simulation entitled "Slime" that represents the life cycle of the slime mould. They were asked to read the instructions in the "INFORMATION" window (for example see Appendix D.5) that provided the "setup" directions on how to use the simulation (e.g., the controlling mechanism referred to as the "slider" which changes pre-defined range of variables, which were manifested as behavior or changes of the "turtles"). In addition, this window included suggestions on "things to notice" once engaged in the simulation therefore, the functioning of the simulation was transparent. It is important to remember that Starlogo is intended for students K-12, therefore the reading level of the embedded text information is age appropriate.

After one run of the simulation at the default setting, the student was asked to describe his/her observations relating to the behavior of the slime mould – also referred to from time-to-time as "turtles" the programming terminology. Concurrently, throughout the entire exercise she was encouraged to engage in the "think aloud" protocol and describe her actions, observations as well as elaborate on her reasoning.

Next, the student was asked to change one or more of the variables controlling the behavior of the slime mould. The coach provided encouragement for systematicity in using sliders, however, it was not a rigid requirement due to the self-directed inquiry approach. After two to three instantiations, the researcher called upon the student to explain the observed behaviors – the intention was for the student to demonstrate the type of inferences, explanatory frameworks, constructed from these experiences with the models.

Observation Points of Session 1

The following are the types of questions used as prompts and formed the basis of the observation data collected:

1. What changes to the "sliders" did you try?
2. What were the results of these changes? (i.e., describe your observations).
3. How would you explain the behaviors? (i.e., what inferences could be drawn from these behaviors?)
4. Could you predict behavior of future changes in the controlling variables?
5. If you were told that these behaviors were typical of some complex systems, could you name the most identified behaviors/characteristics that could be then be used to construct a list of attributes or behaviors of complex systems in general?
6. Can you relate these behaviors to anything in your life experiences?

(NB. Participants were treated as independent cases and the way the session unfolded was dependent on their level of interest and the need for coaching. Therefore, some of the questions listed above may or may not have been asked instead more paraphrasing or direct tutoring may have been necessary).

Most likely Observations From Slime Simulation

1. Emergent levels of organization – particularly through visible aggregation and pattern formation.
2. Local interaction of agents.
3. Dynamic homeostatic behaviors and self-organization.
4. Random action of agents.
5. Small scale fluctuations lead to nonlinear effects.

Session 2

Session two followed the pattern of inquiry-based learning that was established in session one but this time with the GasLab: Free Gas simulation. The student was first asked to experiment with the simpler GasLab simulation (2-molecule gas) to ensure his understanding of the type of behaviors exhibited by the molecules (i.e., turtles). They were then asked to run the "Free Gas" simulation in which many gas molecules engaged in a behavior that created something quite different from the individual level of the two Gas molecules. This was followed by a request to comment on the differences between these two different outcome results from similar individual behaviors.

Once experimentation of the variable options were exhausted the student was asked to compare the behavior of the GasLab simulation to the behavior of the Slime mould simulation. The coach prompted for comparisons of observed similarities and differences. Each student was asked to draw up a personal list of characteristics they identified as common to the complex systems they had investigated (i.e., the two simulations).

In the final minutes of the session the student was given a concept-mapping task. He was provided with 12 terms generally associated with complex systems. These terms were placed on "post-it notes" squares and stacked on top of each other on a flat 11x17 board. The student then was asked to arrange these terms so that related concepts would be close together (i.e., construct a concept map). No specific instruction on how to make a concept map was given, however, the coach questioned each student as to his/her prior experience in making these types of maps. All students were new to making concept maps, however all appeared to arrange the terms in such as way as to form prepositional associations (i.e., links and nodes). When questioned specifically on their mapping strategy, all students confirmed that they had in fact used some type of propositional association strategy (i.e., reading their maps like prepositional phrases).

Observation Points of Session 2

1. Observation of development of hierarchical levels, this time with more subtle and abstract content. Different behavior of agent (individual gas molecule) and system/meta-agents (gas laws, e.g., pressure energy, Pv=nRT).

2. Behavior of closed systems to reach equilibrium state with time.
3. The effect of numbers of agents on the attainment of equilibrium state.

Most Likely Observations From GasLab Simulation

1. Emergent levels of organization – however, the macro-level was more abstract and required an understanding of graphs.
2. Local interaction of agents.
3. Dynamic equilibrium and self-organization.
4. Probabilistic nature – particularly related to large numbers and the formation of "normal distributions" (Wilensky & Resnick, 1999).
5. Small scale fluctuations lead to nonlinear effects.

Session 3

The third session was one designed to demystify the operation of Starlogo. The student was given the programming tutorial documentation and asked to follow the instructions. While entering the programming code she was asked to describe what her thoughts were on how the simulations were put together. This exercise called for precision in coding protocol. The hour session was insufficient to complete the entire tutorial, however, it did provide the participant with sufficient experience to arrive at an understanding of the programming language and functioning of the simulations. The session concluded with the concept map exercise.

Observation Points of Session 3

1. To "see" the programming from the turtles' point-of-view.
2. To discover that organization arises through simple algorithmic decisions. For example, organization, like the behavior of 'gliders' can arise from three lines of programming code. Therefore, don't look for the complicated features, check out the possibility of simple rules first.

Most Likely Observations From StarLogo Tutorial

1. Precision required for the programming. This would be a great teaching point to teach the role of error in the creation of variety. That is, the role of random noise in the system.
2. Simple rules.
3. Random actions.

Session 4

In the fourth session the student was asked to read a portion of an article[25] describing specific systems' concepts (see Appendix D.6). The article and the concepts were selected because of their relevance to the complex systems represented by the multi-agent models and the emergent causal processes described. The objective was to provide the student with some formal structure and terminology to accompany their growing intuitions of emergent causal processes. The document acted as a metacognitive tool to trigger discussion, elaboration of ideas and reasoning about the phenomena observed in session one through four.

Observation Points of Session 4

The participants were asked the following questions:

1. What do you understand from the text? The meaning of each concept was explored.
2. Does having a definition make the concept clearer or does it do little to help clarify understanding?
3. Delayed posttest questions: (a) Ants foraging; (b) Butterfly and weather patterns; (c) Traffic formation; and (d) Town planning.
4. Concept map exercise.

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[25] The level of language in the text was somewhat sophisticated but the content offered the most condensed yet explicit definitions regarding self-organization and emergence that I could find in a search of this literature. It was important that the definitions be as accurate and not summarize to the point of being patronizingly vague or too dependent on a higher level of interest in complexity.

Most Likely Observations From Session 4

The second half of the session collected data using the outcome measure, emergent framework questions. The decision to assess the students before the end of the intervention was made to ensure that no data would be loss because of attrition. The session concluded with the concept mapping activity.

Session 5

In the fifth and final intervention session the student was asked to explore the simulation entitled "Wolf-Sheep" predation. The procedure unfolded in a manner similar to sessions one and two. The student experimented with the pre-defined variables and was asked to think aloud through the process. Questions or prompts were provided when necessary to elicit more of the student's reasoning and beliefs. The session concluded with the concept mapping activity.

Observation Points of Session 5

1. Same list of questions as sessions 1 & 2.
2. Concept mapping exercise.

Most Likely Observations From the Wolf-Sheep simulation:

1. Emergent levels of organization.
2. Local interaction of agents.
3. Dynamic equilibrium and self-organization.
4. Flows of resources (i.e., multiplier effect).
5. Small scale fluctuations lead to nonlinear effects.

Session 6

This final opportunity to assess the learning was conducted as an interview. The student was asked questions concerning her recall of the terms and concepts learned. Data collection was conducted through the use of the final posttest outcome measure. These questions were posed to the student and responses were aural. In the final minutes of the session the student was asked to once again turn to the concept maps constructed one year prior. She was asked to review it and make any changes or modifications that better reflected her present understanding of the complex systems behaviors.

Observation Points of Final Interview

1. Recount what you remember about the instructional sessions?
2. Can you explain what you remember about complex systems and their characteristics?
3. If I were to say that this was a way of thinking about observations (phenomenon) did you ever have the opportunity to use this way of thinking in your courses?
4. Final Posttest Questions: (a) Birds flocking; (b) Evolution of corn seeds.
5. Concept mapping exercise.

6.4 Data Collection Methods – Study 2

Data consisted of the observations of the coached instructional sessions, interviews, and written artifacts produced during the sessions. The data from the instructional sessions were audio taped, and session 3, 4, and 5 were videotaped as a means of preserving greater authenticity and atmosphere, that is, to enrich the description of the subject's composure and attitude to help when transcribing and analyzing the data. There were two transcribers for the audiotapes, however, the primary transcriber established the style and checked for accuracy. Authenticity and accuracy of transcriptions was established through random selection of one transcript from each subject and comparing it against the audiotape. The tapes were deemed to be accurate and a few of the muttered and unrecognizable words were clarified in the process, however, no significant changes were required.

All written documentation (includes pretest-posttest questions, and concept maps) was added to the data corpus. Additionally, the principal researcher kept a reflective journal documenting observations on the coaching process and progress. These reflections included brief summaries and reviews of technique and suggestions for modification of procedure for the next session.

Table 6.1 Review of list of data collected and analyzed in both studies.

Data Collected	When	Data Analysis Technique	Coding Taxonomy Used
Pretest	Study 1	Mental model coding	1. Original Ontological – 2000 2. Revised Ontological – 2002
Immediate Posttest	Study 1	Mental model coding	1. Original Ontological – 2000 2. Revised Ontological – 2002
Delayed Posttest	Study 2	Mental model coding	1. Revised Ontological – 2002 2. Complex Systems – 2002
Transcripts sessions	Study 2	Qualitative coding methods (categories, themes)	Categories emerged from the data.
Concept Maps	Study 2	Qualitative coding methods	Combined method (Ruiz-Primo & Shavelson, 1996).
Final Transfer Test	Post Intervention	Mental model coding	1. Revised Ontological – 2002 2. Complex Systems – 2002

6.5 Data Analysis Methods – Study 2

Both Merriam (1998) and Yin (1994) describe methods of analyzing case studies. According to Merriam (1998), there are three main methods of analyzing qualitative data: (1) descriptive accounting of findings, (2) category constructions, and (3) theorizing; whereas Yin (1994) suggests two general strategies: (1) the descriptive framework, and (2) the development of theoretical propositions. Although using different words, both authors suggest that the descriptive level is the less in-depth analytical technique. At the descriptive level meaning is conveyed through the compression and linking of data, which is then presented in a narrative format. Most case studies generate some type of narrative presentation, however, many strive for the more sophisticated method of analysis involving the construction of categories or themes that captures recurring patterns flowing throughout the data. To emphasize this point, Merriam (1998) states: "category construction *is* data analysis" (p. 180).

Construction of categories. Categories are not the data themselves; rather they are abstractions derived in both a systematic and intuitive manner. Glaser and Strauss (1967) suggest that the categories should be "emergent" (this meaning should not be confused with the way "emergent" has been used thus far in this study); that is, they should be born out of the data and in so doing be a perfect fit thereby explaining most of the data collected. Categories may also be considered lenses through which the data may be viewed. In many instances, including this current study, categories are informed by the purpose of the study as well as the literature. I therefore began the data analysis process by first looking at my purpose statement and made the decision to focus on evidence of mental models (e.g., observations, explanations, vocabulary use, analogies, and relationships of concepts). This should not suggest that I ignored the possibility of emerging data categories that more aptly describe the evidence. For instances, categories related to epistemological beliefs, need for social interaction, and coaching behavior (see Table 6.2). These are very interesting categories but lie outside of the scope of this dissertation, however, they may provide new directions to follow for future studies.

Construction themes. The next level of data analysis is more abstract and involves the construction of explanations through the linking of categories. In case study research, this is considered the cross-case analysis. Merriam's (1998) description of this process is consistent with the qualitative post-positivist movement, by comparison, Yin's (1994) is reminiscent of the quantitative approaches suggesting the identification of dependent and independent variables. Whichever approach is selected, Yin tells us that "the analysis of case study evidence is one of the least developed and most difficult aspects of doing case studies" (p. 102). This current research viewed this challenge of constructing themes and testing the links between categories as an important part of the data analysis. The decisions of which themes I constructed and which I chose to follow will be discussed in the upcoming section.

6.5.1 The Process of Constructing Categories

The process of constructing categories from the raw data started with the following procedure: transcripts from one student were annotated and a preliminary coding scheme was recorded in a coding logbook. Because of the theoretical nature of the research design, *a priori* coding schema were used to develop certain categories. One such category used the complex systems taxonomy (CST). The decision to use this taxonomy, rather than the ontological mental models taxonomy (OMMT), was made because it provided a broader palette from which to describe emergent causal processes. Another *a priori* category was cognitive strategies. In the first round of coding they were identified as 'descriptions' and 'sense-making'. Also identified were the categories of emotional response, for example, frustration and fatigue, as well as the larger category defined by the coaching itself. Development of a coding scheme for the latter category was put on hold until the categories for the learners were fully developed.

Undertaking a second round of coding using the same documents provided a finer articulation of the cognitive strategies category. 'Sense making' was elaborated into concepts of 'paraphrasing', 'explanation', and 'analogies'. I then went back to the literature to look for further theoretical descriptions and explanations of these cognitive processes. Entwistle (1988), and Marton (1981) provided insight into the cognitive processes involved in concept formation, whereas Keil and Wilson (2000) provided me with greater insight on possible ways to code for the category heading of 'explanation'.

The category of 'emotional responses' was changed to 'social interaction behaviors' and 'motivation' (motivated to participate because of: need for social contact; feelings of importance; money; interest in topic) and defined to include such concepts as 'anxiety level', 'tolerance for ambiguity', 'need to please', 'feelings of contribution', 'need to appear smart'. In this round of coding, another category appeared to emerge, that of epistemological beliefs (see Table 6.2).

The third round of coding took the categories developed in the first and second round and applied them to two other case studies in the cohort. The two selected were believed to be quite different from the original case. The data fit the categories, as defined, and few data points remained uncategorized. Nonetheless, there was a further articulation of the cognitive engagement category where it was felt that metacognitive strategies were being used in the sense-making process. Furthermore, there appeared to be examples of what could be described as "meta-model" thinking[26] where the student attempted to use the new explanatory framework to problem solve using the computer models representations as analogies. It was therefore decided to make this a category unto itself. A testable coding scheme appeared to emerge (will be shown later in Figures 6.4 and 6.5) through these repeated cycles of testing and refining or modifying or eliminating the categories.

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[26] I suggest that this metacognitive activity is distinct from metaconceptual awareness since the focus is on thinking or reasoning with the representational model rather than evaluating the explanatory framework.

Table 6.2 Early draft of categories from the transcript data.

Ontological beliefs: assessed using mental models	Cognitive engagement activities – concept development.	Metaconceptual: use of the concept to think about other concepts.	Epistemological beliefs. (Hofer & Pintrich, 1999)	Social interaction behaviors	Coaching behavior.
Reductive ↔ Emergent	Observation High ↔ Low	Metaconceptual High ↔ Low	Knowledge – certainty Certain ↔ Uncertain	Test anxiety High ↔ Low	Need for prompts High ↔ Low
Determinist ↔ Probabilistic	Explanation High ↔ Low	Metacognitive High ↔ Low	Knowledge-source: from Authority ↔ from Reasoning	Level of frustration High ↔ Low	Need for motivating High ↔ Low
Linear ↔ Nonlinear	Use of analogy High ↔ Low		Knowledge – structure Simple ↔ complex	Tolerance for ambiguity High ↔ Low	Use of abstract examples High ↔ Low
	Use of generalization High ↔ Low			Fear of being incorrect High ↔ Low	Level of involvement High ↔ Low
	Self directed questioning High ↔ Low			Feelings of contributing High ↔ Low	Errors in directions High ↔ Low

Category reliability check. After the third round development I decided to bring in another point of view to ensure that the identified categories indeed fit all the data. Selecting a totally new transcript (i.e., one that was not part of the database used for the study and not transcribed by the research assistant), I met with the research assistant (RA) and provided him with some background information concerning the types of things that had been coded; for example, evidence of cognitive strategies such as explaining through examples, or evidence of complex system's concepts. The RA was asked to use his judgment and intuitions to identify any other categories that he recognized from the transcript. In other words, to let the categories and coding emerge from the data itself - a grounded theory approach.

What followed was a three-stage process. First, we each independently read and annotated our copy of the same seven-page transcriptions. Then we looked at the coded document and discussed his coding decisions. The RA had made several interesting and unique observations, which were discussed and evaluated based on their significance to the generation of useable categories. The categories that appeared to be most fruitful were added to the already existing list of categories. Some categories such as psychological interpretations were left out because of their subjective nature and the belief that they are not central to the research.

The final task was to compare the documents coded by the RA. Although the RA did not address all the complex systems categories, the agreement on the other categories was very high. In several instances we discussed the name assigned to the coded passages or words that describe sub-elements of the major cognitive strategies category, in other words, the dimensions of the category. By the end, there was consensus on the segments of text that were coded and the category assignment of those segments of text.

6.5.2 The Process of Development Themes

The process of developing themes was informed by Merriam (1998), who tells us that the importance of themes is to test out explanations and hypotheses through the linking of categories. Figures 6.2 and 6.3 provide a visual representation of the stages in this procedure starting with the raw data at the bottom of the page and moving upward through the emerging categories, as described above, to the construction of themes. It is important to note that as the themes emerged they also influenced the types of questions that could be explained by the data, hence modifying the central questions of the qualitative phase of this dissertation study. Table 6.3 (also referred to as a "data display" in Anfara, Brown, & Mangione, 2002) demonstrates another way that I explored the potential hypotheses and explanations as I attempted to link the categories of data. This also was a way to ensure having multiple data sources for triangulation of the data analyses.

Table 6.3 Finding themes within the data and testing of possible links.

Questions that could be explored through the linking of data.	Pretest/ Imm.Post Study 1	Transcript	Concept Map	Delayed Posttest Study 2	Nelson Denny	GPA	NYA science courses
1. Interaction of sessions and learning of Emergent Causal Processes (ECP) affordances of simulations		X	X				
2. Learning of ECP and transfer to explanatory framework, elaborations of EFMMs		X	X	X			
3. Interaction of students' profiles and ECP.		X	X	X	X	X	X
4. Use of analogous models and improved understanding of ECP.		X		X			
5. Affordances of understanding specific EFMMs concepts - emergent self-organ. - probabilistic causes - dynamic nature - decentralized control - random actions - nonlinear effects	X			X			
6. Synthetic mental models.	X	X	X	X			
7. Correlations of coding schema OMMT and CST.		X		X			

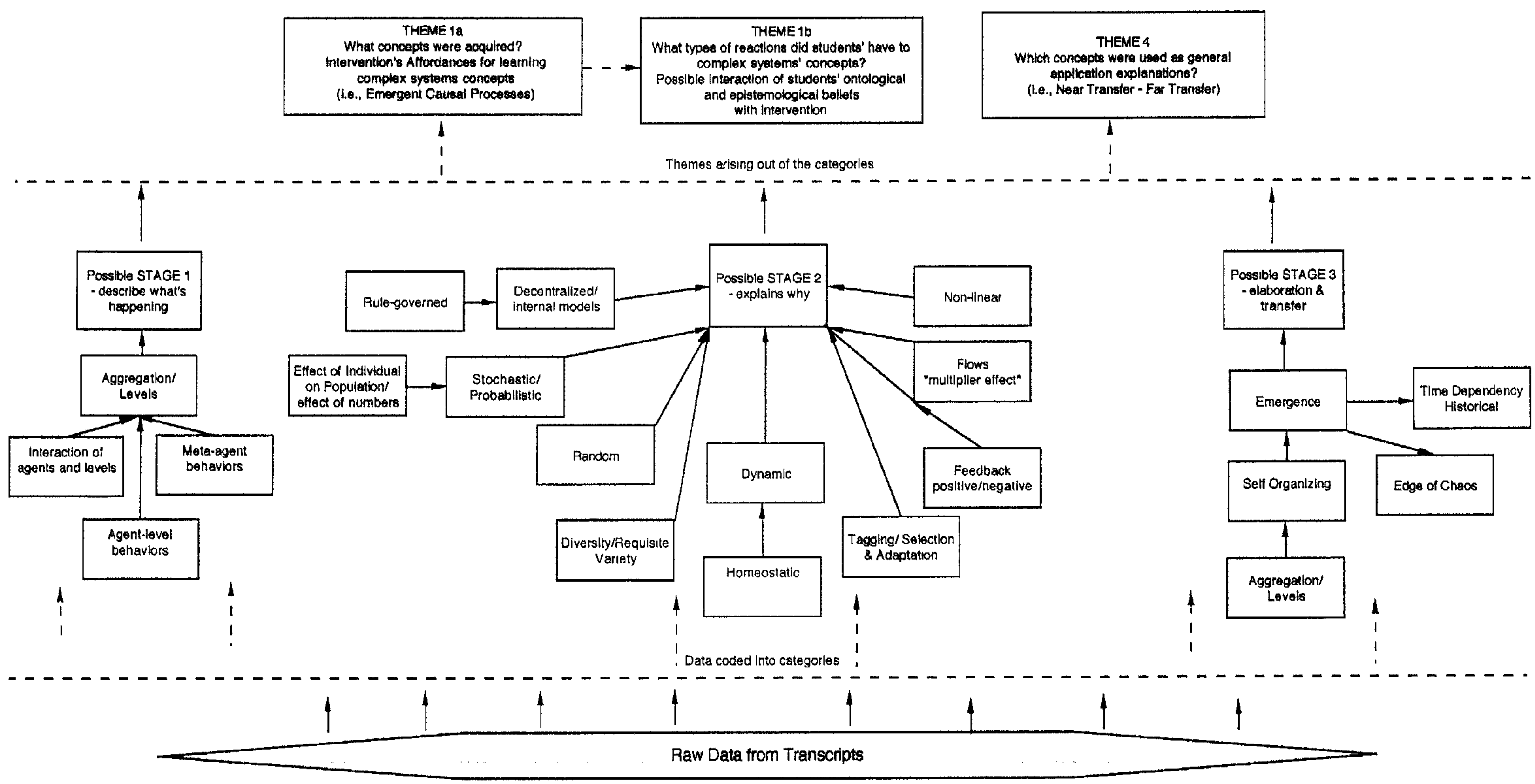


Figure 6.4 “Code Mapping”: Iterations of analysis of raw data to categories to themes based on *a priori* CST categories. (to be read from the bottom up)

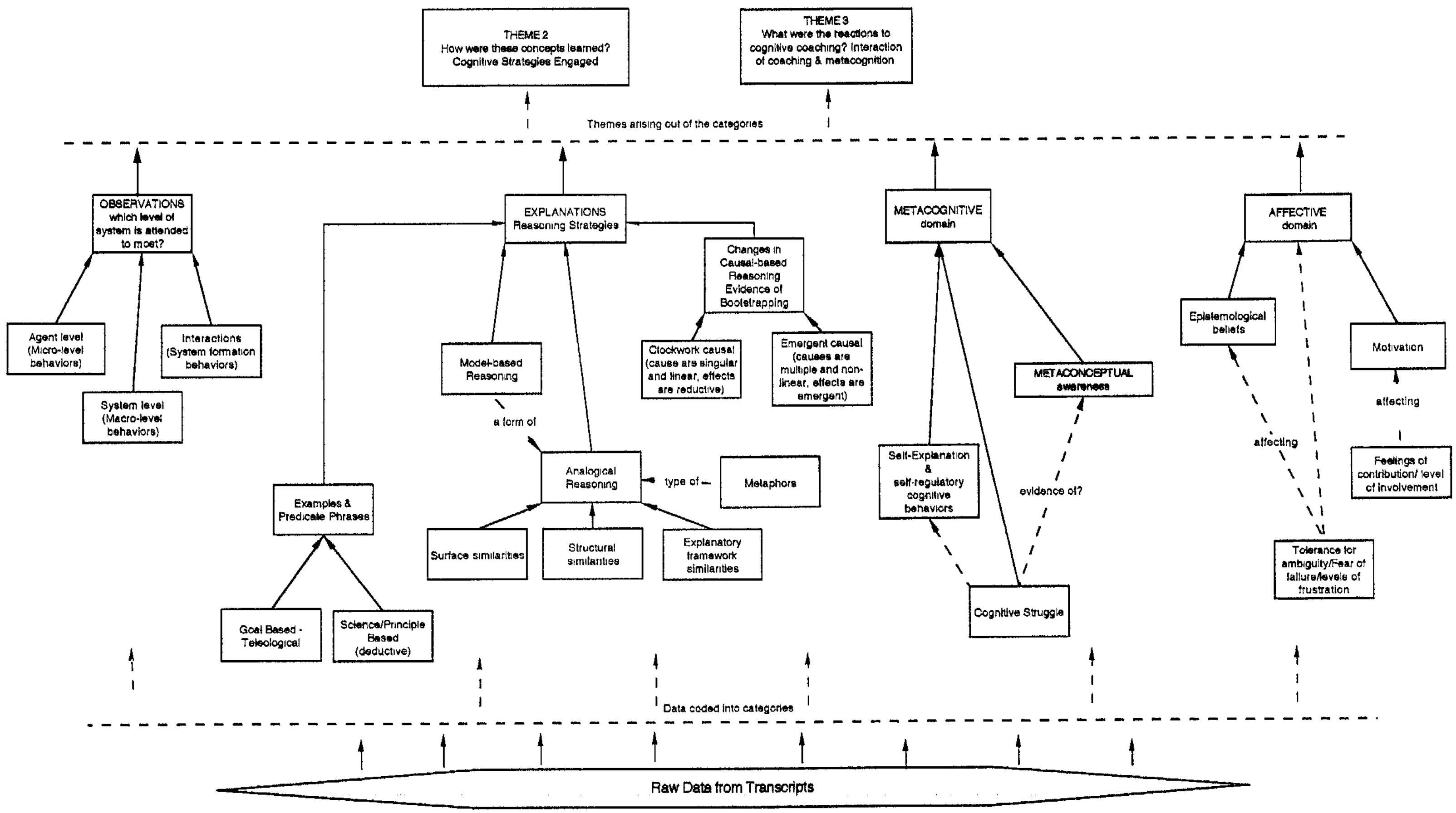


Figure 6.5 "Code Mapping": Iterations of analysis of raw data to categories to themes, categories that emerged from the data. (to be read from the bottom up)

6.6 Issues Related to Data Verification and Researcher Ethics

Verification of data. The protocol for verifying the data collected from each instructional session was as follows: (1) meet with non-participant observer at the end of each week to discuss the progress of the sessions; (2) critically review field notes and make a random check of audio and video quality; and (3) use the reflections from the field notes and discussion with non-participant observer to make modifications for the next session.

Confidentiality of data. The researcher upheld the requisite "human research ethics" measures to insure confidentiality of the entire data corpus. All students are referred to by their pseudonym and raw data were shared only with my committee members and coders.

Ethics of conducting human research. Because my role was that of a researcher /coach and not a teacher, I did not actively insist that the student attend to faulty mental models, however, I prompted for reconsideration of their statements (e.g., "do you really think that is what would happen?"; "could you explain that to me again."). However, in my commitment to do no harm, if a student appeared to be creating a new mental model (e.g., "aha, I never thought it was that way…"), which was a classic misconception, I would actively intervene to halt this construction before it was reinforced.

Other considerations. As a researcher with a limited science background, it was important to ensure the veracity and accuracy of the science content. All the instructional materials pertaining to the science content were authenticated and accepted by three members of the science program faculty (i.e., one from each of the major departments: biology, chemistry and physics). They also evaluated the credibility of the selected resources (i.e., web-sites, handouts, etc.). In addition, these same individuals, along with an expert in the field of cybernetics were responsible for the group instruction delivered in the first phase of the research.

During the case study sessions, since I was the sole administrator, I curtailed discussion that pertained to direct science phenomena that reached beyond my level of accurate knowledge. I also was cautious with my use of scientific analogies. Whenever, questions or discussion moved into areas of science, or complex systems, that were beyond my scope, my response was generally "to get back to them with an answer". Fortunately, these situations did not arise very often, and when it did, it was primarily with one student whose cognitive skills were far in advance of the norm. I have identified only one occasion where I misunderstood this student's questioning and mistakenly provided him with an inaccurate answer, which I attempted to rectify in our subsequent session.

6.7 Establishing Validity (i.e., Trustworthiness and Authenticity)

Different authors suggest that validity of case studies should be established through a variety of methods (Erickson, 1986; Patton, 1990; Merriam, 1998; Yin, 1994). Some of the generally agreed upon ways of establishing validity include: (1) the collection of different data sources thereby allowing for the cross-validation of findings (i.e., triangulation); (2) the use of two or more evaluators to review material in each case and make independent judgments and interpretations (i.e., inter-rater reliability); (3) an adequate amount of data collected over an adequate amount of time to provide a range of cases (i.e., confirming and disconfirming cases); (4) accuracy of facts and interpretation of data evaluated by the cases themselves.

Attempting to reduce the first and third threats to validity, this study used multiple measures to generate the data corpus over an extended period of time. Because the data collection process spanned almost two years it allowed me to collect a substantial amount of evidence of the students' changes over time. I was able to establish a good rapport with the nine students thereby increasing the "emic" component of the data. Subsequently gathering evidence of both confirming and disconfirming cases.

The second recommendation to improve validity was addressed by having several different individuals code the data to obtain an inter-rater reliability correlation score. Lastly, accuracy of the facts and interpretation of the transcripts was attempted by having the participants themselves review the data – what Creswell (1994) calls "members checks". Because the final session occurred months after the case study intervention, the written transcripts were available for the students to review. Additionally, I provided the student with his/her summary case reports and reviewed it with each respectively. This allowed for some corrections as well as confirmation of their opinions as to how they had experienced the intervention. A final effort to confirm conclusions regarding concept maps was made by sending JPEG versions to the student by email. I requested feedback if the maps were not representative of their current understanding. No one requested changes, although I did receive a few emails of salutations confirming that they had received the mailing.

CHAPTER 7

RESULTS OF THE CASE STUDY INTERVENTION

> Case study is a part of scientific method, but its purpose is not limited to the advance of science. Whereas single or a few cases are poor representation of a population of cases and poor grounds for advancing grand generalization, a single case as negative example can establish limits to grand generalization.... Case studies are of value in refining theory and suggesting complexities for further investigation, as well as helping to establish the limits of generalizability" (Stake, 1998, p. 104).

Overview of the Chapter

The mixed method data analysis allowed for in detail exploration of individual student's experiences as well as qualitative cross-case comparisons and statistical comparisons on the results of outcome measures (i.e., delayed posttest and final posttest). It also permitted the triangulation of different types of data thereby adding to the credibility of the data analysis. Because of the multiple data collection and analysis reported in this chapter, I have divided it into six distinct sections. The content of each section is described below and in Table 7.1. Additionally, a glossary of the terminology used throughout this section is provided in Table 7.2.

Table 7.1 Overview of the data analyzed and reported on in chapter 7.

Chapter 7	Data Collected	When	Data Analysis Technique	Coding Taxonomy Used
Section 7.1 7.3 7.4 7.5 7.6	Transcripts sessions	Study 2	Qualitative coding methods (categories, themes)	1) CST used for emergent causal concepts 2) Other categories emerged from the data.
Section 7.2	Concept Maps	Study 2	Qualitative coding methods	Combined method (Ruiz-Primo & Shavelson, 1996). 1. concept pairing 2. criterion maps
Section 7.7 – 7.9	Delayed Posttest	Study 2	Mental model coding *t* test analyses	OMMT
	Final Posttest	Post Intervention	Mental model coding *t* test analyses	OMMT
Section 7.10	All data	Study 2	Correlational analysis Triangulation of data sources	

Table 7.2 Glossary of complex systems terminology used throughout chapter 7.

COMPLEX SYSTEM CODING TAXONOMY	DEFINITIONS	EXAMPLES
EMERGENCE	• Ascending hierarchical organizations reveal the phenomena of emergence. Emergence organized through communication and control mechanisms of the hierarchy. • Emergence makes use of the mechanisms of: (1) *tagging*, (2) *internal models*, and (3) *building blocks*. Mechanisms from lower levels provide constraints and suggest what to look for at higher levels. Emergent phenomena show up in a multitude of science disciplines: • atoms - structure • gases and fluids • molecules in chemistry • organelles in microbiology • cells in biology • organisms • ecosystems	• Slime mold • Bird flocking • Traffic jams • Termites • Economy GDP • Immune system • Nervous system • Genome vs. Phenotype • Individual vs. Population vs. Species
Self-Organization	• Self-organizing system comes together based on rules. They exhibit goal seeking behavior. The reasons that animate things do not fall into entropy. Negentropic or homeostatic activities prevent entropy.	
1. Local interactions.	• Local interaction of many individual agents result in the formation of higher level entity.	
2. Simple rules produce complex results.	• Simple rules produce complex results through a complex interplay of local interactions.	
3. Decentralized control	• Emergent systems exhibit organization without centralized control. (i.e., decentralized control). Agents are independent and competition among themselves.	
4. Random behavior	• Behavior of the individual agent is uncertain because of the innumerable possible local interactions.	
5. Tags	• Tags are an organizing mechanism that allows the agents to select among agents or objects that would otherwise be indistinguishable. They are filtering, specialization, and cooperation devices. Tags are the mechanism behind hierarchical organization-the agent/meta-agent/meta-meta-agent/...organization.	• Internet header on a message • Immune system operation. • Pheromone trails.

6. Flows	• Flows of information/resources throughout the system using networks involving: node → connectors → resources. • Flows through networks vary over time. Moreover, nodes and connections can appear and disappear as the agents adapt or fail to adapt.	• Local adaptation - survival advantage in evolution • Species - food web interactions - biochemicals for ecosystem • Tropical rainforest
• Feedback (positive or negative) .	• Feedback is where the influence of an element impacts on other elements through a series of relationships that return to the initial point, i.e., feeds back on itself. *Multiplier* effect is the result of (positive feedback). Example of positive feedback (amplification of the initial state. Out of control if it goes to far). Helps achieve contained contraction or replication and growth or can lead to uncontained and unstable contraction or growth. *Recycling* effect - also defines the constraints.	• Predator/prey relationships. Example of negative feedback (a way of maintaining a steady state). • Runners' experience of a metabolic high can turn into burn out of the metabolism and death.
7. Internal models	• Internal models (schemas) give the agent the power to anticipate - tacit internal models simply prescribes a current action/ overt internal models uses lookahead protocols.	
8. Diversity/ variability	• Diversity also known as "requisite variety". A control system must have adequate variety. The variety of the control system must be greater than the variety of the controlled system or the environment.	• Ecosystems - tropical rain forest. Phenomenon of convergence - nature filling in a void to accommodate necessary number of interactions. If a species disappears then another takes its place. • Genetic variation • Mammalian brain • NY city's economy based on neighborhood merchants

9. Modularity	• Hierarchical nature of systems allow for recycling of useful components. • Building blocks are the components of a complex system that can be used and reused in a great variety of combinations like a set of Lego building blocks. These reusable components make it possible to make sense of novel situations. Subassemblies are building blocks of the emergent complex system.	
10. Pattern formation	• Pattern formation: Prominent among simple mathematical models that capture pattern formation are local activation / long range inhibition models.	• Turing patterns, and the work of Prigogine. • Weather - cells of airflow, protein - alpha and beta structure, • Physiology - processes of pattern formation in development, • Brain/mind - various patterns of interconnection and pattern recognition mechanisms (on-center off-surround), • Magnetic bubble memories • Patterns of species in phenome or genome space • Economy/society - patterns of industrial/residential/ commercial areas.
11. Open/closed systems	• Generally emergent systems are open systems but can be closed (e.g. gas pressure).	
12. Multiple Levels	• Systems are nested. Therefore complex systems are made up of many subcomponents that may themselves be nested systems.	Economy → Organizations→ Departments → Individual employees→ Bodies → organs → cells
13. Probabilistic	• Probabilistic behaviors have non-deterministic outcomes. Population size affects the results. The larger the sample size the more reliable the prediction of outcome and the more the outcome reflects a "normal distribution" curve. The smaller the sample,	• Bell curve

	the more likely that individual differences will make it difficult to predict the outcome.	
14. Nonlinearity	• Nonlinear systems are more complex than linear systems. A feature of nonlinear systems is that different starting points lead to different end points and can cause the model to become unstable. Behavior is often counterintuitive.	• Lorenz's attractors • Weather patterns • Predator/prey interactions • Genetic drift
15. Criticality	• Lever points wherein small amounts of input produce large directed change; threshold effect (e.g., phase changes).	
16. Dynamic equilibrium	• Homeostasis /Dynamic equilibrium with fluxes in and out. • The notion that organisms (systems) exchange information, materials and/or energy with their environment in order to survive therefore over time the materials that make up the organism (system) has partially or totally changed. • Multiple (meta) stable states. Small displacements (perturbations) lead to recovery, larger ones can lead to radical changes of properties. Dynamics on such a landscape do not average simply. Mathematical models are generally based upon local frustration e.g.. spin glasses, random Boolean nets. Attractor networks use local minima as memories. Examples: weather - persistent structures, proteins - results of displacements in sequence or physical space, physiology - the effect of shocks, dynamics of e.g. the heart, brain/mind - memory, recovery from damage, economy/society - e.g. suggested by dynamics of market responses.	• Human body • Institution • Standing wave • Traffic jam
17. Adaptation	• Adaptation is defined as agent and environment interactions. An example is "fitness landscape". • "Fitness landscape". Part of a Hill-climbing algorithm in which the search space turns into a fitness landscape, where every point in the space ("horizontal") is associated with a "vertical" fitness value, so that a landscape with valleys and peaks appears. Problem-solving then reduces to "hill-climbing": following the path through the fitness landscape that leads most directly upward.	• Evolution
18. Selection	• Selection suitability of the particular trait an agent has for surviving long enough to reproduce in a particular environment. • It is also defined as information (a la Shannon's	• Natural selection

	theory). Selection as information is relevant to the issue of multiple selection: replication (reproduction) with variation, and comparative selection (competition) as a mechanism for POSSIBLE increase in complexity. Consistent with modern biological views of evolution it is essential to emphasize that selection does not have to increase complexity.	
19. Time scale.	• Time scale is a critical feature in development of complex systems.	
20. Multiple causality	• Emergent systems are dependent on multiple actions and interactions to create their complexity. Therefore the number of agents in an environment with multiple components to interact with will create infinite possibilities of outcome.	

7.1 An Overview of Who Acquired Which Concepts from Complex Systems Intervention

The results in Table 7.3 represent the itemized scores for 15 out of the possible 20 categories identified in the complex systems taxonomy (CST) for all nine students over the course of three instructional sessions that employed simulations. There are two important aspects of this global perspective that will be discussed: (1) the combined scores (far right column), and (2) the scores for the individual sessions (see section 7.3).

Looking at the combined "raw score" (far right column blue shading) shows us that all the students discussed, and possibly learned, something of emergent causal processes over the course of each session. Examining the "percentage score" (far right column no shading) shows us how the individual's score compares to the combine totals for all students for the session in question. From this we can see that there was a range of individual differences resulting from the intervention.

Table 7.3 Complex systems concepts identified by student and reported by session.

		1	2	3	4	5	6	7	8	9	10	11	12	15	
	Student	multi levels	local interactions	open/close sys	Probability	random	tags	flows	homeostatic	simple rules	decentralized	diversity	nonlinear	pattern	Combined Scores
Session 1 – Slime Simulation	norman	8.4	4.6		2.3	2.1	1.3	0.4		0.1					19.1
		40%	22%		11%	10%	6%	1.9%		0.4%					10%
	penny	9.1	2.2	0.7	2.2	0.7	1.1			0.1	1.5			0.4	17.9
		43%	10%	3.3%	10%	3.3%	5%			0.4%	7%			2%	9.5%
	emilie	12	2.4	0.3	0.1		0.4		0.1						15.4
		57%	11%	1.4%	0.4%		1.9%		0.4%						8%
	moniq	6.7	2		0.3		0.4	0.2	0.3	0.1	0.1				10.1
		32%	9.5%		1.4%		1.9%	1%	1.4%	0.4%	0.4%				5%
	walter	9.6	4.4	0.5	2.3	0.3	1.1		0.3		0.2				18.9
		46%	21%	2.4%	11%	1.4%	5%		1.4%		1%				10%
	mitch	12.5	6.6	1.1	3.2	0.6	1.5		0.2						25.7
		60%	31%	5%	15%	3%	7%		1%						14%
	sidney	12.2	6.3	0.3	4.1	2.5	0.4	0.4	0.1	0.3	0.2	0.3			26.8
		58%	30%	1.4%	20%	12%	1.9%	1.9%	0.4%	1.4%	1%	1.4%			14%
	greg	11.4	7.8	1.3	5.2	1.6	1.3	1	0.3	0.4		0.3		0.7	30.9
		54%	37%	6%	25%	8%	6%	5%	1.4%	1.9%		1.4%		3.3%	16%
	sam	11.5	6.4	1.1	2.1	1.9	0.5			0.4	0.5			1.6	25.6
		55%	30%	5%	10%	9%	2%			1.9%	2%			8%	14%

Table 7.3 continued.

Session	Student	multi levels	local interactions	open/close sys	probability	random	tags	flows	homeostatic	simple rules	decentralized	diversity	nonlinear	pattern	Combined scores
Session 2 - GasLab (Free Gas) Simulation	norman	3.7	2.7	0.7	1.5	0.7					0.2				9.5
		28%	21%	5%	11%	5%					1.5%				9%
	penny	4.4	2.1	0.6	1.7	0.1			0.2		0.1		0.1		9.3
		34%	16%	5%	13%	0.8%			1.5%		0.8%		0.8%		9%
	emilie	4.1	1.4	0.3	0.9	0.2									6.9
		31%	11%	2%	7%	1.5%									7%
	moniq		1		2				0.2						3.1
			7.7%		15%				1.5%						3%
	walter	4.8	2.3	1.4	2				0.1				0.1		10.6
		37%	18%	11%	15%				0.8%				0.8%		10%
	mitch	5.8	5.6	3.7	3	1.3		0.2	0.2		0.2		0.2		20.2
		45%	43%	28%	23%	10%		1.5	1.5%		1.5%		1.5%		20%
	sidney	4.3	3.2	1.4	4.3	0.4			0.2		0.1			0.1	14
		33%	25%	11%	33%	3%			1.5%		0.8%			0.8%	14%
	greg	8.4	7.9	6.8	5.1	0.2		0.2	0.2				0.2	0.2	29.2
		64%	61%	52%	39%	1.5%		1.5%	1.5%				1.5%	1.5%	29%
	sam	5.6	3.1	1.5	2	0.6	0.3	0.1	0.3		0.2				14
		43%	23%	11%	15%	4%	2%	0.8%	2%		1.5%				14%
Session 5 - Wolf-Sheep Simulation	norman	4	8	2	2	0.3	0.3	0.5	0.1				0.1	0.5	17.8
		20%	40%	10%	10%	1.5%	1.5%	2.5%	0.5%				0.5%	2.5%	13%
	penny	2.2	2.3	0.8	1.3	0.1		0.2		0.1	0.3				7.5
		11%	11%	4%	6.5%	0.5%		1%		0.5%	1.5%				5%
	emilie	4.9	4.7	1.6	1.6	0.3		0.1			0.6				13.8
		24%	23%	8%	8%	1.5%		0.5%			3%				10%
	moniq	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	walter	6.5	6.3	2.2	2.4	0.7		0.7	0.2		0.1		0.1	0.8	20.2
		32%	31%	11%	12%	3.5%		3.5%	1%		0.5%		0.5%	4%	14%
	mitch	7.7	8.4	0.6	5.4	0.8		1.0	0.2		0.1			0.1	24.4
		38%	42%	3%	27%	4%		0.5%	1%		0.5%			0.5%	17%
	sidney	14.3	7.6	0.7	2.4	0.8		0.5	0.1	0.1	0.2	0.1	0.1		27.1
		71%	38%	3.5%	12%	4%		2.5%	0.5%	0.5%	1%	0.5%	0.5%		19%
	greg	6	10	4	2.7	0.6		0.8	0.5		0.3	0.1	0.3		25.7
		30%	50%	20%	13%	3%		4%	2.5%		1.5%	0.5%	1.5%		18%
	sam	5.2	8	1.5	3.2			0.8			0.6	0.4		0.2	20
		26%	40%	7.5%	16%			4%			3%	2%		1%	14%

Table 7.1 further shows us that the kinds of complex systems concepts acquired vary widely depending on the student and the simulation they were working with (i.e., the session). From this presentation of the data we can also see that some concepts were less likely to be recognized and discussed during the intervention. In the following section I will discuss the significance of each of these observations.

7.1.1 Summary of Complex Systems Concept Identified

Table 7.4 provides a summary of the results from the larger data display (as shown in Table 7.3). These scores support the contention that students' experiences were different but that they all appeared to have identified some emergent causal process from the complex systems intervention.

Table 7.4 Summary of complex systems concepts identified during the three sessions.

Summary scores for Emergent causal concepts	Students								
	norman	penny	emilie	monique	walter	mitch	sidney	greg	sam
Raw scores	46	35	36	13	50	70	67	86	61
% of combined totals	10.7%	8%	8%	3%	11.7%	16%	15.7%	20%	14%

Illustrating these data in a bar graph (see Figure 7.1) provides a better perspective from which to make cross case comparisons. Based on increments of 10 points, it appears that students could be classified into at least four groups of Emergent Causal Processes Identifiers (*ECP Identifiers*). Greg, was identified as an outlier at the high end and classified as at a "*sophisticated level*" *ECP Identifier*, whereas Mitch, Sidney and Sam all fell within a 10 point spread (60 – 70 points) and could be described as "*high-moderate*" *ECP Identifiers*. Walter and Norman were within the range of (40 – 50 points) and could be considered "*moderate*" *ECP Identifiers*, compared to Emilie and Penny whose scores of (30 – 40 points) classified them as "*novice*" *ECP Identifiers*. Even when Monique's score was compared to averaged scores she still was classified as an outlier on the low end.

The importance of these data and these classifications will become clear as I continue describing the results of this research study. For the present, nonetheless, they should be viewed as a first level description of the qualitative results gathered that support the contention that complex systems instruction can facilitate the acquisition of awareness, and possibly learning, of emergent causal processes.

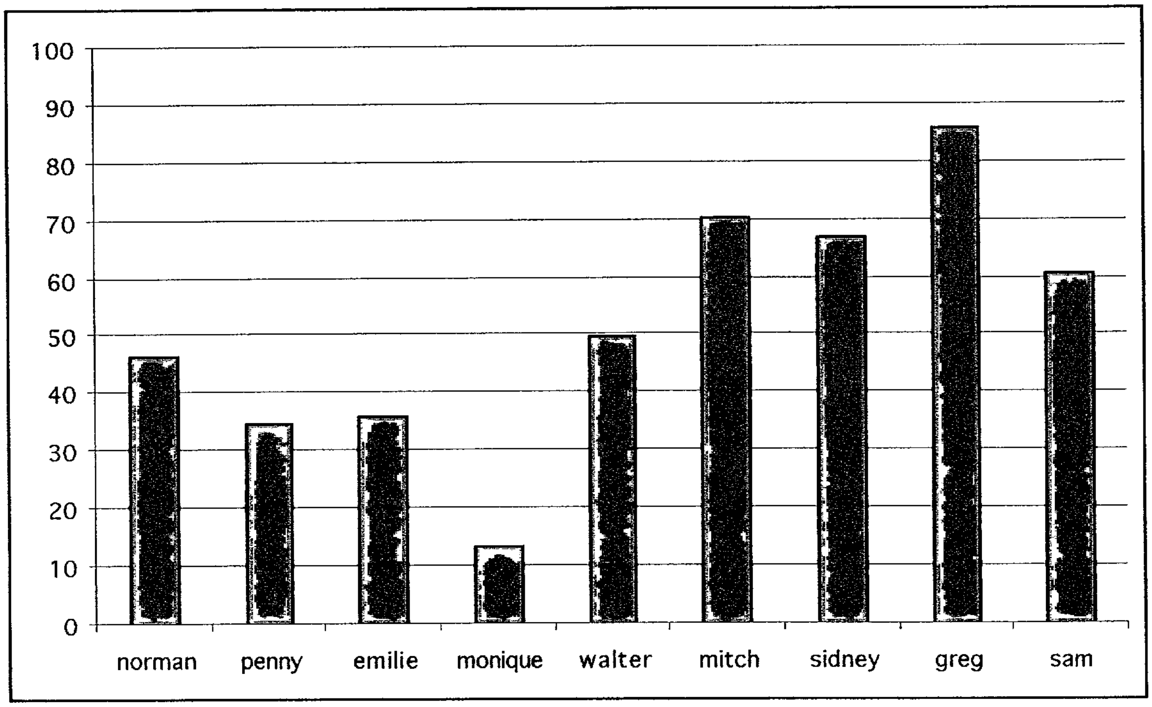


Figure 7.1 Bar graph of individual student's results for *Emergent Causal Processes* identified over three sessions.

Identifying differences and similarities between the students' experiences helps us to understand more about what variables are important to the learning of emergent causal processes. In other words, it allows us to closely examine which of the variables (the intervention, the learner, the conceptual knowledge) played a greater role in producing the results observed on the outcome measure. In the upcoming sections I will continue to describe these differences and similarities between students as well as the interactions between their characteristic and the different simulations used during the sessions.

7.2 Individual Expressions of Understanding Revealed in Concept Maps

> Concept maps "are idiosyncratic representations of domain-specific knowledge. Consequently, they are neither 'representative' nor 'typical' of any group. Nevertheless, as examples, the maps offer insight into some of the characteristics that are frequently seen in students with differing levels of conceptual understanding" (Wallace & Mintzes,1990, p. 1038).

This dissertation study did not use concept maps as a primary assessment measure. Nor did it investigate the mapping process as a dependent measure. Rather, concept maps were viewed as a means of generating another source of data to describe the process of conceptual change; in the process it provided a pictorial data set for triangulation purposes. It also allowed me to answer the research question: Did the intervention facilitate the learning of emergent causal processes?

The rigor for validity involved in generating the list of concepts used was limited to a review of the literature, whereas, establishing reliability was restricted to inter-rater scoring of the node counts. In the analysis phase, I did not investigate possible interactions between the concept mapping task and the students' cognition; although future analysis may contribute another dimension to understanding the larger questions examined in this study.

Engagement in the concept mapping activity, however, generated rich transcript data and more importantly solicited strong metacognitive responses from the learners. This is not surprising given the cognitive processing required as well as the metacognitive awareness evoked by the activity. In fact, de Simone and Schmid (in press) suggest "concept mapping might be seen as being a "scaffold" because it requires the learner to purposefully draw upon their prior knowledge and metacognitively assess the way they are selecting and organizing the information" (p. 3). Consequently, the metacognitive awareness was viewed as a beneficial by-product of the process.

7.2.1 The Concept Mapping Process

Adhering to the three criteria – a task, a response format, and a scoring system – described by Ruiz-Primo and Shavelson (1996) helped to document the concept mapping process and thereby created an audit trail for this event. In the following section, I will describe each of these criteria and what I did to satisfy them.

The task. Ruiz-Primo and Shavelson, (1996) tell us that the "task" is defined in three parts, (1) what the learner is required to accomplish, (2) the constraints of the performance, and (3) the "task content structures". The latter is described as "the intersection of the task demands and the constraints with the structure of the subject domain to be mapped" (p.578). In this study students' task demands were straightforward: construct a concept map reflecting their understanding of complex systems' behaviors. The task constraints included using the terms provided, however, it was not limited only to those terms only. The students were allowed to arrange the terms in any manner that best reflected their changing understanding. Lastly, no constraints were placed on the structure of the maps therefore the final organizational structures were evaluated as evidence of students' conceptual understanding.

Response format. In this study the student was presented with the 12 terms related to complex systems' behaviors on "post-it" notes and asked to arrange them on a board in such a way as to express their understanding of how the terms may be related. Maps from the first mapping session (session 2) therefore appeared a little clumsy because of this technique, even though students were given the opportunity to draw links or add comments. After the initial activity, the interviewer transcribed the maps into pencil and paper representations. All subsequent mapping activities were made in this dual mode with the student provided first with the paper version of their map, and if they required more freedom to move nodes around, they were provided with the post-it notes on a board. These two modes of response formats were viewed as supporting each other, therefore, they should not account for any variation or change in the concept maps produced between students or sessions.

Criteria Used to Score Concept Maps in Study 2

Informed by the literature (Ruiz-Primo & Shavelson, 1996; Jonassen, Reeves, Hong, Harvey, & Peters, 1997), I selected two criteria to evaluate the students' concept maps: (1) concept pairings (Bell & McClure, 1990), and (2) organizational structure (DeSimone & Schmid, in press).

Criterion 1. The importance of the concept-parings (i.e., node-link-node relationships) was established using criterion maps (experts' maps). The literature tells us that comparisons to experts are always controversial because there is substantial evidence that experts' knowledge representations vary dramatically one from another. However, I attempted to address this limitation by using an averaging technique (e.g., average of experts, average of high achieving students, etc.) as described by Acton, Johnson and Goldsmith (1994). Their findings suggest that average ratings of experts improved the comparisons. Because of my access to a limited number of experts I used a standard textbook definition of complex systems as a starting reference point (see Appendix B).

Establishing the weighting of the links based on the text definition. Among the twelve concepts, three were lexical concept: "complex system", "simple system" and "system". Of the possible pairings it was anticipated that "complex systems" lexical concept would form a central node and be closely linked with the following concepts: decentralized, dynamic, random, self-organizing and probabilistic (represented as "yellow" rectangular nodes in the concept maps); whereas, "simple systems" would not be directly linked to these terms (represented as "blue" rectangular nodes in the concept maps). Therefore the former relationships were assigned a score of 1 point for each direct link. The remaining concepts, centralized, algorithmic, static, predictable, (represented as "white" rectangular nodes in the concept maps) could be linked to either "simple systems" directly, or to "complex systems" but in an indirect fashion; that is, qualified by direction of links and/or propositional statement between nodes. No score therefore were assigned to these and less predictable paired relationships.

Establishing the weighting of the links based on criterion maps. Based on the maps collected from four experts, I determined the weightings to assign for the links between nodes. Starting with the map (Figure 7.2) I established that many concepts were indirectly linked to the central node "complex systems". Furthermore, in addition to that node, the term "self-organization" also formed a central node on other experts' concept maps (see another example Figure 7.3). Three of the four experts generated maps supporting these linked pairs. Hence, these consistently paired relationships were assigned a weighting of 3 points. They are as follows:

self-organizing	paired with	probabilistic / random	= 3 pts
self-organizing	"	dynamic	= 3 pts
probabilistic	"	random	= 3 pts

Two levels of pairings were thus assigned. The former as described by the textbook definition of complex systems, and the latter based on these averaged criterion-map paired relationships. If these terms were linked to a paired concept in more than one fashion, each link was scored as a separate pairing.

Criterion 2. As a second criterion to examining and scoring the students' concept maps I drew upon DeSimone and Schmid's technique for analyzing the deep structure and quality of concept maps (see DeSimone & Schmid, in press). However, because concept mapping in this study was used primarily for eliciting verbal protocols (i.e., more elaborated conceptual reasoning thereby richer transcript data), as opposed to being used as a main assessment activity, I chose to adopt a simplified version of their analysis and scoring technique. Instead of examining the maps at the many possible levels of labeled relationships structures, I applied the scoring only to the organizational appearance of the map. Hence, hierarchical maps were assigned 3 points, cluster formations were assigned 2 points, and chain formations assigned 1 point. In the event of maps that were somewhere between a cluster formation and a hierarchical formation, I assigned a score of 2 points. Only obvious vertical relationships with evidence of subsuming levels of organization were assigned as hierarchical maps.

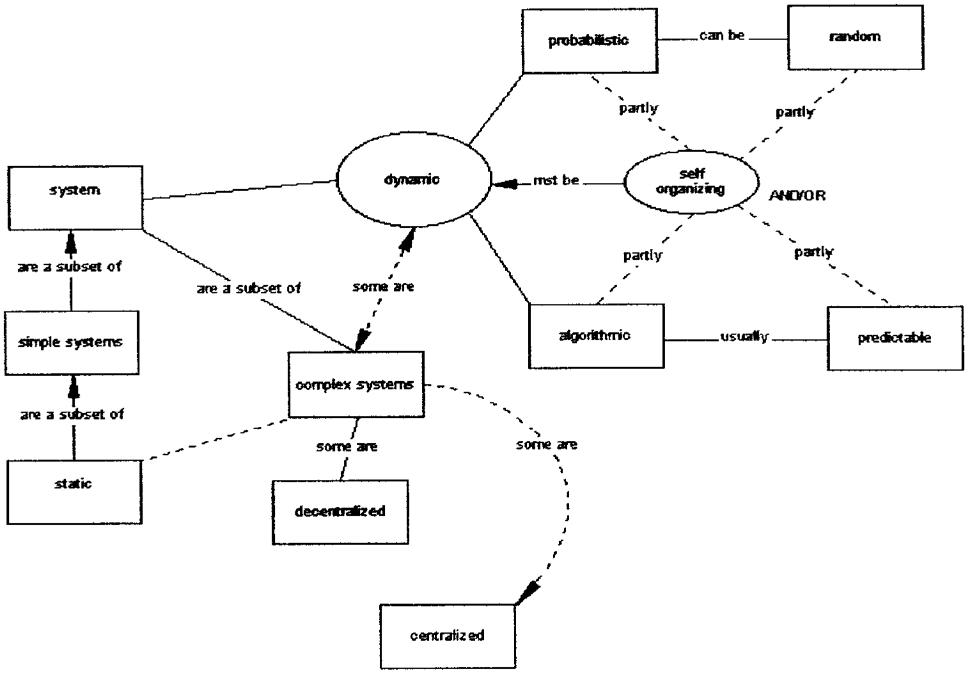


Figure 7.2 Expert's concept map of complex systems concepts.

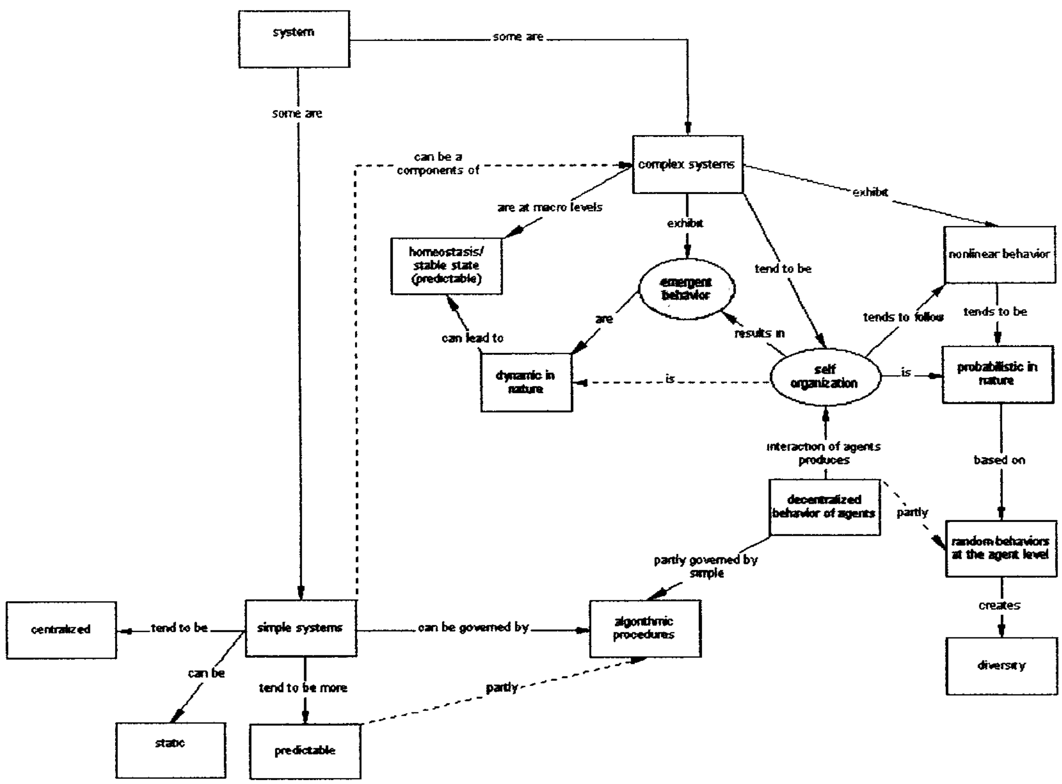


Figure 7.3 Advance-learner concept maps of complex systems concepts.

7.2.2 Scoring of Concept Maps

Examining the scores for session 6 (post intervention) the results show that Greg scored 12 points (Figure 7.4) and Mitch scored 11 points (Figure 7.5) and made a considerable number of desirable concept-pairings; followed by Sam with 9 points (Figure 7.6) and Walter with 9 points (Figure 7.7). By comparison, Sidney scored 7 points (Figure 7.8) and Norman scored 5 points (Figure 7.9) both displayed a moderate degree of desirable concept-pairings. Finally, Emilie with 3 points (Figure 7.10) and Penny with 2 points (Figure 7.11) both scores are substantially lower than the average. Monique's maps are not shown because she did not complete session 5 and 6, which were crucial in the development of the other students' maps.

Table 7.5 Scoring of Concept maps on criteria 1 & 2 over time.

Quantitative Scoring of Concept Maps		Norma	Penny	Emilie	Walter	Mitch	Sidney	Greg	Sam
Session 2 -initial	Criteria 1	1	1	0	2	3	4	2	2
	Criteria 2	1	1	1	2	2	2	2	2
	Sub total	2	2	2	4	5	6	4	4
Session 6 -post	Criteria 1	3	1	0	7	9	5	9	7
	Criteria 2	2	1	3	2	2	2	3	2
	Sub total	5	2	3	9	11	7	12	9
Total		7	4	5	13	16	13	16	13
Change		+3	0	+1	+5	+6	+1	+8	+5

In summary, the change over time resulted in large gains for Greg, and moderately large gains for Mitch, Sam, and Walter. Whereas, Norman's results showed moderately small gains, Sidney and Emilie showed very small gains. Penny was the only student to show no change between assessments. Although these quantitative results allow for comparison across cases as well as triangulation with other results, additional and rich information was gained from a qualitative inspection of the maps.

Over the course of the next few pages I will present the concept maps created by the students in session 2 and the final meeting, session 6. These maps almost speak for themselves in as much as they show some dramatic changes in understanding of emergent causal concepts that are framed within the context of complex systems thinking. As the scores above suggest, the maps clustered the students into three groupings: (1) "*sophisticated*", (2) "*moderate*", and (3) "*novice*", understandings of complex system relationships. I will present the maps in decreasing order of elaboration therefore the first ones with represent the most sophisticated understandings.

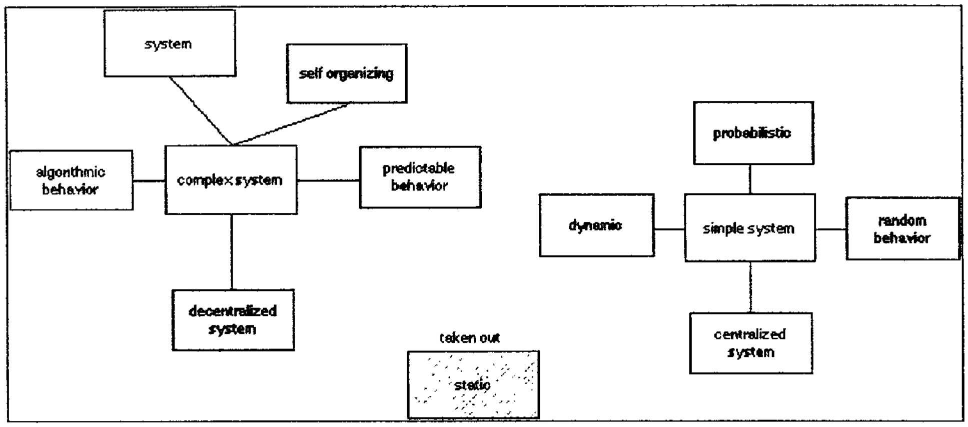
This quantitative scoring method established a baseline of difference within cases (time series), as well as allowed for between students comparison. Afterwards, I examined the concept maps in a qualitative fashion for evidence of qualitative changes both across time, as well as cross-case analysis.

7.2.3 Group 1, "Sophisticated" Understanding of Complex Systems Relationships

Both Greg (Figure 7.4) and Mitch (Figure 7.5) produced hierarchical type maps and demonstrated elaborated understanding of the term "complex systems" and its relationship with the concept of "self-organization". In particular, both students appeared to recognize the important connection between it as a central node and the many other associated influences; for example, random action (Mitch) and probabilistic lined to random behaviors (Greg). A further level of understanding was revealed by Greg's addition of the term "emergence", also viewed as a central node. He independently chose to add this term, and, as we can see, he connected it directly to "complex systems" as well as "self-organization". I contend that, from the perspective of this study, this was an important conceptual shift.

An important consideration. Although not accounted for on the scoring schema, how students came to understand this relationship between "emergence" and the other complex systems concepts merely through observations and interactions with the StarLogo environments was important to this study. The intentional omission of this term therefore provided a means to assess the sophistication of the students understanding. (N.B., when the term is present in the student's concept map it is identified as a "green" elliptical shaped node).

Greg's Concept Map



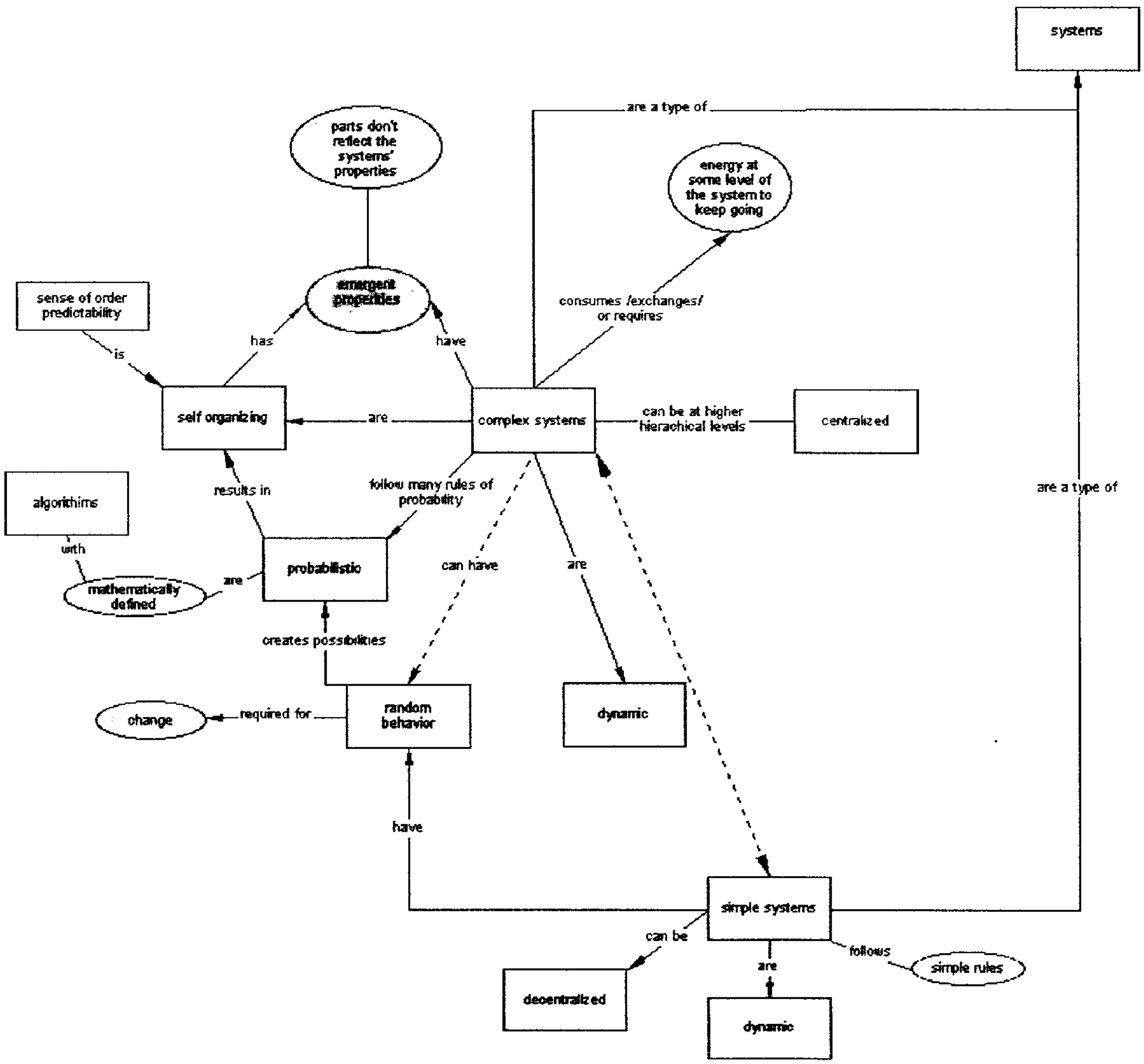
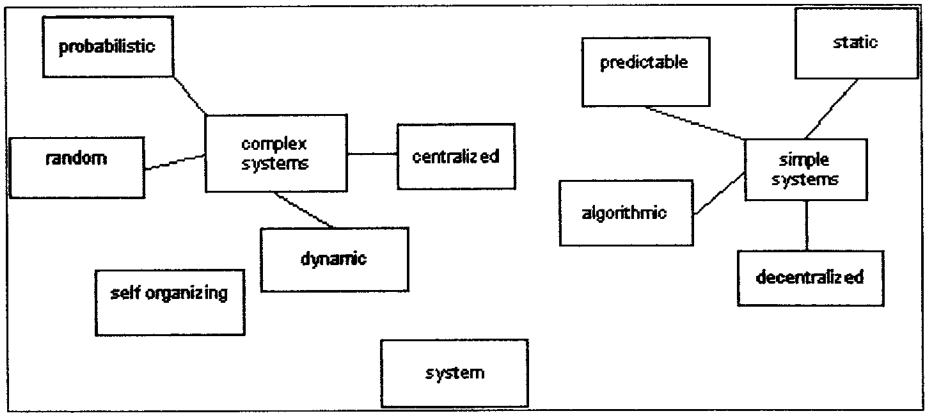


Figure 7.4 Greg's concept map - Session 2 & 6 (session 2 upper, session 6 lower).

Mitch's Concept Maps



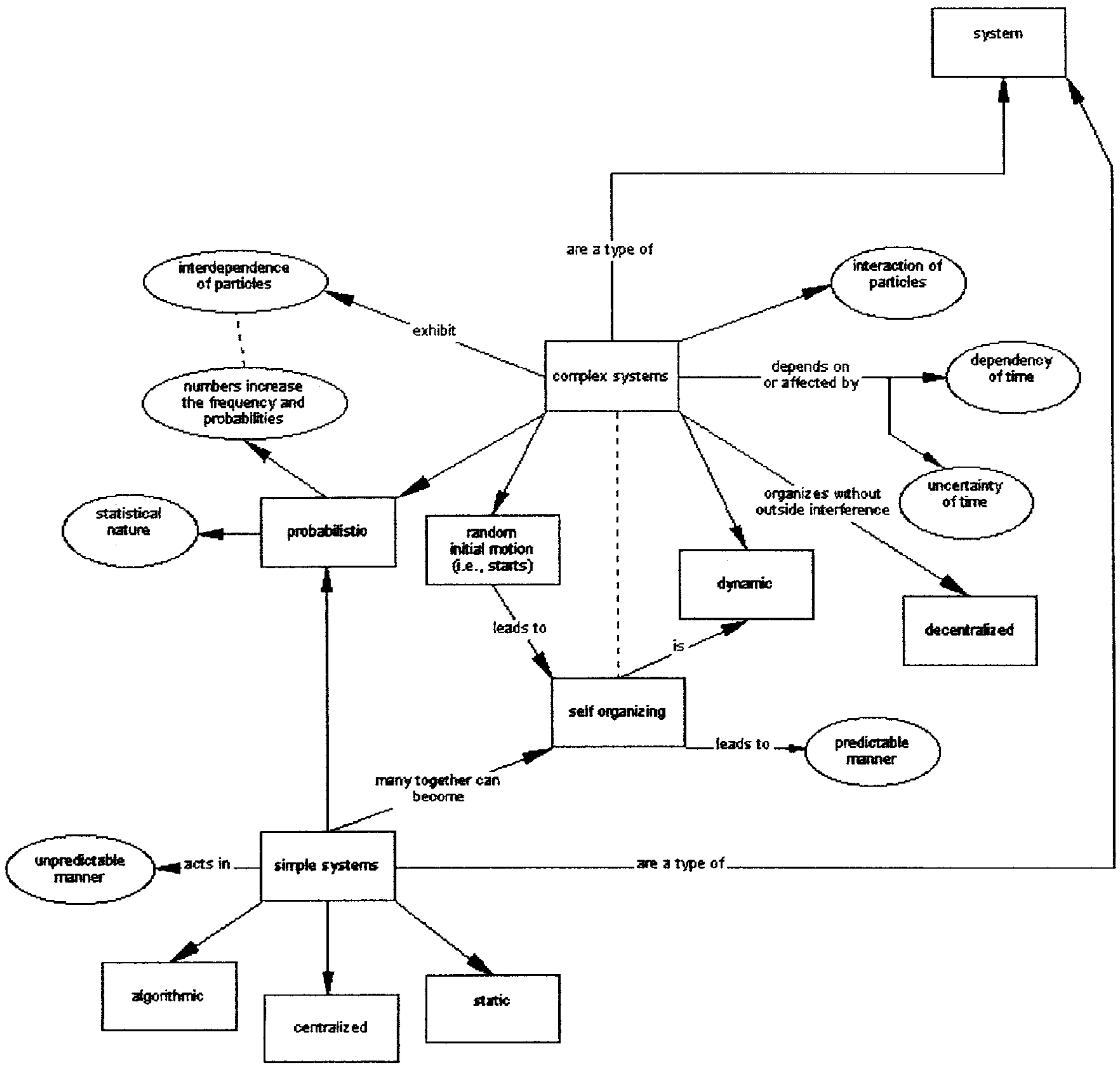


Figure 7. 5 Mitch's concept map - Session 2 & 6 (session 2 upper, session 6 lower).

Sam's concept map (Figure 7.6) was a cluster formation and looked very different from those described above. However, his organization of terms revealed a level of sophistication that placed him in a unique sub-category of group 1. His identification of concepts was more similar to the expert (Figure 7.3) in that he created a central node out of both "self-organization" as well as "dynamic". Because of these relationships I argue that Sam's clumping of terms into equilibrium-type complex systems and dynamic-type complex-systems demonstrated a higher-level view of complexity. When asked to explain this organization, Sam was able to be reflective and in fact made a small revision to his map based on the conversation below.

I: What's happened between then, which is a long time ago and now (laughs) to make you change? 199

Sam: I think I changed a lot of the way I studied. So I tried to link things a bit together. Not like a concept map, but I tried to link... I do try to go from cause to effect, the results a lot, I guess. So I use just complex system as the basic centre, and I'm working off of that. So I decided that dynamic and static were two different kinds of complex systems, and that all these others were descriptions of a dynamic system while, centralized and all these others were descriptors of static system. And, there, I don't, I don't agree with what I said at all anymore, because to me a static system doesn't have to be a simple system. 201

Sam: Systems that are self-organizing don't have to change that much, and if it's predictable, it's static, if it's algorithmic behavior it follows rules, so it's got to stay pretty much, in a certain area, it's not dynamic like a system that might, rely on chance and random behavior, and isn't centralized.

I: OK, and why did you take away self-organizing? You don't think a dynamic system can be self-organizing? 207

Sam: I think it can... On a bigger scale, I guess. If you look at it from a big scale, a system that relies on random behavior, might, organize itself in the end, but I mean... 209

(pause 4s)

Sam: You see I hadn't thought of that. Now I'm not sure anymore. 213

I: No, no, I'm not suggesting that you're wrong... 215

Sam: I know, but you brought it up and...(laughs) I didn't question that.218

Sam: Because a dynamic system you look at on a bigger scale, to be self-organizing. While a static system I think is more self-organizing, but on a smaller scale. 221

Sam: Pretty much. Like I'm saying it goes, up and down. Like if you're looking at a chart, and it goes up and down, it's not continuous, if you're looking at it from far enough away, it does look like, one straight line I guess, if you're looking at it from far enough away, and that's... That's the way I was thinking about it, I guess. 229

Sam's Concept Maps

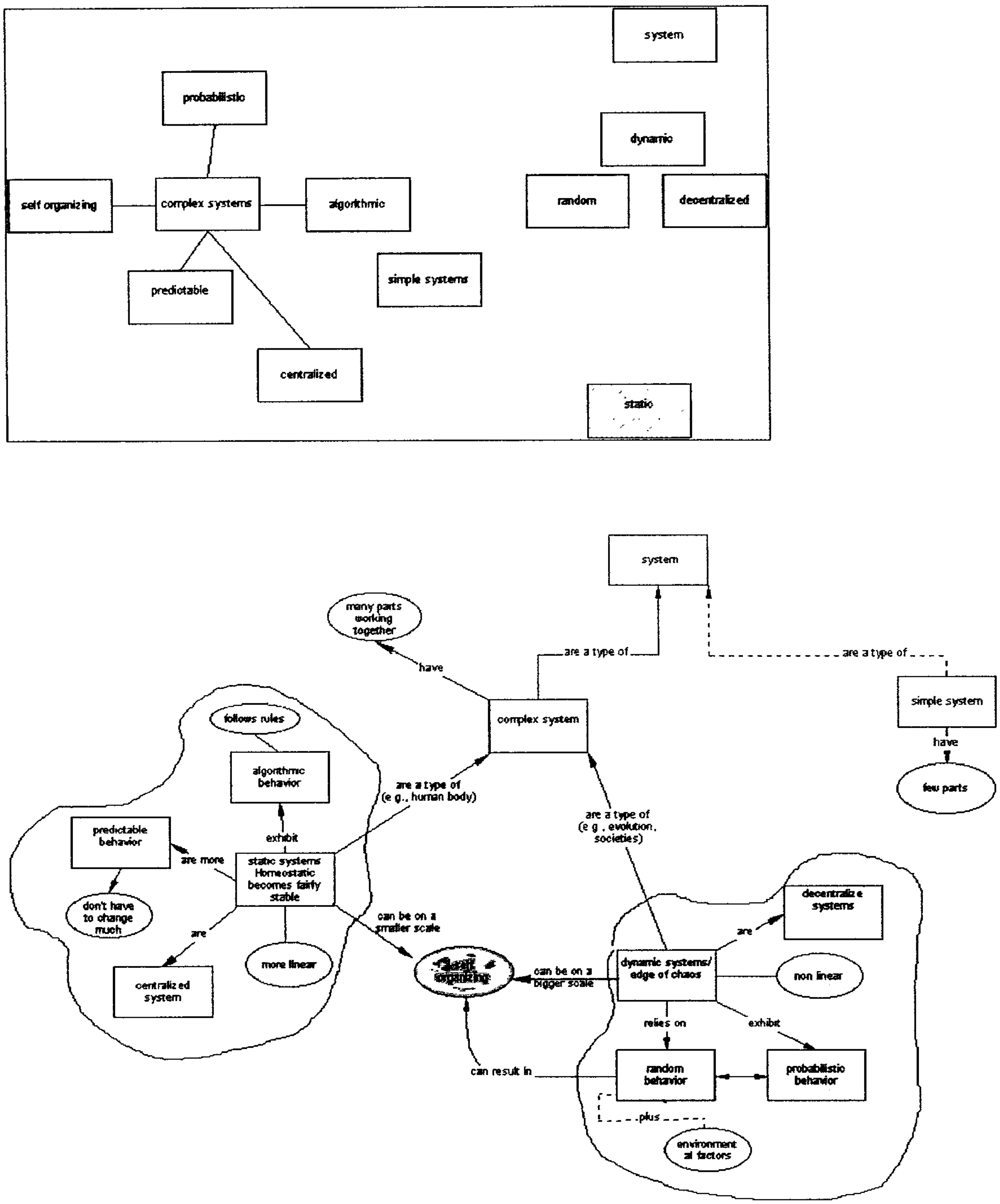


Figure 7.6 Sam's concept map - Session 2 & 6 (session 2 upper, session 6 lower).

7.2.4 Group 2, "Moderate" Understanding of Complex Systems Relationships

Walter, Sidney and Norman all fell into this classification. Whereas Walter's (Figure 7.7) map is more similar to Greg and Mitch (see above) in its somewhat hierarchical organization, Sidney and Norman produced a cluster type concept map. Walter like Sidney, views "self-organization" only as a link between types of systems – simple system and complex systems. Compared to Sidney (Figure 7.8), Walter demonstrated some understanding of the probabilistic nature of complex systems and the role of random actions. As argued in the section above on scoring, I contend that this was an important recognition therefore placing Walter's understanding above that demonstrated in Sidney's maps

Sidney does not have many important linked relationships. For instances he did not suggest any link between "self-organization" and "random" or "probability". In fact, most of his node-link relationships were single attachments radiating out from the central nodes of "complex system" and "simple system". Nonetheless, he demonstrated that he had elaborated his understanding demonstrated through the additional terms attached (shown in pink).

Finally, both Walter and Sidney added the term "emergent" to their maps, suggesting that they were aware of this concept as a central feature of the intervention. In fact, Walter described why he added the term in the excerpt below.

I: Yeah, it wasn't part of the set of things I gave you. The ones in grey were the ones that you added. Which I thought was a good thing to add. 237

Walter: Yeah. 239

I: I was very pleased that you added those. 241

Walter: Well yeah, because we observed these things in the computer programs that we were looking at. 243

I: And what's an emergent property again, how would you describe that? 245

Walter: From what I remember it's just, um from observing the system there's certain properties that are characteristic of that system, that you begin to notice after you observe it for awhile. 247

I: OK and an example...?

Walter: (talking over I) I remember, I remember like the... The clusters there, of like the ants, like the ant hills or whatever... 255

Walter: Like that, that I could... I felt that that was an emergent property, because you know that they're going to, form clusters. But you don't know exactly where they're going to be, exactly, because it's still governed by probability or whatnot, but you know that they're going to occur. 259

Norman (Figure 7.9) like Walter also had a somewhat hierarchical structure to his concept map. Like Sidney, he too displayed the radiating type of relationship of concepts suggesting a less sophisticated relationship between terms.

Two important differences in Norman's map are (1) is removal of the term "random", and (2) his failure to add the term "emergent". Unlike other students within this classification, Norman did not integrate the purpose of the study with this activity. It appears that from a metaconceptual point of view he experienced the simulations as completely separate from the assessment activities. This point will become clearer when looking at the results of the outcome measures.

Although Norman experiences a substantial change between session 2 and 6 as evidenced in the changes in his maps; and although he demonstrated a moderate understanding of emergent causal processes through the connection of the terms "self-organization" and "probabilistic" behavior; he also appeared to seriously hampered by his component beliefs. Looking at his concept map the placement of the term centralized directly beneath self-organization without additional qualification, and placing decentralized under algorithmic are tell tail signs of the conceptual struggle describe earlier (see page 147 for excerpts of discussion relating to this). I contend that this is more evidence of the strong clockwork component beliefs guiding his thoughts and limiting his understanding of emergent causal processes.

Walter's Concept Map

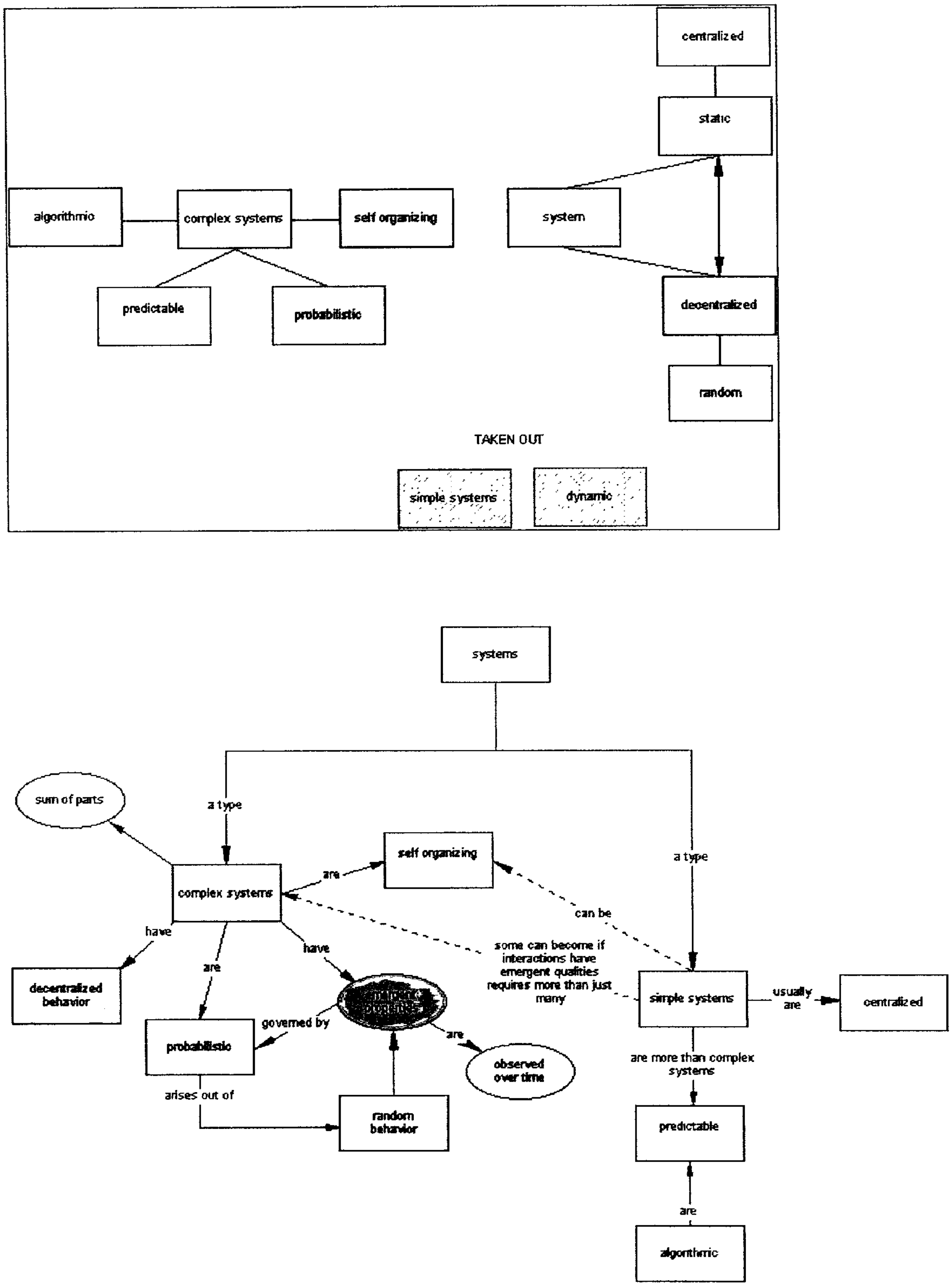


Figure 7.7 Walter's concept map - Session 2 & 6 (session 2 upper, session 6 lower).

Sidney's Concept Map

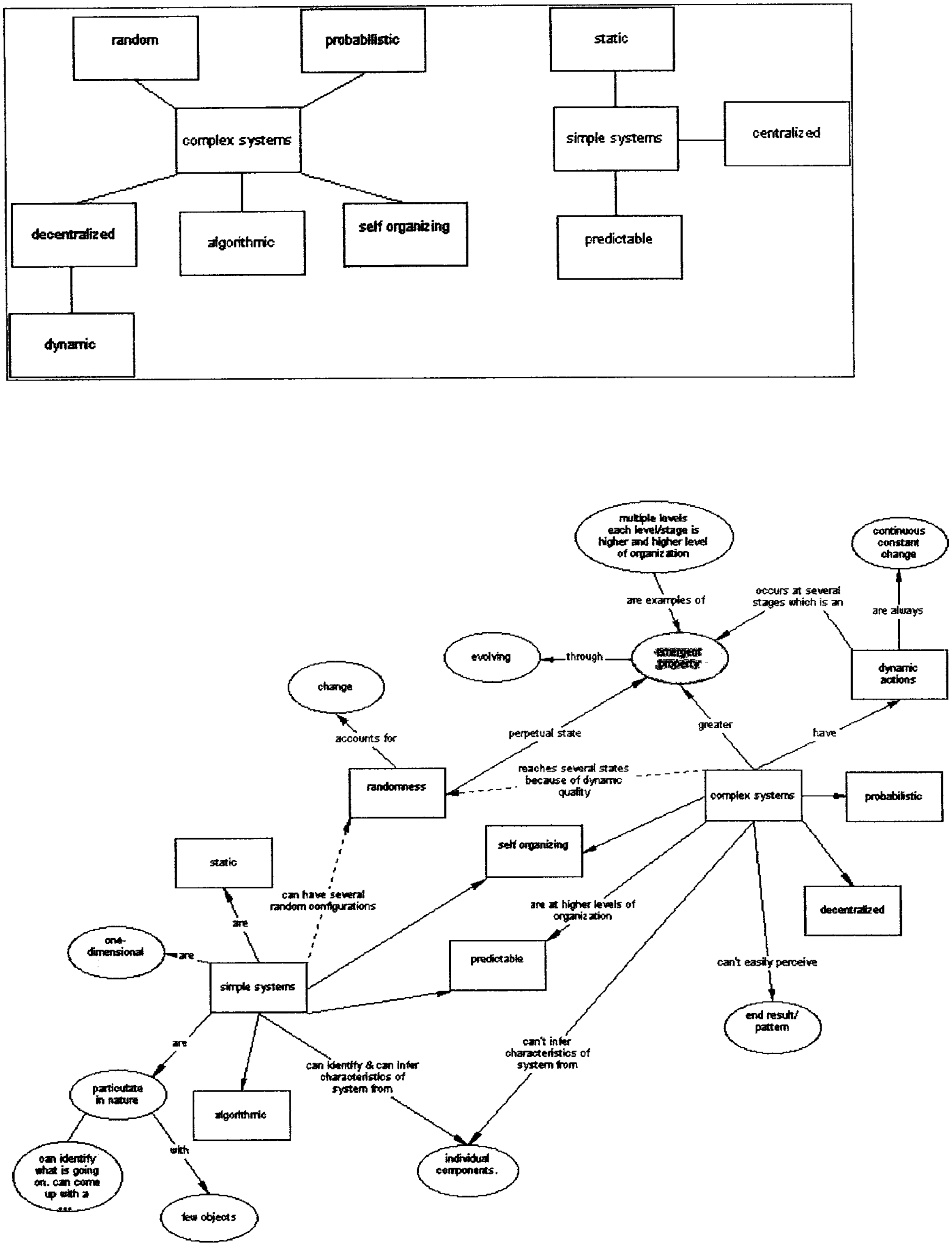
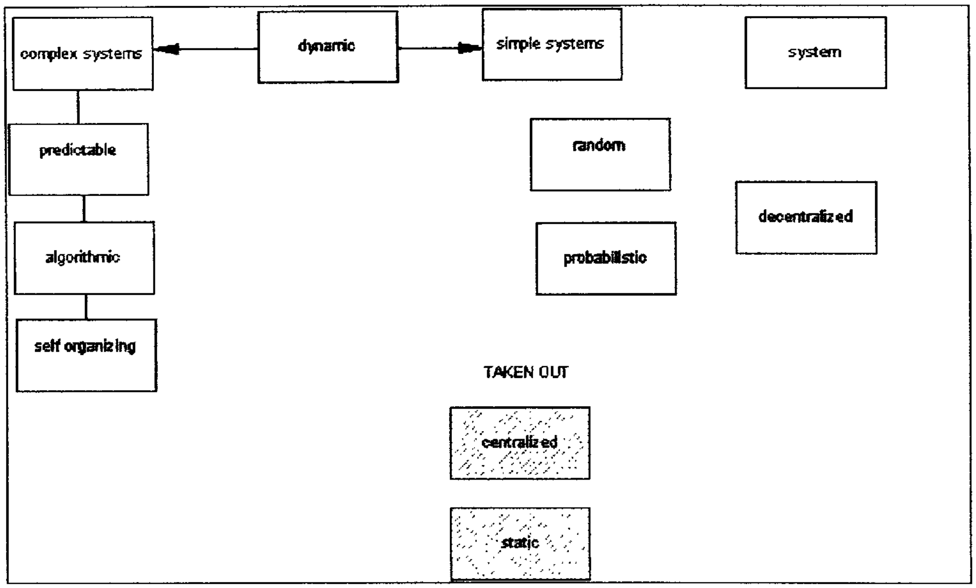


Figure 7.8 Sidney's concept map - Session 2 & 6 (session 2 upper, session 6 lower).

Norman's Concept Map



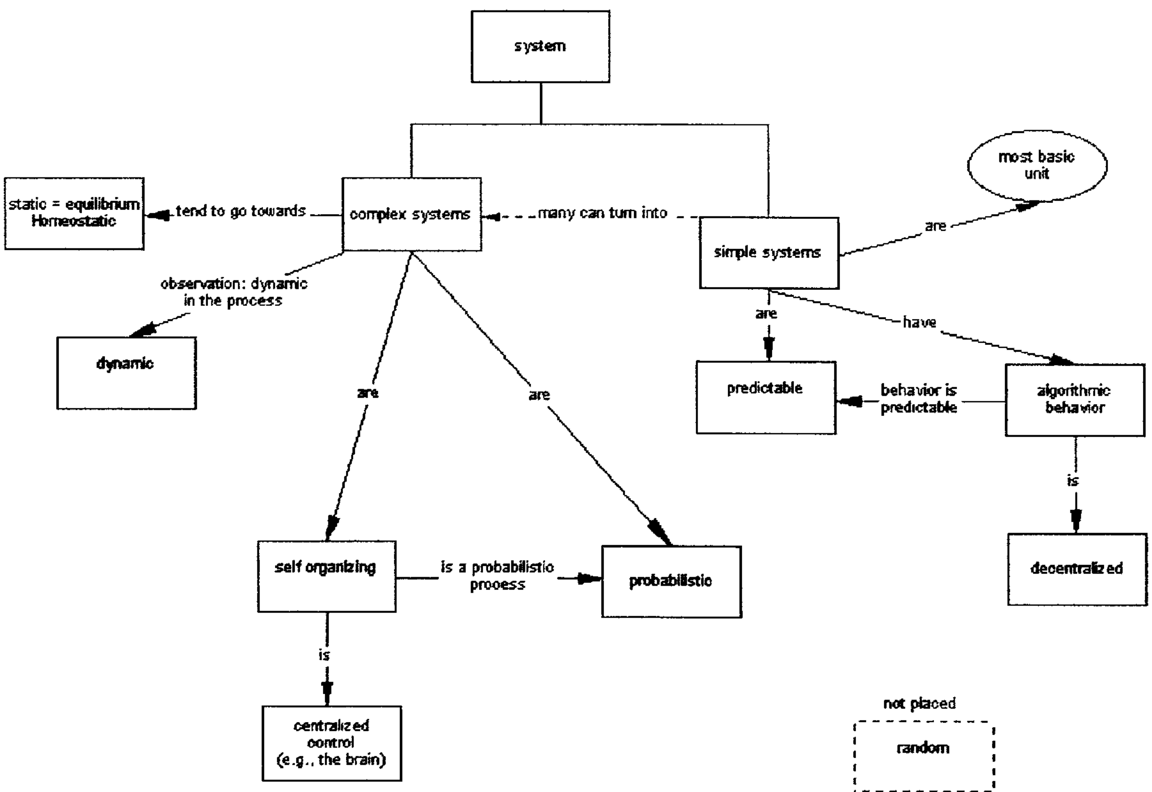


Figure 7.9 Norman's concept map - Session 2 & 6 (session 2 upper, session 6 lower).

7.2.5 Group 3, "Novice" Understanding of Complex Systems Relationships

Penny and Emilie fall into the third classification of maps. Both students constructed very different types of representations, however both are at a "novice" level of understanding. Whereas Emilie (see Figure 7.11) drew a hierarchical map, Penny (see Figure 7.10) created a chain-like map quasi-procedural type map (Ruiz-Primo and Shavelson, 1996). Therefore it may be that Penny viewed this knowledge in more of a procedural fashion or maybe she felt safer sticking with a simple explanation because she did not know how to describe her developing understanding. This interpretation is consistent with DeSimoni and Schmid's (in press) findings that students' fall into one of three classification of mapping strategies. From their description it appears that Penny could be labeled a "safe player" whereas Emilie would be best described as "limited processor". Both these types of strategies may have affected how much either student acquired knowledge from this concept mapping process. For instances, even with the direct intervening of the coach, and although she is dissatisfied with her map, Penny does not change the arrangement of her map. I contend that this "safe player" strategy is mainly due to her understanding of the concepts. As will be demonstrated elsewhere, Penny found the content itself to be challenging.

Penny: Um, it's, here it says it has self-organization...	973
I: Mm-hm.	975
Penny: ...which, is part of both of them?	977
I: It's part of both of them?	979
Penny: Yeah.	981
I: OK, both of...?	983
Penny: Both simple and complex.	985
I: OK.	
Penny: Which is, I think, what I thought before.	989
I: Mm-hm.	991
Penny: First I think I put it under, simple, but then I changed it.	993

(pause 7s) 995

I: Yeah. (pause 18s; papers ruffling in background) 999

I: Yeah this was the last... OK, you have self-organization... Yeah. First you had a sort of linear description... 1001

Penny: Yeah. 1003

I L: ...with self-organization as simple, and then you went to, you re-drew it, and you had, self-organizing system connected to complex, and simple. And with this thing... 1005

(pause 4s) 1007
Penny: Um... Well this part for sure. But uh, after seeing different, uh, systems, and how they're not linear, I don't know if I should have put them linearly, even though, it makes sense... 1009

I: Mm-hm. 1011

Penny: ...to me, right now, but... Somehow I think, it should be arranged, but I don't know how. 1013

I: How? OK. 1015

Penny: I don't, like... (pause 8s) 1019

I: It's OK, you know, it's just it was... 1021

Penny: No, it, it still makes sense. 1023

I: OK... 1025

Penny: Well because like, when I put it this way, it doesn't mean that, this whole stack that follows that, it just means that they're all, related. 1027

Emilie's map. Examining Emilie's concept map, we also see a great deal of difficulty in the development of her understanding. From her transcript data I interpreted her efforts to create a hierarchical structure more as a reflection of her clockwork mental model. It appeared that the general framework used to understand the simulations, what may be better described as an "analogy", appeared to be a non- emergent hierarchy (i.e., a political system). If fact she explicitly states this on several separate occasions.

Session 4

Emilie: Now I'm thinking more than one, like, one sort of system. Like, sort of like mini-system I was going to say, in the um, in the, let's say, in the bigger system. Then you have like different kind of structures in each system, kind of like... Hm. Kind of like politics.

Later in session 4 she again states:

Emilie: I don't know, um, like you got, what do you got you have Liberals, you've got Conservatives, and they're all in the same kind of, you know they're all in Ottawa, and, you know, they're always obviously fighting all the time, but I think it's they're all part of the same system which is politics, and you know, the way Canada is going to work, or...

Again during session 5 she says:

Emilie: I don't know, I guess I always understood the um, I don't know, the social world better, like um... I guess, it wouldn't only be political but... So now, you know, I don't know when I talk about systems and complex systems and then simple systems driving from that, of a system I think more like a country, a complex system, would be kind of smaller than this huge system, it would be more like uh, provinces as I said. And then each system, sorry, each simple system, would be um, would be like a town. Or you know either, oh now, that I think rural and urban, I should maybe still do that. Um... 481

Finally, there appeared to be a robust reductive clockwork component belief in Emilie's thinking. In fact, it almost seems to be a stubborn streak in which Emilie resist "seeing" the evidence as demonstrated by the simulations as well as the coach's prompts. Her reaction is best described by Chinn and Brewer's (1993) description of the fifth reaction to anomalous data "reinterpret but retain original theory". Therefore in addition to trying to understand the content knowledge she is also challenged by her component belief. Below is an excerpt from her discussion in which she insists that systems can be reduced. Of all nine participants, Emilie was the only one who appeared to demonstrate this level of conceptual conflict and this level of entrenched clockwork belief.

Emilie: It's just... it's not more confusing, it's just what I.. I don't know. It's just that, well I still stick to what I say earlier, is that I would not think of let's say one making, of like decomposing a complex system, I would not think of it, like there's only one way to do that. Like in politics I see this totally in a different way, or... Not totally, but I don't know, still kind of a different way, I would put... 954

I: OK, you've mentioned that a couple of times. Decomposing a complex system. Do you think you can really do that effectively, of should it be the other way around? 956

Emilie: What do you mean, the other way around? Like... Like the way you analyze a new sentence, is that what... 958

I: Yeah, the way that you would try to understand it. 960

Emilie: I think you would more like go and put things back together, and sort of, you know, separate them, because you end up with... 962

(pause 10sec)

I: Think about your body? If we broke it apart would you be the same? 972

Emilie: Sure, why not? (laughs) I don't know... 974

I: Could we put you back together again, afterward? 976

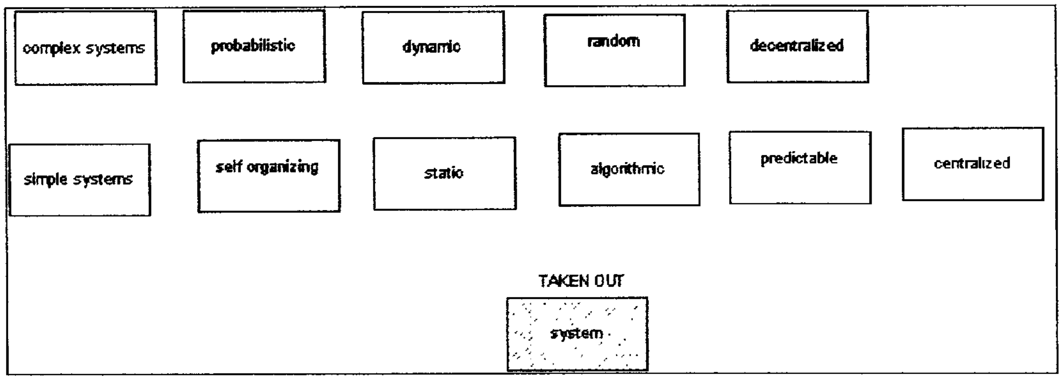
Emilie: Probably not. 978

I: Yeah, and why is that? 980

(pause 5s) 982

Emilie: I don't know, probably because you're used to some certain structure, and the way they are, and like, the idea of putting them back together, we'll not put them back in the right place, or they'll not necessarily know how to function. And, I don't know, the sort of so-called human body. I don't know.
Because I'm, I'm thinking of like all those things they do with, I don't know, like take the example of fish, like fish that are, or I don't know some animals, they take them into the zoo, in order for them to reproduce, and, like, they've never really tried to put them back in their environment, like, if they, if they've been born in the zoo, and they've been fed by a human, and if they've never really caught their own prey, and then if you want to put them back into nature, they would not necessarily know how to survive or how to react. So... I don't know. I'm thinking that this would probably not... 986

Penny's Concept Map



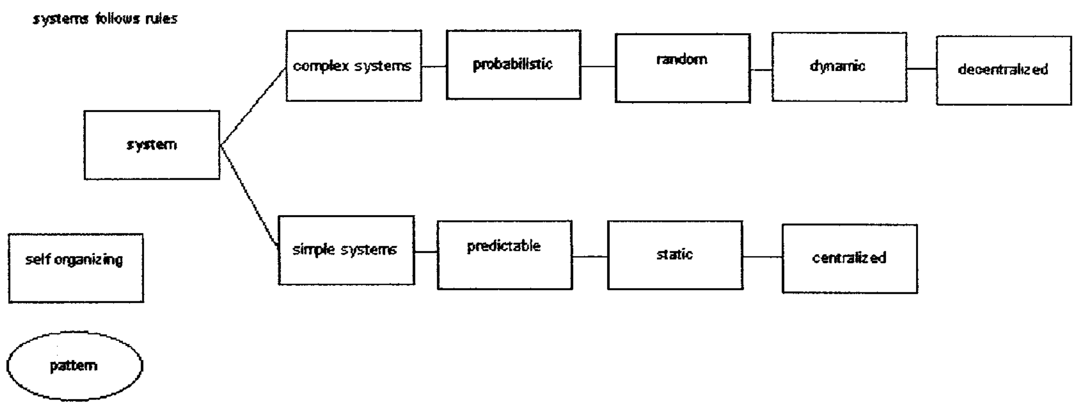


Figure 7.10 Penny's concept map - Session 2 & 6 (session 2 upper, session 6 lower).

Emilie's Concept Map

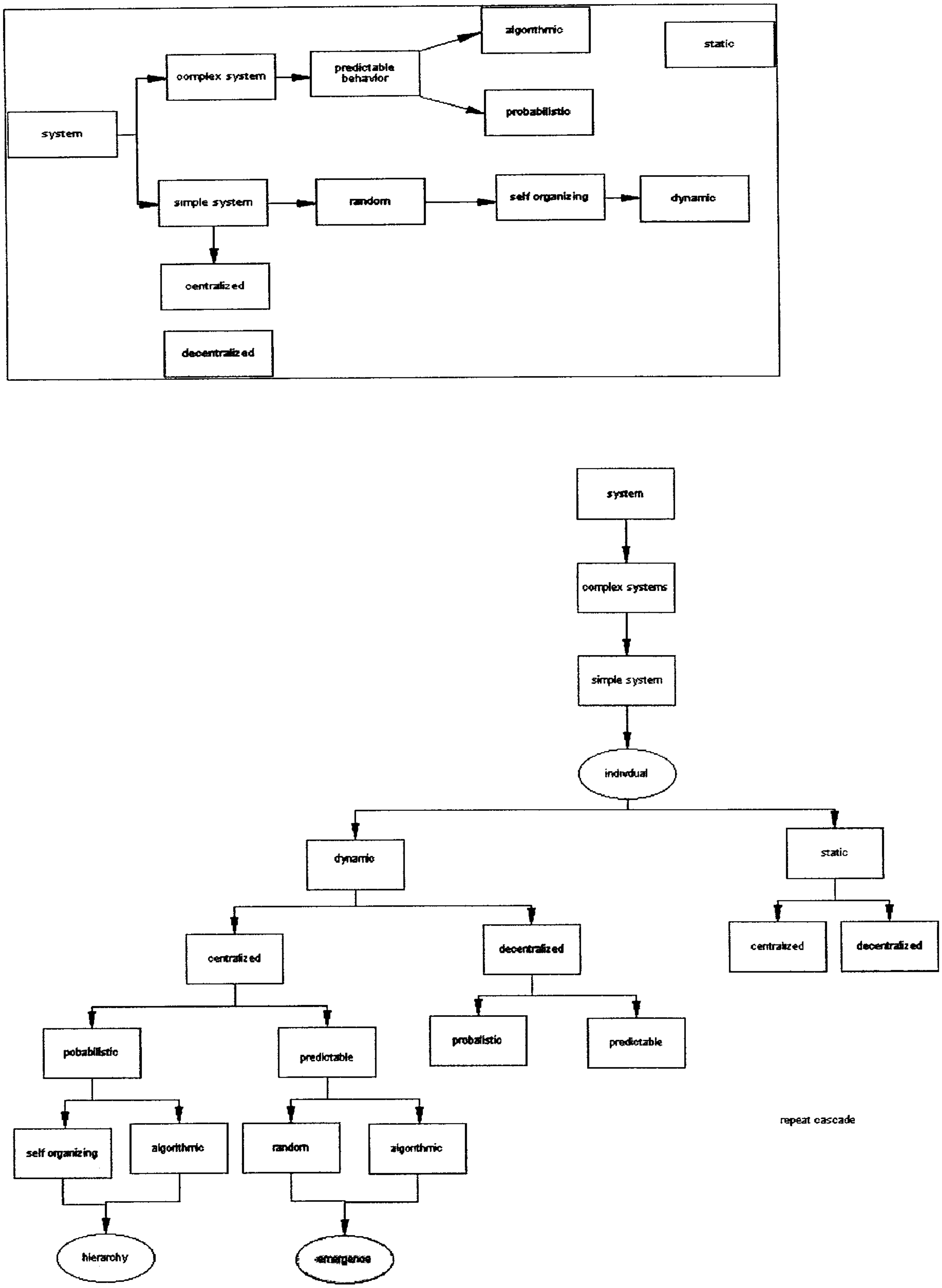


Figure 7.11 Emile's concept map - Session 2 & 6 (session 2 upper, session 6 lower).

7.2.6 Summary on Results of the Concept Mapping Activity

The concept maps show that most students evidenced considerable development in their understanding of the concepts regarding complex systems behaviors. Over half were able to construct relationships between the key concept nodes of "complex system", "self-organization" and "probabilistic behaviors". This understanding was also seen in the transcript data (evidence discussed in the next section). Four students were able to identify the importance of the concept "emergent behaviors" by deciding on their own to incorporate the term into their concept maps. This marked a significant development in their understanding of how complex systems are related to emergent causal processes. I contend that this was noteworthy because some of these changes to their maps were made at the final interview, one year after the end of the intervention (i.e., session 6).

Lastly, one other important observation was made from these concept maps. It appeared that the concepts of "random" and "predictability" were particularly problematic for some students – a common finding in the literature (e.g., Wilensky 2001). In fact, Norman completely removed the term "random" from his final map; and links "predictable" to simple systems. For others, like Sidney, it appeared that although he had developed a good understanding of randomness as accounting for change he still did not link it to the probabilistic nature of complex systems. This was surprising given his transcript data indicated otherwise. However, he demonstrated a more sophisticated understanding of "predictability" by annotating the link with the conditional statement of "at a higher level". This suggested that his understanding of "predictability" was more in line with the greater stability exhibited by higher levels meta-agents as demonstrated by the simulations. On the other hand, Greg, Sam and Walter, from their maps appeared to understand the important relationships between "randomness" and "predictability". However, as will be shown in the following section, this should not suggest that it was without a certain degree of cognitive struggle.

7.3 Two Independent Case Studies – "The Student's Voice"

The main intention of this upcoming section of the results chapter is to provide two contrasting case study examples of the types of restrictions that component beliefs appeared to place on the development of emergent framework mental models; additionally, the different ways students used aspects of the intervention to facilitate change in their conceptual frameworks. In so doing I will address two aspects of the research questions:

(2.a) Which of the ontologically-based concepts are more difficult to change? (2.c) What role do cognitive scaffolding and other metacognitive support play in this learning process?

Why did I select these two cases and not others? Although other cases also provided important insights into the challenges involved with learning about emergent causal processes, I contend that these two cases are most closely contrasted because of the seemingly similar starting points of the participants. Both students demonstrated some level of emergent framework component beliefs, but their experiences produced very different stories.

Lastly, these cases bring to light one of the significant considerations regarding ontological barriers. Both these students struggled with the attribution of "determinate causality" but from slightly different perspectives. I contend that although the concept of "random" actions appeared to be one that the students accepted, it was also challenged by a deep ontological commitment to "determinate" causality. This point will become clear as these cases are developed in the following section.

7.3.1 Greg's Case Study Report

What did Greg learn about complex systems thinking and emergent causal processes? How did he come to acquire this knowledge? Two things that I focused on with Greg were: (1) the mental model that he changed (i.e., deterministic behaviors); (2)

the mental model that he elaborated (i.e., emergent self-organization) particularly through the concept of "flows of information".

Greg's Pretest Results

From the pretest answers Greg demonstrated evidence of only one clockwork attribution, that of "determinate" causality (i.e., predictability). His answer displayed evidence of predictability and procedural protocols – in other words, "if-then" types of statements. Although not coded as CWMM his answers did not meet the coding rubric's requisite level of evidence for five out of the six EFMM categories (see Chapter 3 for OMMT coding taxonomy). The coders did infer some evidence of probabilistic "Final Causes" in the proposition: "when there are multiple attractions the stronger one will attract more ants".

The ants walk around smelling and when they are attracted they aggregate towards the center of attraction [food]. They then remove the food and take (it) back home. When there are multiple attractions the stronger one will attract more ants.

Greg's pretest results for the "Ant" question suggested that he was typical in his lack of EFMM attributions; however, there was evidence from the other answers that he understood a great deal about systems. In fact, he uses the term systems twice.

Butterfly answer:

This uses chaos theory on an exponential basis. What happens is that the disturbance is amplified as the particles within the system communicate [react]. This rarely occurs because many disturbances counteract each other.

Traffic answer:

Traffic jams form when one car stops or slows down. Since reaction isn't instantaneous there is a lapse between the first and second car slowing down. This happens exponentially if the cars are close enough to be affected.

Robot answer:

They would need to distinguish gold and then begin to remove it. But they would factor in structural integrity of the mines. This more complex system requires many robots working in tandem. Once a mine is empty they split up and search again.

These additional data placed Greg as an outlier in the cohort of participants. Thus identifying him as one of the individuals that I would choose to follow more closely to determine how he would elaborate his EFMMs and if he would restructure the CWMM (predictability) of which there was evidence.

Final Posttest – Pre-Case Study Interview

One of the questions in the pre-case-study interview probed for explanations of the student's prior beliefs and questioned if there was change: "Did any of your ideas or beliefs change because of the workshop, and if so, which ideas or beliefs?" Greg's answer to this question revealed his use of a conceptual anchor (i.e., conceptual model), his knowledge of Boolean algebra.

G: Um, none of them really changed I guess, because like I came in not knowing much about complex systems, well not much, not anything about complex systems… But I just realized that, in the end, like almost all matters of science, like math and chemistry, do relate a lot in the end, by simple mathematics, and rules and concepts. Like I'd always thought that, but now, I've made it much stronger.

I: Anything specific? Was there any one thing specifically that was sort of the moment, where you said 'ah, this is how I can relate all of these together'?

G: Um, there was when we were asked to write our own notes for a little bit, on I forget what subject it was…

I: OK.

G: …and it was then that like, in my own notes, I tried to explain it to myself. So that's like, that would be actually a moment where I felt, hey, this is like Boolean algebra.

I: OK.

G: And it just started from there.

I will show how other students also used a conceptual model to build their understanding of complex systems. Each model would have its strengths and weaknesses. In addition, I contend that in this case, the logic of Boolean algebra provided Greg with a very robust model on which to build his understanding but it also provided him with the limitations of a conceptual deterministic model (i.e., at the level of the logic truth table), which he would be challenged by. This problem was a challenge to several of the students who understood the procedural nature of the computer models by interpreting this as always having a deterministic outcome.

7.3.1.1 Greg's Conceptual Struggles (Determinate causality versus Randomness)

Greg when provided with an ontological prompt during session 1, answered with an explicit statement describing the Slime mould model as being deterministic. His view was that the computer program limited the options and therefore the outcome was determined a priori, therefore predictable.

> I: So, do you think there's anything driving these kinds of system? Are there some variables that make it more deterministic or is it all happening without having any kind of plan?
>
> G: Yeah, I think it's more of a deterministic system. Because like even looking at the way that this is set up there was a minimum number of turtles that you could have and I think it starts off as a system that has a plan and that all the other variables just act on whether like it's your plan is to have a one circle or a lot of small groupings or clusters so you have a deterministic system.

He would again challenge his understanding of how the elements of chance operated within these systems. From session 2, when returned to a second look at the Slime mould model he again debated the operations of the system. This time he articulated his beliefs in a running discourse that took him through the untangling of where the element of randomness was attributable and where it was not. He eventually reflected on the non-isomorphic relationship between the individual and the system.

> G: No, it's like making, um, axioms or something. if you start off with something like although you say it's the probability of it happening, it will happen over time. It's not really a probability as much as it depends as a rule.
>
> I: But, isn't the rule being given to the individual?
>
> G: But even though the rule is being given to the individual. I guess like, lets say if I said, if I switch the nose angle up to 180. Its increases the probability of them conglomerating into groups…
>
> I: Mm-hm.

G: With them staying there. But the thing is for the individual it increases that but the whole system, it means it will have those groups, like what are the chances.
I mean it just make it kind of a rule, like I switch it and it happens. It's not really the chance of it, it has an increased chance but that increased chance makes it a rule. It's like an axiom of it.

I: OK. Are you suggesting that within this particular system it becomes deterministic?

G: Yeah. If you change certain things.

I: OK.

G: For the individual it's still chance, it alters your chances for the whole system

I: You think so?

G: I find, well look at this, here I have a nose angle like that … see at zero how quickly it expands, right away.

I: OK. Let me understand this more clearly.

G: It's because the individual, like because the system has order. So like order isn't based on chance, order is based on rules, more … So by changing the chance of the system, no, by switching the chance of the individual you change the order of the system

I: OK.

G: Which is why, like last class [session] I said that these things like they're not really affecting the individual as much as they are affecting the system because they change the order of the system whereas they only change the chance of the individual. Like chance isn't always the outcome, it's just the most likely outcome.

I: So, if I'm understanding you correctly, if we're looking at the different levels, at the level of the individual, it's probability…

G: yeah.

I: But on the level of the system , it almost becomes deterministic?

G: yeah.

G: yeah. And that's the whole basis of a complex system though, isn't it? Like it has um, like the individuals wont mirror the system itself. The system itself has a sense of order. It's not determined by the individual.

His understanding of the concept of randomness again showed signs of challenge and development in session 5 when constructing his concept map. At this point he recommended removing the term "random" since he didn't see it as truly representative of complex systems' behaviors. He decided that the term "unpredictable" should replace it. This level of debate was a very sophisticated one. As described under the heading of affordances for learning emergent characteristics, I point to this as an example of the limitations of the Multi-Agent simulations employed in this study. Hence the comprehensive understanding of the concept of randomness may be difficult to acquire because the simulations have not built in the generation random "noise" within the system. Therefore, I did not judge this as an example of Greg's inability to understand predictable actions versus unpredictable (random action) environments, rather, his coming to terms with the representation presented by this conceptual model; therefore, a challenge for him to overcome.

> (looking at his old concept map)
>
> G: Take off random. I really wouldn't think that they're that random anymore.
>
> I: No?
>
> G: Alright. Like I don't think… I'd say more unpredictable. Am I allowed to add words?
>
> I: Yeah, absolutely.
>
> G: I'd also say that [unpredictable is] not being the same as random.
>
> I: To you random means?
>
> G: It's just like. Um it's not even totally unpredictable. It's just that it's not always predictable. Whereas random means like totally unpredictable. So this is sometimes predictable.

Eight months after the instructional intervention Greg demonstrated his integration of this concept into his EFMM. Using his knowledge from his science courses, particularly biology, he expressed a substantial development in his understanding of the concept of randomness.

> G: OK, I think the one thing that I'd do, is that I would add random to the single system, to the simple system.
>
> I: Why?

G: Because uh… There's the uh, the factor of change involved. And just like the small, minute things that each uh, each simple system does… That, that will get uh, like, absorb into the complex system without really having any real effect on it, unless there's a lot of random events. But uh, you know there has to be randomness somewhere, it's not like, as I'm far I'm concerned, I mean random events happen.

I: OK, and what's made you change this idea?

G: Um, well I don't know why I took random out in the first place. I really, can't remember. So uh… So for me it's not really changing it, it's just uh… Just you know…

The coach takes out the notes and reminds him of the debates he had concerning this concept. Since he cannot remember exactly what his original thinking was, he was asked to explain once again how he now wished to construct his concept map. Before taking biology Greg did not appreciate the role that random noise, like mutations, played in providing the system with opportunities for variety thereby changing the direction of the system's outcome. In session 6 however, he was able to eloquently express the function of randomness within the complex system stating: "it creates possibilities". He also appeared to have integrated this concept with that of probabilities which provide the system with a sense of order.

G: OK, so you want me to explain it like a friend to you?

I: Yeah. (laughs)

G: OK, well, I'd say, a complex system is uh, is made up of simple systems. Of which it can be uh, I'm trying to get away from this light but not in my face, OK… A complex map is made up of simple systems. And these simple systems are random, and dynamic. Like, they follow simple rules, but there's also the whole probability of chance. Like chance is a factor. And so that creates um, randomness, and that creates possibilities, also. That if there were no random events, then you wouldn't have those possibilities. Um, but all these chance events, they, when they get absorbed into the complex system, they have very little effect. It's like throwing a pebble into a river. Sure, you might course the river in a one in billion chance or something, but chances are it does nothing. It's not going to affect the flow of the river in any way. Uh, so, what that means is that complex systems, they follow more rules of probability, and they, they… They I kind of guess being mathematically defined, with algorithms I guess, because they're more likely to, have, um, a real sense or order, that the simple system itself won't have. So what that means is that it's self-organized, and it's uh, um… It's called emergent properties. Um… A complex system is obviously a system, I think that's, a little bit uh, redundant. And there is the chance of uh, unpredictable events, for example, you did throw the pebble. That pebble might stop the flow of the water, by the grace of God or something, so nothing is for sure I guess, there is always the element of chance involved. But they're by and large more predictable than simple systems. And… I think I used everything here.

In a closing comment regarding this concept Greg says:

G: I guess it's just, they've become morel like, more apparent to me, like… That you need probability and chance, I guess I just finally realized it today a little bit more, that you need, like there has to be, different levels, otherwise it's like it's not a complex system. That's the whole, notion of it. And that there's some type of emergent properties in the system. Because otherwise you wouldn't use a system to, to describe it.

7.3.1.2 Emergent Framework Component Beliefs – Greg's Elaborations

Emergent Self-organization (higher-level understanding)

The other concept that Greg developed was that of "emergent self-organization". Greg developed an understanding of self-organization through the recognition of the mechanism of "flows". By grappling with what works to keep the system together he enriched this particular mental model. It started with a minor comment on the interaction of the Slime mould in session 1.

G: Umm, the angle I guess, it's a factor that states whether it will stays where it is or go and search out another group, because if you have a large enough nose angle and it kind of turns into a circular motion it smells the one behind it and the one behind it smells the other and they just never move they can stay in the same place without, without moving and the more you have, the larger of a chance that they never will move from the circle. So if you have a small nose angle it forces them to seek out other smells so it kind of causes a lot more movement and smaller groups aggregate into clusters.

He developed the idea further by reciting the thing that keeps the emergent system together in the case of the GasLab model. It is not clear if he realized at this point that it is the rules of collisions that is guiding and organizing this particular system.

G: Although I think the system will eventually just still follow the same pattern it just wont be as (pretty?). It will be a lot more gentle so... Cause like, um, it's just like a few principles like even looking at the screen there's no reds, less reds than blues. And, you know, the green is always the majority.

I: Right. And, if you were to look at the histogram?

G: Yeah, it's still like the curve.

I: Do you know why?

G: Why? It's err, it's just the bell curve… I couldn't tell you the reason exactly. it's like, without thinking about it makes sense to have more of them in the average. I think it's just that if you think about when they um, collide, if you have 2 greens they're more likely to stay green. And if you have a red and a blue they're more likely to stay green. If you have a red and a green, one will stay green, for sure. And a blue and a green one will stay green. So like everything favors the average value pool. Like I mean …

Exploring the concept of emergent self-organization further, he began to see how the environment can affect the way the system behaves and in so doing he developed an explanation that allowed him to draw an analogy which reflects a high level far transfer skill.

G: And also, just like this has no exterior environment affecting it. Like I mean, I still think you'd have the system formed but it wouldn't form in the same way. And, it would have like constant pressure from the exterior. I think it would actually make it more orderly because it has to respond always to the same pressure.

I: OK. That's a really interesting point. So one of the key things that you would have to consider then would be the environmental pressures. What made you think of that?

G: The environmental pressures or the other question?

I: Well the environmental pressure.

G: Um, its just don't know, like, I was thinking about, like if you have an area that's always hot obviously the trees would grow all this time…and so your system has order in the fact that like all these trees have like, they respond to the your outside environment and they also respond to each other by somehow by roots and stuff.
And it's here too they'd all have something in common that takes away some of the chaos in the fact that they have an exterior environment that they're responding to and that that should cause more order and keep some sort of flow throughout the system so that it stays the same.

Here is an example of how he reasoned it out in the session 5. He recognized the behavior and in a metacognitive type of effort to make sense of it he says the following:

```
G: um, what's weird thought is the system, um, in a sense acts like it has
conscious thought. Like when you think of it in terms of um like edge of
chaos.
It's just like it wont let itself end so like it forces those last sheep to
always be able to reproduce or something to form more sheep. Or, I don't know
like, that aspect of systems I just find kinda crazy.
Just like they that they can keep going and such, periodic functions. It's
like, I don't know, I just find it weird.
```

After a few exchanges discussing the system's moving towards equilibrium he concluded with the following:

```
G: So it's just enough to, I guess, it's like, this I think would be the
ideal complex system like there's no chance of either party being extinct.
Cause like with the other one if you ever had like a really low sheep count,
if there was a disease or something, then you'd loose it.
More like a low count. Whereas here, it's kind of perfect because they're
both relatively high, and they don't like shift around too much, and there's
not like edge of chaos really.
```

Five exchanges later he described the concept of "flows of information" throughout the system. It appeared that his dialog with the coach acted as a form of self-explanation and metacognition. This was very important because this relationship of information flowing within the system and holding it together is a very important one. One that Greg was able to articulate in his answers to the "ant" question. Here we can see how he again reflects on this behavior of complex systems.

```
G: I think that could be because for something like this the grass affects,
like a sheep is the only thing that's um correctly affected by the grass, so
they kind of um, they take the stress from that and then like its kind of
filtered, like a little bit, through the sheep to the wolves wouldn't feel it
as much, and it wouldn't affect them as much as it would the sheep, I think.
```

After quite a bit more discourse he came to the following realization:

```
G: Ok. Yeah. As a complex system, like which it seems to be, I would call it
self-organizing.

G: Yeah. That's why I said that like it seems like someone like's controlling
it. Because like that I guess is another way of looking at self-organization.
Because like, um, like as the individuals work there're not, like I mean,
they don't know what's happening here, like how their being organized and
stuff.
But like as a whole system it is working.
```

> But it's just the fact that complex systems are their individuals don't organize themselves but the whole system does.

An important understanding of this type of complex system, which is non-adaptive was made when he described the types of systems where history and learning do not play a role. He was the only one to mention this concept and realize its importance in interpreting complex systems behaviors. One of the limitations of these computer models was their lack of history and adaptation. However, the complete new "start up" also models certain types of complex systems like stock markets, and weather patterns, that do not adapt per se, but exhibit patterns and trends. The system is always reacting to the current set of conditions.

> G: yeah. Um. For this I don't think there's the numbers of sheep and wolves, I don't think it affects it very much. It's only for the first initial state. Because, since it's always oscillating, like I mean, um, like as soon as you have a very few sheep, I mean, you lose all your wolves. Or if you have no wolves, or like a very small number, what you had earlier is irrelevant. It's like a new system. It's like a cycle, I guess. So I don't think um it's just for the initial state. and after that it like evens out to what it would be with any number of sheep or wolves.

Greg's use of particular analogies support this growing understanding. For example, here is one that he draw using the stock market to make is point:

> G: I'd.. in a way I see the stock market as being like this. Like when the money is worth a lot people invest and then they build it up there's such inflation that there's a crash.
> (sound of his hand hitting the table to emphasize the crash).
> Not like a huge crash like there was. Like it is Um, like there's some sort of crash and then people pull back and then they start building up again. Like there's a cycle like that.
> Like I mean, I think it reaches a point where people have mathematically figured out the stocks without even knowing what they're buying.
> Like they're still making money because they like they mathematically figured out when to buy and stuff.

Using the evolution as complex systems graphic, Greg explained what he understood. He expressed himself very well and described the concept of homeostasis.

> G: yeah. You've got simple systems that all follow simple rules they um act in similar fashions.

I: Mm-hm..

G: That like um they are part of a higher level which is like the self-organizing complex systems, I mean, you have simple systems inside simple systems.

I: Mm-hm..

G: Inside complex systems. And these… complex systems they don't, like you're not able to know like how they act based on the actions of the simple system and they can give rise to even more complex systems. And it's all yeah.

I: and the notion of time?

G: time, um.

(Time lapse 3 seconds.)

I: again this really is meant to help you explain evolution so..

G: ok. evolution. I think, well it's just that there two conflicting things. Like I mean we learn that complex systems are usually, like they find a state of equilibrium and how they act. Like I mean although the, for example the wolf and sheep populations like fluctuate.
There're never too high or too low, that like you would loose all your wolves or sheep. But also like because of time and chaos, systems change over time. They, evolve.
Like that's the whole point of like evolution that we change. so in that sense I guess that time, like um, when you really think about it um although it shows like something is being like a system in that it's continuous, like in whatever way, it also changes it I think over the long run.

I: OK. And do you think all complex systems evolve or just some complex systems?

G: I think they all have to evolve because they're all affected by stress from the outside. So like I mean they all have to change in certain ways. Like they never have the same conditions like as they had before.

Post-Case Interview.

In the final interview, Greg's understanding of emergent self-organization was very strong. Here is an excerpt from his answer to the "V-formation created by birds":

G: How is it a complex system? That, um… In a few ways it's like uh… I seem right about this, because I almost did my comprehensive assessment on this… Like, things that, the, the flock can fly in a straight line, even though each individual bird is not flying straight, it might be moving a little bit to the left, a little bit to the right, but it gets damped over the whole um, system, like, if, if the bird in front of you moves 5 feet to

```
the left or something, you're only going to move half that amount, so that's
two feet, and the bird behind you will move a foot and then, half a foot, or
whatever, and so over the whole system, there's a lot less change than the
one individual that moved five feet, like the whole, like average I guess, of
movement is smaller, because it's damped over the whole amount of birds.  So
that um, as a whole, it will stay as a V, even though certain birds aren't
flying in the, like in the exact V formation.  So it's uh,  I guess that's an
emergent property, the V, even though like, it's not like each bird is
purposely trying to do that, like each bird is not a V itself, it's just the
whole V comes out of the system.  And uh, so… That's the end of the complex
system in terms of the shape and formation.
```

His conclusion about complex systems:

```
G: So I guess that um, I would add to your three definitions that complex
systems are relative I guess, depending on how you look at them.  Like it can
be considered simple if you're looking from above, and as complex if you're
looking from below.

I: OK, and you also mentioned the word interact, which I think you've
mentioned on several other occasions.

G: Yes, OK.

G: OK yeah, the exchange of information, it's uh… Like it's the interaction
with the environment which creates most of the probability and randomness, in
a system.  Like it's all, a response to interaction.
```

7.3.1.3 Summary of Greg's Experience

Greg's case is an example of a learner who appeared to hold some emergent framework "component beliefs" before entering the study; and more importantly was immediately affected by the initial intervention (see later section 7.6 for details). It may therefore be argued that was not a typical novice learner.

I contend however that although his experience may indeed portray the "sophisticated" *ECP identifier* (Emergent Causal Processes identifier. For reminder, see p. 142), he nonetheless demonstrates that even these individuals are challenged by some components of the clockwork ontological framework. This close examination of his conceptual acquisition provides insight into what may provoke the requisite changes. It appears that the cognitive coaching in this case coupled with metacognitive and metaconceptual reflections allowed him to eventually resolve the inconsistencies between is understanding of randomness and this new way of thinking about how it operates within complex systems. More will be discussed about this experience compared to the other students later in this chapter.

7.3.2 Norman's Case Study Report

What did Norman learn about complex systems thinking and emergent causal processes? How did he come to acquire this knowledge? Two things that I focused on with Norman were: (1) his facility with some notions of emergent causal processes; however, (2) the entrenched clockwork belief in centralized control and determinism, and his struggle to acquire an alternative explanation.

From the original testing[27]Norman appeared to have a good grasp of emergent type processes. He was one of the few who identified the requisite flow of information through the system, supported by a pheromone (organizing mechanism), which creates the pattern of an "ant chain". The mention of these three components that are important to the process of self-organization and emergence was an important indicator that Norman, like Greg, was among the small group of individuals who already had some knowledge of this concept and used this mental model to explain phenomena.

Ant question

Specific cast of ants are sent out to explore and find a route to food source. Then they exchange information and create an ant chain that goes along a pheromone route from the anthill to the food source and back…

However, his far transfer task indicated that he did not apply this explanatory model to other similar phenomena. In fact he doesn't mention any emergent processes in his response (i.e., no signs of local interactions, tagging or organizing agent, flows of information, and pattern formation).

Robot question

Assign each robot a different task [dig, extract, return load] they would be coordinated by a computer located on a satellite that would act or.

---

[27] Norman belonged to the control group therefore his results are from the immediate posttest.

What was apparent in both answers was Norman's attribution of centralized control, in that each agent was assigned a specific task ("specific cast of ant" – "each robot") as well as the notion of an external controller of the agents ("a computer… on a satellite"). These responses also provided evidence that he did not imply organization to random behaviors of the agents but in fact attributed a predictable and purposeful behavior to the agent ("explore and find a route"). The analysis of Norman's data were therefore to look at what happened to these attributions, what changed if anything.

7.3.2.1 Emergent Framework Component Beliefs – Norman's Elaborations

Understanding Emergent Levels of Organization

There was evidence that Norman easily observed and identified several concepts without difficulty. One of these was the differential behavior of agents and meta-agents (i.e., emergent levels of organization). Starting as early as the first session, he described the organization that occurred because of the rules being followed by the individual, as well as the differential types of results which is a prelude to describing the emergence of a meta-agent (i.e., the colony).

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Session 1
I: Are the turtles trying to cause an aggregate?

N: no, it happens by chance. But they [the aggregates] are the product of
the setting of the individuals...

I: ok

N: so indirectly it will be because of the individuals... The formation is
dependent of the individuals... The result is by chance.

I: ok.

N: yes. It has err... the, the commands of the simple units [the turtles]
are to follow pheromone which makes the colony. That wasn't the purpose but
that's what was at the end result.
They came together and became a bigger... you could consider the aggregates
as another organism. That doesn't have the functions of the separate units.
```

He again elaborated on this during session 2, through the following statement:

> Session 2
> N: ...here, this was the case, too. Like, when they catch up [to] the pheromone trail... they tended to form, uh...forms [colonies], and are no longer just turtles moving around.
>
> I: OK, just explain it a little bit more to me, you know, so that I can understand it a little bit more.
>
> N: Well… Well the principles that... I've observed from this slime simulation was that... The complex systems didn't, didn't show the characteristics of the units [individual]. And, it's the same thing with the molecule, [in the] chemical reactions (referring to the GasLab simulations).

Although Norman had a great deal of difficulty expressing himself in English, he appeared to describe the differences between the behaviors of the StarLogo agents (i.e., slime mould in the Slime simulation, and molecules in the GasLab simulation) and the meta-agent. In session 5 when he was specifically asked about how complex systems operate, he responded that there were differences between the ways that the system functions compared to the individual within the system. Although he was able to make this distinction, he was tentative in explaining and elaborating on his understanding, provided the following insight:

> Session 5
> N: Of complex systems... Well, um, that uh, some things, or some phenomenon, take place at the level of the complex system, and not at the level of the individual.

Understanding Concepts of Multiple Causality (a category on CST)

Norman's discussions provided evidence that he was able to understand the simultaneous nature of the agents reactions to the stimuli of the pheromone in the slime simulation. He explained that there was the likelihood that, at the same moment in time, there are several pheromone trails forming that are of differing intensities and that it was possible that the slime mould may not get to the strongest one because of limitations of one of the variables. This description also shed light on his ability to reason out the stochastic quality of the interactions that exist in these complex systems.

```
Session 1
N: maybe, the trails aren't the same intensity at the same moment. So that they
have to go with the one that's nearest but if they can also find more
[pheromone] at the same time that are stronger... if they have a small [nose]
angle... By the time they find one [a trail] it has evaporated... and the
threshold wouldn't help. Their sensitivity wouldn't help anyway because... they
would have found it too late.
```

By session 5 he was also able to detect the indirect relationship between agents that do not interact in a direct manner. For instances, he explained how the wolves and the grass, in the Wolf-Sheep predation simulation, have an indirect relationship.

```
N: If there is a change in the... in the grass, the change in the delay (i.e.,
the variable that controls the rate of growth for the grass).  I think like,
the result would have been that less of the wolves would have changed their
reproduction rates, according to the change that have occurred with the grass.
To uh... not intentionally but as a result of the grass delay, which maintains
the equilibrium.
```

7.3.2.2 Norman's Conceptual Struggles

Where the real difficulty for Norman appeared to be was with the concepts of decentralized control and deterministic causality (i.e., predictability). I will discuss evidence of each of these in turn.

Attribution of Centralized Control

```
N: Because each turtle secretes the pheromone

I: uhm.

N: the more pheromone there is, the more concentrated they become. (can't make
out
```

From the very first evidence of Norman's mental model, it was apparent that he held some notions of a central organizational structure; either with the queen ant sending out food gathers to collect food, or a centralized computer directing the behaviors of the robots in their hunt for gold. However, it appeared that it was not so much the behavior that he could not identify but the words describing the behavior. He continually described the behavior of the turtles as "they", implying that "all" do certain things or respond to certain conditions; he, however, never explicitly used that qualifier.

Session 2
N: Uh, decentralized system, I think, would be uh associated with uh, randomness? And chance. Since it uh, doesn't relate to our, non-determinism instruction. Whereas, [a] centralized unit that is, follows orders.

Norman struggled to understand the way that the terms centralized and decentralized were used in this context. In session 2 he engaged in a long back and forth dialogue trying to reason out what type of control was being exhibited in the case of a living organism an its DNA instructions. In essence, was that an example of decentralized organization, compared to the central nervous system and the functioning of the brain? In order to provide a flavor of the type of reasoning I selected a few excerpts of the exchange. In this conversation, Norman was engaged in assembling the terms in a concept map. One of the terms was centralized and the other was decentralized. He responded to prompts to describe an example of where the commands do not come from a single source.

Session 2
N: Like a, living organism that, has information in, like I should say, its DNA. That's where uh, all the, instructions come from.
I: Yes, except, is that an example of centralized control, do you think?

(pause 5s)

N: When you were saying with humans…what example would you use?

I: The brain, maybe.

N: The brain right.

I: Yeah. The brain controls everything else.

N: Mm-hm.

I: That would be a central system. However, your DNA, how's your DNA...

N: Like in, you would need it, since it's not a, system... Like it's just information.

I: No, no. It's, definitely an important part of the system. But, you know, it's a very good example. Your DNA is where?

N: In the nucleus, of the, each cell… From where the, it makes its commands.

I: (talking over N): Yeah, but it's, the operative words there, that you just used, is that in each...

N: Cell.

Continuing this conversation, the coach encouraged Norman to explore this line of reasoning until he described how the DNA that is present in the cells could be an example of decentralized control.

Session 6

I: But, on the other hand, I think that, what you suggested was some really interesting ideas. The DNA, inside the cell, it's like the instructions for each cell, right?

N: Mm-hm.

I: Sort of like, the programming of each turtle. And yet, the turtles, what they did, with that instruction...

N: They made up systems…OK, and they attract other units...

N: Yeah, I think... Oh yeah, it's decentralized, uh, if uh all the cells that compose the liver, uh, the instructions come from all the cells, they are the same. Because they all have the, DNA, so yeah, that would be, decentralized.

Although it appeared that Norman had come to some resolution as to where centralized and decentralized should be placed on his concept map, in subsequent sessions he experienced similar struggles with these terms. He saw the ultimate control of the system as being in the hands of one central controlling body. Even when he described cases where there were more localized control, such as in the case of the muscles, and so forth. These concepts did not become easier for him to understand or come to terms with as the sessions progressed.

Session 6

N: Uh… Well. When, a system… OK, when there's a complex system, it tends to uh… Like assign it's… Well… Well, the command centre seems to be a…

Well, what, what coordinates the whole system. So it would be centralized, yeah. It would have a centralized command centre.

I: OK.

N: Well the, the orders to coordinate all the elements of the complex system would tend to be in one single place, meaning that the...

I: How does that work?

N: How does that work?

I: Yeah. Give me an example.

N: The human body and the brain. The robot and its satellite.

I: OK.

N: Or wherever the command centre would be.

(pause 4s)

N: Uh... Yeah, basically giving order from, some place, to coordinate, to make the coordination. And decentralized, if there's simple elements have not, grouped enough, for them that would lead to a complex system, uh, each one goes his way, and their actions do not, are not specifically aimed to the better being of the higher system.

I: OK.

N: So that would be a decentralized state.

I: OK.

Attribution of Randomness versus Determinate Causality

Norman showed evidence of understanding the notion of random behaviors. For instances, he specifically mentioned the word "random" in his description of the slime moulds' actions (see above excerpt for centralized control). He further suggested it was possible to control the degree to which the agents exhibited random movement through the manipulation of the variables (i.e., the sliders) contained in the simulation. In session 2 he also explained the behaviors of the molecules as random.

Session 2
N: Well yes, but uh, now we, we can control the randomness...

I: OK.

```
N: so, and it's part of the program.  When they collide, they choose a,
random direction.

I: To deflect off of, yeah.
N: I don't know if I understood it correctly, but also the speeds are, kind
of, random.
```

Norman nonetheless, found himself in a conundrum because he did not know how to deal with the assertion that things could have random starts although they formed patterns and developed into stable states. He described a recent lecture from one of his Philosophy courses in which the topic of determinism was discussed. As a point of clarification, the concept of casual determinism versus random actions is highly interwoven with probabilistic causes. In fact, I would argue that one may need to accept the notion of randomness at the agent level to fully appreciate the probabilistic causes at the system level. Therefore Norman's consciousness of the implications on the notion of randomness that he was experimenting with was an important step in learning, however he was not able to come to terms with how these processes within a "microworld" simulation were not meant to be explained in a deterministic fashion.

```
Session 2
N: It's a, philosophy [from one of my courses]. We were talking about uh, a
division, that's called determinism.

I: OK.

N: We're, we're talking about, [that] everything has a cause... and, causes
lead to certain results, [certain] things. And uh, this is, what is
causing...  Like, here, on these simulations, we have control over the
variables.

I: Right.

N: And, we can uh...  Yeah we, we can get basic principles out from them,
from looking at the, what takes place, and predict that this would happen.
And, in life that occurs. It's just that we, we aren't, we don't have the
consciousness [to know] about those [things], all those factors that can
lead to, the [result]...  So uh, with human behavior, how a human will
respond to certain things...
```

7.2.2.3 Summary of Norman's Experience

Norman, like Greg, began the research study with some level of emergent framework "component beliefs". He appeared to construct some elaborations on aspects of the concepts involved but seemingly struggled with others. Unlike Greg, his conceptual struggles over the concept of randomness did not resolve itself with time. Furthermore, unlike Greg, he appeared to be restricted by a more robust clockwork component belief specifically related to the concept of decentralized control and deterministic causality. Although for a time during the intervention phase of the study, supported by the cognitive coach, he seemingly began to make clearer observations and explanations (i.e., perhaps best described using diSessa & Sherin's (1998) notion of "causal net" bootstrapping) he reverted to his old explanations in the final session held one year later. Furthermore, Norman, unlike Greg, was unable to understand the role and the limitations of the models. Schwarz (2002) refers to this as the results of misunderstanding the epistemic form and suggest that meta-modeling knowledge may be an important part of learning from models in science education. Later in the chapter I will describe other students of Norman's experiences with the concept of "randomness" as well as the other categories of concepts identified from the transcripts using the CST coding.

7.4 Interaction of Intervention, Learner, and Conceptual Knowledge

7.4.1 Section Overview

One of the major themes constructed from the categories to emerge from the transcript data suggested an interaction not only of the student with the content knowledge (i.e., the anticipated effect of "component beliefs" on the learning of emergent causal processes reported in other research) but also an interaction with the simulations' conceptual and physical representations. I refer to these as the intervention's affordances for learning emergent causal processes. This section attempts to describe how these affordances appeared to affect the amount or kinds of awareness, and possibly learning, of the specific concepts as assessed using the complex systems taxonomy (CST). In so doing, this section addresses the qualitatively inspired research question:

2.b) What were the affordances of StarLogoT (and possibly other multi-agent modeling language generated simulations) for promoting the learning of emergent causal processes?

7.4.2 Simulations' Affordances for Learning Emergent Causal Processes

In order to describe the differences between the students' experiences with the simulations I constructed the following 4-point scale based on a hypothetical assumption that all the simulations should provide opportunities for learning the six major categories of complex systems identified in the CST.

- *High affordance* = above 34%
- *High Moderate* = 33% - 17%
- *Low Moderate* = 16% - 8%
- *Low* = 7% - 3%

Although there was no empirical data to support this claim, the anecdotal evidence collected from the experts' ratings (see sample rating form in Figure 6.3) suggested that it was reasonable to use this assumption as a starting point. Hence, a measurement of awareness scale could be as follows: All things being equal, the learner should generate a score equaling 17% utterances (i.e., observation data) for each of the six categories. Clarifying by way of example, if a student discussed the topic of probability for more than 17% of their utterances, then it would be considered that the simulation offered a *high moderate* affordance for learning that concept.

Using the scale described above, the evidence showed us that the students' combined scores over the three selected sessions produced results that fell within the range of scores indicating a *high* and *high moderate* degree of awareness (and possibly learning) of two complex systems concepts: "multiple levels of organization" with 43%, and "local interaction" with 30%; a *low moderate* degree of awareness for the category of "probabilistic nature" with 15%; and a *low* degree of awareness for the category "random actions" which produced 4% of the total observation data (see Table 7.6). The other categories in the coding taxonomy produced fewer than 3% of the total observations and therefore were considered to indicate a weak affordance for learning. In short, thereby suggesting that these categories required closer inspection to determine if indeed the lack of observation data were more likely to be the result of the individual or the intervention.

The evidence also suggested that the types of simulations presented influenced the students' experiences and awareness of the complex systems concepts. For instance, when looking at the total averaged "raw" scores (Table 7.6 far right shaded column) we see that GasLab simulation generated substantially fewer observations (total = 100) compared with the Slime simulations (total = 187.7) and Wolf-Sheep simulation (total = 140.6). In fact, the Slime simulation produced 87% more observation data compared to GasLab, and 34% more than Wolf-Sheep.

These percentages suggest that students' demonstrated a substantial amount of awareness, and possibly experienced learning, of the categories of "multiple levels" and "local interactions" during the indicated sessions. Therefore it would not be surprising if these percentages were also highly correlated to the changes observed on the related OMMT sub-category, specifically "emergent self-organization" (identified also as item #1). In addition, the category of "probabilistic nature" also indicated a moderate level of awareness thereby suggesting that an equivalent change may be observed in the OMMT category by the same name.

Table 7.6 Observations coded for 9 CST categories.

Complex Systems Characteristics	1 Multi levels of organization	2 Local Interactions	3 Probabilistic nature	4 Random actions	5 Tags	6 Flows	7 Decentralized control	8 Nonlinear effects	9 Homeostatic behavior	Combined scores
Session 1 Slime	93.4	42.7	21.8	9.8	8	2	5.2	0	1.3	187.7
% of total observations	50%	23%	12%	5%	4%	1%	3%	0%	0.7%	100%
Session 2 GasLab	41.1	29.3	22.3	3.5	0.3	0.5	1.1	0.6	1.4	100
% of total observations	41%	29%	22%	4%	0.3%	0.5%	1%	0.6%	1.4%	100%
Session 5 Wolf-sheep	50.8	55.3	21	3.6	0.3	5.3	2.6	0.6	1.1	140.6
% of total observations	36%	39%	15%	3%	0.2%	4%	2 %	0.4%	0.8%	100%
Overall total	185.3	127.3	65.1	16.9	8.6	7.8	6.3	1.2	3.8	428.3
% of total	*43%	*30%	*15%	4%	2%	2%	1%	0.3%	1%	100%

(N.B. Shaded categories represent items that when combined are similar to the "Emergent-self-organization category in the OMMT). * Indicates high percentage of awareness.

Individual Summaries

Slime simulation. Looking at the individual simulations' affordances (Table 7.6) for learning of these concepts it appears that the Slime simulation was particularly good at generating observation data regarding these concepts: "multiple levels of organization" (50%), "local interactions" (23%), "probabilistic nature" (12%), "random actions" (5%), and "tags" (4%).

GasLab (Free Gas) simulation. On the other hand the GasLab simulation provided the student opportunities to identify and explain the complex systems concepts of: "multiple levels of organization" (41%), "local interactions" (29%)," probabilistic nature" (22%), and "random actions" (4%).

Wolf-Sheep simulation. Lastly, the Wolf-Sheep predation simulation appeared to afford the learning of the following concepts: "multiple levels of organization" (36%), "local interactions" (39%), "probabilistic nature" (15%), and "random actions" (3%). Additionally, it produced observational data for the concepts of "flows" (4%).

7.4.3 Summary of the Opportunities for Learning Provided by Simulations

Table 7.6 indicates that all three simulations provided affordances of at least high moderate for two complex systems concepts: "multiple levels of organization and "local interaction". They provided a low moderate affordance for the complex system concept "probabilistic nature" and a low affordance for the complex systems concept of "random behavior". The other categories in the coding taxonomy produced fewer than 3% of the total observations and therefore were considered to indicate a weak affordance for learning.

All the simulations provided opportunities to observe and discuss "multiple levels of organization", local interactions" and "probabilistic nature" albeit to different extents. Only the Slime simulation provided opportunities to observe and discuss "tags" but it did not provide opportunities to observe and discuss "open systems"; the Wolf-Sheep simulation did not provide opportunities to observe and discuss "random behavior". All the simulations had only weak affordances (< 3%) for all the other complex systems concepts. However, despite the similarities in the affordances of the simulations, students did not acquire the complex systems concepts equally well from all simulations as will be discussed shortly. In addition, in the upcoming section I will speculate as to possible reasons for these different results in the opportunities to learn the CST concepts from the different simulations.

7.5 Explaining the Affordances for Learning CST Concepts

The objective of this section is to provide a picture of how awareness and possibly learning of the three concepts, rated as "high" to "moderate", were experienced by the students. These concepts are "local interactions", "multiple levels or organization" and "probabilistic causes". In part this section also addresses two research questions:

2. If provided with appropriate content and learning environments, what do students' experiences tell us about acquisition of this content knowledge?
3. What does this study tell us about the usefulness or limitations of these types of models as tools for acquiring emergent framework mental models?

7.5.1 Category of "Local Interactions"

How did students gain awareness and knowledge of the concept "local interactions"? "Local interactions" refers to the behaviors of agents as they operate within the environments of the simulations. In order to be coded at this node, the student had to generate evidence of their awareness of individual agents (e.g., slime mould, molecules, sheep), and that these agents' actions were not isolated from each other but in fact significant changes arose that because of the different ways in which they could encounter each other or affect each other. In short, the student needed to demonstrate that they could reason about both the individual behaviors of the agents as well as the impact of potential interactions such as attractions or collisions. In order to code for this category, I adopted several key predicate indicators (many of which appeared to be used regardless of the simulation content): *interact, attract, collide, aggregate, come together, hit across, form, react to, cluster, move towards, affect, communicate with, organize, change each other*. There were also another group of predicates used to demonstrate local interactions, which I suggest were telltale signs of "teleological beliefs"[28] that constrained the development of the concept "probabilistic causes": *find, look for, build, and join.*

[28] The data showed that the students who used these predicates were more likely to attribute purpose to the actions of the slime mould and the colonies as demonstrated by other utterances in their verbal protocols.

Therefore these predicates provided insights into more than just how student acquired the concept of "local interaction".

Turning back to the specific concept being examined, here are statements by Norman and Walter related to adjusting variables involved in a simulation:

> Norman: the pheromone concentration are formed when they aggregate. 11
> Norman: yeah. Because they were apart and now they're coming together. I don't know maybe this will happen with these two. 27

> Walter: well, there are a bunch of turtles moving around randomly and they seem to be giving off these green secretions in their wake and it seems as when they get a strong enough secretion they kind of like come together. They kind of like attract each other. 5

Greg dialog provides an illustration of this level of awareness generated from engagement with the Slime simulation.

> Greg: uhm. Unless there's a large enough group centered in one area, they won't aggregate there at all. so that makes it impossible unless you increase the numbers... what about 2000... 23
>
> Greg: um, I'd say that the nose angle just makes it since it's at 180, they can pretty much smell behind themselves and they just form groups of small clusters from wherever they start off as ... 56
>
> Greg: Ahh. I don't think there're enough turtles to actually aggregate to keep together. 100

Session 2 – GasLab Simulation

Results from sessions 2 and 3 were similar in that they too reflected different types of references and levels of discussion that were coded as awareness of "local interactions". For example, Emilie uses the term interaction and basically describes what she sees on screen, whereas Penny appears to have come to some realization that collisions ("hitting each other") are resulting in some larger event.

> Emilie: There, there would be always the less, the less number, like the less number of interactions, that decreased. Because they kind of have to travel further, and that takes time. Like, in order to reach one another. 133

> Penny: Yeah. If you look at just look at the molecule itself, it's consistent because, since if, well, if they're hitting each other then they're affecting which event takes place. 1049

Mitch, on the other hand, fittingly describes the interaction of molecules in the GasLab simulation as collisions and goes into a science-based explanation of what the interactions produce.

> Mitch: Because, it is a system that... Whereas, a collision between a fast and a slow particle, it... They're all elastic collisions, so the energy is considered, in one way or the other. So every elastic collision's going to change the speed of each particle in the system, but it's not going to change the speed of the whole system. So, that's why the average speed is staying around 8.8 or 8.9... 11

Session 5 – Wolf-Sheep predation Simulation

The Wolf-Sheep simulation also produced these differential, but all on category, responses. For instances, Walter describes the ecological chain-like interaction of the three variables in this final session's simulation.

> Walter: well, the sheep eat the grass. The wolves eat the sheep. 116
>
> Walter: obviously, when there's no sheep there's going to be no more wolves eventually because they're all going to die out. Because they're not going to have nothing to eat. 169

> Greg: I think that could be because for something like this the grass affects, a sheep is the only thing that's um directly affected by the grass, so they kind of um, they take the stress from that and then like its kind of filtered, like a little bit, through the sheep to the wolves wouldn't feel it as much, and it wouldn't affect them as much as it would the sheep, I think. 271

Summary of Affordances for Local Interactions

From the above it is apparent that the each simulation provided a different opportunity to learn about the concept of local interaction. Awareness and possible learning observed from the slime simulation may be attributed to perceptual level display of tightly coupled interactions and aggregation of mould into colonies. On the other hand, local interactions in the wolf-sheep simulation may have been observed because of the expected causal change of events, "sheep eat the grass. The wolves eat the sheep". Hence, one explanation for the increase in observations may be because students are intuitively familiar with these moderately coupled interactions that make up ecological systems.

Another explanation, however, may be a consequence of their changing ability to observe (i.e., "readout" strategies) different causal processes. In this interpretation of the data, the increased number of observations would be described as a consequence of better understanding of relationships between agents and not necessarily attributed to the representational affordance of the simulations. Alternatively, it may be an interaction of the two. Both alternative explanations could be explored further through other data in this current study and perhaps in future studies.

Differences between types of simulations. The GasLab: Free Gas simulation offered weaker representational affordances related to local interactions. These results suggest that dissipative complexity models (whose organization is most apparent at statistical means) may be less likely to generate observations of local interaction, which is congruent with the type of complex system represented by the model. Consequently, it should be viewed as one step towards establishing credibility of the findings. In fact, the modest level of local interaction recognition may be explained by the cognitive scaffolding that cued students to look for similarities across simulations; therefore, in no way attributable to affordances to promote the concept of local interaction generated by this simulation. A fuller discussion of this point is found in the next chapter.

It appears that examining the individual students' experiences would provide a better explanation for the weak affordance for learning with this simulation. Figure 7.12 provides a good overview of these differences. With that said, it is worth noting that two students, Mitch and Greg, nonetheless showed high percentage of their time focused on this concept with observations of 43% and 61%, respectively.

How can these students' differences be explained? Both students belong to a cohort of high academic achievers and both had above average scores[29] in NYA physics and chemistry: Greg, 97 (intro. chem. 99), Mitch, 84 (intro. chem. 86). It may be argued that Sidney also achieved high grade in chemistry (80) but is reported to be aware of this for a mere 23% of his observations. Looking at his grade in physics (70) revealed a more

[29] Introductory physics is a course in mechanics (Physics NYA avg. 69.5); introductory chemistry is a course in chemical bonds and states of matter (Chemistry NYA avg. 68). Sam's grades for both 68 phys NYA/ 63chem NYA.

likely correlation between variables, hence plausible alternative explanation. These results suggest that there may be an interaction between the student's level of understanding of physics (specifically collisions) and the ability to observe local interactions. Further investigation into this possible relationship is required.

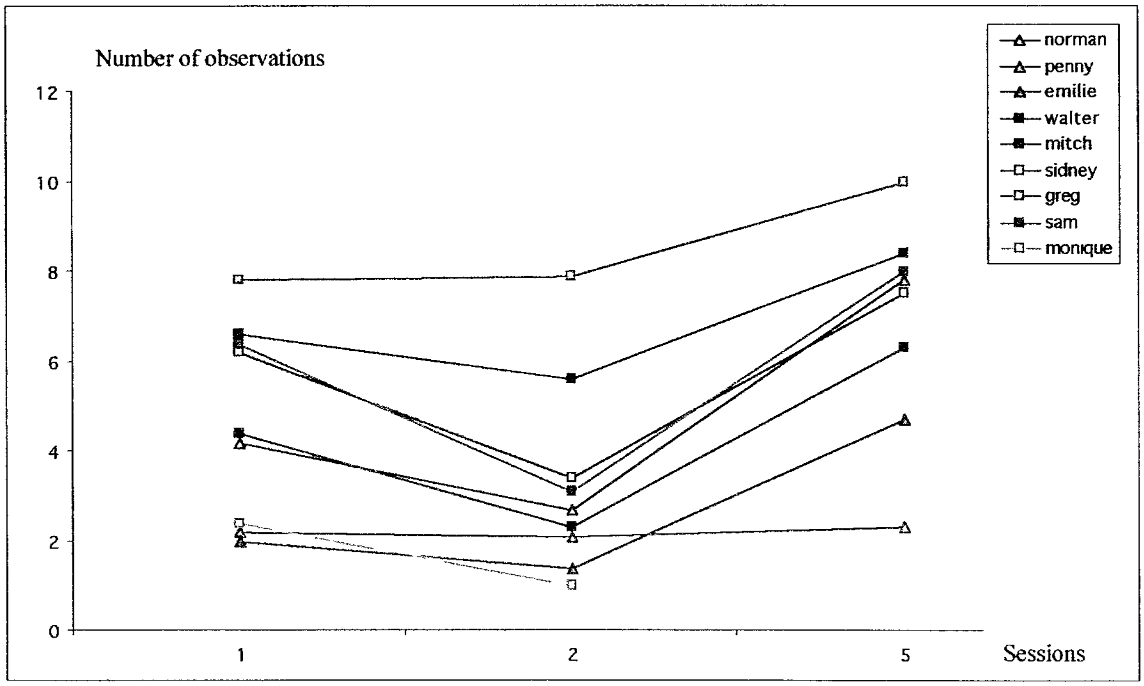

Figure 7.12 Line graph comparison of students' observation data relating to local interaction of agents over the three sessions.

Final word. This difference between learning with this simulation compared to the other two was demonstrated for other concepts as well. Consequently, these results lead to possible explanations that may have important implications for future research. This will be discussed in the next chapter.

7.5.2 Category of "Multiple Levels of Organization"

The multiple levels of organization within the system are an important component of the aggregation emergence process. Typical items from the sessions coded at this node are described below. A typical observation for this category would be that individual agents behaved in one manner while systems (meta-agents) behaved in a different manner. Observation of differential behaviors often resulted in terms such as "random" or "unpredictable" individual agent actions versus "stable" or "orderly" meta-agent actions. Additionally, descriptions could extend to homeostatic behaviors, although that concept was a unique node on the complex systems coding taxonomy (CST).

Therefore what the students appeared to learn was that individual turtles behave randomly (Slime simulation) or unpredictably (other simulations) but when they form a meta-agent or change states, this new level of organization behaves in a more stable and predictable fashion. This observation created some constraints in the students' understanding of where the term "predictable" fit into a concept map related to complex systems. Consequently, it may account for some of the difficulty experienced in removing the ontological barrier related to attributions of determinacy. This possible interaction between the concept and what is observed from the intervention is examined more fully in the discussion chapter.

It should also be noted that the data analysis for GasLab (session 2) and Wolf-Sheep predation (session 5) was not as clear-cut as for Slime mould (session 1). In essence, coding for levels of organization required reading several phrases to capture the distinction that the students made between either the agent and the meta-agent attribute of net changes (e.g., pressure, total energy within the system), as described for GasLab; or between the individual and population levels as well as the level of the system itself, as described in Wolf-Sheep. For instances, key terms or phrases such as "population", "system", and references to the graphical readout "parabolic curve", "sine wave", to list a few, were identified as evidence of reference to the macro-level.

Session 1 – Slime Simulation

```
Greg: yeah, you can see that sometimes they leave but the whole system stays
constant no matter if they leave or join the clusters the system seems to
follow the same pattern.                                                 273
```

```
Walter: they [the groups] seem to be constant. They seem to be... well the
people are always changing in them but the groups themselves, they stay in the
same position. Um, I think they've actually moved a little bit though.
                                                                       273
```

For Emilie this concept is somewhat challenging although she does make a correct observation.

```
Emilie: The group would be functioning kind of, well, at this, at this point
the group would be functioning kind of, you know, in a stable way, but the
individuals like some of them would not be...would not be...would not...I don't
know how to put this.                                                  647
```

<u>Session 2 – GasLab Simulation</u>

```
Sam: Cause there's only a certain amount of energy in the entire thing.
It's just that the individual molecules changes... All together [however] they
own the same amount of energy throughout.                              426

I: so to paraphrase, there's one characteristic behavior that's happening to
the overall system, which is it's in equilibrium. But the individual within the
system...                                                              428

Sam: Is constantly changing.                                           430
```

An important observation relating to the differences between the two models (Slime and GasLab) is apparent from Sam's statement (see above) and Sidney (see below).

```
Sidney (talking over I): Well I don't view this as an equilibrium space, I mean
because in this case they're ultimately forming, they're ultimately going
toward a goal, it's not kind of like they're going back and forth, back and
forward, it's kind of like in the long run they're going to form one big amoeba
type shape, and they won't be exiting and coming back, it'll be, it will remain
the same.                                                              634
```

At the time this difference did not seem to be of great importance but later it suggested an important nuance and understanding of the difference between systems that are dissipative and those that are tightly coupled and organizing, that is, moving toward a neg-entropic state.

Session 5 – Wolf-Sheep Simulation

Sidney: I don't think it was the simpler one with which we had the altruistic and the selfish ones, because in that one it did not have to eat grass, or uh eating something. And in that case when, where you added more of one, the other one didn't counter-balance it, so there's not kind of an equilibrium state. And what's really odd is the population is somehow, the entire population, or like the population of the... sheep and the wolves has reached some kind of constant stability. They're going up and down but in a small, a small frame. And I would call this like uh, a stable state. Because... 177

I: Mm-hm. 179

Sidney: ...because what's happening is at, at one point the sheep are...the sheep population is greater than the wolf population, and the next moment it's the reverse. 181

(pause 5s)

Sidney: But this is where I have everything equal, where I have the, the initial sheep and the initial wolves the same. But I want to try let's see now. Now I'm going to make the wolves' population twice the number.

I: OK, but what do you think is going to happen once you do that? 187

Sidney: At first I would think perhaps maybe now that the wolves would, would finally overpower the sheep, but somehow I don't think so. 189

I: OK... 191

(pause 4s)

Sidney: You can see what's happening once again. They've reached, they're reaching the, these are gonna, like a parabolic curve they're taking. 195

Sidney: Well that beats the top one. And once again they've reached some kind of equilibrium state. 199

Summary of Affordances for Multiple Levels of Organization

All students appeared to acquire and use the concept "multiple levels of organization". However, there reference to it decreased over the three simulations. Whereas 50% of the total observations made during the Slime simulation referred to multiple levels of organization, during the GasLab and Wolf-Sheep simulations the percentage of statements coded to this concept falls to 41% and 36% respectively. The three simulations offered great affordances for learning this concept. Possible reasons for these results will be discussed in the discussion chapter.

7.5.3 Category of "Probabilistic Causes"

As described above, all the simulations generated a fair number of observation data coded as "probabilistic causes". This category was defined by two key features related to probabilistic behaviors: (1) the significance of large numbers of agents to the probabilities of system formation and subsequent behaviors of the meta-agent; and (2) the importance of the environment/conditions and changes of components therein to the probability of system formation.

Effect of numbers. For example, early on in session 1, Greg, recognizes the significance of large numbers of agents on the formation of slime colonies.

Session 1 – Slime Simulation

I: what general principles, can you identify from what you've observed?

Greg: I feel what's the important variable is the number. The number of turtles. Cause it's just, like... as long as they're packed in a region no matter whatever other variables there are, they'll automatically try to aggregate in a certain way... Like towards more large clusters in the pack. Whereas like, if you have a small number [of turtles] no matter what your other variables are, like a random chance will make it so that it wont be able to...come to be a cluster at all... I'd say that's probably going to be one variable. 192

Walter: so when you have a denser environment, the probability of something happening is going to be more frequent. And when you have a scarce, sparse, environment, um, the probability of like I guess, here in this case a deflection happening is not going to be as significant. 296

Sidney: ...and therefore they'll all, ultimately they will hit, they're so close-by to each other. But I would suppose that if you had less numbers it would take a little bit...like... it wouldn't be more of an equilibrium and you will have a long time while one of the molecules will remain fast, slower, neutral, and some... and even less you know, it will even... it will take a longer time for the...the molecules to become fast and slow and... 102

Effect of environment/conditions. Reaction to conditions within the environment and the probabilistic outcome of such responses was another common observation for the GasLab and Wolf-Sheep simulations. There is substantial evidence that most students could describe and explain the effects of changes caused through control of the variables (i.e., sliders) or the random starting positions of the agents.

Walter: yeah. So basically what happened we have figured that one out, they're going to collect in more groups cause they're going to have a wider field of vision there. They're going to be able to catch onto the pheromones more easily. 338

Mitch: OK, they're starting to pool. Because they have, they can, it's like a field of vision. If you can see more, you can… If you have a wider field of vision you can see more, so that if they can sniff in a wider field of sniffing, they'll be able to of course find more pheromone, and they'll, they'll concentrate in that area. 132

Norman: maybe, the trails aren't the same intensity at the same moment. So that they have to go with the... the operation... 217

I: ok. right. 219

Norman: and if they can find more at the same time whereas...those with a small angle. By the time they find one it has evaporated. 225

Penny: when you increase the angle you increase the chance of... if you increase the angle that a turtle is able to see, you increase the probability of it contacting or bumping into another turtle. 215

I: OK 217

Penny: it happens faster that's because they're so close, they're so packed in so they're going to bump into each other, but I'm sure that with the lower numbers it's going to take longer ... 219

Penny: Like to some extent they all [the pre-identified variables in the sliders] increase the chance, but do it more, like they increase the chance more that the others. 230

Even though Monique has great difficulty with the ability to express herself in English, the statement below suggests that she understands the probabilistic nature of the systems' behavior. She relates the movement of the turtles as dependent upon the concentration of pheromones, knowing that there is the potential of multiple simultaneous sources of pheromone within their environment.

Monique: But they [the turtles] keep on moving still but like, it's really uh, I don't know how to say it... Where there's chemicals, more chemicals, I don't know. If there's, like really strong chemicals in a place, they're all going to go there but, since there's other places also, where there is strong chemicals so that's... Yeah, I think, that's, that's why, they keep on moving, to one from another place. Because they, they have chemicals where they are, but they also sense like there's other chemicals around... 208

<u>Session 2 – GasLab Simulation</u>

Sidney: I would suppose that there's a greater chance of...one of the molecules hitting at an angle where they'll lose this elastic energy than gain elastic energy, slightly...not by a lot, but there's a, I guess the chances like, dictate that...they'll, the chance that they'll when they collide they'll gain energy or lose energy they'll rather lose energy than gain energy. 158

Sidney: I have a feeling it's gonna, all of them will be turning to red, because now the chances that they will, that they will hit are gr-, significantly greater and therefore now it'll be kind of static equilibrium and they'll reach a state where they will all be red. 256

<u>Session 5 – Wolf-Sheep Simulation</u>

Norman: With the... We didn't have... If there is a change in the... in the grass, the change, delay. I think like, the result would have been less of a, the wolves would have changed their, their reproduction rates, according to the change that have occurred with, with the grass, to uh... Not intentionally but as a result of the grass delay, which maintains the equilibrium. 271

Mitch: You start in a different position. If all the sheep start next to one wolf, they're all dead. 594

Mitch: Well, you run it a hundred times, and... If you run it enough times to get through every single positioning, I guess, using some form of statistics, how many times it reacts depending on this type of situation. Like if you have 50 of the wolves are near 50 of the sheep, those 50 get eaten right away, but the other 200 sheep don't get eaten, so they all reproduce. I guess if you figure out, using a graph to figure out how long the thing would take to end... 598

Sam: ok. So it delayed. So um, when it went down the amount of sheep... sorry, when delay went up the amount of sheep decreased so there was more chance for the grass to spread so the amount of sheep increased radically. And then, it continued doing that up and down, but the wolves probably... 89

(pause.3secs)

Sam: ... yeah there was a drought when the sheep weren't there for a while so the wolves just decreased the population until they disappeared. But the sheep and the grass could probably act in, fairly stable for the rest of the way. Oh no, as the sheep increase now there's no more wolves. 90

I: umm. And then the grass isn't changing. 92

Sam: so the grass will end up probably dying down... or reducing, possibly. 94

Summary of Affordances for Probabilistic Causes

There is substantial evidence to support the statement that all the simulations supported the moderate development of probabilistic causal reasoning. One explanation is that unlike the other categories, there is no interaction between the type of system represented by the models and the opportunity to learn the concept of probabilistic reasoning. Another explanation would be that there was a change in the observation and explanatory capabilities of the students and therefore a development of their causal nets. In other words, as they proceeded through the instruction the student became more aware of the effect of numbers and the importance of the environmental conditions in determining the outcome of the interactions (i.e., system formation). This explanation was triangulated against the concept map data (see section 7.2). Both showed that more students made a substantial improvement in their understanding of the concept of "probabilistic" causes and its relationship to other causal processes.

7.6 Explaining the Weak Affordances for Learning of CST Concepts

While it appears that all three simulations offered support for the concepts of "local interactions", "probabilistic nature", "multiple levels" and "random actions", this support was not equal across concepts. In fact, the percentages of awareness varied quite substantially particularly among learners (looking back to Table 7.3), the most noticeable of these being the concept of "random actions". Seemingly, all the simulations did not provide sufficient modeling of this concept to support a strong awareness or construction of this understanding.

Interpreting the evidence for "random actions", as well as the other low awareness categories (nonlinear effect, decentralized control and homeostatic behavior/dynamic equilibrium), as apparently weak affordances for learning these concepts may not necessarily be the correct conclusion to draw. It may be argued that a low level of observation data does not necessarily mean a lack of awareness or understanding of a concept. Indeed, it may indicate that the learner readily recognized the behavior described by the concept and choose to focus instead on other concepts that were more challenging or interesting. In an attempt to accept or reject this important alternative explanation, I will to present excerpts from the transcript data to support my conclusions regarding this issue.

Concept of Decentralized Control

Pursuing this interpretation, I would agree that the evidence suggests this might in fact be the case for the concept of "decentralized control". All students understood that all agents were programmed with identical programming; and most accepted that identical programming could result in pattern formation and emergent levels of organization. For instances the following excerpts:

> Monique: Yeah, so that's why they all go to the same place. Like everyone, it's like uh, if I know that there's a party, I'm not going to tell everybody to go, but I'll decide to go myself, I'm just going, and others are going to be going, so that's why it's going to be a full house.
>
> Norman: Oh yeah, it's decentralized, uh, if uh all the cells that compose the liver, uh, the instructions come from all the cells, they are the same. Because they all have the, DNA, so yeah, that would be, decentralized.
>
> Walter: yeah. They all seem, they all follow the same variables, the same program.
>
> Penny: Well, aren't they all suppose to be the same? They're all suppose to behavior in a certain way....That each, um, particle follows the same set of rules.
>
> Sidney: They all have to follow a rule, that's the thing, in this simulation they're all following a rule...
>
> Sam: they all follow a general rule but I mean, how they go by it is ... the rule is that they're all looking for pheromones.
>
> Mitch: Algorithmic behavior, and they all follow rules...
>
> Greg: yeah, [all] the individual must follow the rules.

Furthermore, this interpretation is supported by the literature (Resnick, 1994; Wilensky & Resnick, 1999). However, it was at this higher-level discussion related to the self-organizing outcome of decentralized control that difficulties in understanding were revealed. Norman's struggles exemplifies this argument (see pp.183-186).

Therefore, the low number of observations is not related to a limited opportunity for learning this concept, but may be better described as a behavior that is taken for granted by this population and age of student. However, at the level of ontological commitment, it is still an issue for some students who experience cognitive conflict as they attempt to come to terms with the inconsistency between data and theory. Norman's experience when he explains the behavior of the ants as being controlled by their assigned role is a good example of the "reinterpretation" response to anomalous data as described by Chinn and Brewer (1993).

Concept of Nonlinear Effects

No such counter evidence exists in the transcript for the concept of "nonlinear effects". Only a few students even come close to mentioning what could be interpreted as this effect of emergent causal processes however, the exception was Greg who first specifically mentions the concept in a discussion during the GasLab simulation. This excerpt captures some of the problems that may be related to the affordance of nonlinearity by the simulations; in essence, a confounding of the several concepts. While the simulations amply support the acquisition of the concept of probability they do so at the expense of the concept of nonlinearity. For the most part systems with large numbers attain stability with individual changes having little or no effect (e.g., numbers of fast or slow molecules). While small populations are the only ones affected by these changes. Additionally, there may be a confounding that is part of the whole notion that all agents do the same thing therefore there is little experience with the idea that one agent's action may therefore result in a nonlinear process.

GasLab Simulation

Greg: And, any small individual changes from like one thing changing from red to blue or something wont really affect the whole system because like because there're so many more you have, if the red turns to blue, you'd have a blue turn to red at the same time. But if you have a smaller system its not the same way like you have a lot more changes and like one change of like one from red to blue affects the system to a larger proportion. 117

Another example came from Sidney when answering the butterfly question. Once again the limitation of how to interpret the importance of large numbers gets in the way of his viewing the possible nonlinear effect. Therefore his awareness of the behaviors observed when the simulations had a large number of turtles does not facilitate his reasoning for the significant effects of small changes.

Sidney: In this case I would use it as a concept of numbers. Numbers causing a reaction. Because I don't believe... well I don't believe that one butterfly could cause this, this snowstorm. If tons of butterflies were flapping their wings think about like they're moving the air very rapidly, they're causing waves to go through the air, and these waves being amplified.. being superimposed might create a sudden disturbance on the..on the clouds, causing a snowstorm to occur. 171

Sidney: Numbers having an effect on the reaction. Or whether the reaction proceeds or not. Or adds to the grandeur of the reaction. How big will the reaction be. 195

True example of nonlinearity. One of the few real statements of understanding nonlinearity in the sense that one small change may lead to exponential growth/collapse affects is made by Greg as he engaged in the wolf-sheep simulation.

Wolf-Sheep Simulation

Greg: um. It's just that the thing that I guess, like the really small changes, like seem to have the largest effect I find. Like when we worked with that, with the ants and whether they turn left or right like their tendency, like although it seems entirely irrelevant at the time like it has an effect. Like I guess, every aspect of a system is important in the end. Given the whole system itself. Like switching something very small can have a large effect on the system. 101

Greg: it's just like I mean. Um, what this is affecting is, how quickly the sheep will die... Theoretically, most of the sheep will be eaten by wolves. Like you wouldn't find many of them not be eaten. So, it only affects a small number of sheep you would say, pretty much like [muttered], most of them are eaten to keep the wolves, but it makes it far more, um, periodic I guess. [mutters something else too low to catch] 114

I: ok... so if I can paraphrase what you said. That a small change in the metabolism produced a big change in the overall system. It made it much more periodic? 116

Greg: yeah. Say like here. I guess with this change all the sheep died. 118

An example of these possibly confounded notions (i.e., "nonlinear effects" with the functioning of systems containing small numbers of agents) is demonstrated in Mitch's statements. He dismisses the potential to observe nonlinear effects (i.e., the line going up and down) and interprets them as the result of the small numbers of agents within the system. This was a more common observation made by students and reinforced by the simulations.

Mitch: Because a lot of them are just running around and, haven't even touched anything yet. 291

I: In terms of the stability of the system, how stable is it? 293

Mitch: Well, it's stable. The equilibrium point is not, it's not a straight line, versus when it was, the number was at 2000, it was virtually a straight line. This one's going up and down, and the line's jagged. 295

In conclusion, although the experts' rated the simulations as displaying "nonlinear effects" (see Figure 6.3), I contend that the paucity of student observations of nonlinearity is more a case of an interaction between this limited affordance and the learner's mental models. Indeed, Greg was more like an expert learner than the other students. Therefore this evidence suggests that observations of this concept require a more sophisticated understanding of emergent causal processes and in fact it may be that experts "see" the deep structure (e.g., nonlinear effects). Hence the interaction of intervention, concept, and individual attributions needs to be taken into consideration.

<u>Concept of Random Actions</u>

Was learning of the concept random actions not supported by the simulations or is there another explanation? Random behaviors were illustrated by movement of the turtles and was somewhat controlled by the pre-defined variables "sliders" in the Slime simulation. The students also encountered the term in a direct fashion during session 3 when they engaged in a programming tutorial and were allowed to set the degree of randomness for the starting positions of the turtles. From a perceptual level it appeared that all the simulations offered equal opportunities to observe randomness of agents' actions; and, if fact, the GasLab simulation demonstrates "Brownian motion", a classic example of random behavior.

Why then did students not provide more evidence of this awareness; and why did some appear to be challenged by this concept? To answer these questions required first the examination of the individual student's results (see Figure 7.13). From this data there appeared to be two categories of experiences. In one category, students like Greg, as described in this case report (section 7.3), and Mitch (in the excerpt below) were hampered by the fact that within a computer environment all parameters are predefined and therefore can eventually be determined, even if it takes a long time; consequently, this is perceived as being a sign of no "real" randomness and more a function of statistics.

> Mitch: That it's uh... Oh, it depends on... Chance, is how it happens. Those happened twice, or three times, that it stopped, and once that it went to... If you kept, you kept on going to the simulations, you could figure out how many times it would happen, find out the stats for it. 582
>
> Mitch: Well, you run it a hundred times, and... If you run it enough times to get through every single positioning, I guess, using some form of statistics, how many times it reacts depending on this type of situation. Like if you have 50 of the wolves are near 50 of the sheep, those 50 get eaten right away, but the other 200 sheep don't get eaten, so they all reproduce. I guess if you figure out, using a graph to figure out how long the thing would take to end... 598

As was described in the last section case report on Greg, it was possible to overcome this limitation of viewing randomness as merely something that can be logically reasoned away. Instead, he came to recognize the deeper role that randomness plays in producing the probabilities expressed by the system. With the aid of the coach and with the benefit of time and domain knowledge acquired in biology, Greg was able to "see pass" the confines of the computer environment and explore the concept as it exist in unrestricted and adaptive environments.

> G: Because uh… There's the uh, the factor of change involved. And just like the small, minute things that each uh, each simple system does… That, that will get uh, like, absorb into the complex system without really having any real effect on it, unless there's a lot of random events. But uh, you know there has to be randomness somewhere, it's not like, as I'm far I'm concerned, I mean random events happen.
> Like chance is a factor. And so that creates um, randomness, and that creates possibilities, also. That if there were no random events, then you wouldn't have those possibilities.

On the other hand, there were students like Norman (also described in a case study – see section 7.3), who although generated a considerable number of utterances coded at the category of "random" (see Figure 7.13) were still possibly constrained by their synthetic mental models, composed of clockwork component beliefs regarding the attribution of causal "determinacy". Furthermore he did not appear to understand how to use the model and where to extend it past the limitations of the computer environment.

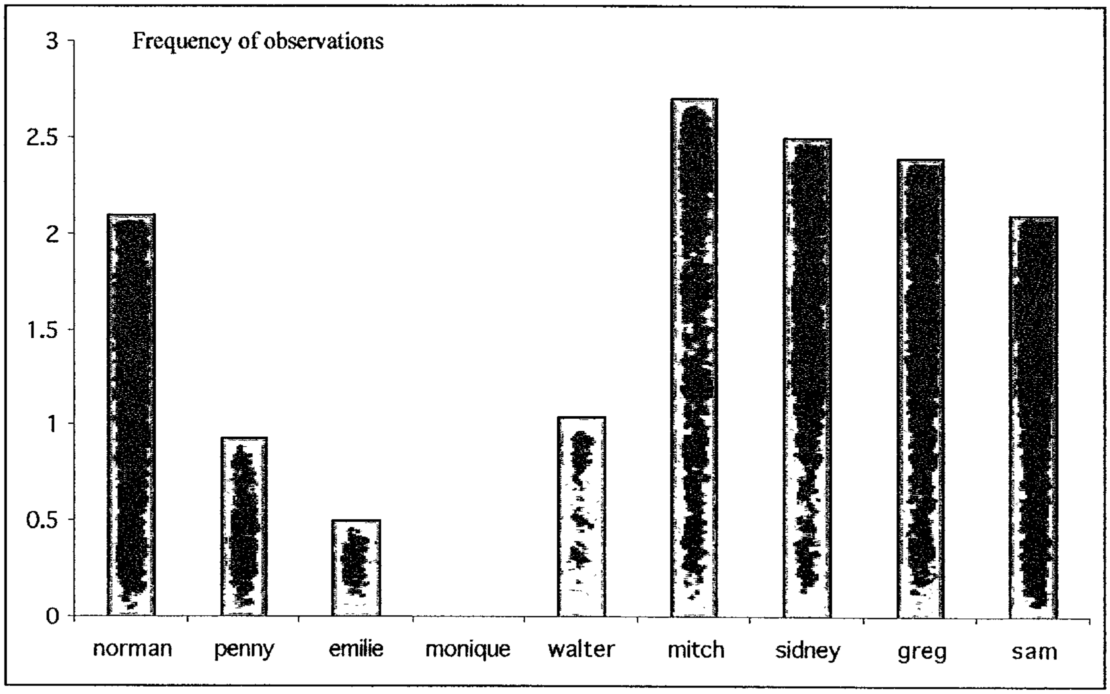

Figure 7.13 Bar graph of summary scores for nine students over three session generated on the category of random action (identified from CST coding).

In summary it was important to look more closely at the meaning behind the students' understanding of random. There are different ways and levels of understanding this concept as it relates to day-to-day "random" events, compared to its role in emergent causal processes. These important nuances make it a different concept to assess and a difficult one to learn. Moreover, there is the current usage of the term in the popular vernacular of adolescences (e.g., "Yeah, I just had a random thought ...") that had to be teased out of the analysis.

7.7 Changes in Mental Model Using OMMT – Delayed Posttest

In review, Study 1 established that students in the ontologically based intervention (a two day workshop attending to complex systems concepts), compared to those in a placebo control group, produced a statistically significant difference between the pretest and posttest, thereby suggesting conceptual change had occurred. The students appeared to acquire an emergent explanatory framework (EFMM) and applied it to answer problems with familiar settings (near transfer problems). By comparison they reduced their tendency to use CWMMs when solving these problems. The results for problems with unfamiliar settings (far transfer problems) were less conclusive, although they too were statistically significant. Therefore, the second study was designed to take an in-depth look at this change process.

By comparison, Study 2 was concerned with the process of concept acquisition as discussed in the sections 7.1 through 7.6 of this chapter. It also was interested in assessing the transfer of this knowledge acquisition as a general application explanatory framework. The following research questions guided this exploration:

1.a) Does a longer duration ontologically-based intervention support a different learning experience as demonstrated by more elaborated emergent framework mental models?

b) Which dimensions of the ontological categories change?

c) What are the effects of time on this content knowledge and the students' ability to perform these transfer tasks (i.e., ecological validity)?

d) Does this intervention increase transfer of the emergent causal framework to a wider range of ontologically analogous problems?

7.7.1 Review of Assessment Measures

Changes in case study students' mental models (explanatory frameworks) were determined through comparison of the post-case (referred to as *Delayed Posttest*) results with those collected from Study 1 (the post-workshop, referred to as *Immediate Posttest*). Study 2 used a similar dependent measure to Study 1 (see Appendix F.1 & F.2) and the same revised OMMT (see pp.65-67).

7.7.2 Changes in Mental Models Recorded in Delayed Posttest

Addressing Research Question 1a

Does a longer duration ontologically based intervention (five weeks) support a different learning experience as demonstrated by more elaborated emergent framework mental models? In order to answer the question, I compared the students' responses from the delayed posttest to the immediate posttest. The results described an increase in the number of emergent framework mental models (EFMMs) used by students in this heuristic process, but, little or no change in the number of clockwork mental models (CWMMs) concepts used (see Table 7.7). There was a decrease in the number of categories for which no evidence of model (NM) was found.

To determine if these changes were statistically significant, I performed a within group paired samples *t* test on the three similar questions. The results of analysis indicated that the students' use of EFMMs were significantly increased between the delayed posttest (M=12.7, SD= 5.8) and the immediate posttest (M= 5.6, SD= 5.6), p=0.000 (one-tailed). As anticipated, it also indicated that the changes in the CWMMs were statistically insignificant with the delayed posttest (M= 3, SD= 2.8) and immediate posttest (M= 3.4, SD= 3), p=0.314 (one-tailed). However, the decrease in NMs were statistically significant with delayed posttest (M= 5.9, SD= 3.2) and immediate posttest (M= 10.7, SD= 3.1), p=0.003 (one-tailed).

Table 7.7 Study 2 gains in students' mental models for all three questions (n = 9).

Scores on	Immediate Posttest		Delayed Posttest	
	M	SD	M	SD
Emergent Framework Mental Models (EFMMs)	5.6	5.6	12.7*	5.8
Clockwork Mental Model (CWMMs)	3.4	3	3	2.8
No Model (NM)	10.7	3.1	5.9*	3.2

* Significance at $\alpha = 0.01$ on one-tailed independent samples t test.

Figure 7.14 describes the results of the immediate posttest and delayed posttest comparison by illustrating the increase in emergent framework mental models (EFMMs), while there was a small decrease in the number of clockwork mental models (CWMMs). However the number of none-codeable mental models (NMs) changed significantly between times.

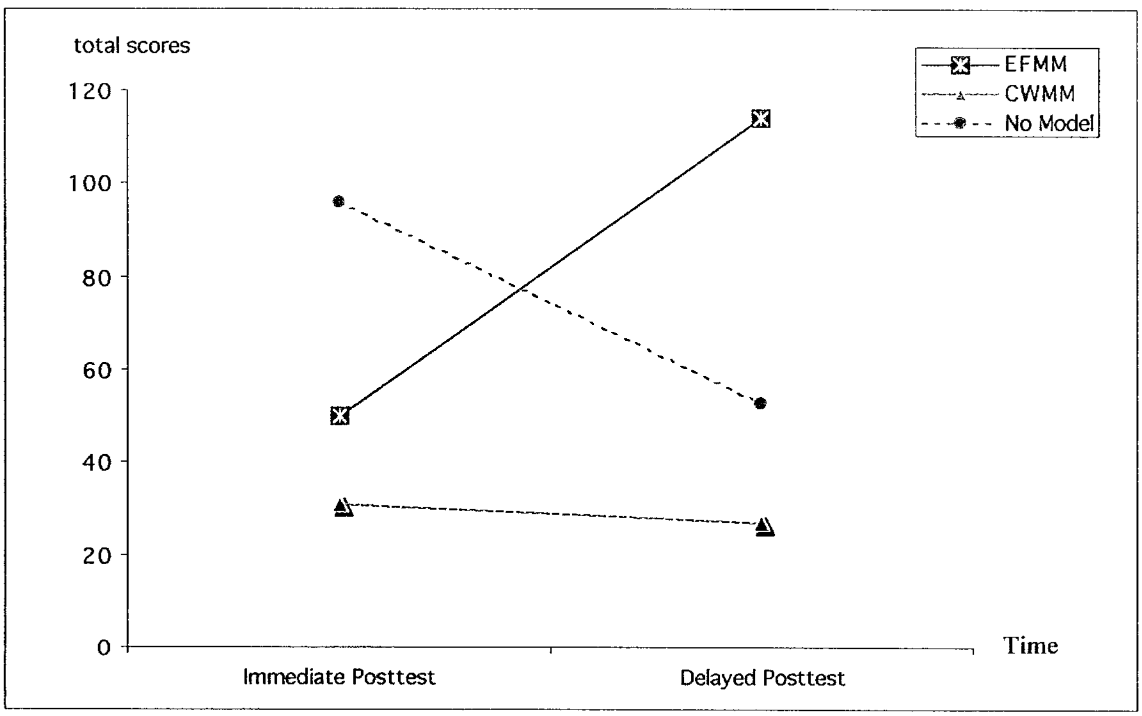

Figure 7.14 Change in mental models over time (i.e., between immediate posttest and delayed posttest).

The change to EFMMs described above supports the findings from Study 1 in as much that the there were substantial gains in the number of items coded at the emergent framework ontological category. Unlike Study 1, the number of CWMMs did not decrease, but remained unchanged; whereas, the number of NMs reversed trends going from no change to show a considerable decrease. In fact, CWMMs and NMs are almost a perfect switch (compare Figure 5.2 to 7.14).

Examining the Results from a Qualitative Perspective

These results can also be looked at from a more qualitative perspective (see Table 7.8). This perspective describes the raw numbers generated by the scoring of all three questions and shows that the students were better able to provide answers to all the questions. Particularly noteworthy, however, was their improved ability to provide answers for the "Butterfly weather pattern" and "Traffic jams" questions. It is important to note that nowhere in their case study training did the students receive information on the content knowledge related to "Ants", "Butterflies", and "Traffic" (although some did explore the simulation after the assessment). What is also very important is that the change in CWMMs was almost nil for these questions. In fact, there was a decline in CWMMs for the "Traffic" question.

The increase in EFMMs can therefore be attributed to a reduction in NMs. This suggests that students were more able to provide explanations for these types of questions. The results also support the claim that students were not likely to gain CWMMs as a result of the training.

One possible explanation accounting for these changes may be "maturation" and/or non-treatment related experiences (i.e., course content, information from a media source, etc.) between the immediate posttest (August, 2000) and the delayed posttest (April 2001). I contend that the data does not support either of these explanations. In fact, the session one transcripts of the control group students (Norman, Penny and Emilie) showed no evidence of "intuitions" or spontaneously generated analogies to emergent type phenomena. However, some students from the experimental group (Walter, Sidney, Monique, Sam and Greg) did show evidence that they had continued to construct a conceptual understanding of the CST concepts between posttests, as demonstrated by references to everyday experiences in which they had cause to recall the treatment (e.g., when caught in a traffic jam; when observing social groupings, etc.). This result does suggest that there was some between treatment conceptual change experiences; a topic worthy of its own study but outside the scope of this current research design.

Table 7.8 Changes to mental model categories between immediate – delayed posttest.

Simulation	Emergent Framework Mental Model (EFMM)		Clock Work Mental Model (CWMM)		No Model (NM)	
	Immediate Posttest	Delayed Posttest	Immediate Posttest	Delayed Posttest	Immediate Posttest	Delayed Posttest
Ants	27	44	13	14	24	13
Butterfly	9	28	9	9	36	23
Traffic	11	42	9	4	36	17
Collective scores	50	114	31	27	96	53

7.7.3 Changes in the Six Dimensions of the EFMM Category

Research Question 1b

Which dimensions of the mental models changed? Examining the data with this question in mind provided insight into which ontological barriers were more changeable and which were not.

Figure 7.15 illustrates the results of the immediate posttest, whereas figure 7.16 illustrates the results of the delayed posttest. Both figures visually demonstrate the relationships between the numbers of propositions coded to the dimensions of CWMMs and EFMMs.

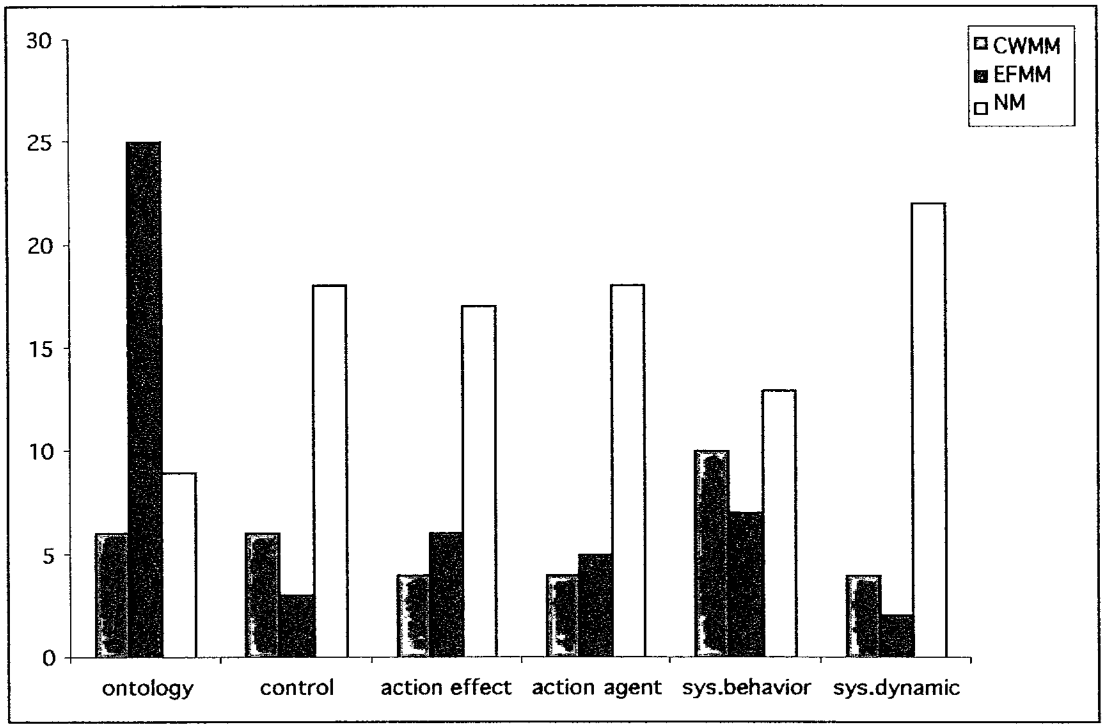

Figure 7.15 Immediate posttest results for 3 questions over 3 categories (bar graph).

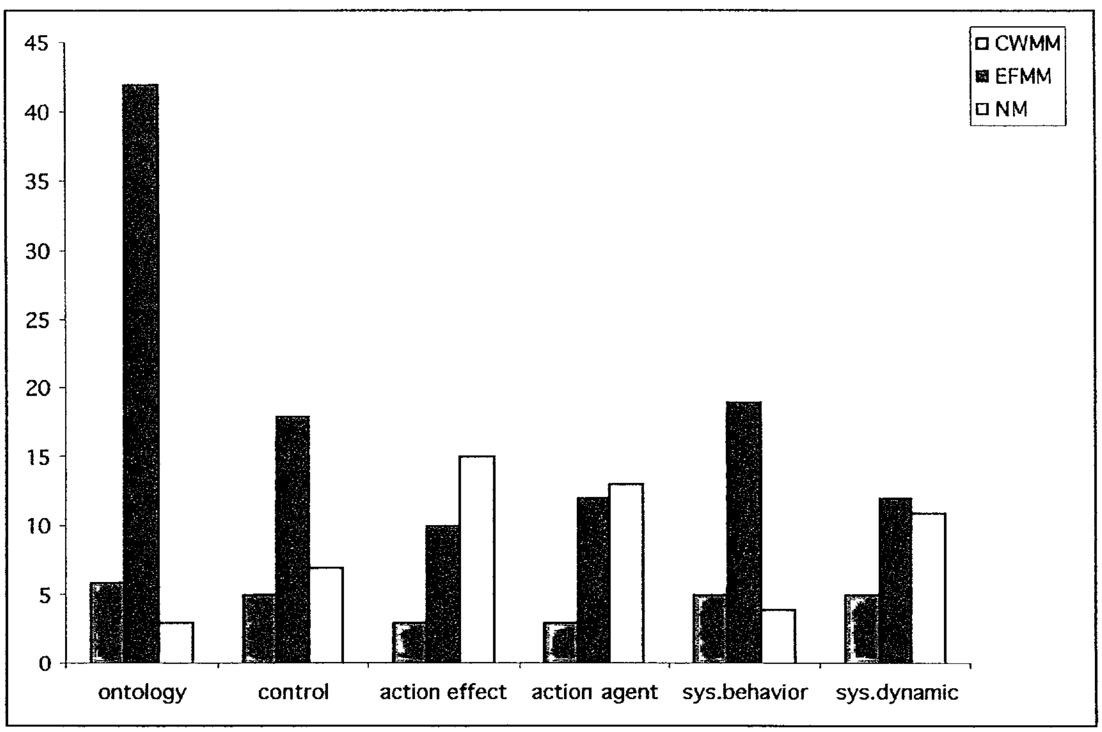

Figure 7.16 Delayed posttest results for 3 questions over 3 categories (bar graph).

Converting the visual display into a table allowed for the inspection of differences between the immediate posttest and delayed posttest. As indicated in Table 7.9 there were substantial differences among the dimensions of the EFMM category. For example, in the delayed posttest the students were more likely to understand and apply "emergent self-organization", "probabilistic causes", "decentralized control", and "dynamic nature" explanations compared to "nonlinear effects" and "random actions" explanations. These results again suggest that students were holding synthetic mental models composed of both clockwork and emergent framework beliefs.

Table 7.9 Change in EFMM over time (immediate posttest – delayed posttest).

Emergent Framework Mental Models *Immediate Posttest & Delayed Posttest*	**Emergent Self-organizing Ontology**		**Decentralized Control**		**Nonlinear Effects**		**Random Actions**		**Probabilistic Causes**		**Dynamic Nature**	
	Immediate	**Delayed**	Immediate	**Delayed**	Immediate	**Delayed**	Immediate	**Delayed**	Immediate	**Delayed**	Immediate	**Delayed**
Collective scores	25	42	4	18	6	10	6	12	7	20	2	12
Change btw. observations	+17		+13		+4		+6		+13		+10	

Table 7.10 shows that there were few differences among the dimensions of the CWMM category. From a non-statistical perspective it appeared that the category of teleological behaviors were substantially different from the others. In fact there was 100% decrease in propositions coded to this category. This shows that the category of "emergent self-organization" accounts for a substantial amount of the changes observed in the delayed posttest. Additionally, the ability to describe the "probabilistic nature" and "decentralized control" of the systems featured in the outcome measures were also increased. Looking at the delayed posttest scores for each of these categories suggests

that students more frequently produced explanations using "emergent self-organizing" framework and "probabilistic nature" framework, with "decentralized control" framework in a close third place. By and large they continued to have difficulties with the concepts of "nonlinear effects", "random actions" and "dynamic nature".

Table 7.10 Change in CWMM over time (immediate posttest- delayed posttest).

Clockwork Mental Models Immediate & Delayed Posttest Results	Reductive Ontology		Centralized Control		Linear Effects		Predictable Actions		Teleological Causes		Static Nature	
	Immediate	Delayed	Immediate	Delayed	Immediate	Delayed	Immediate	Delayed	Immediate	Delayed	Immediate	Delayed
Collective scores	6	6	6	5	4	3	4	3	8	5	3	5
Change btw. observations	0		-1		-1		-1		-3		+2	

7.7.4 Summary and Explanation of Results for Delayed Posttest

These results might partly be explained as a consequence of familiarization with the questions since they were used as the pretest and immediate posttest. This argument is unlikely for two reasons: first, the delayed posttest was administered eight months after the immediate posttest; and second, the evaluation was not merely quantitative but also qualitative. As a consequence, it may be argued that this length of time should account for some normal forgetting of terminology if this were no more than a learned response. Thus, if the experimental students actually remembered their responses, it supports the strength of the initial training. If, however, there was normal forgetting, then the case study produced an even bigger effect than is reported.

The qualitative differences in responses generally took the form of elaborations of explanations. Because of these longer statements (the delayed posttest was aural) the students were able to more fully express themselves. In so doing, it provided the raters with more content to code and thereby the potential to identify more evidence of any existing mental models. The fact that there was a reduction in CWMMs even with this greater opportunity supports the interpretation that students were less likely to produce this category of reasoning.

It may be argued that the students learned to format their answers in such a way as to avoid using CWMMs explanations. This may explain the experience of the experimental group. However, there was evidence of fewer CWMMs from the control group who did not receive the possible reinforcement of the pretest-immediate posttest results.

Taking all these alternative explanations into account, I contend that the change demonstrated in the delayed posttest is indicative of a genuine change and elaboration in mental models. That said, we must look at the data to distinguish if this change occurred for all students or was it experienced only by a few, but large enough to affect the averages. In both the following sections (7.9 and 7.10) I will conduct these cross-case comparisons.

7.8 Changes in Mental Models One Year Later – Final Posttest

Background Information

The final assessment data (referred to as the *Final Posttest*) were collected in an interview (April 2002) 12 months after the conclusion of Study 2 (April – May 2001). Composed of two completely new questions (see Appendix F.5), their objective was to assess problem solving transfer skills at different levels of difficulty. The extreme time gap provided added challenge to demonstrate knowledge of transfer. In this case, the transfer task required to apply a structural *base* (i.e., emergent frameworks mental models) to the concept of evolution, which was a *target*[30] domain acquired as part of the students' compulsory science program (Biology NYA). The intent was to provide a test of the proposition that ontological training can result in conceptual reassignment or conceptual change as proposed; as proposed in the earlier research reported in Slotta and Chi's (1999) paper.

Assessment Measures for Final Posttest

Question 1 – "*what programming would be required to have robotic birds display a similar behavior resulting in the V-shaped formation that is created by a flock of birds*?" – was selected from the bank of complex systems questions (collected by Jacobson, 2000). Similar to the previous assessment measures, it called for the student to problem solve in un-instructed content areas. Therefore it was an assessment of their ability to transfer the emergent explanatory frameworks (EFMMs) acquired during the intervention (Study 1 and/or Study 2).

Question 2 – "*describe how the process of evolution might proceed for corn plants under different environmental constraints*" – required that the student explain several mechanisms of evolution, which are taught in an introductory Biology course[31].

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[30] This notion of *base* and *target* are borrowed from the literature on analogical reasoning (e.g., Gentner & Gentner, 1983; Duit, et. al, 2001). The definition of a base is something that is known to the learner, while the target is the unknown. I contend that transfer of the structural components of the emergent explanatory framework (EFMMs) is similar to the process of analogical reasoning in that it acts as a base. In the problem-solving task selected for this final assessment, the process of evolution was the target.

[31] Biology NYA is the compulsory biology course for all Science Program students. It is given in semester two (for Health Science students) and semester 3 (for Pure & Applied Science students) of the respective

This problem assessed both declarative and procedural knowledge of that content area, as well as solicited the requisite transfer of the explanatory framework. In essence, I hypothesized that if the student had acquired a structural level understanding of evolution then they would be able to explain the phenomenon as an example of an emergent process, thereby using EFMMs. If they had not, then their explanations would not necessarily contain EFMMs but, in fact, might reflect many of the naïve evolution misconceptions described in the literature (Jacobson & Archodidou, 2000; Jensen & Finley, 1996; Anderson & Bishop, 1986). The demands of the question were particularly challenging because of the time delay between the students' engagement with the intervention, as well as the delay between the biology course and assessment.

7.8.1 Results of Final Posttest

Research Question Addressed in this Analysis

1.c) What are the effects of time on this content knowledge and the students' ability to perform these transfer tasks?

To answer this question, I compared the final posttest and delayed posttest scores on the dependent variable of EFMM. The results of a paired samples *t* test analysis (see Table 7.11) indicated that the students use of EFMM were significantly different between the final posttest (M= 4.5, SD= 3.8) and delayed posttest (M= 12.7, SD=5.8), p = 0.000 (two-tailed).

The corollary to the above question considered the effects on the CWMMs and the NMs. Comparing final posttest CWMM scores (M= 2.11, SD=1.7) and delayed posttest CWMM (M= 3, SD= 2.8), p = 0.26 (2 tailed) showed no change to CWMMs

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two-year science programs. Evolution is covered as a major topic generally occupying three to four weeks (15% - 20%) of the course content. Although the students would have been assigned to different sections taught by different teachers, the course has common standards and common tests. No formal effort to control for possible teacher-learning interaction was attempted. An analysis of the Bio NYA grade and EFMMs generated by the evolution problem-solving response produced correlation $r = 0.71$, $df=6$, $\alpha = 0.05$.

over time. Looking at the final posttest NM scores (M= 4.8, SD=3.15) and delayed posttest NM (M= 5.9, SD= 3.2), p = 0.48 (2 tailed), also reported no statistically significant change between assessments.

Table 7.11 Study 2 change in students' mental models from delayed posttest to final posttest one year later (n = 9).

Scores on	Immediate Posttest		Delayed Posttest		Final Posttest	
	M	SD	M	SD	M	SD
Emergent Framework Mental Models (EFMMs)	5.6	5.6	12.7*	5.8	4.5	3.8
Clockwork Mental Model (CWMMs)	3.4	3	3	2.8	2.11	1.7
No Model (NM)	10.7	3.1	5.9	3.2	4.8	3.2

* Significance at $\alpha = 0.01$ on one-tailed independent samples *t* test.

These results indicate that students reduced the number of EFMMs used to explain the behaviors of the systems in question. On the positive side, the change was not matched by a symmetrical gain in CWMMs. There was also a small decline in the number of NMs recorded.

7.8.2 Cross-Case Comparison – Final Posttest Results

Examining the results from a qualitative perspective shows how the individual student responded to the final posttest questions (see Table 7.12). From this point of view, we can see that some students produced a substantial number of EFMMs even one year later. Additionally, the number of CWMMs had not increased. However, some students still had difficulty producing responses that could be coded to either mental model, this probably indicates that certain sub-category dimensions were still difficult to use as an explanatory framework therefore could be viewed as evidence of synthetic mental models.

Table 7.12 Summary of final posttest mental models categories by individual cases.

Final Posttest	EFMM	CWMM	NM
Norman	1	3	8
Penny	2	4	6
Emilie	0	3	9
Walter	2	4	7
Mitch	7	2	3
Sidney	6	0	6
Greg	11	0	1
Sam	7	2	3
Total	34	19	43

(N.B., shading represent students who produced a substantial number of EFMMs. Also note that Monique was removed from this table since she did not complete this phase of the study).

7.8.3 Comparisons Between Delayed and Final Posttest – Cross Case Comparison

Accounting for the Change in EFMMs

Did the EFMM change correlate to old patterns? Accounting for the observed change in the emergent framework mental models called for a closer examination of the data. Comparisons between the students' final posttest with their delayed posttest produced a high correlation of $r = 0.92$, ($r = 0.81$ with equalized scores) $df = 7$, $\alpha = 0.01$. This suggests that the differences in EFMMs were within the students' established mental models pattern.

A non-statistical examination of the data also supported this finding (see Table 7.13). For instances, Sam produced high EFMM scores on the delayed posttest (average of 4 EFMM points per question) and maintained these high levels on the final posttest (average of 3.5 EFMM points per question) even while his mean EFMM score changed (delayed posttest M=6.3; final posttest M= 3.5).

Table 7.13 Average EFMM score per final posttest and delayed posttest questions.

EFMM Score per Question	Delayed Posttest	Delayed Posttest (equalized score)	Final Posttest	Change btw. Final – Delay (norm)
Norman	2.3	1	0.5	-0.5
Penny	2.3	2.3	1	-1.3
Emilie	2.7	1.7	0	-1.7
Monique	2	1.7	***	***
Walter	4.7	2.7	1	-1.7
Mitch	5	4.3	3.5	-0.8
Sidney	5.7	4.7	3	-1.7
Greg	7	4.7	5.5	+0.8
Sam	6.3	4.3	3.5	-0.8
Total	38	20.7	18	-2.7

(NB. The entry *** = missing data).

Looking at the "equalized" scores[32] on the EFMM variable (Table 7.13) it showed that three students (Mitch, Sam, & Greg) produced almost equivalent results on the delayed posttest and the final posttest even after a one-year gap and could be considered "sophisticated" *EFMM producers*. Norman also shows little change but his delayed posttest score was reported very low EFMMs. Although Sidney produced an almost equal number of EFMMs compared to Mitch and Sam, his decline was considerable (loss 1.7 points out of a possible 6). On the other side of the table, the results also showed that three students (Walter, Emilie and Penny) loss a substantial amount of their acquired ability to use this explanatory model and could be described as "novice" *EFMM producers*.

In summary, these results (see Table 7.13) are very promising and suggested that almost half the case study students were still able to use the emergent causal explanatory framework even after a one-year period in which no planned reinforcement of the intervention was administered. Therefore this ontological training may be beneficial for science education. More about this will be discussed in the upcoming chapter.

[32] Method for obtaining the "equalized" scores is described in section 7.8.

7.9 Cross-Case Comparisons of Explanatory Frameworks (Mental Models)

In order to understand the phenomena more fully, the next questions to be explored concerned the differences among the students. This analysis was guided by the specific questions: (1) Which students used emergent explanatory frameworks (EFMMs) as part of their heuristic processes? Was there evidence of pre-existing EFMMs or were they generated only after the intervention? (2) Was there evidence of pre-existing CWMMs and if so did they change? (3) Was there evidence that those who expressed neither mental model (NMs) experienced changes (i.e., acquired some framework)? As well as the more global questions: Did change mean a shift and/or replacement in mental model? Or was change an elaboration to an existing mental model?

To answer these questions I examined the data on two levels. Firstly, on the level of the equalized scores (a process described below) which allowed me to compare equivalent gains and losses. Secondly, on the level of the elaboration of mental models that involved looking at the raw gains in emergent frameworks.

Overview of Method Used to Compare Cases

Comparisons of individual's gains and losses were possible because of the coding method whereby propositional phrases were coded into all six dimensions of the ontological category as either EFMM, CWMM or NM, therefore the total score always equaled six (Total=6 points). Therefore a gain in one of the three framework totals indicated a loss in either of the other two. For example, Penny's scores, as indicated in Table 7.14, always total 18 for the three posttest questions, however, the frameworks used in her explanations changed over time. Hence it was possible to study where the changes were occurring and what those changes might mean to the students' understanding and use of this alternative explanatory framework.

Table 7.14 Individual changes in mental models between immediate posttest and delayed posttest – example from Penny.

Penny	EFMM	CWMM	NM	Total
Delayed Posttest	7	1	10	18
Immediate Posttest	0	7	11	18

Elaborations. Further information on changes in mental models was possible because the EFMM category of "emergent self-organization" was a unique category that could generate a maximum score of 4 ("emergent self-organization" column max score = 4 points). For instances, if a student elaborated on the mechanisms related to the emergent process, they would generate more points under this category. That said, any question that produced a total greater than six indicated that the student had produced more Non-reductive explanations.

By way of another example, Greg generated more elaborated responses to questions as he proceeded through the treatment. Therefore his total scores as he went from pretest to delayed posttest were 19, 24 and 27 respectively, indicating that he had elaborated on the dimension of "emergent self-organization" (see Table 7.15). Using these results I could better describe the gains in the EFMMs of the individual student.

Table 7.15 Greg changes in mental models over time – raw scores.

Greg	EFMM	CWMM	NM	Total
Delayed Posttest	21	0	4	25
Immediate Posttest	14	2	8	24
Pretest	6	2	11	19

However, in order to compare all the students against each other and to describe where the changes in CWMM and NM had taken place, I equalized the EFMM scores by removing the gains from the elaborated "emergent self-organization" category thereby producing a table with equalized comparative scores (see Table 7.16). With both types of tables it was possible to interpret the results from both the with-in case perspective as well as perform cross-case comparisons.

Table 7.16 Greg changes in mental models over time – equalized scores.

Greg	EFMM	CWMM	NM	Total
Delayed Posttest	14	0	4	18
Immediate Posttest	8	2	8	18
Pretest	5	2	11	18

7.9.1 A Summary of Changes to Mental Model – Equalized Scores

Changes in EFMMs.

To answer the questions, which students changed and what did the change mean to the stability and coherence of the mental models represented, requires the examination of the equalized scores. Table 7.17 shows that some students began Study 1 with prior knowledge of and ability to use emergent mental models. In fact, Sam (9) and Greg (5) both answered the pretest questions with a strong demonstration of emergent explanatory framework (EFMMs). One other experimental group student, Walter (2), and two control group students, Norman (2) and Emilie[33] (1), also provided modest displays of EFMMs on their initial assessment measure (pretest for experimental group; immediate posttest for control group).

The immediate posttest (end of 2 day workshop in Study 1, August, 2000) showed that all experimental group students provided EFMMs explanations when answering the problem solving tasks. In fact their gains ranged from 3 to 4 points (n=6); with the exception of Walter, who loss one point between assessments, which is not significant (see Table 7.18 for gains and losses).

The change between the immediate posttest and the delayed posttest (end of session 4, Study 2, April, 2001) also produced a substantial increase with individual gains ranging from 1 to 10 points (n=9). The biggest changes were from Mitch (+10), Sidney (+10), Walter (+7) and Penny (+7); whereas, Sam (+1), Norman (+1) and Monique (+1) reported few changes between these assessment measures.

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[33] Upon interviewing Emilie it was shown that she had copied the answer to the Butterfly question off the Internet therefore displayed signs of emergent frameworks when in fact she did understand emergent phenomena.

Table 7.17 Summary of mental models categories by individual cases.

Name	Assessment	Mental Model		
		EFMM	CWMM	NM
Norman	Delayed Posttest	3	5	10
	Immediate Posttest	2	3	13
Penny	Delayed Posttest	7	1	10
	Immediate Posttest	0	7	11
Emilie	Delayed Posttest	5	8	5
	Immediate Posttest	1	6	11
Monique	Delayed Posttest	5	3	10
	Immediate Posttest	4	4	10
	Pretest*	0	1	17
Walter	Delayed Posttest	8	6	4
	Immediate Posttest	1	8	9
	Pretest*	2	8	8
Mitch	Delayed Posttest	13	0	5
	Immediate Posttest	3	0	15
	Pretest*	0	6	12
Sidney	Delayed Posttest	14	2	2
	Immediate Posttest	4	0	14
	Pretest*	0	6	12
Greg	Delayed Posttest	14	0	4
	Immediate Posttest	8	2	8
	Pretest*	5	2	11
Sam	Delayed Posttest	13	2	3
	Immediate Posttest	12	1	5
	Pretest*	9	3	6

(N.B. the EFMMs scores are "equalized" scores, therefore the rows are a constant sum = 18. Note that * indicates the Pretest scores obtained from Study 1. Also note that the first three students belonged to the control group and therefore did not take the pretest).

Change in CWMMs.

The results of the pretest assessment showed that all students used CWMMs in their problem solving (see Table 7.17). In order to understand the meaning of the CWMMs, it is best to relate them to the NMs column. In this way, it is possible to describe if a report of low clockwork models (CWMMs) represented real change or merely insufficient ability to answer questions[34].

Turning to the pretest scores, Walter (CWMM =8, NM=8), Mitch (CWMM =6, NM=12), and Sidney (CWMM =6, NM=12) expressed a substantial numbers of CWMMs; Monique's low score (CWMM =1, NM=17) was attributed to unanswered questions thereby producing no codeable propositions (hence her score of NM=17). On the other hand, Greg's (CWMM =2, NM=11) and Sam's (CWMM =3, NM=6) low CWMMs scores, were not attributable to unanswered questions, but is a true reflection of CWMMs use, and NMs.

The immediate posttest showed that most experimental group students provided fewer CWMMs explanations in this second assessment (see Table 7.18). The reductions ranged from 2 to 6 points (n=6). Walter (0) and Greg (0) did not decrease their CWMMs between these measures. Monique (+3), however, gained CWMMs. This is explained by the fact that she had acquired some understanding and therefore attempted to answer the questions when she had not done so in the pretest (note NMs=10, a change of –7). The immediate posttest column also showed that the control group students began with CWMMs. Norman (3) was at the low end while Emilie (6) and Penny (7) held somewhat higher CWMMs.

Differences between the immediate posttest and the delayed posttest generally were insignificant with three students showing decreases (Walter, Greg, and Monique) and one with no change (Mitch, CWMM= 0 change, NM= –10). Penny (CWMM= –6, NM= –1) had a substantial change in the number of CWMMs she produced in the delayed posttest. By contrast, Sidney (CWMM=+2, NM= –12), Sam (CWMM= +1, NM= –2), Emilie (CWMM= +2, NM= –6), and Norman (CWMM= +2, NM= –3) all produced gains in their CWMMs. However, they had varying degrees of losses to NMs, with Sidney, Mitch and Penny being most able to add propositional statements reflecting either mental model.

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[34] Possible explanations for unanswered questions, or questions that were so poorly answered that they did not provide evidence of either mental model were: (1) not understanding the question, (2) fear of failure therefore limited risk taking, (3) lack of content knowledge, or (4) limited ability to express themselves.

Table 7.18 Differential changes to mental models categories by individual cases.

Name	Assessment	Mental Model		
		EFMM	CWMM	NM
Norman	Delayed - Immediate	1	2	-3
Penny	Delayed - Immediate	7	-6	-1
Emilie	Delayed - Immediate	4	2	-6
Monique	Immediate - Pretest	4	3	-7
	Delayed - Immediate	1	-1	0
	Delayed - Pretest	5	2	-7
Walter	Immediate - Pretest	-1	0	1
	Delayed - Immediate	7	-2	-5
	Delayed - Pretest	6	-2	-4
Mitch	Immediate - Pretest	3	-6	3
	Delayed - Immediate	10	0	-10
	Delayed - Pretest	13	-6	-7
Sidney	Immediate - Pretest	4	-6	2
	Delayed - Immediate	10	2	-12
	Delayed - Pretest	14	-4	-10
Greg	Immediate - Pretest	3	0	-3
	Delayed - Immediate	4	-2	-4
	Delayed - Pretest	9	-2	-7
Sam	Immediate - Pretest	3	-2	-1
	Delayed - Immediate	1	1	-2
	Delayed - Pretest	4	-1	-3

(N.B. The first three students identified belonged to the control group and therefore did not take the pretest).

Summarizing and Interpreting the Changes

From these results, it appears that although all students increased their ability to respond to the questions using emergent framework mental models (EFMMs), not all were able to do so with a relative reduction in their clockwork mental models (CWMMs).

Only two students (Mitch and Greg[35]) reported high levels of EFMMs with low levels of CWMMs and low levels of NMs, indicating that their mental models were becoming increasing more coherent and stable. However, it should not be forgotten that Greg began Study 1 with a moderate level of pre-existing EFMMs.

Sam[36] and Sidney also produce substantial increases to EFMMs but maintained moderate CWMMs, with small NMs. These results suggest that although their mental models were becoming more coherent, (i.e., losses in NMs) they were still somewhat unstable because of the reappearance of CWMMs.

According to Vosniadou and colleagues (e.g., Vosniadou & Brewer, 1994; Vosniadou et al., 2001) synthetic models are formed in the problem-solving context as learners attempt to reconcile the "new" view with the existing underlying ontological and epistemological presuppositions, which are referred to as "component beliefs" (in Jacobson & Archodidou, 2000). Therefore, this evidence from the current case study of students appearing to move between the "new" emergent framework beliefs (EFMMs) and existing clockwork presuppositions (CWMMs) may also be described as examples of different levels of *synthetic mental models.*

Walter and Emilie both generated a moderate number of EFMMs but also held onto moderately high CWMMs, and moderate NMs, thus suggesting that they too held synthetic mental models but to a greater extent. Furthermore, their levels of NMs suggest that their mental models were still a in the process of gaining coherence.

Finally, Penny, Monique and Norman all produced moderate to low numbers of EFMMs, held onto moderate to high levels of CWMMs, and high NMs (10 points). These results indicate that not only did these three hold synthetic mental models, but more importantly, their high NMs scores point to a real problem in understanding the material or their ability to express themselves. Both explanations are plausible in some cases. In fact, Penny's CWMM to EFMM ratio was 1 to 7 which supports the contention that she did not have conflicting mental models (i.e., synthetic models). Rather, she

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[35] However, it should not be forgotten that Greg began Study 1 with a moderate level of pre-existing EFMMs. Consequently, his change (+9) between pretest and delayed posttest was not a substantial as Mitch's gains (+13).

[36] Sam also started the study with high EFMMs. His change (+4) is very moderate by comparison to Sidney's gains of +14 points between pretest and delayed posttest.

appears to be unable to understand the material. For example her discussion with the coach in session 5 reveals her difficulty with understanding (see p.). Norman, on the other hand, maintained high CWMMs that were not moderated by the intervention. Despite the fact that English was Norman's third language he appeared to understand the material. His struggle, however, was with particular dimensions of the emergent framework (EFMM) and therefore he did not show a shift to this explanatory model (see pp.143-149). English was also a second language for Monique and this may explain her difficulty to reduce the number of NMs and increase the EFMMs. Her struggle was with expressing herself and understanding some of the language used by the coach and the materials used in the intervention. When she finally grasped a concept she was able to understand it but it took her much longer than the other students.

7.10 Triangulation of Data Sources

Triangulation of data collected from different sources is a recommended practice used primarily, but not exclusively, in qualitative research studies to establish validity (i.e., trustworthiness and authenticity). This procedure of drawing together and comparing data collected from different techniques addresses the threat of experimental bias, which may be inherent in particular data sources, investigator bias, and methods (Creswell, 1994). The benefit of employing a mixed methods research design as in this current study was that it provided these requisite differences between data sources.

In order to conduct the triangulation, I brought together the results from the three main data collection instruments used in the case study: (1) OMMT, (2) CST, and (3) concept maps. I also considered data from other documents, for example the students' scores on the Nelson Denny Comprehension and Reading test, as well as their course grades. Comparing these sources to each other provided both quantified correlational results as well as a qualitative picture of the experience from the individual students' perspective.

Table 7.19 shows the results of correlational analyses between the OMMT data, specifically the two ontological perspectives of emergent frameworks mental models

(EFMMs) and clockwork frameworks (CWMMs), and the other data collected. For example, the EFMMs produced a statistically significant positive correlation (r=0.89, $\alpha = 0.01$) with the results of the CST measure (number of emergent causal processes identified). By contrast the CWMMs produced a low negative correlation with CST results (r= -0.40). Correlations of the OMMT results and the totals produced from the concept map scoring procedure reveals the same relationship of significant positive results for EFMMs and low negative correlations with CWMMs.

Examining the results of the correlational analysis between the objective data sources (i.e., Nelson Denny vocabulary and comprehension scores, and the students' GPA for the four semesters at the college) also shows the same pattern. In fact, the Nelson Denny comprehension score correlated against the CWMMs produces a high negative correlation, however, not statistically significant.

Table 7.19 Correlations between different data sources collected in case study.

OMMT scores	CST totals	Concept Map	Nelson Denny		GPA's
			Vocabulary	Comprehension	
EFMMs	0.89*	0.91*	0.91*	0.91*	0.87*
CWMMs	-0.40	-0.46	-0.56	-0.60	-0.32

$df_r = 7$, * indicate significance at $\alpha = 0.01$

These consistent correlation results supports the claim that the data collection instruments were measuring the same phenomena. This statistical triangulation of the data sources adds trustworthiness to the data analysis methods.

In conclusion, a non-statistical comparison of the data sources describes a similar overlapping of results. Specifically, the classifications of student experiences identified from the CST results (*ECP Identifiers*), as well as the concept map results (*Understanding of ECP Relationships*), lastly the OMMT results (*EFMMs Producers*). These three data sets show the same students, more or less, classified as equivalent levels of understanding across these measures (see Table 7.20). This consistent pattern is another way of demonstrating the triangulation the three data sets collected in this study.

Table 7.20 Classification of case study students across the three data sources.

<table>
<tr><th rowspan="2">Classification</th><th colspan="3">Descriptions from Data Sources</th></tr>
<tr><th>ECP Identifier</th><th>ECP Relationships</th><th>EFMMs Producers</th></tr>
<tr><td>Sophisticated</td><td>Greg</td><td>Greg</td><td rowspan="2">Greg
Mitch
Sam</td></tr>
<tr><td>High moderate</td><td>Mitch
Sam
Sidney</td><td>Mitch
Sam</td></tr>
<tr><td>Moderate</td><td>Walter
Norman</td><td>Walter
Sidney
Norman</td><td>Sidney</td></tr>
<tr><td>Novice</td><td>Penny
Emilie
Monique</td><td>Penny
Emilie</td><td>Walter
Norman
Penny
Emilie</td></tr>
</table>

(N.B. EFMM Producers based on final posttest results).

CHAPTER 8 – DISCUSSION

This dissertation study produced results that fall under three main headings. First, there are results related to the interaction of the learner and conceptual knowledge. This aspect of the findings addresses important considerations regarding ontological barriers that constrain the learning of emergent causal processes as described in the literature (e.g., Chi et al., 1994; Chi & Roscoe, 2002; Jacobson 2000; Penner, 2001). Second, there are results related to the interaction between the learner and the intervention. This aspect of the findings responds to practical concerns regarding the usefulness of modeling tools such as StarLogoT for helping students acquire conceptual knowledge about complex systems; thereby contributing to the growing body of literature related to the use of these multi-agent representations (e.g., Resnick, 1994; Wilensky & Resnick, 1999; Wilensky, 2001). Finally, there are results related to what appeared to change in the learner's ontological framework, and how this change appeared to take place. I contend that this aspect of the findings contributes to the literature on conceptual change theory. By providing insight into the conditions under which conceptual change was or was not observed we are better able to shape the development of this theory.

8.1 Discussion of the Theoretical Results – Overcoming Ontological Barriers

Chi (2000) proposed that there are three major limitations (inter-related barriers) to the understanding of the ontological category of emergence: (1) assignment of micro level behavior as linear, (2) lack of consideration of local interactions between agents, and (3) a lack of understanding that macro level emergence is the result of collective interactions of agents and environment – "interaction in dynamic collection". Additionally, the literature concerning science misconceptions identified six ontological barriers[38] that in many ways overlap with those described above. Slotta and Chi (1999) further proposed that ontological training could remove these barriers.

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[38] 1) Isomorphic behavior of both micro and micro levels behaviors (reductive ontology) to emergent aggregation behaviors (non-reductive ontology);

The results of this current study shows that not all of these identified barriers are equally challenging, in fact the instructional intervention demonstrated great effectiveness in changing at least two (i.e., attributions of reductive behavior and isomorphic hierarchical levels) of the six subcategory dimensions. However, the evidence also suggests that two of these ontological barriers (i.e., attributions of linearity and causal determinacy) are not affected by the chosen intervention, and at least one of these appears to form a firmly entrenched belief that requires special conditions before it may be addressed. In the following sections I will discuss how the intervention appeared to support the acquisition of understanding of emergent causal processes, thereby building on both Chi and colleagues' work in the field of conceptual change as well as Jacobson's work in the study of how complex systems thinking may form part of a cognitive theory of learning.

8.1.1 Overview of Results from the Case Study Intervention

The evidence in this work shows that the intervention – specifically the simulations used in sessions one (Slime mould), two (GasLab), and five (Wolf-Sheep predation) – produced non-equivalent distributions of awareness to (and possibly learning of) the main complex systems concepts. For instance, the concept of "local interactions" was acknowledged 22%, 24%, and 34.5% for sessions one, two and five respectively. This small but steady increase is the type of result one would expect from an instructional intervention, which produced a significant improvement in learning, the dependent variable. However, the changes observed in this study also suggest several levels of interactions between the intervention, the concepts and the students.

If we look at the evidence supporting students' awareness of the concept "multiple levels of organization" we see a different picture. Whereas 50% of the total observations made during session one (Slime simulation) referred to multiple levels of

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2) Centralized control to distributed or decentralized control (decentralized control);
3) Linear causal explanation of macro-level behavior from micro-level interactions (i.e., additive, linear) to multiple nonlinear causal explanations (nonlinear effects).
4) Determinacy to indeterminacy (random actions);
5) Intentionality (i.e., teleological) to stochastic causes (i.e., probabilistic causes);
6) Static processes (i.e., beginning-end processes) to dynamic homeostatic behaviors (dynamic self-organizing nature).

organization, during sessions two (GasLab simulation) and five (Wolf-Sheep simulation) the percentage of statements coded to this concept falls to 35% and 32% respectively. A similar decline in percentage of observations is recorded for the concept of "random actions" with session one accounting for 5%, compared to 3% for session two and 2.5% for session five.

Looking at the concept "probabilistic nature" shows us still another picture with a rise in awareness from 11% in session one, to 19% in session two, only to fall back to 13%) in session five. Lastly, the concepts of "homeostatic behaviors" and "nonlinear effects" do not appear to generate enough substantial discussion to result in codeable scores that rise above 2% awareness.

From the perspective of general complex systems thinking (i.e., total of all concepts in the taxonomy) the evidence shows that session one (Slime simulation) was by far the most effective and generated 87% more codeable units compared to session two (GasLab simulation) and 34% more than session five (Wolf-Sheep simulation).

I think that these differences can be explained as a consequence of both the affordances for learning these concepts that are offered by the intervention as well as the individual differences of the students, particularly their initial mental models. Over the course of the next few pages I will discuss each of the important concepts learned from the intervention.

8.1.2 Limitation of Understanding Macro-level Emergence

Differences of understanding of the concept of multiple-levels may be viewed from several different perspectives. For the sake of a finer-grained examination of these findings, I have categorized them under three headings[39]: conceptual, perceptual, and individual differences.

Clarification of Differences Between the Models Used in the Intervention

Understanding the concept of "multiple-levels" requires that the learner is able to appreciate the different behaviors exhibited by the "agent" (as an independent unit within

[39] Although I would agree that we should not lose sight of the fact that these may all be highly interrelated and therefore the learning of this concept may itself be an example of an emergent process.

the system), as well as part of the "meta-agent" (the emergent aggregate unit at a higher level of organization within the system). The literature (Duit et al., 2001; Jacobson & Archodidou, 2000; Penner, 2000) and Chi (2000) suggest that grasping this concept is not an easy task.

How did the learner come to understand this concept? I suggest that the simulations offered great affordances for this concept. For example, the Slime simulation, as an example of a tightly coupled organized complexity model, exhibits emergence through a physical and perceptual coming together (aggregation) of agents. Once these agents are in their aggregate form, they display perceptually different behaviors.

The GasLab simulation, as an example of a random disorganized, dissipative, complexity model, exhibits emergent aggregation at more abstract levels. For instance, the meta-agent behaviors may be seen at the statistical level of probabilities where larger populations of molecules produce more stable and predictable results. In addition, the meta-agent may be understood at the mathematical symbolic level in which the equation $Pv=nRT$ operates to relate different pressure, or temperature values (interpreted as energy and speed on the GasLab simulation) depending on the number of molecules and their initial velocities.

On the other hand, the Wolf-Sheep predation simulation is an example of a complex system somewhere in-between these two other types of complexity models. Like the GasLab simulation, it too requires the learner to be cognizant of a somewhat abstract level of organization (i.e., the oscillating sine wave population variation which is the graphical interpretation of the symbol level Lotka-Volterra equation: $dn_1/dt = n_1(b-k_1n_2$ and $dn_2/dt = n_2(k_2n_1-d)$ used in predator prey interactions).

Conceptual Differences

If one accepts the argument put forward in this research that emergent causal processes, as an ontologically distinct category, are difficult to understand and may be at the root of many scientific misconceptions, then the subcategories themselves may offer different levels of challenge. I contend that the evidence supports the conjecture that when learning about multiple-levels of organization (emergent levels) students were less likely to understand this concept when working with dissipative models of complexity than when they were working with tightly coupled organized models of complexity.

One explanation might be that dissipative systems are a more difficult to understand subcategory of the emergent causal processes. Therefore they may require more time, cognitive effort, scaffolding, or a certain type of "ontological readiness" to facilitate understanding. In fact, the observed difficulty of understanding the concept of "multiple levels of organization" from dissipative models correlates with the literature regarding misconceptions and difficulties in understanding dissipative systems: diffusion, gas laws and equilibrium in chemistry (Wilson, 1998); electricity in physics (Chi, Feltovich, & Glaser, 1981; White, 1993); and diffusion and osmosis in the biological sciences (Odom, 1995; Settlage, 1994).

By contrast, students appeared to have little difficulty with understanding "multiple levels" from the Slime simulation. It may be that its representation of tightly coupled organizing complexity is more accessible to novice learners. After all we experience such on a daily basis (e.g., social groupings like families and friends, neighbourhoods, schools, etc.). Furthermore they are more easily identified in nature, colonies of ants, flocks of birds, sheep, for example. Therefore Chi's observation of limitations to understanding the ontological category of emergence (labeled item #3) may rest more in the subcategory of understanding the concept of emergent levels of order arising from highly dissipative systems.

Perceptual Differences

Whereas the Slime simulation produces a visible clustering of agents (mould) into the higher-level meta-agent (colony), there are no such visual observations in the other two simulations. There the learner is dependent on other visual devices such as window displays of graphs. Learning such abstract meta-level states may impose a greater cognitive workload or demand a higher level of knowledge in order to understand the different representation. From the multimedia literature we are told that visual representations such as text and images presented simultaneously are more taxing to working memory (Mayer & Moreno, 1998; Clarke & Paivio, 1991). It is therefore possible that a similar cognitive overload is at work when students attempt to decode both the animation of the agents' lower level behaviors and the graphs of the systems' higher-level behavior.

Individual Differences

The evidence shows that except for Greg, Mitch, and Sidney, the students required appreciable amounts of scaffolding to interpret the output graphs being produced during the GasLab simulation. This suggests that this type of simulation requires more time-on-task, and more cognitive scaffolding in order for learners with weaker science backgrounds to gain the full benefit of learning about the emergent processes represented as well as the behaviors of dissipative systems at the level of the individual.

8.1.3 Limitations of Considering Local Interactions Between Agents

In comparison to the five other emergent framework mental model (EFMM) subcategory dimensions identified throughout this study, the evidence supports that "local interactions" (part of the "aggregation emergence" dimension) is possibly the most susceptible to learning using the chosen intervention. In essence, all students appeared to show substantial gains in awareness as they proceeded through the instructional sessions, and all students appeared to transfer some of this knowledge to their explanation of the ontologically analogous problems.

Explanations

Understanding of "local interactions" arising from the simulations may be explained as a consequence of two features: (1) the surface level visual cueing of tightly coupled interactions and aggregation that were seen in the Slime simulation, and (2) the causal chain cueing in the GasLab, and Wolf-Sheep simulations. In short, the collision of one molecule in the dissipative loosely coupled system still created a change in trajectory which would result in another collision and so on. Meanwhile, the ecological systems' food chain of "sheep eat the grass... wolves eat the sheep", with moderately coupled interactions, was also easily apparent.

I argue that the steady increase in observations of local interactions from one session to the next could also be explained as a result of the students' improving ability to observe emergent processes at a more structural level (i.e., readout strategies). For instances, students "saw" more than the direct interactions between the wolf, sheep, and grass, and in fact described the indirect relationships in this food chain. Although not all students were able to identify the nonlinear effects of these local interactions, they all spent considerable time trying to explain how the grass affected the overall balance and survival of the systems.

Other studies looking at learning of complex systems concepts have also reported similar results. Using conceptually similar, although very different, measures and media ("talus slope" and "Life" simulation), Penner (2000) reported that students increasingly recognized that micro level interactions were important to the systems' behavior. However, it was difficult for them to "see" how small changes could result in large changes, for example through positive feedback as is discussed further in the section on nonlinearity).

Individual Differences

The evidence suggests that awareness of the concept of "local interactions" was not only related to the opportunities provided by the simulations, but also by the abilities of individual students. In fact, Greg and Mitch both demonstrated high levels of awareness of this concept during their engagement with the GasLab simulation (61%, and 43% respectively). These scores are far above the norm and highlight a potential interaction of prior domain knowledge (e.g., the physics of particle collisions) and ontological concept development. This would be unremarkable if they both also demonstrated high levels of emergent framework mental models on the pretest assessment measure, however they did not. Greg, however, did show significant gains in the testing directly following the initial intervention (i.e., the immediate posttest) thereby suggesting that he had experienced a change, which was more in line with a switch being turned on. By comparison, Mitch did not have the same experience, although he too showed some changes in his emergent framework mental models (see Figure 7.17).

How then do we explain the substantial difference in awareness related to the GasLab model? As discussed in chapter seven, the examination of the larger data corpus, showed that both Greg and Mitch belonged to a cohort of high academic achievers and both had above average scores in their science courses, particularly in college introductory level Physics. These results suggest that there may be an interaction between the student's domain knowledge and their ability to perceive these collisions as interactions of objects that although inanimate, engage in a flow of energy through the system; therefore, displaying behaviors that could be described using a general explanatory model, which could also apply to systems as diverse as slime mould. In fact, it may be that the successful results reported by the StarLogo researchers (e.g., Resnick, 1994, Wilensky, 1999, 2001) were due to this ability to "think like a turtle". That is, most of the research up to now has been conducted with younger children. It may well be that there is a fine line between anthropomorphizing and the ability to think at the level of the individual agent; and, that Greg and Mitch, although not children but advance-level science students, could think at this level and could "see" the collision of gas molecules as interactions and all that they entail (i.e., flows of energy through the system, etc.). Further investigation into this possible relationship is required.

Additionally, looking at the specific fine grain differences, Mitch as early as session one, began describing the interactions of agents (the slime mould in this instances) using predicates that better describe molecules (e.g., "collisions", "collide", "hit across", to list a few). This may explain his underlying understanding of the importance of local interactions and consequently this dimension of the emergent ontological category.

Significance of Results for the Concept of "local interactions

This evidence, taken in concert with Study 1 (few emergent framework mental models in the category of local interactions used in problem solving explanation), establishes support for Chi's supposition that novice learners may indeed have limitations in their appreciation of differences in phenomena based on ontologically distinct behaviors (listed as item #2: "lack of consideration of local interactions between agents"). The results of Study 2 as discussed above provide evidence that ontological instruction may help remove this barrier.

8.1.4 Limitations of Assigning Solely Linear Attributions to Micro-level Behaviors

The evidence shows that there was little awareness and recognition of nonlinear effects in all the simulations. However, the experts' evaluations of the simulations (see chapter 3) suggest that there were at least three different types of nonlinearity exhibited by these simulations (saturation, positive feedback loop, and negative feedback loop); albeit at higher levels of abstract knowledge. Consequently it was not surprising that all students did not recognize it as a concept in session 1, and only four made passing references suggesting this knowledge was available through the GasLab and Wolf-Sheep simulations.

My interpretation of these results is that in addition to the weak opportunities provided by the simulations for learning this concept, there are possibly ontologically-based restrictions. In fact, Chi (2000) identifies this as the first of the three ontological barriers based on novice learners' predisposition to explain micro-level behaviors as linear in nature and leading to linear predictable outcomes (labeled item #1).

Therefore, is it a question of StarLogo's affordances for teaching this concept or is it the concept itself? As stated before, Penner's (2000) study examining the use of a "talus slope" tool and the "Life" simulation, reports that students provided evidence of some recognition that small micro-level changes can have significant macro-level effects. Unfortunately he does not provide details on the number of students and percentage of change, therefore it is difficult to compare these tools to StarLogo models. However, his study suggests that other tools may be more successful representations of this phenomenon. Therefore the removal of this barrier through training is still an unanswered question. What can be stated from the evidence is that students like Greg, Mitch, and Sidney (to a lesser degree), who are conceptually prepared and understand other aspects of emergent behaviors are able to appreciate the impact of nonlinearity in the systems created in StarLogo. This effect is amplified through the coach who was able to prompt for more elaboration and metacognitive explanations.

8.1.5 Adding a New Item to Chi's List of Ontological Barriers

One of the ontological barriers not identified in Chi's (2000) three major limitations is the attribution of causal determinacy (i.e., difficulty in acquiring the concept of random actions). This current study shows that, possibly because of weak affordances of the models for learning this concept, students experienced difficulty with the notion of randomness. This finding is supported by a recent study conducted by Klopfer and Um (2002) of fifth and seventh grade students using StarLogo in a learning environment with scaffolding called "Adventures in Modeling". They inform us that students experienced difficulties with learning the concept of random events; although in the latter portion of their 14 sessions intervention (twice weekly for seven weeks, 45 minutes with seventh graders and 90 minutes with fifth graders) students were reported to grasp this concept.

I contend, however, that this apparently weak affordance is not sufficient to explain the observations in this study. The evidence shows that all students at some level were challenged by this concept. In fact, it was the main stumbling block for Greg who otherwise acquired an understanding of all the emergent causal processes without exceptional cognitive struggle. What this suggests perhaps is that even though students accept the randomness of some happenings, as indicated in their answers to the question about ants foraging, at a deeper level they struggle to accept the lack of some means of predicting future outcomes, even if these predictions are infinitesimally small or remote. This deep level understanding is further confounded by the limitations of the programmed environment of the simulations, which indeed may confirm beliefs that there is some level of predictability because random number generation machines are behind these calculations. In fact, this is the level of discussion that Greg, Mitch, and Sidney all at some point conducted with the coach.

How then did any of the students show signs of acquiring a deeper level understanding of this concept? The evidence suggests that Greg was the only student to describe random actions at the deeper level of understanding as an element of true in causal determinacy and "noise". He appeared to accomplish this as a consequence of both cognitive scaffolding and other domain knowledge. In essence, during the final interview session, one year after the intervention, Greg was asked to explain his concept map. During this discussion, he elaborated on the role played by random actions in the behavior of systems. This required him to reflect and in doing so, he referenced his course work from biology and how the "noise" of random events creates the "possibilities" of the future states.

I argue that for most learners the clockwork attribution of causal determinacy may be at the root of this conceptual challenge. Either because of the learners' component beliefs, as in the instantiation of the case study Norman, or because of the confounding of concept and programming limitations as demonstrated by Sidney, Mitch and overcome by Greg. The contention that the attribution of causal determinacy is a key obstacle to understanding emergent causal process, may come as no surprise to those investigating the cognitive processes involved in reasoning about uncertainty (e.g., Shauhnessy, 1992; Tversky & Kahneman, 1974). In fact, Metz (1999) points to the spurious causal attributions that result from misunderstanding of randomness and probability (already discussed in chapter two of this dissertation). What is surprising is that this same barrier also may account for a major difficulty in learning emergent causal processes such as evolution. This contention is supported by research from Zaïm-Idrissi, Désautels, and Larochelle (1993). In their study working with 15 graduate level biology students (master's level), they concluded that the majority of the sample held deterministic forms of reasoning about the topic of evolution, therefore accounting for one direction to the process of evolution and attributing an omnipresent and omnipotent property to the process of natural selection. These authors uncovered several inconsistencies in the belief systems of the study's participants, primarily, the conflict between deterministic and probabilistic reasoning. Although I disagree with some of the conclusions made by these authors, I argue that their findings of deterministic reasoning on the topic of evolution, even with graduate level students, supports the evidence found in this current study.

Therefore, it is possible that this causal determinacy attribution may be one of the most widely interconnected beliefs that affect other related beliefs such as probabilistic causes, and even decentralized control. It may well fit Chinn and Brewer's (1993) description of the evidentiary supporting schema. They state: "It appears, then, that well-developed schemas are not necessarily entrenched. The key is whether the schema is also embedded in evidentiary support and is used to support a wide range of other theories and observations that the person believes" (p. 17). Future research is required to try and untangle the possible confounding of the interventions' limitations and the ontological belief. Additionally, more investigation is required to understand the importance of this attribution and its possible connections with other clockwork beliefs.

8.2 Discussion of the Practical Results

8.2.1 Addressing Differential Affordances for Learning

To start off the discussion, differences between the simulation models' affordances for learning certain concepts is not surprising in itself given that the models used during the different sessions simulated three entirely different types of domain areas (biology, chemistry, and ecology) and three different types of complex systems. However, the literature does not discuss these differences. In fact it tells us that models built with multi-agent-modeling languages are powerful tools for supporting the learning of complex systems concepts such as decentralized control (Resnick, 1994; 1996; 1999; Resnick & Wilensky, 1997), multiple levels of organization (Resnick, 1994; Wilensky, 1999; Wilensky & Resnick, 1999) and even probabilistic reasoning (Centola, McKenzie & Wilensky, 2000; Resnick & Wilensky, 1997; Wilensky & Stroup, 1999). These affordances for learning emergent causal processes as demonstrated by the complex systems in the StarLogo simulations even extend to younger children using the Wolf-Sheep model that allowed them " to 'dive into' the model (Ackermann, 1996) and make use of what Papert (1980) calls 'syntonic' knowledge about their bodies" (Wilensky and Resnick, 1999, p.18). Why then did my findings suggest that the simulation models were not all equally effective at producing awareness of specific complex systems concepts?

One plausible explanation is that the research described above, to my knowledge, has not conducted systematic comparisons of models' differential abilities to offer opportunities for learning the complexity concepts identified in this current study. Another possibility is the difference in modes of use – modeling versus engagement as a simulation – produces different affordances for learning concepts. Most of the reports cited refer to the reasoning capabilities of students as they engaged in building models with StarLogo. Only recently have there been studies of the effectiveness of pre-built simulation models, exceptions being ChemLogo (Stieff & Wilensky, 2002); and to a lesser extent HubNet (Wilensky & Stroup, 1999) and NetLogo (Wilensky, 1999). The

ChemLogo inquiry in particular deals with learning of specific domain knowledge (chemical equilibrium) therefore does not help to explain my findings. I therefore conclude that further investigation of possible differences between models' affordances for learning about complexity is needed.

8.2.2. The Role of Model-based Reasoning

Given the important role the models played in this study as supports for transfer of emergent causal reasoning, it is necessary to take some notice of how they function. From the body of literature related to learning with models there is substantial evidence that models are powerful tools for learning and reasoning (Lehrer & Schauble, 2000; Papert, 1980; Resnick, 1999; White & Frederiksen, 1998; Wilensky & Resnick, 1997).

What is newly apparent from these results is the interaction of the individual students' characteristics and their use of the models. Although students were similar in their model engagement strategies, there were differential amounts of *model-based reasoning*, which may also be considered analogical reasoning (Lehrer, Horvath, and Schauble, 1994). In short, some students used the models as analogies to transfer knowledge from one known concept (called the "base" or "source") and to solve a problem in an unknown domain (called the "target"). Indeed they exhibited "thinking with" the model.

For example, Greg, Mitch, and Sidney were comfortable "thinking with" the StarLogo models to reason out the problem solving questions. On the other hand, Penny and Walter applied only the Slime simulation model during their problem-solving reasoning. By contrast, Sam, Norman, Emilie and Monique did not demonstrate evidence of using the models from the intervention in their problem-solving activities. However, of those four, Sam was the only one who was also a high producer of emergent causal explanations (high level *ECP* producer). Therefore Sam's experience provides what Stake (1998) considers the case study that puts limits to "grand generalization". Hence, although three of the more successful students used overt "thinking with the model" strategies in their problem-solving reasoning, it cannot be asserted that this a necessary part of learning to use emergent causal frameworks.

Furthermore, if we equate model based reasoning with analogical reasoning, we find that other research involving learning in this content area supports that analogical reasoning as a means of maintaining learning. Duit et al. (1998) found that "analogies also proved a valuable means for students to reconstruct understandings during interviews carried out 10 months after the instruction" (p. 1065). This is indeed true for this current study. In fact, the explanatory framework of the slime mould simulation again was the featured model used to reason out the "Bird flocking" question, during the final posttest, even one year after the intervention.

Those students who were more capable of using models as part of their reasoning strategy also appeared to be more metaconceptually aware of applying their emergent framework mental models to understanding or explaining both the problem solving questions as well as the behaviors of later simulations. Perhaps it may be necessary to explicitly teach students how to interpret models and how to use them. In fact, Schwarz (2002) suggests that meta-modeling knowledge may be an important part of learning from models in science education.

8.2.3 Understanding the Use of and how to Use Models

There are two empirical studies that report on findings of a relationship between students' general understanding of models (i.e., *meta-modeling*[40] understanding) and the understanding of physics content knowledge (Schwarz, 1998; Schwarz & White, 2001). Therefore one reasonable explanation may be that not only are there different affordances of different types of simulations for learning certain characteristics of emergent phenomena, there may also be an interaction of the students understanding of how to learn with models. The evidence from this case study strongly shows that Emilie, in particular, was extremely uncomfortable learning with models and expresses this in her

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[40] Schwarz (2002) defines meta-modeling knowledge as: "people's understanding of the nature, utility, and evaluation of models, their understanding of the process of modeling, and how this understanding is used in their reasoning with models... Meta-modeling knowledge is different from metacognition or the awareness and regulation of cognition, reflection may provide a critical mechanism that produces awareness or understanding for both metacognition and meta-modeling knowledge" (ICLS 2002, p. 414).
Her description of meta-modeling knowledge extends to the notion of knowledge of *epistemic forms and games*, as described by Morris & Collins, 1995.

final interview. Although this is probably not a gender-determined issue, it is worth noting that two of the three females were less comfortable using the simulations.

This possible relationship between the use of models to teach emergent causal processes and the epistemic form is an important direction to follow in future research. Whether we should also look at the possible connection to gender related learning styles is an issue I would suggest may also be considered.

8.3 Discussion of the Theoretical Results – Conceptual Change Theory

8.3.1 Issues Related to Changes in Mental Model

Overall Changes Observed

The delayed posttest data strongly supports that for some of the students, the ontological training facilitated the creation of emergent framework mental models (EFMMs). However, four of the students' scores accounted for most of the 126% increase in EFMM responses (see Table 7.7 and Figure 7.14). By contrast, the change in CWMM was a mere reduction of 13%. Compared to the results obtained from the near transfer task in Study 1 this figure was surprising (see Figure 5.2). However, these results were consistent with the far transfer task that produced small changes in clockwork frameworks (see Figure 5.4). Furthermore, the changes to the no model category (NM) showed a substantial decline of 45%. This was a dramatic change from the results of both the near and far transfer tasks in Study 1.

These results suggest three independent but related possibilities: (1) similar to Study 1, ontological training supported the acquisition and use emergent framework mental models (EFMMs). In fact, all nine students gained some level of awareness of emergent causal processes and all demonstrated some level of transfer ability in solving emergent analogous problems; (2) clockwork mental models (CWMMs) do not change substantially as a result of emergent ontology instruction, and possibly emergent frameworks mental models indeed do not replace clockwork mental models but clarify circumstances for their use; and (3) where no prior evidence of mental models existence, students with emergent ontology training will more likely acquire and use emergent framework mental models in future testing. I assert that the issues raised by the second and third findings are important for the discussion of conceptual change theory development.

Addressing What Appeared to Happen to CWMM

The result described above is a reasonable outcome of the ontological intervention in this study, particularly given that the intervention made no direct attempt to remove the clockwork framework (CWMMs). In fact, Chi (2000) suggests that her model does not support the use of conflicting evidence. Therefore should the results here be considered conceptual change? I contend that if we are to consider Vosniadou's suggestion that the process of conceptual change includes the generation of *synthetic models*, then we should be looking at these changes not as a zero sum game where losses in one category must be accompanied by gains in another. I suggest instead that it is the stability and coherence of the new mental models that are important and a testimony of change. This is in keeping with diSessa and Sherin's (1998) discussion of *invariance* (what I refer to as stability) and *integration* (what I refer to as coherence). Therefore, I have described the evidence from this study in a taxonomy of synthetic models ranging from the stable coherent models that could qualify as conceptual change by most people's definition, to the fragile representations with unstable changing ontological assignments (losses and gains in CWMMs) or incoherent models with a large percentage of 'no identified models' suggesting that the learner does not have an organized explanatory model, or is unable to explain themselves clearly, or a mix of both.

Mental Models Coherence and Stability

What do the changes mean? What we need to look at are two issues: (1) the relative change between categories, and (2) the consistency of change. One consistent trend across students[41] was the general increase in EFMMs over time. In determining the relative coherence and stability of the observed changes I focused only on examining changes between CWMMs and NMs.

The logic of the argument is that while increasing EFMMs, the student consistently reduced the number of CWMMs, but did not increase the NMs, then they

[41] Walter was an exception but only marginally so with a 1 point decrease between the pretest and immediate posttest.

were in fact increasing their understanding of EFMMs (i.e., evidence of a "stable" mental model). However, if the student consistently increased the number of propositional statements that could be coded (i.e., losses of NMs) they were in fact increasing the "coherence" of whichever mental model showed gains. In essence, they had begun to think more deeply about the question, maybe because of new content information or because they were more willing to take risks (see Table 8.1). Mental models lacking "stability" and "coherence" would qualify as "Novice" mental models.

Table 8.1 The meaning of changes in mental model categories.

Mental Model			Status	Label	Students
Emergent Frame-work (EFMM)	Clockwork (CWMM)	No Model coded (NM)			
+	–	–	Desired state. Learning of EFMM occurs. It is stable and coherent (i.e., integrated into understanding).	Emergent Mental Model Group	Greg
+	+/–	–	With gains in both mental models, they are unstable, but the learner is aware of their explanations therefore more coherent.	Synthetic 1A Mental Model (increasing coherence)	Mitch Sam Sidney
+	–	+/–	With losses in CWMMs the learner is moving towards a more stable mental model but with gains in NMs it means that they are unsure and therefore lack coherent understanding. Therefore they cannot bring their ideas together to generate coherent explanations.	Synthetic 2A Mental Model (increasing stability)	Walter
+/–	–	+/–	With gains and losses in EFMMs, and gains in NMs it suggest that the mental models are unstable and incoherent	Novice Emergent Mental Model	Emilie Norman Penny Monique

(increase = +, decrease = –)

With this analysis, we see that most students in this case study showed evidence of synthetic mental models. This supports Vosniadou et al.'s (2001) contention that this may be a necessary part of the conceptual change process.

8.3.2 What are the Necessary and Sufficient Conditions for Conceptual Change?

Necessary and Sufficient Conditions?

It appears that the intervention (simulations) and conscious application (metaconceptual awareness) may be sufficient to evoke the of use emergent framework mental models to solve ontologically analogous problems. It appears that some naïve CWMMs such as centralized control can coexist with EFMMs to create what Vosniadou considers synthetic mental models (i.e., misconceptions according to Vosniadou).

Degree of Novice Attributions

It appears that not all naïve learners have a full compliment of all the clockwork mental model CWMM attributions. Like other cognitive attributes, the degree to which naïve learners hold emergent framework EFMM or clockwork CWMM mental models is dependent on their prior experiences. Trying to create a profile of learners with high levels of EFMMs has lead to the following conclusions:

1. It does not appear that the pre-existence of EFMMs is highly correlated with high grades in science. Mitch, Emilie both received high grades in high school science (averages of over 90%) but both scored low in EFMMs. However, Sam who had very high pretest EFMMs scores was strong in biology and physical science, but average 80's for physics, chemistry and math. Therefore high grades in high school science may be a necessary but not a sufficient requirement for EFMM.

2. There appear to be several common characteristics among students who scored high in EFMMs, such as:

A. They had taken biology (senior level) in high school. For example Sam enjoyed biology, and had been introduced to complex systems (as a concept) in his high school biology course. He proudly states: "I was really lucky, I had a really good teacher. She went through complex systems, just explaining the relationships between certain things. She didn't really go into details, but I guess like, simple relationships". Norman as well had taken biology and also had high pre-intervention EFMM scores. (This relationship holds for three others who took part in Study 1). However, Greg who shows signs of EFMMs in his pretest did not take a senior level biology in high school. On the other side, Emilie, who had taken senior level biology, had no EFMMs, and in fact was one of those who never demonstrated many EFMMs. Her results also suggest that her answer to the ant question was attributable to content knowledge. Since approximately 30% of Study 1 students had taken biology in high school, but less than 10% answered the questions with EFMMs, suggests that a background in biology may be another necessary but not sufficient component to explaining the existence of EFMMs in students' pre-instruction answers.

B. Sam and Greg shared another common feature, their extremely high scores on both parts of the Nelson Denny Test. Their comprehension scores placed them above 16 years of schooling. Once again there are examples of students with high Nelson Denny scores that are not among those who exhibited EFMMs. However, the delayed posttest and transcript data support that among those who best understood the complex systems concepts, all had very high Nelson Denny scores (Greg, Sam, Mitch, and Sidney). On the other side, those students who had greater difficulty with these concepts scored low on the Nelson Denny (Monique, Penny, Emilie).

C. Finally, as an interesting observation, both Sam and Greg reported being avid readers of science fiction. One reported this in the pre-case study interview, whereas the other was in response to a direct question at the final interview. In response to a direct question regarding the problem solving questions used in the initial study (called the "brainteasers"), Sam responds that he had read a lot science fiction and in fact the robot question had reminded of Isaac Assimov's "laws of robotics". In the final interview (session six) when Greg was asked about his reading habits, he confirmed that he enjoyed reading, specifically science fiction. He states:

> Greg: Yeah I know. Because, it's just like it makes you open to new possibilities. Because like, you know people are like um, writing about things that, are theoretically impossible right now, or just that like, people haven't thought about, like no-one's ever designed it. So, like, just like you have to, accept it for the book, so, you like, you just learn to accept things that are kind of more far-fetched, that are more, like that, differ from the way of thinking...

Therefore understanding emergent attributes may indeed be a matter of awareness of certain behaviors of entities and therefore a highly learnable ontological category. However, it requires that both high comprehension levels as well as greater openness to different ideas about how the world "works" presumably, in other words, the existence of appropriate ontological beliefs.

8.4 Summary of the Three Main Findings

1. A major limitation to the development of a robust understanding of emergent causal processes is the clockwork attribution of causal determinacy.

2. The affordances for learning aspects of emergent causal processes offered by the multi-agent models/simulations are highly related to the type of complex system represented and also to the students' background understanding of science. In particular I found that more students had difficulty learning with representations (simulations) of dissipative system complexity compared to those using representations of tightly coupled organization models of complexity.

3. I conclude from this study, in the context of previous work, that significant conceptual change requires not only robust conceptual representations (e.g., models that can be used as analogies) but also metacognitive scaffolding and ongoing metaconceptual prompts during the instructional phase. Once initiated (i.e., once synthetic mental models are created), maturation over time and experience with complementary domain curricula appear to have positive effects on the development of more elaborated emergent framework mental models.

8.5 Implications of the Study

8.5.1 Implications for Conceptual Change Theory

Was change replacement or elaboration? The evidence from this study, and recent research (e.g., Jacobson & Archididou, 2000; Vosniadou et al., 2001), supports the assertion that conceptual change was more a process of elaboration than replacement of original conceptual belief. Students in this study appeared to construct qualitatively different and more elaborated representations (i.e., emergent framework mental models) as they progressed through the intervention. With time, they also appeared to be able to apply these mental models on a more frequent basis as well as to a broader category of questions.

Furthermore, the evidence supports this position on elaboration, rather than replacement. In other words, while emergent framework mental models increased an equivalent decrease in clockwork mental models was not necessarily experienced. The results of this study show that in fact only two students in the final posttest appeared to demonstrate no clockwork mental models while using a high number of emergent framework mental models in their answers. This finding supports Vosniadou's contention that conflicting mental models can co-exist in a synthetic explanatory framework. In fact, instruction, introduces the novice learner to the alternative framework, hence it sets up conditions under which learners construct these synthetic models.

Concerning the assertion that conceptual change as a gradual change, the results of this study show that the process of change was not a smooth continuous linear process. Not only did learners hold synthetic mental models composed of varying degrees of emergent and clockwork component beliefs, the trajectory of mental model change showed that the change is not a one-way increase in the use of emergent frameworks. This evidence suggest that the new emergent framework mental model was not necessarily stable or coherent, whereas the evidence regarding clockwork mental models shows that they were more stable and exhibited a small decline for some students.

This evidence may be explained as a normal part of acquiring new causal explanations as described by diSessa and Sherin (1998) posited "readout strategies" and "causal nets". The slow but steady change in observing instantiations of emergent causal processes (i.e., "integration" and "invariance"); coupled with the "see-saw" like oscillation of the application of emergent framework mental models to explain ontologically analogous questions (i.e., "causal nets"), which do not change as quickly, may create the observed effect. Put another way, the knowledge of emergent causal processes integrated with existing knowledge in new ways so that this new causal explanations could be consciously tried out. Because this new causal explanation is not firmly integrated, it is not always used when appropriate. However, more opportunities to observe emergent causal processes and more opportunities to apply them to appropriate and varied cases could build coherence of this alternative mental model.

On a similar vein to Chi and colleagues (e.g., Chi & Roscoe, 2002; Slotta & Chi, 1999), Vosniadou et al. (2001) state that conceptual change theory "should also try to relate these internal representations to external variables that influence them" (p.395). This study attempted to link the external variable of intentional instruction of emergent causal processes to the development and reassignment of explanations to emergent framework mental representations (EFMMs). I contend that identifying which parts of this internal mental representation changed is a contribution to the conceptual change literature, and to the development of a conceptual change theory.

8.5.2 Educational Implications

Three main educational implications can be drawn from this study. The first implication concerns the ease with which certain students can acquire components of emergent framework mental models from short-term interventions. Even with only the six hours of treatment over the two-day workshop, certain students showed considerable gains in learning about emergent causal processes and were able to apply some of these concepts to transfer problems.

The second implication refers to the need for a greater understanding of emergent causal processes by curriculum developers (e.g., instructional designers) and teachers so that they are more aware of the many opportunities to apply this knowledge. In fact, many teachers and curriculum developers lack an appreciation of the constraints imposed by their own linear, reductive thinking. Therefore, part of the challenge will be to convey to the educational institutions that prepare teachers, instructional and educational technologists an understanding of the benefits of emergent causal thinking as a general problem-solving application framework. Ammunition for this argument could be the results from studies such as this current one with evidence that suggests that once students became more familiar with this type of thinking, they were more willing to take up the challenge of explaining less structured and more complex types of questions.

In addition, until recently there has been a lack of representational tools to readily convey emergent processes as demonstrated by complex systems and thereby provide the necessary scaffolding for learning these concepts. While these tools are making their way into the educational system, there is a need to develop the easily accessible curricula topics that demonstrate complex systems behaviors. For instances, there are several topics such as respiration, and cardiovascular circulation in the health sciences and the behavior of geological and ecological systems in the natural sciences that are better taught as complex systems. Here are a few examples of recent studies that have explored different aspects of teaching particular content from the current science curriculum with a complex systems perspective: Azevedo and Cromley (2003), Hmelo, Holton and Kolodner (2000), and Hmelo-Silver, Pfeffer, and Malhotra (2003).

The third implication may be that this alternative explanatory framework may be beneficial for all disciplines not just science. If students are better able to explain the social, political, and economic interactions they encounter with more than a linear perspective they may in fact do a better job of understanding the unpredictable, and probabilistic nature of many of these phenomena. In fact, some proponents of complexity theory suggest that interpreting political interactions in terms of complex adaptive systems would have foretold of recent world events better than the current linear, reductive models.

8.6 Future Directions

This study shows us that it is possible to use newly available representational technologies to create specific content models to teach general knowledge of emergent causal processes. However, affordances of different models for learning specific emergent causal processes are interwoven with the content domain knowledge and representational characteristics. If we are to make better use of existing models, we need to know more about their capabilities. Therefore, these potentially confounding interactions of content and model representation of emergent process need to be closely monitored.

Greater attention needs to be paid to what types of emergent causal process understandings are required for learning particular science phenomena. At the same time, there is a need to better comprehend the affordances of various media, not just computer simulations, for helping students construct the mental representations necessary to understand important complex systems knowledge of relevance to the natural and social sciences. Once these specific subcategory dimensions can be more explicitly identified, we can then go about the task of matching intervention to concepts to be acquired.

8.7 Conclusion

This inquiry began with three major points of focus: (1) does ontological training facilitate conceptual change? (2) by observation of learners, what can we learn about this cognitive reorganization process (i.e., conceptual change)? and, (3) what can be learned about the prescribed tools and teaching methods that form the treatment condition? The two-part study that spanned the period of approximately two years, allowed me to gain insight and some answers to these questions.

The results of Study 1 showed that ontologically-based change, characterized as gains in emergent framework mental models, was possible for students in the treatment condition. Compared to control group students, the experimental group students were able were able to acquire and apply aspects of this explanatory framework in problem solving, however, this ability was limited mainly to questions that closely resembled the treatment condition.

The results of Study 2, by contrast, provided greater insight into the types of synthetic mental models the nine case study students constructed as they moved toward more coherent and stable mental representation containing more components of the emergent framework mental model (EFMM) taxonomy. This conclusion was supported by evidence of more scientifically appropriate explanations to questions that were similar to the treatment condition as well as those that were similar only on the deep conceptual level. Evidence of this ability to use structural knowledge, as opposed to surface features, to reason and problem solve was a particularly encouraging result because of the consistent difficulties described in the cognitive research literature involving learning for transfer. These findings lend support to the possible uses of emergent causal explanatory frameworks in facilitating both conceptual change, defined as an ontological shift, as well as a way to support learning for transfer.

Furthermore, the results suggested that the representational affordances of multi-agent models and simulations for learning aspects of emergent causal processes are highly related to the type of complex system represented and also to the students' background understanding of science. These results lead us to question how our development of the tools which facilitate learning of the emergent causal process concepts of "randomness" and "nonlinearity". Moreover, this finding suggests that now more than ever it will be important to form a union between technology designers and cognitive scientists in order to make the best use of these powerful representational tools.

Finally, the results added moderate support to the conjecture that conceptual change requires not only robust conceptual representations (e.g., models that can be used as analogies) but also metacognitive scaffolding and ongoing metaconceptual prompts during the instructional phase. This line of inquiry needs to be expanded to examine the significant role played by the affective domain such as epistemological beliefs, motivation, and self-regulation, in the process of conceptual change.

Each of these findings leads us to other interesting points of departure for further inquiry. Undoubtedly this is a fertile area of research that will keep researchers, instructional designers, and educators occupied for years to come.

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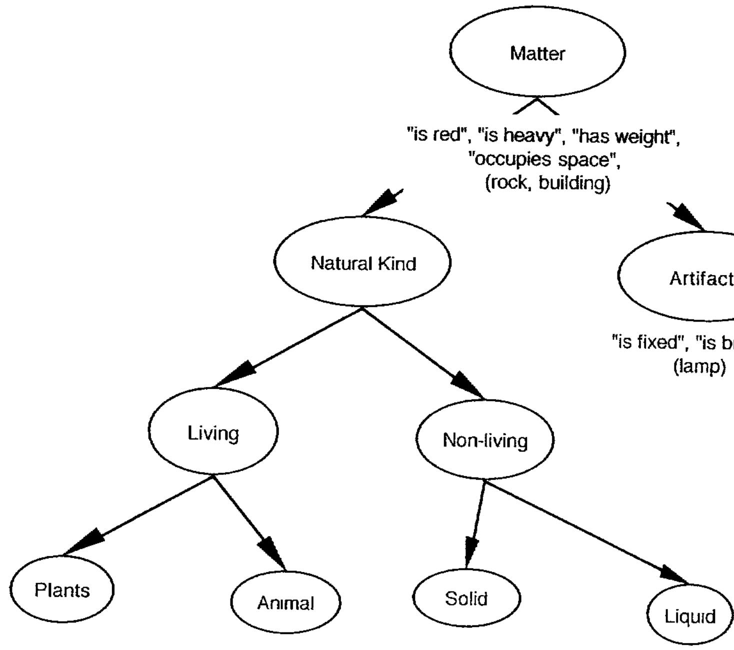
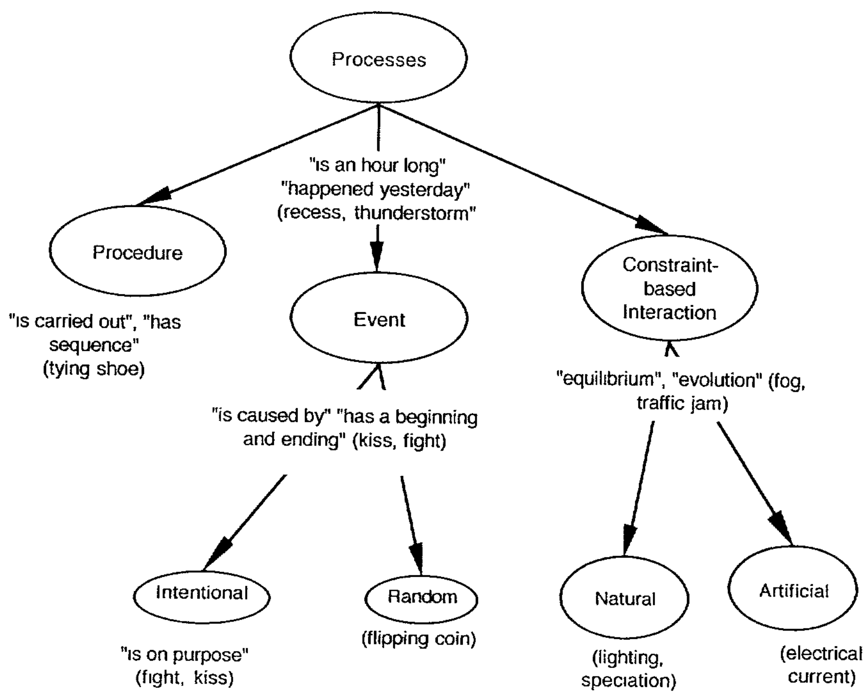
APPENDICES

APPENDIX A

Two ontologically distinct categories of Matter, and Processes
(adapted from Chi, Slotta, & deLeeuw, 1994).





APPENDIX B

Building on Bar-Yam's table of complex systems (Bar-Yam 1998)

System	Element	Interaction	Formation	Activity
Bar-Yam's example				
Physiology	*Cells*	*Chemical messengers* *Physical support*	*Developmental biology*	*Movement* *Physiological functions*
Life	*Organisms*	*Reproduction* *Competition* *Predation* *Communication*	*Evolution*	*Survival* *Reproduction* *Consumption* *Excretion*
		RESEARCH QUESTIONS		
Ant colony (food collection)	Ants	Communication: (releasing chemical markers) Cooperation: (following chemical markers)	Trail of ants	Movement: releasing chemical; following chemical; transporting food
Weather	Butterfly (all the other possible components of the system – e.g., fronts)	Coupling of energy inversions	Vortices Energy inversions	Physical laws of generative mechanisms
Traffic	Cars & other vehicles	Reaction to red break light of vehicle in front	Traffic flow (e.g., traffic jam, or unobstructed traffic flow)	Movement – slowing down or speeding up
Robot	Robots	Communication (release signal) Cooperation (follow signal)	Assembly line	Movement Search Signal Follow signal Mine Transport
Town planning	Services e.g., housing food health, transportation, financial, energy, sanitation	Cooperation = sharing & distribution Competition = profit making Reproduction = expansion	Civic system	Survival Expansion

V-formation	Birds	Communication: Reaction to natural or generated vortices. Cooperation: Reaction to changes in physiological markers (e.g. fatigue)	V-formation	Follow vortex Movement = fly
SIMULATIONS				
Slime	Slime mold	Reaction to chemical markers	Colonies of slime mold	Movement: Release chemical; Follow chemical; React to concentration of chemical
Gas law	Gas molecules	Collisions	Equilibrium PV = nRT	Collisions of molecules according to laws of Thermodynamics
Wolf-Sheep	Wolves; sheep; grass	Predation Reproduction Consumption	Ecosystem	Survival Reproduction Consumption

APPENDIX C

Prototypes of Answers Coded Using Ontological Mental Models Taxonomy (OMMT)

Table C.1

Prototypical Answers to Butterfly Questions Coded to EFMM Taxonomy

EFMM	Components of coding	*Butterfly* question
Ontological perspective: Emergent	1) Local interactions among agents, 2) leads to the creation of something that exhibits a differential behavior than those of the component agents; 3) this interaction is made possible due to some type of identification (tagging device), 4) and, communication (flows of information and/or resources).	As an individual butterfly's flapping its wings may create a temporary vortex which could potentially interact with other local vortices. If there is a steep temperature inversion present this initial condition could feed energy into the system.
Control of system Initial causes Decentralized	1) The individual agents are independent of each other, yet they all operate under the same rules; 2) the systems organizes itself through the interactions of these independent agents both with each other as well as with the environment.	Prigogines theory of order generation in highly distributed systems. Rules are not involved. Physical laws, generative mechanisms and initial triggering conditions are involved.
Action effects Non-linear	1) Because the system is organized through individual and independent actions, it is possible that one agent's actions can have exponentially significant results.	Like many atmospheric systems that are chaotic, it can be poised on the cusp of an instability, and it can take only a miniscule nudge to push the system into one "basin of attraction" or another. Once the process is initiated the system will tend to slide towards the center of the chosen basin.
Agents' actions Random	1) Agents at the lowest level appear to act in random fashion.	The initial condition is unpredictable. The single butterfly creating a vortex sufficiently powerful, in a location which will set the chain of events into motion cannot be predicted.
Underlying causes Probabilistic	1) The system organizes itself based on the interactions of the agents as described above, therefore the resulting structure is probable. 2) Like other probabilistic processes, larger numbers over longer time periods are more likely to result in the formation of normal distributions.	If a vortex is created is created it is by chance. If it grows it is by chance. If a large number of vortices are created simultaneously it is more likely that one of them may contain sufficient energy and be close enough to a steep temperature inversion to create an amplifying effect.
Systems' Nature Dynamic	1) Once the system, the recurring structure, emerges it exhibits a more stable quality; 2) yet all the component agents have the potential to be replaced by other similar independently operating agents.	The weather system has many different phenomena that create vortices and temperature inversions. As one vortex dies (is dampened) another one is formed. Only when all the elements interact in a certain way do these events grow to a discernable size to be considered a visible weather pattern.

Table C.2

Prototypical Answers to Traffic Questions Coded to EFMM Taxonomy

EFMM	Components of coding	*Traffic* question
Ontological perspective: Emergent	1) Local interactions among agents, 2) leads to the creation of something that exhibits a differential behavior than those of the component agents; 3) this interaction is made possible due to some type of identification (tagging device), 4) and, communication (flows of information and/or resources).	Cars interact by responding to the car directly in front of them. The rules of operation are as simple as respond to a signal, red tail lights. Therefore, when an individual driven sees red brake lights go on they too must put on their brakes. This starts a chain of events in which the drivers behind also respond to this red brake light, an so on and so on. This flow of information from one driver to the next creates a wave of cars with decreasing speeds.
Control of system Initial causes Decentralized	1) The individual agents are independent of each other, yet they all operate under the same rules; 2) the systems organizes itself through the interactions of these independent agents both with each other as well as with the environment.	All drivers must operate under the same rules otherwise there will be not only traffic jams but fatalities as cars crash into each other.
Action effects Non-linear	1) Because the system is organized through individual and independent actions, it is possible that one agent's actions can have exponentially significant results.	If one driver chooses to slow down, as indicated by their bake lights, then all drivers behind them must slow down as well.
Agents' actions Random	1) Agents at the lowest level appear to act in random fashion.	The behavior of the individual driver is totally unpredictable. There is no way to determine ahead of time what of many possible things could make an individual driver slow down. (discomfort, distraction, disregard for rules, external conditions).
Underlying causes Probabilistic	1) The system organizes itself based on the interactions of the agents as described above, therefore the resulting structure is probable. 2) Like other probabilistic processes, larger numbers over longer time periods are more likely to result in the formation of normal distributions.	Once the initial conditions establishing the slowing down of an individual car occurs, the formation of a traffic jam is dependent on many different factors, however, it is never certain that this simple act alone will cause a traffic jam. It may not if the driver resumes speed, or changes lanes, etc. However there are factors which will make it more likely that the initial condition will form into a traffic jam. One of these is numbers. The larger the number of cars on the road, the more likely this initial action will cause a jam. Another is alternative routes available. If there are multiple lanes available it is less likely that the initial condition will result in a jam.
Systems' Nature Dynamic	1) Once the system, the recurring structure, emerges it exhibits a more stable quality; 2) yet all the component agents have the potential to be replaced by other similar independently operating agents.	Cars are always on the road and they are always slowing down and speeding up. Therefore these signals of red bake lights are always going on and off. Therefore to have a single incidence of this slowing down produce a traffic jam will be dependent on a variety of things, one of them is time of day. During certain times day the volume of cars

		increase therefore the likelihood of forming a jam increases. Once a jam is formed it maintains itself by acting as a backward moving wave: as cars in front leave the jam, cars at the rear enter the jam. When the volume of cars is reduced, the potential for a jam is still there, it is just at an insufficient numbers to reach that critical self-organizing point. Therefore the traffic system exists without the traffic jam.

Table C.3

Prototypical Answers to Robot Questions Coded to EFMM Taxonomy

EFMM	Components of coding	*Robots* question
Ontological perspective: Emergent	1) Local interactions among agents, 2) leads to the creation of something that exhibits a differential behavior than those of the component agents;0 3) this interaction is made possible due to some type of identification (tagging device), 4) and, communication (flows of information and/or resources).	Individual robots would communicate with each other and with the ship through some type of signaling system. The signals would enable them to identify each other, the local of the ship, the discovery of gold deposits, locations that are easier, trails to follow, etc. Once gold is located the signal can be used to draw other robots to the location and form some type of physical trail of robots moving back and forth from the deposit to the ship.
Control of system Initial causes Decentralized	1) The individual agents are independent of each other, yet they all operate under the same rules; 2) the systems organizes itself through the interactions of these independent agents both with each other as well as with the environment.	All robots would be programmed to the same thing: search for the particular markers, if sufficient gold deposit is identified send out signal to draw other robots to the site. In the case of multiple signals respond to the closest one.
Action effects Non-linear	1) Because the system is organized through individual and independent actions, it is possible that one agent's actions can have exponentially significant results.	If one robot identifies the location of a gold deposit, the signal will draw many others to the site.
Agents' actions Random	1) Agents at the lowest level appear to act in random fashion.	The individual agent is programmed to search randomly until they identify a deposit or they are attracted by some signal.
Underlying causes Probabilistic	1) The system organizes itself based on the interactions of the agents as described above, therefore the resulting structure is probable. 2) Like other probabilistic processes, larger numbers over longer time periods are more likely to result in the formation of normal distributions.	Once the initial signal is sent out, the system of multiple robots working together is dependent on the number of robots that are in the location to receive the signal. It is also dependent on the number of other signals that may be within the system (other robots also sending signals). Once sufficient numbers of robots are working together, they will attract more robots to join them by amplifying the

		initial signal. In addition, as the trail of robots grows the physical obstacles within the environment will become worn thereby making the path easier to move along.
Systems' Nature Dynamic	1) Once the system, the recurring structure, emerges it exhibits a more stable quality; 2) yet all the component agents have the potential to be replaced by other similar independently operating agents.	In this process, an individual robot may at any point be part of the digging crew, transportation crew or delivery crew. Once a site is exhausted, the individual will go back to randomly searching until there is another discovery and the formation of another crew.

Table C.4

Prototypical Answer Coded to CWMM Taxonomy

CWMM	Components of coding	Example for Butterfly question
Ontological perspective: Reductive	1) agents' act in isolation. 2) simple stepwise description.	Storms are local. One to one relationships. Actions are cumulative therefore one butterfly is too small to matter.
Control of system Centralized	1) orders/controls come from outside. Or is within the system but not attributed to the individual agents within. E.g., different agents have different rules. e.g. mention of hierarchy.	Weather systems are controlled by higher level (top down) forces.
Action effects Linear	1) one thing leads to another. E.g. direct link between controller and controllee. e.g., action→reaction	Small actions and small size cannot affect large systems.
Agents' actions Predictable	1) agents' actions are predictable. e.g., they (it) will perform the action. There is no mention of randomness or chance in their actions.	Implication that agents' actions can be calculated and factored out.
Underlying causes Teleologic	1) it knows the end point. E.g., it knows it has to survive.	Underlying cause of storms cannot be attributed to agent levels probabilities. Storms are determined by larger forces outside our control.
Systems' Nature Static	1) explicit descriptions of non changing system.	The effects of the butterflies are local and therefore do not account for changes to the system. All actions are local and terminate.

Appendix C.2
Example of Coding EFMMs Only

Pretest

Sam: I believe ants must find their food through random wanderings and communication with other ants who have had luck. They all wander, one finds food, returns with information on its location and a number of ants collect it.

random behavior; chance happenings; independent behavior of the individual

Sam: I believe ants must find their food through random		
	random behavior	

Delayed Posttest

Sam: How do Ants find their food? I think that ants go about finding their food by sending out "scouts", ants that wander randomly, maybe following paths or general directions in which
Random behavior
they previously found food, maybe not. As these ants walk, I
role of history probabilistic behavior
think they leave a trail of pheromones that they can follow back to the ant hill. If per chance they find food, they can go back
probabilistic behavior
to the ant hill by following their trail and "stimulate" other ants to follow it back to the trail of food, all the while
positive feedback – flows
following the pheromone. As for rules and a complex system, I would think that the simple rule the ants follow involves nothing much than finding the said food. In other words going out and
Simple rules – algorithmic behavior
perhaps wandering aimlessly until they find the food or run into an obstacle which would break the randomness, for they would have to act in response to this new stimulus.
variability
So it's probability I guess, once again. Yeah. Cause the chance
Probabilistic behavior
that they'd wander in one direction might be because of the weather. Like if it's wet on one side and dry on the other they'd most likely take the dry side. So the probability that they'd take one path might lead them to the food.
Probabilistic behavior
S: When looking at the entire system, we would look at the ants, their goal (food), stimuli (obstacles and weather), which are all directed by a sense of "chaos" for it is impossible to figure out where or when the ants will encounter any of these. The ants are
Probabilistic behavior
the components that interact

with their environment and follow general rules, even if those rules are to wander randomly. The environment, food and stimuli, only follows the basic rule that it must be present at some place or another. The system comes together and is organized by the goal,
Self-organization – goal seeking driven by internal forces
that of finding the food, which is the basic rule to the entire system. If the ants, don't have a goal the system is unorganized and the components cannot come together.
Self-organization

APPENDIX D
INSTRUCTIONAL MATERIALS

Appendix D.1
Study 1 – Complex Systems Lecture

Part 1

(a) Emergence. Discussion of cell development in human embryos was used as a vehicle to inform participants on the concept of emergence in complex systems. An eight-minute video clip on cell division and embryonic development was used to demonstrate the process. The materials for the lecture were projected using a PC computer and LCD station set up in the classroom. The total time of this presentation was one hour.

(b) Aggregation. The concept of aggregation was demonstrated using the StarLogo computer model called "Slime". The model was used at the default setting since this setting best describes the notions of necessary and sufficient conditions for aggregation. Slime model (aka turtles) are programmed to move around in random fashion searching for deposits of pheromone – *unpredictable movement of agents*. These deposits must meet a specified level of potency before the turtle will stay with the deposit.

(c) Requisite variety. The process of requisite variety was delivered using traditional overhead projection materials. Content was adapted from lecture material on systems' behavior used for the Educational Cybernetic course in the Educational Technology program.

Source Materials Used

To demonstrate human embryo development, a clip from the Biology NYA textbook* CDRom was used.

Requisite variety was explained using overhead transparences that were developed by the cybernetics subject matter expert. Further information could be obtained from the following web address:http://artsci-ccwin.concordia.ca/edtech/ETEC606/index.htm.

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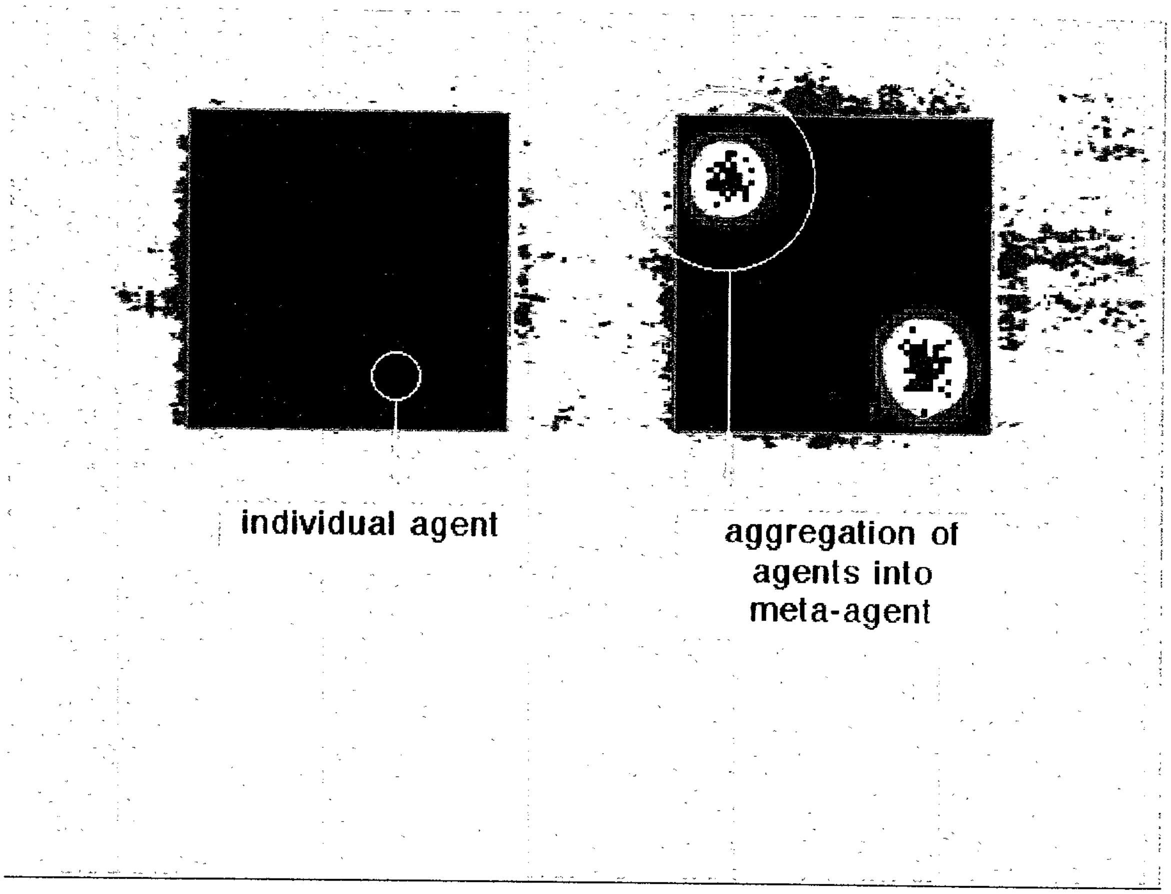
* Campbell, N.A., Reece, J.B., & Mitchell, L.G. (2000). *Biology: Concepts and Connections*, 3rd Edition. Menlo Park, CA: Benjamin Cummings, Inc.

Appendix D.2

Screen Shots of Slime Mould



Appendix D.3

Screen Shots of Simulations Used in Study 2

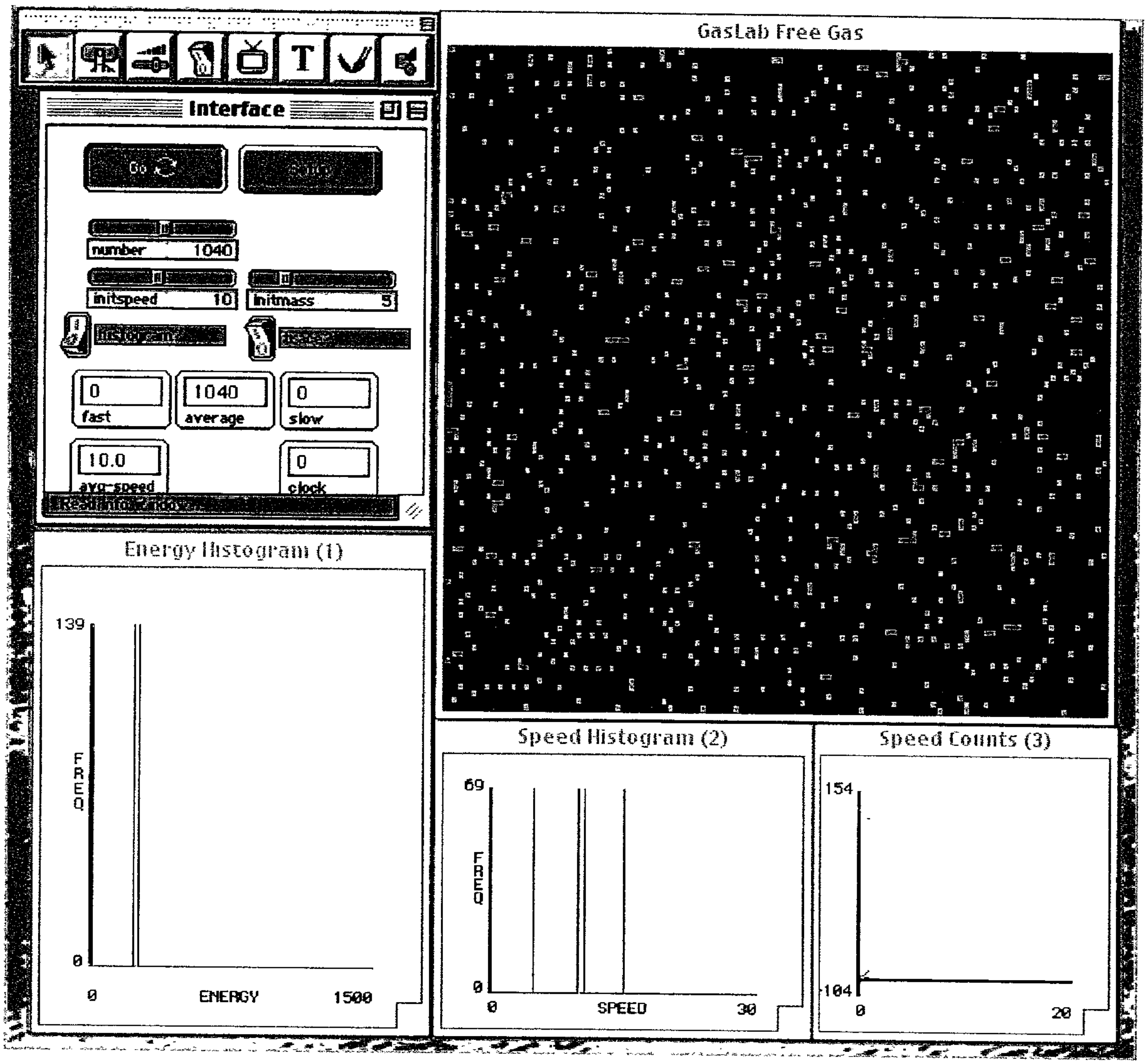


Figure D.1
GasLab Free Gas simulation start up condition.

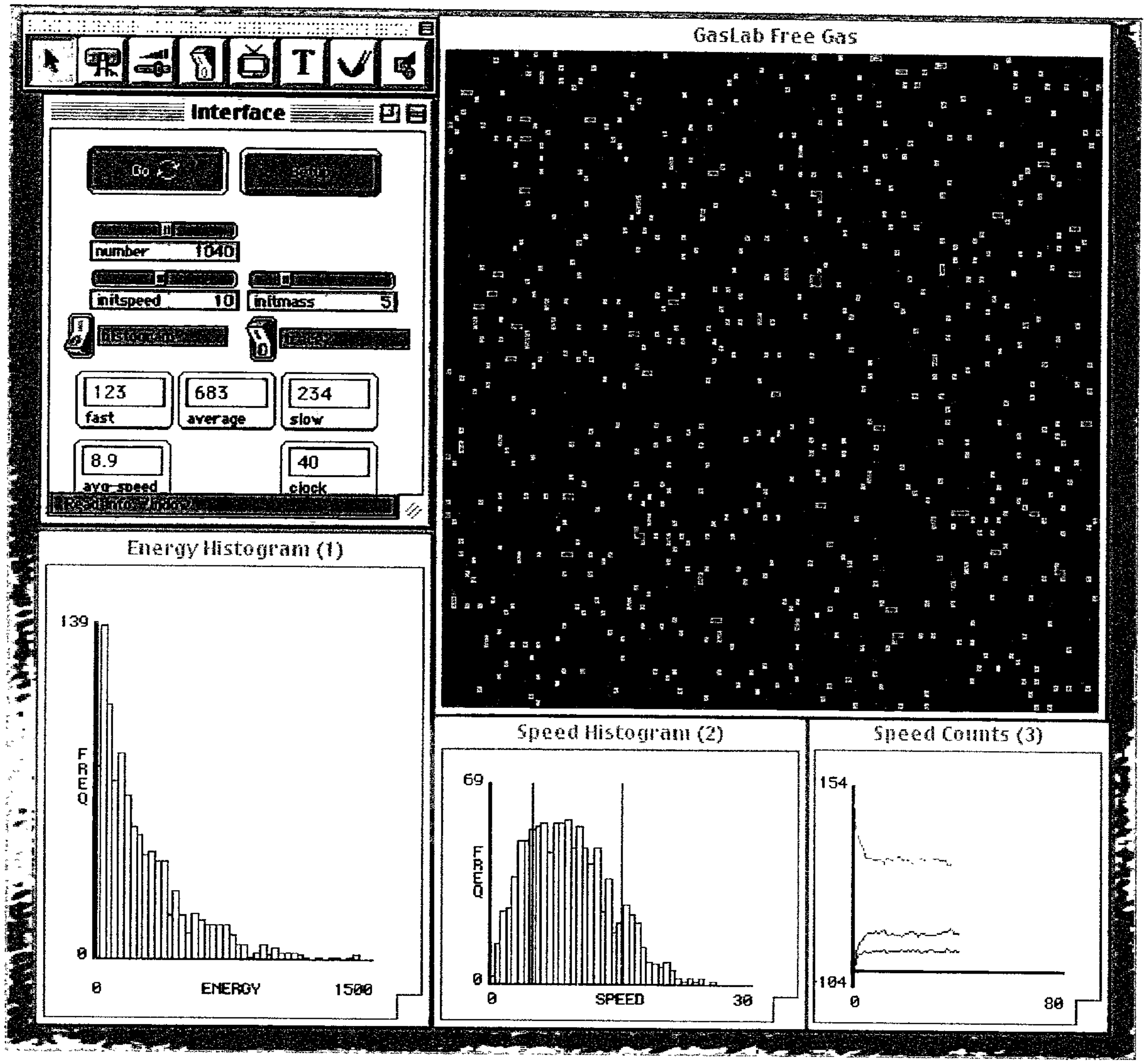


Figure D.2
GasLab Free Gas simulation, running condition. Graphs describe the normal distribution of speed and energy within the system.

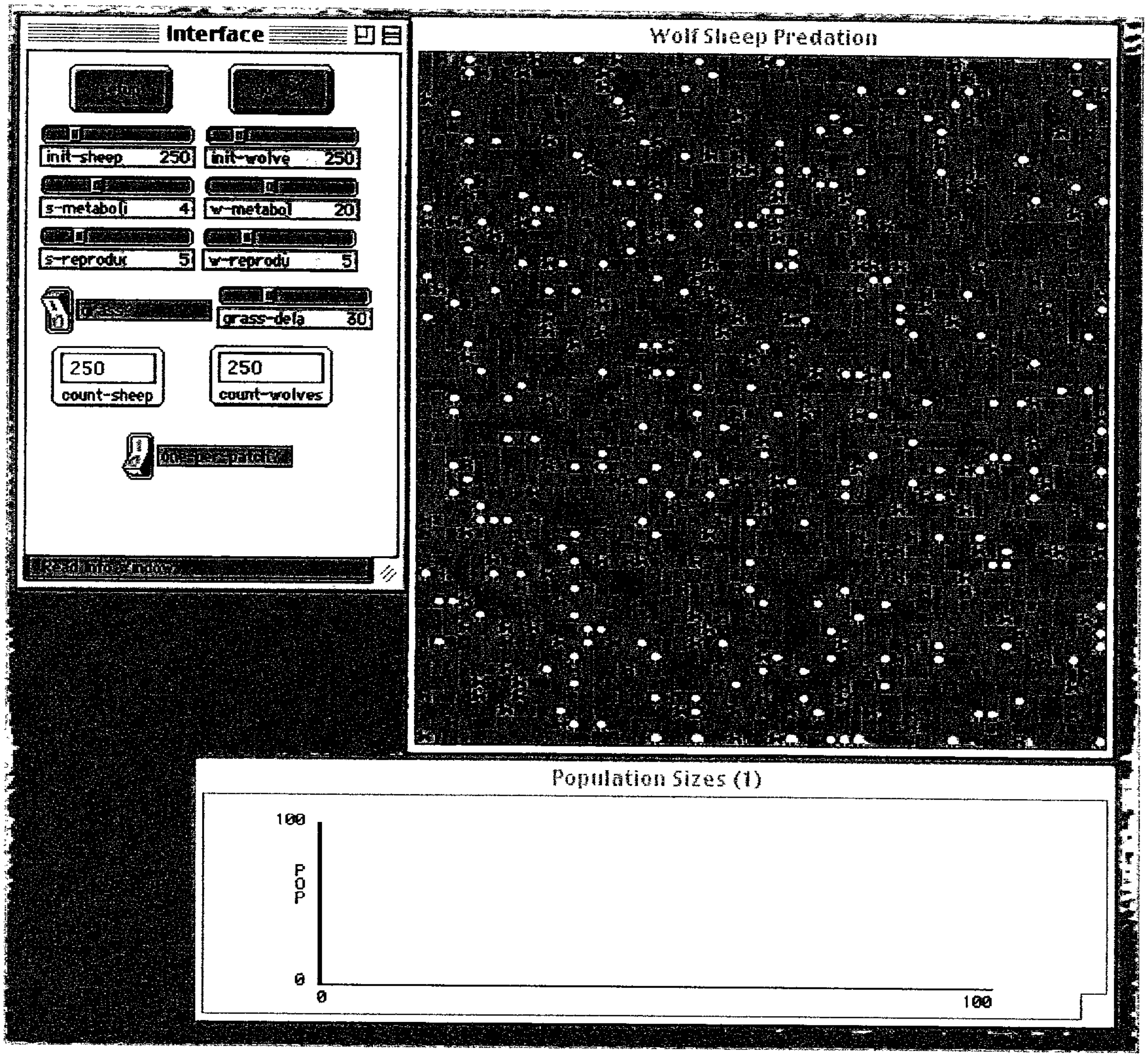


Figure D.3
Wolf-Sheep Predation simulation start-up condition.

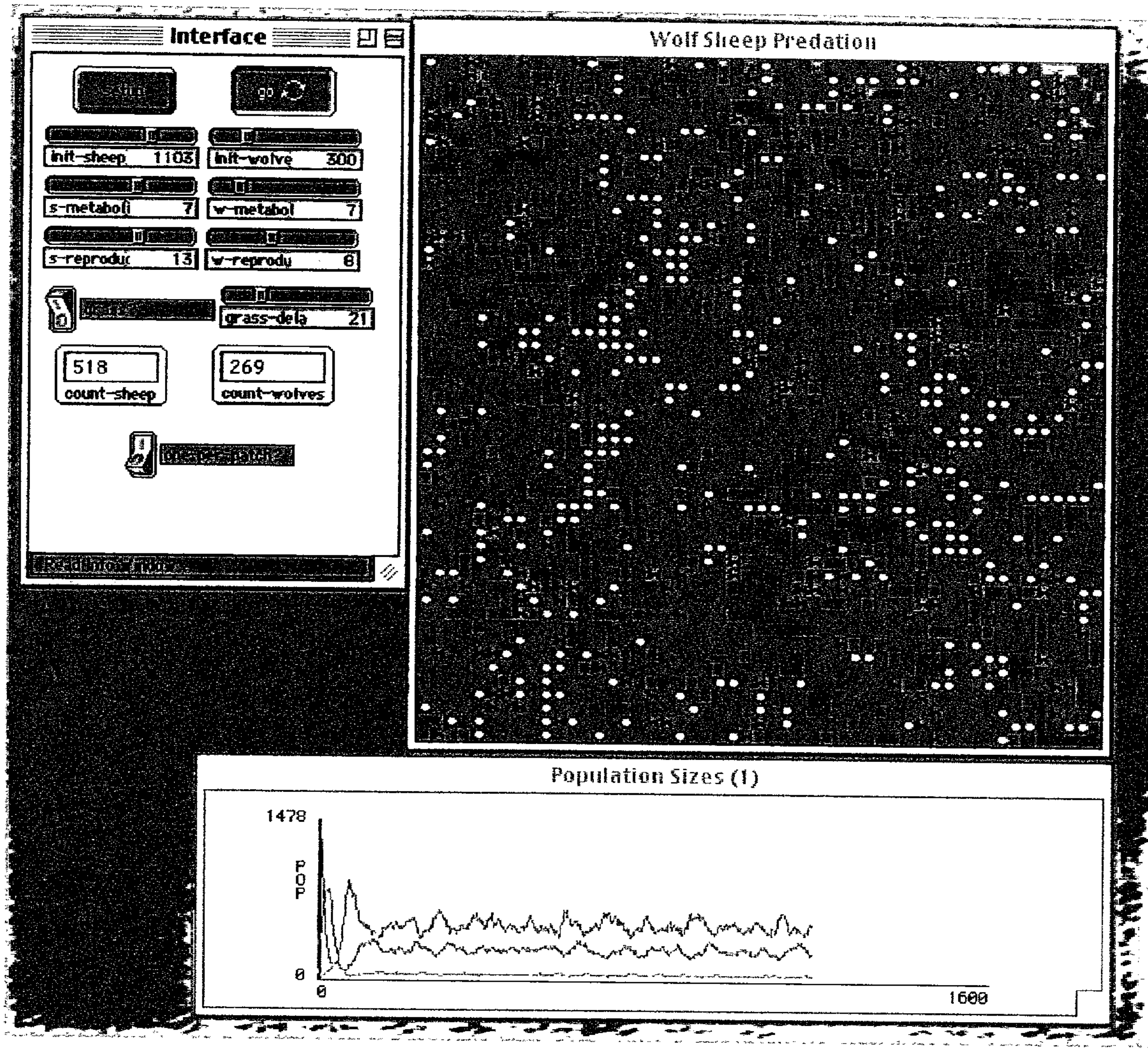


Figure D.4
Wolf-Sheep Predation simulation running condition. The graph describes the system after 3 to 4 minutes. Note the oscillation of the sheep and wolf populations.

Appendix D.4

Reading Material for Session 4

Reading material may be found at the following website:

Self-Organizing Systems FAQ for Usenet newsgroupcomp.theory.self-org-sys
http://www.calresco.org/sos/spsfaq.htm#9.3

1. Introduction

1.1 Science of Self-Organizing Systems

The scientific study of self-organizing systems is relatively new, although questions about how organization arises have of course been raised since ancient times. The forms we identify around us are only a small sub-set of those theoretically possible. So why don't we see more variety? To answer such a question is the reason why we study self-organization.

Many natural systems show organization (e.g. galaxies, planets, chemical compounds, cells, organisms and societies).Traditional scientific fields attempt to explain these features by referencing the micro properties or laws applicable to their component parts, for example gravitation or chemical bonds. Yet we can also approach the subject in a very different way, looking instead for system properties applicable to all such collections of parts, regardless of size or nature. It is here that modern computers prove essential, allowing us to investigate the dynamic changes that occur over vast numbers of time steps and with a large numbers of initial options.

Studying nature requires timescales appropriate for the natural system, and this restricts our studies to identifiable qualities that are easily reproduced, precluding investigations involving the full range of possibilities that may be encountered. However, mathematics deals easily with generalised and abstract systems and produces theorems applicable to all possible members of a class of systems. By creating mathematical models, and running computer simulations, we are able to quickly explore large numbers of possible starting positions and to analyse the common features that result. Even small systems have almost infinite initial options, so even with the fastest computer currently available, we usually can only sample the possibility space. Yet this is often enough for us to discover interesting properties that can then be tested against real systems, thus generating new theories applicable to complex systems and their spontaneous organization.

1.2 Definition of Self-Organization

The essence of self-organization is that system structure often appears without explicit pressure or involvement from outside the system. In other words, the constraints on form (i.e.

organization) of interest to us are internal to the system, resulting from the interactions among the components and usually independent of the physical nature of those components. The organization can evolve in either time or space, maintain a stable form or show transient phenomena. General resource flows within self-organized systems are expected (dissipation), although not critical to the concept itself.

The field of self-organization seeks general rules about the growth and evolution of systemic structure, the forms it might take, and finally methods that predict the future organization that will result from changes made to the underlying components. The results are expected to be applicable to all other systems exhibiting similar network characteristics.

1.3 Definition of Complexity Theory

The main current scientific theory related to self-organization is Complexity Theory, which states:

> ***Critically interacting components self-organize to form potentially evolving structures exhibiting a hierarchy of emergent system properties.***

The elements of this definition relate to the following:

- Critically Interacting - System is information rich, neither static nor chaotic
- Components - Modularity and autonomy of part behaviour implied
- Self-Organize - Attractor structure is generated by local contextual interactions
- Potentially Evolving - Environmental variation selects and mutates attractors
- Hierarchy - Multiple levels of structure and responses appear (hyperstructure)
- Emergent System Properties - New features are evident which require a new vocabulary

We explore and explain the terms comprising this definition in this FAQ. The form of the definition given here is the slightly rephrased result of a discussion on the SOS newsgroup, where the editor of this FAQ offered an initial definition and the concept was refined, but the elements included are found in most treatments of self-organization, in one form or another.

2. Systems

2.1 What is a system ?

A system is a group of interacting parts functioning as a whole and distinguishable from its surroundings by recognizable boundaries. There are many varieties of systems, on the one hand the interactions between the parts may be fixed (e.g. an engine), at the other extreme the interactions may be unconstrained (e.g. a gas). The systems of most interest in our context are those in the middle, with a combination both of changing interactions and of fixed ones (e.g. a cell). The system function depends upon the nature and arrangement of the parts and usually changes if parts are added, removed or rearranged. The system has properties that are emergent, if they are not intrinsically found within any of the parts, and exist only at a higher level of description.

2.2 What is a system property ?

When a series of parts are connected into various configurations, the resultant system no longer solely exhibits the collective properties of the parts themselves. Instead any additional behaviour attributed to the system is an example of an emergent system property. A configuration can be physical, logical or statistical, all can show unexpected features that cannot be reduced to an additive property of the individual parts.

2.3 What is emergence ?

The appearance of a property or feature not previously observed as a functional characteristic of the system. Generally, higher-level properties are regarded as emergent. An automobile is an emergent property of its interconnected parts. That property disappears if the parts are disassembled and just placed in a heap.

APPENDIX E
DOCUMENTATION OF ETHICAL STANDARDS

Appendix E.1
Recruitment Letter

Dear Student,

One of the College's faculty members, Elizabeth Charles is looking for students to take part in a research project which follows the Science program orientation event of 14 August, 2000. This research will provide students with specific skills (outlined below) as well as examine the potential of a contemporary scientific way of thinking and its benefits on learning.

Specific Skills:
1. How to use First Class Client software in order to communicate with other students and faculty.
2. How to facilitate working in a collaborative and cooperative manner (i.e., working as members of a team).
3. How to use simulation software (i.e., use of simulation software).
4. How to observe phenomena and develop hypotheses (i.e., working with simulations and interpreting data).
5. How to approach scientific inquiry from a systemic point-of-view.
6. How to summarize and critique data findings (i.e., group discussions and writing summaries after working on simulations).
7. Participating and understanding the research process.

If you agree to participate you will be expected to attend one full day and two half day sessions starting 15 August to 17 August. You will also be asked to participate in an on-line learning group until midterm. This involvement will take up no more than one to two hours per week. The primary aim of the follow-up sessions is to keep you on track and act as on-line mentoring. Please note that it would be beneficial to own a computer and have an Internet connection <u>but it is not essential</u>.

By now you must be asking yourself, what's in this for me? As with most research, it will be mainly the FUN of being part of an ongoing quest for knowledge about how human beings learn. As well, these workshops will allow you to meet some of the people at the College - both faculty and students - as well as get better acquainted with the physical layout of the College. You will receive a FREE LUNCH each day. And, finally, your name will be entered into a drawing for one of TWO GRAND PRIZES of $250 for participants who complete the full project (workshop & follow-up).

If you are interested or wish further information, please contact us at the following email address: echarles@place.dawsoncollege.qc.ca
Or at 931-8731 ext 3214 and leave a voice message

Appendix E.2

Consent Form – Study 1

STUDENT CONSENT FORM

Elizabeth Charles is asking for your help in completing a research project entitled "A Systems Approach to Science Education". This project will study the effects of systems-based instruction on the learners' approach to problem solving of several interesting topics (e.g., evolution, diffusion, etc.). To do so this research will use computer simulations, web-based and traditional instruction. Ms. Charles is asking for your permission to collect data, starting today and ongoing until the end of your first year at Dawson College. These data will be in the form of written questionnaires and interviews that will assess your understanding of the material covered by the instruction. She also is requesting permission to collect information from questionnaires that assess goal orientation, learning preference, and formal reasoning. As well, she would like your permission to access the results of your Dawson College English Placement Test and grades from your science courses.

ALL INFORMATION COLLECTED FOR THE PURPOSE OF THIS RESEARCH WILL BE KEPT STRICTLY CONFIDENTIAL. NO NAMES OR ANY OTHER IDENTIFICATION WILL BE USED IN ANY PUBLICATION(S) THAT MAY RESULT OUT OF THIS STUDY AND, NO NAMED DATA WILL BE RELEASED TO ANY DAWSON FACULTY

Your cooperation is voluntary. You have the right to decline participation in any part(s) of this study. Also, you have the right to discontinue your cooperation at any time. Your non-participation or withdrawal will in no way affect your standing in any course(s) or program(s). Please indicate your wish to participate by filling in the appropriate section below. If you do not wish to participate draw a large X in the middle of this form.

Any questions or concerns you have with respect to this research should be addressed to Elizabeth Charles via email at **echarles@place.dawsoncollege.qc.ca** or via a phone message at **931-8731 local 3214**.

I agree to participate in this research project conducted by Elizabeth Charles. I have carefully read the above description and understand the agreement. I freely consent and agree to participate in the collection of data for this research project.

Name (please print) ____

Student ID ___________________________

Student's signature ______________________________ Date ______________

(Parent's signature if a minor)

I would like a copy of the study's findings when they are available. __ yes __ no

Appendix E.3

Consent Form – Study 2

STUDENT CONSENT FORM

Elizabeth Charles, is asking for your help in completing a research project entitled "*A System's Approach to Science Education*". This project will study the effects of a systems-based activity on the learners' approach to problem solving (e.g., evolution, diffusion, ecology, etc.). It will provide you with an opportunity to explore new concepts in science education, namely, complex systems thinking.

If you agree to participate you will be expected to schedule six one-hour sessions over a period of six consecutive weeks during which you will be asked to work with computer simulation software called StarLogo. You will be expected to talk about your experiences and understanding of complex systems concepts gained through the use of these simulations; this is generally referred to as a "think aloud" protocol. No formal preparation and no homework will be assigned.

Furthermore, if you agree to participate you will be paid $10/session.

She is asking for your permission to collect data, which includes: interviews (audio and video taped), written questions, and questionnaires that assess goal orientation, and learning preference. These forms of data collection are intended to assess your understanding of the material covered by the simulations. As well, she would like your permission to access the results of your Dawson College English Placement Test and grades from your science courses.

ALL INFORMATION COLLECTED FOR THE PURPOSE OF THIS RESEARCH WILL BE KEPT STRICTLY CONFIDENTIAL. NO NAMES OR ANY OTHER IDENTIFICATION WILL BE USED IN ANY PUBLICATION(S) THAT MAY RESULT OUT OF THIS STUDY AND, NO NAMED DATA WILL BE RELEASED TO ANY DAWSON FACULTY.

Your cooperation is voluntary. You have the right to decline participation in any part(s) of this study. Also, you have the right to discontinue your cooperation at any time; however, you will be paid only for the sessions attended. Your non-participation or withdrawal will in no way affect your standing in any course(s) or program(s) at the College. Please indicate your wish to participate by filling in the appropriate section below.

Any questions or concerns with respect to this research should be addressed to Graeme Welch, the Dean of Pre-University programs and the chair of the Human Research Ethics Committee, 931-8731, ext. 1685.

If you agree to sign below, it will be taken as evidence that you have carefully read, and freely consent to participate in the research project as described above.

Name (please print) ________________________________

Student ID ______________________

Student's signature ________________________ Date ____________

(Parent's signature if a minor)

If you would like a copy of the study's findings when they are available, please check the appropriate space.

__ Yes __ No

Thank you for your time and cooperation.

APPENDIX F
DATA COLLECTION INSTRUMENTS

Appendix F.1
<u>Pretest – Immediate Posttest (Brain Teaser Questions)</u>

BRAIN TEASER QUESTIONS

Name ____________________ **Date** __________________

DIRECTIONS: You are <u>not expected</u> to know the "real" scientific explanations, however, you may have some personal "theories" or understanding about the following phenomena from science articles, novels or movies. Therefore, please answer these questions using your intuition (best guess) or knowledge from informal learning experiences.

1. How would you explain how ants find and collect their food. What rules do you believe they follow? Try to explain using only the space provided. If you don't know, just make a "X" in the space provided.

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2. It has been said that a butterfly flapping its wings in Brazil can jiggle the air and thus can help cause a snowstorm in Alaska. Is this possible? If so, how would you explain this phenomena? What type of rules would permit this to occur? If not possible, what rules do you believe would prevent them from occurring? Try to explain using only the space provided. If you don't know, just make a "X" in the space provided.

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3. How would you explain the formation of traffic jams? Are there rules that would direct this type of activity? Try to explain using only the space provided. If you don't know, just make a "X" in the space provided.

4. Suppose large deposits of a cancer-curing mineral were discovered on a distant planet. It is too dangerous and costly to send human astronauts to mine the mineral. If thousands of robots were sent. What type of programming would be necessary to ensure that the robots would be able to find the mineral, mine it, take it back to the space ship and then return to their exploration and mining tasks? In other words, what type of rules and strategies should the robots have to follow? Use as much space as required.

Thank you very much for your cooperation.

Appendix F.2

Demographic Questionnaire

DEMOGRAPHIC BACKGROUND

DIRECTIONS: Please answer these questions in the space provided.

NAME:______________________ I.D. # ______________
(please print)

5.(a) What language(s) do you speak at home? ______________________

(b) What was the main language used for instruction at the high school you attended?
____

6. What is your age? ______________

SCIENCE BACKGROUND INFORMATION

DIRECTIONS: Please answer these questions in the space provided.

7. What science courses did you take in high school? ______________________
____

8. Do you have any other relevant experience in science or medicine (e.g., summer job as a lab technician; voluntary at a hospital)? ______________________

9. Do you read science magazines? ___________

10. If yes which ones?______________________________________

11. What type of science topics interests you the most?______________________

12. Have you ever participated in a science fair?_______

13. If yes, did you ever win an award or honorable mention?_____

14. Briefly describe the project you exhibited?_________________________

15. Have you ever participated in a science camp?________

16. If yes, when and how often?____________________________

17. Before today, have you ever been a participant in a research project? _____

18. If yes, briefly describe it.______________________________

What type of computer skills do you have? ( ) High ( ) Medium ( ) Low

19. What software do you use most often? ______________________

20. Do you know any programming languages?_________________________

Appendix F.3

Final Posttest

EVOLUTION
DELAYED POSTTEST – CASE STUDY

1. Monsanto (an agricultural engineering company) has developed genetically identical corn seeds in their laboratory in California. They sell them to farmers across the world, for example: (1) a farm south of Montreal (cool, short growing season, moderate temperatures); or (2) a farm in Kenya, East Africa (warm, longer growing season, short rainy season). Assuming that the corn will evolve over time, and using your intuition about these types of systems, try to describe how the process of evolution might proceed by directing your answer to include the following:

   a) Will the number of seeds planted have an effect on the process of their evolution? What would happen if you planted 100 seeds? What would happen if you planted 100,000 seeds?
   b) What elements in the environment do you think could affect the evolution of this population of corn? Discuss how the effects would progress.
   c) Are there any conditions under which you would expect drastic changes in the genetic make-up and appearance of the offspring (i.e., a new species of grain)?

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2. You have most probably observed the migration of birds in the spring and fall. Again using your intuition, what programming would be required to have robotic birds display a similar behavior resulting in the V-shaped formation that is created by a flock of birds?

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Thank you very much for your cooperation.

Appendix F.4

Concept Map Terms

INSTRUCTION FOR CONCEPT MAPPING OF COMPLEX SYSTEMS TERMS

Please take a look at the terms listed below, then place them into any arrangement that you believe best describes your understanding of their meaning and relationship to each other. If you do not see any way that a term is related to the others, place it on the bottom of the page. After you have completed this task I will ask you to explain your decision.

(The terms are listed in alphabetical order that has not significance to their meaning).

- algorithmic
- centralized
- complex systems
- decentralized
- dynamic
- predictable
- probabilistic
- random
- self organizing
- simple systems
- static
- system