IMPROVING COLLEGE STUDENTS' COMPLEX SYSTEMS THINKING WITH AN ECOLOGICAL SIMULATION: DOES SCAFFOLDING HELP?

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ABSTRACT

Complex systems comprise interconnected elements that follow simple rules without central controls and give rise to unpredictable behavior (Mitchell, 2009); characteristics of complex systems are called *components*. If understood, complex systems components may serve as unifying principles that help students understand systems across domains such as biology, economics, or engineering. Nevertheless, complex systems are difficult to understand because of the variety of changing interactions of their elements as well as the non-linear effects of such interactions. Such non-linear effects are often removed from causes through both time and distance. The purpose of this study was to examine adult understanding of complex systems components, to investigate whether an agent-based participatory simulation, with one of two types of scaffolding, might improve this understanding, and finally to determine if either simulation or scaffolding would help students transfer their new understanding to another context.

The study took place at a mid-sized, public university in the Mid-Atlantic region of the United States. Participants included 96 undergraduate and graduate students enrolled in a class about complex systems in the School of Architecture. The study and intervention were informed by a pilot study, as well as previous research by the study author. A 2x2 pretest-posttest quasi-experimental design was employed to test whether participation in an intervention improved students' complex systems understanding and whether participation in one of either two scaffolding treatment groups helped improve

this understanding. As part of their class, participants attended one of two workshops that served as treatment conditions (Self-Monitoring or Ontological Scaffolding) and participated in a gameplay of the UVA Bay Game, an agent-based participatory simulation. Students completed identical pretest and posttest assessments of complex system component understanding and an open-ended essay-style posttest transfer prompt.

Student understanding of complex systems components was analyzed using descriptive statistics, non-parametric tests, as well as coding for emergent themes amongst student responses. Non-parametric quantitative analyses revealed that student understanding significantly improved for Agent Actions (r = .17, p = .02) and Processes-based Causality (r = .13, p = .045) components while Action Effects understanding decreased (r = -.19, p = .01); 3 other components showed no changes. Student understanding differed by scaffolding condition only for the component Order (r = .24, p = .02), with Self-Monitoring students' scores decreasing non-significantly while Ontological Scaffolding students' scores increased non-significantly. Finally, no differences between treatment groups were found on transfer items, though all students' scores increased for Action Effects and Order over other components, which varied depending on the type of system students chose as the topic of their essay.

This study is the first to use a quasi-experimental design to investigate the effectiveness of agent-participatory simulations in teaching college students complex systems understanding. Although most effects were small, the study shows promise for how such a classroom-based intervention might help students learn such a difficult topic.

Dedication

This dissertation is dedicated to my ex-girlfriend, Claire.

Thanks for agreeing to marry me.

And for all of your time, patience, and love of writing.

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No man is an island. Most people probably aren't peninsulas. However, given the amount of people who have helped me throughout this process I'm pretty sure I'm Lesotho, completely landlocked as I am surrounded by kindness.

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CHAPTER 1: INTRODUCTION

Changes in computational power have transformed science, with modeling and simulations emerging as a third pillar of science alongside traditional pillars of theory and experimentation (Jackson, 1996; Sabelli, 2006). The ability to propose theories and then test them with computer models allows researchers to go beyond constraints such as time or physical scale. Modeling also allows scientists to account for increasingly complex behaviors and processes within systems such as ecosystems. As a result of technological advances, people can now investigate how the parts or agents of a system interact to give rise to the often unpredictable macro outcomes, or behavior of a system. With non-linear interactions and emergent behavior among large numbers of variables, modeling of complex systems was previously underdeveloped (Bar-Yam, 1997; Kauffman, 1995). Technological and computational advances have made it possible to study phenomena of greater complexity, and therefore to determine which problems are surmountable at a given time (Mainzer, 2007). For example, increased computing power now allows researchers to study events that have multiple causes and outcomes (Jacobson & Wilensky, 2006), a process that would be too taxing for a person to reason theoretically through induction. Disciplines such as economics (P. W. Anderson, Arrow, & Pines, 1988; Farmer & Foley, 2009); climate science (West & Dowlatabadi, 1999); business (Axelrod & Cohen, 2000); education (Maroulis et al., 2010) as well as genetics; the internet; and meteorology (Jacobson & Wilensky, 2006) now use complex computational models to explain much of their phenomena (Penner, 2000).

Complex Systems and Unifying Principles

Complex systems consist of interconnected elements, without central control, that follow simple rules and give rise to complex and often adaptable behavior (Mitchell, 2009). For example, ant colonies demonstrate order and adapt without leaders because their individuals follow simple rules such as "bring food back to the colony, when a food supply is exhausted search for a new one." Examples such as honeybee behavior, traffic jams, and weather represent the variety and breadth of these systems.

Complex systems comprise several important components or unifying principles. One deep principle in complex systems is *emergence*, which occurs when "local interactions of elements in a complex systems at a microlevel can contribute to higher order macrolevel patterns that may have qualitatively different characteristics than the individual elements at the microlevel" (Jacobson & Wilensky, 2006, p. 16). In other words, the sum is substantially and qualitatively different than the parts. A second principle is *decentralized control* where order arises not from a top-down leader, but from the local goals and behavior of the agents. Ecosystems thrive without leaders because parts adapt to fit their local needs. Finally, complex systems have nonlinear interactions and effects where small actions through causal chains may result in large effects (i.e., *non-linear effects*), such as the introduction of an invasive species into an ecosystem.

Complex system concepts crosscut multiple domains. For example, self-organization and adaptation apply to biological systems (Resnick, 1994); economics (Epstein & Axtell, 1996); and engineering (Amaral & Ottino, 2004; Ottino, 2004). In biological systems, diet may change depending on environmental conditions or animals may migrate without directions from leaders. Within economics, markets organize and adapt around available goods, consumer preferences, and a variety of other parameters. Even within engineering, it is proposed that the design of effective systems not only allows for adaptation during design phases, but that adaptation should be built into the system (Ottino, 2004).

Understanding Complex Systems

To become scientifically literate as citizens or as future scientists, students need to understand the principles behind complex systems and behavior (Jacobson & Wilensky, 2006) and to develop new skills and ways of thinking (Klopfer & Yoon, 2004). Scientists and educational groups have advocated a movement towards explicitly teaching students about complex systems (Kaput et al., 1999; National Research Council, 1996, 2012; NGSS Lead States, 2013). For example, the Next Generation Science Standards explicitly call for students to understand cross-cutting concepts of systems and system models, stability and change within systems, as well as cause and effect within systems (Achieve Inc., 2013).

Because the principles of complex systems apply across many domains, explicitly teaching students about complex systems may help them build conceptual links to understand their increasingly complex world (Lemke & Sabelli, 2008). For example, comprehending and learning to recognize a deep principle such as emergence in ecology may help a student to understand and recognize this behavior when they encounter it in economics. Applying an understanding of a deep principle in a new context is an example of far transfer, which is difficult to achieve in education (Detterman, 1993; Gick & Holyoak, 1980; National Research Council, 2000). By explicitly teaching students about complex systems and phenomena, students might be able to learn to interpret situations according to underlying principles and use these for navigating subsequent encounters (e.g. Slotta & Chi, 2006). Additionally, explicitly teaching students about complex systems may help engender an interdisciplinary way of thinking, which may help students see things differently in other domains than they might have without this underlying knowledge (Jacobson & Wilensky, 2006; Shen, Liu, & Sung, 2014).

Complex systems comprise many interacting parts that function across different time scales and have effects in multiple places. Thus, although teaching about complex systems is necessary to understand much of how the world works, such systems are complicated, counterintuitive, and often require more than experience or knowledge to understand (Abrahamson & Wilensky, 2005; Goldstone & Wilensky, 2008). Students of all ages have difficulty learning about complex systems. Both students and pre-service teachers have been shown to focus on the superficial structure of systems (Hmelo-Silver, Marathe, & Liu, 2007). For example, novices identified visible components of an aquarium system such as rocks and fish, yet they failed to identify the more meaningful less tangible behaviors and functions of the system. In a different study of seven engineering students, Jacobson and colleagues (2001) found that novices had difficulty recognizing (a) where control existed in systems, (b) that there were multiple causes (non-linear effects), (c) that agents acted randomly, and (d) the processes within systems.

Barriers also arise due to the nature of schooling. K-12 education has often been criticized for covering too many topics at a superficial level, so that students never reach a deep understanding of any domain (National Research Council, 1996, 2000). Although some complex systems concepts are commonly taught in science classes (e.g., natural selection, homeostasis, and equilibrium) and less explicitly in economics and sociology classes, connections are not made across subjects. In order to become scientists and informed citizens, students will need to recognize and know how these underlying concepts occur in the world and what these patterns mean.

Complex Systems Instruction

Meaningful learning involves understanding underlying deep principles as opposed to superficial shared features. In classrooms, complex systems are either not taught formally; or examples of systems, such as ecosystems, are taught using outdated paradigms that fragment systems and ignore the dynamic interactions of the parts (Koppal & Caldwell, 2004). Often instruction relies on textbooks that cannot convey the important elements and interactions of complex systems (Weiss, Pasley, Smith, Banilower, & Heck, 2003). Static, simplified representations of complex systems preclude students from making connections between parts and from experiencing what is most important about complex systems—the often dynamic, invisible, or time delayed interactions and effects (Feltovich, Spiro, & Coulson, 1993).

Although we are constantly surrounded by complex systems, components of these systems are difficult to visualize. For example, even though fish may die off suddenly in a river, the cause of this die off may not be an event but an invisible process that has occurred over a long period of time such as chemicals leaching into the ground from a nearby factory. Furthermore, the source of this change may occur far away from the effect such as distant traffic causing acid rain over a pond (Grotzer, 2012). Other processes such as crystallization or diffusion may be invisible to the naked eye (Blikstein & Wilensky, 2009), while others such as climate change may occur over periods of time that are too prolonged to observe in a classroom setting.

Simulations and models enable students to experience and visualize the true characteristics of complex systems. Simulations such as NetLogo (Wilensky, 1999) allow students to change inputs at the micro level of systems and to observe resulting changes in outputs at the macro level. Another simulation, EcoMUVE, allows participants to explore an actual ecosystem and move through time to determine cause and effect within this complex system (Grotzer, Kamarainen, Tutwiler, Metcalf, & Dede, 2013). Simulations can also help make unobservable components of complex systems visible (e.g. Honey & Hilton, 2011).

An especially promising kind of simulation to help students understand complex systems are agent-based participatory simulations (Pahl-Wostl, 2002). Participatory simulations allow students to take the role of the parts within complex systems and then to witness the macro outcomes from their behavior (Colella, 2000). With participatory simulations, students not only observe complex systems, but they also experience the opportunities and constraints by taking on the roles of component parts (Wilensky & Stroup, 2000b). As an agent in the complex system, students can investigate how their actions can affect the overall system. Perspective taking, social interaction, and experimentation within the simulated complex system may help students to better and more vividly understand certain difficult components of complex systems such as decentralization and non-linear interactions.

Despite their advantages, simulations do not mean students will not struggle with learning complex system components. For example, although research demonstrates that computer models can help secondary students recognize and understand the function of components of complex systems, students still had difficulty identifying the behavior of these components (Hmelo-Silver, Marathe, et al., 2007; Vattam et al., 2011). Similarly, when using agent-based models and hypermedia, post-secondary students had difficulty with problem solving tasks that required complex systems understanding (Jacobson, Kapur, So, & Lee, 2011). In other words, computer-based simulations may allow students to be able to study and investigate phenomena they could not otherwise, yet the use of simulations does not guarantee deep learning.

Scaffolding Complex Systems Understanding

Given the inherent difficulty of learning about complex system behaviors, even after using simulations, students need support when learning about complex systems from simulations. Research demonstrates that providing scaffolding, i.e., learning supports within simulations, can benefit learning (McElhaney, Chang, Chiu, & Linn, 2015). Two main types of scaffolding may be particularly beneficial for students who are learning about complex systems. First, *ontological support* in the form of explicitly teaching about components may help students to deepen their understanding from simulations. Ontological scaffolding benefitted students using simulations to learn about electricity as an emergent process (Slotta & Chi, 2006). Providing ontological scaffolding before using a simulation may help students to better recognize and understand complex systems components. Students may create “conceptual rigging” (Goldstone, 2006, p. 41) to help them correctly interpret what they experience during the simulation. The practice of looking for and recognizing these specific components may help students to create more complete and distinct categories of systems, and possibly to transfer this understanding to a new situation.

Second, *self-monitoring* scaffolds, which assist sense making; process management; and reflection, may also benefit students by helping them manage a complicated amount of information during the simulation. Students must attend to both micro-level actions, shifting interactions, and the often invisible and time-delayed effects these have. Self-monitoring scaffolds may help students more effectively plan and guide their investigations (Sandoval, 2003) and reflect on what they are learning (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Recker & Pirolli, 1995).

Creating support for students to manage and guide learning in a complex environment may help students to better deal with the difficult content they are learning. Therefore appropriate scaffolding is crucial (Hmelo-Silver, Duncan, & Clark, 2007), both to help students create categories for complex systems components and to recognize them, as well as to help them manage the large amount of complex information they must process. Designing effective scaffolding for complex systems has nevertheless proven difficult. In a study using NetLogo simulations and a hypermedia system with ontological scaffolding, students made some gains in understanding complex systems, yet differences between scaffolding conditions were largely mixed (Jacobson et al., 2011). Students who were able to use the scaffolding to develop ontologies about complex systems performed better. However, not all students benefitted from the scaffolding. Research is needed to investigate what kinds of scaffolds may be beneficial for learning about complex systems with simulations.

Purpose

While research into complex systems understanding has been done within confined ecological environments such as aquaria (Hmelo-Silver, Marathe, et al., 2007), little research has examined larger ecosystems (Assaraf & Orion, 2005; Eilam, 2012; Grotzer et al., 2013). More importantly, there have been no investigations on simulations that allow students to take part in an ecosystem as agents or to observe how people interact with and affect these systems. Another limitation is that the majority of research on student understanding is at the secondary level (Chi, Roscoe, Slotta, Roy, & Chase, 2012; Grotzer et al., 2013; Hmelo-Silver, Duncan, et al., 2007; Wilensky & Stroup, 1999). Both Hmelo-Silver, Marathe, & Liu (2007) and Jacobson (2001) have shown that even adults hold alternative understandings and novice ways of thinking about complex systems. There has only been one study with mixed results (Jacobson et al., 2011) showing whether older students can enrich their ontological understanding of complex systems or for which components alternative understandings are more robust (Jacobson, 2001). A better understanding of how adults in post-secondary education and beyond view complex systems is therefore needed. Finally, scaffolding approaches to date are not explicit about categories of complex systems, and do not address far transfer. Therefore the research questions of this study are the following:

1) Can interactive instruction using an agent-based participatory simulation of the Chesapeake Bay watershed improve student understanding of complex systems?
    a) For what components of complex systems (e.g., decentralization, nonlinear action effects, and Agents) do students demonstrate improved or limited understanding?
    b) Can students transfer their understanding of complex systems to another context of architecture?

2) How does ontological scaffolding versus self-monitoring scaffolding during instruction using an agent-based participatory simulation of the Chesapeake Bay affect student understanding of complex systems?
   a) How does understanding of complex systems components compare for students receiving ontological scaffolding versus students receiving self-monitoring scaffolding?
   b) How does the ability to transfer understanding of complex systems to another context of architecture compare for students receiving ontological scaffolding versus students receiving self-monitoring scaffolding?

If students are able to able to improve their complex systems understanding through an agent-based participatory simulation, this study may illuminate more effective ways to teach complex systems. Whereas previous studies have shown promise with agent-based models, a participatory simulation that allows students to take the role of agents in the system might facilitate understanding of concepts such as self-organization, emergence, and non-linear effects. Second, by having concepts scaffolded before their experience with the complex system, students will practice recognizing and perceiving complex systems components, and thus may be better suited to perceive these components in other systems. Thus this instructional approach may point to a possible way to improve students' far transfer of complex systems understanding.

CHAPTER 2: LITERATURE REVIEW

This chapter begins with an overview of theories of conceptual change that guides the study. Second, a review of complex systems and their components provides an overall picture of expert understanding. Third, a closer examination details why these components are difficult to learn and presents an ontological categories framework with which to understand student understanding of complex systems concepts. Fourth, this chapter reviews studies of simulations that have illuminated both the promise and difficulties in teaching these concepts to students. Finally, an overview of scaffolding provides insight into how to help students learn about complex systems concepts through the use of simulations with ontological and self-regulatory (self-monitoring) support.

Theoretical Framework

To understand how to improve student understanding of complex systems, I use a conceptual change framework. Conceptual change refers to learning as building new ideas in the context of old ideas (diSessa, 2006). Many existing approaches try to capture and describe how conceptual change happens in learners (diSessa, 2006; Posner, Strike, Hewson, & Gertzog, 1982; Vosniadou, 2009). One approach posits that children have *coherent theories* with which they make sense of the world (C. W. Anderson & Smith, 1987; Vosniadou, 2002). For example, when children reason about the shape of the earth, they may begin with simple models which they adjust to cohere to more accepted adult models (Vosniadou & Brewer, 1992). The main focus of coherent theories is that they are largely not context specific and focus on larger grain sizes. Another approach, *Knowledge in Pieces*, asserts that knowledge consists of highly contextualized and fragmented elements called P-prims (diSessa, 1988, 1993, 2006) that are elicited in response to different situations. Instead of having overarching models that organize knowledge, a knowledge-in pieces perspective holds that these elements apply in highly contextualized situations.

A third approach posits that real difficulty in learning happens when learners conceive of processes across ontological kinds (Chi, 2005). Learners do not just have incorrect details about a concept, but misunderstand it at a deeper, ontological level. For example, Chi proposed that there are direct processes such as blood flow where movement is directly caused by movement of the heart, and emergent processes, such as diffusion, where movement is explained by the interactive outcomes of all components (i.e. both dye and water molecules) (2005). Robust misconceptions occur when students conceive of diffusion as a direct process similar to blood flow, giving diffusion the properties of this incorrect ontological category (Chi, 2005).

A final approach considers all learning as a process of transfer (Bransford & Schwartz, 1999; National Research Council, 2000). This approach asserts that although content knowledge is important and necessary, it is not sufficient for learning. Instead of just remembering disconnected facts, learners must apply this understanding to new contexts, beyond those in which they learned the concepts (National Research Council, 2000). When students are able to solve novel problems, they will have shown evidence of transfer.

The conceptual change approach that guides this study aligns largely with Chi's research on ontological kinds as well as Jacobson's research describing novice and expert differences across ontological categories (Jacobson, 2001; Jacobson et al., 2011). This is reflected in the study's focus on specific complex system components and ontological differences between types of systems. Finally, the importance of transfer influences the design of this study through the investigation of student understanding of ontological categories outside the domain in which they are learned.

Complex Systems

A system is an interconnected set of elements organized in a way that achieves something (Meadows, 2008). There are many kinds of systems, and for the scope of this study we will deal with only two kinds of systems: Clockwork and Complex Systems. Clockwork systems refer to complicated systems that have multiple elements with set roles, and whose interactions do not change. Examples of clockwork systems are clocks, airplanes, and computers. Complex systems vary in nature, but overall can be described as systems without central control that follow simple rules, give rise to complex behavior, and adapt through learning or evolution (Mitchell, 2009). Elements or components in complex systems self-organize. Through non-linear interactions, the system shows emergent and complex properties not exhibited by the individual elements (Jacobson, 2001). For example, in traffic jams, cars move according to their own individual goals to reach their destination. As drivers self-organize and switch lanes, hoping to choose a faster path, cars behind them brake and this accumulating braking action spreads backwards to the rest of the cars. As cars move ever more slowly forward, the traffic jam itself emerges and spreads backwards (Resnick, 1996).

Many of today's most pressing problems involve recognizing and understanding complex systems. Whether trying to understand how to address the declining health of ecosystems, how to improve communication or delivery networks, or how to understand and stop the spread of diseases, a complex systems lens is needed if actions are to be effective (Meadows, 2008).

Complex Systems vs. Clockwork Systems

In the following section, I outline the differences between complex systems and clockwork systems. To understand complex systems and student perceptions, it is necessary to know which components are important in defining these systems and therefore the components that students may confuse across ontological categories. While categories are discussed below as distinct, several studies have assessed students' overall understanding of these components as reflecting complex systems understanding (Goh, Yoon, Wang, Yang, & Klopfer, 2012; Yoon, 2008, 2011). Furthermore, learners may not hold distinct or mutually exclusive understandings of these components.

Understanding

The first important difference between clockwork and complex systems is that clockwork systems are reductive or, the sum of their parts. For example, the overall functioning of a clock can be understood by looking at its gears and inner parts. One can predict what the clock will do and how it will function based on the fixed relationships and interactions between these parts. In contrast, in a complex system, the system is non-reductive. For example, within ecosystems, patterns of weather emerge and although we understand the parts and how they interact, we cannot predict the macro outcomes from an understanding of the individual parts. Because of these emergent outcomes, we can neither fully predict how the system will change nor can we see these larger system properties from just the parts. Similarly, by looking at the individual cars in a traffic jam the larger phenomenon of the traffic jam is not observable.

Action Effects

One of the reasons it is difficult if not impossible to predict the macro outcomes of complex systems is because parts within systems often have non-linear effects on other parts of the system. In this way, small actions may lead to large effects, often called the Butterfly Effect. This idea was first popularized by Ray Bradbury in 1952 and the term was coined by Edward Lorenz in 1963. It means that changes in one part of a system may have unpredictable and non-proportional effects in other parts of the system. In contrast, within clockwork systems, effects are proportional and small actions have small effects with no potential for non-linear effects. Complex systems have linear effects as well, but one of their defining features is the potential for non-linear effects.

Order

Within a complex system like an ecosystem, order is decentralized and arises from the interactions within the system. Organisms within an ecosystem make their own individual choices and from these choices and interactions between micro parts, order arises in the system. In contrast, in a clockwork system, order is either centralized within the system, or an external agent imposes order. In man-made machines, order is designed into the system. In companies, order is centralized in a top-down manner where employees (agents, defined as single actors within the system) are controlled by a central authority through levels of rank (e.g. chain of command).

Causes

In complex systems, effects have multiple causes whereas in clockwork systems, causes are singular. For example, in a car, the same components will always interact and cause the desired behavior (unless the system malfunctions): when a brake pedal is pushed, the brake pad will clamp down on the tire and cause the car to stop. Even if there are multiple parts, the cause is still the same. Within a complex system, a variety of causes may give rise to a macro behavior. There may be cyclic causality, where a cause can be an effect and vice-versa (Grotzer, 2012). Cyclic causality may involve feedback loops that reinforce a behavior such as in symbiotic relationships within ecosystems.

Agent Actions/Adaptation

Within clockwork systems, agents' actions are not predictable. In an ecosystem we may know that bears will eat fish, but we do not know which fish, or if one day the bears might choose a different species of fish. Further, because agents can adapt as their environment changes, we cannot predict which parts will interact as the system changes. Perhaps if fish become scarce, bears will begin eating squirrels. In contrast, within clockwork systems, agent actions are predictable and non-adaptive. We can predict which parts will interact because this is designed into the system. Because parts do not adapt, these systems are vulnerable to failures of parts. If a gear breaks in a clock, the whole clock ceases to function. Because of this vulnerability, backup measures are often built into clockwork systems such as emergency brakes, or extra engines on airplanes.

Purpose

The purpose of complex systems is non-teleological. This means that parts within the system are not acting in order to create the system but out of local goals and desires.

In ecosystems, bears do not eat fish because the ecosystem will function better but because they have their own needs to consume energy. Clockwork systems have a teleological end purpose to their existence. The parts are assembled and the system is designed to accomplish a larger goal. The parts exist for the system. This can be seen in the anecdote that the main function of a bureaucracy, an example of top-down centralized control, is to perpetuate itself.

Processes

Finally, complex systems are composed of processes that do not have distinct beginning or end points (Grotzer, 2012; Meadows, 2008). Although relationships and interactions may be determined, they do not have starting points. In clockwork systems, interactions can be described as static events that exist in an order (Grotzer, 2012; Jacobson et al., 2011). For example, a person winds a clock, and then one gear turns another, which turns another, which turns the minute hand. Although parts may function simultaneously, these interactions can be broken down into static events.

Complex Systems Learning Difficulties

This section describes alternative and inaccurate ideas that people have about complex systems, examines why properties of complex systems are so difficult to learn, and then explores the importance of ontological categories.

Alternative Ideas & Biases

Learners of all ages have alternative ideas about complex systems that indicate they see complex phenomena incorrectly as clockwork systems. People believe evolutionary changes are acquired and passed through trait use, such as giraffe necks becoming longer because they are stretched during life (Bishop & Anderson, 1990); that ant colonies are directed by leaders (Resnick, 1996); that chemical reactions stop at equilibrium (Stieff & Wilensky, 2003); or that electricity is a substance (Chi, 2005). Students also tend to assume explanations that involve central control and deterministic causality (Wilensky & Resnick, 1999) and to resist explanations that invoke self-organization, random, or decentralized processes (Feltovich, Spiro, & Coulson, 1989; Resnick, 1996; Wilensky & Resnick, 1999).

Although alternative ideas probably arise from multiple sources of difficulty (diSessa, 2006), a large cause might be due to our intuition and common beliefs, which complex systems often contradict. In general, learners' intuitive knowledge of natural phenomena can clash with scientific explanations of phenomena and these intuitive ideas tend to be robust and resistant to change (Vosniadou & Brewer, 1992). Learners' prior experience can often lead to a misunderstanding of complex systems (Feltovich et al., 1989). One example is the centralized-deterministic mindset, where having experience with top-down systems can lead learners to assume the same top-down control for all systems (Resnick & Wilensky, 1998). Because complex systems are bottom-up systems with decentralized control, students who assume the presence of leadership will misconceive the system and its qualities. Another example is that students often believe that there is a linear relationship between the size of an action and the subsequent effect (Casti, 1994) because they often encounter linear relationships in the world.

Explaining complex systems by applying ideas from clockwork experiences can create alternative ideas. Because of biases such as centralized control (Resnick, 1996) students cannot simply observe to create deeper understanding. Students also do not recognize or consciously experience complex systems on their own, and thus do not create analogs from which to reason about complex phenomena (Abrahamson & Wilensky, 2005; Goldstone & Wilensky, 2008). Therefore, when students begin learning about complex systems, they often start with a base of alternative ideas that may lead them to make incorrect assumptions.

Novices may incorrectly perceive complex systems as clockwork systems because they focus on the more tangible and superficial features shared by both systems. Studies of novice middle school students' understanding of aquaria compared to experts' understanding have found that novices focus on the visible structural features of systems, while experts are able to focus on the behavioral and functional features as well (Hmelo, Holton, & Kolodner, 2000; Hmelo-Silver, Marathe, et al., 2007; Hmelo-Silver & Pfeffer, 2004). One study by Hmelo-Silver, Marathe, and Liu (2007) examined students' mental models for a circulatory system as well as aquaria. Results demonstrated that novices focused on the visible structure, because the dynamic and invisible processes of behavioral mechanisms were difficult to comprehend. In contrast, experts understood relationships between parts of a system, could articulate how emergent properties arise, and used an understanding of complex systems to think about the system as a whole (Hmelo-Silver, Marathe, et al., 2007). In other words, knowing the function and behavior of a system means more elaborate understanding of the interrelationships in the system and a better understanding of the type of system.

In complex systems, causality is often both time-delayed and invisible (Feltovich, Spiro, Coulson, & Adami, 1994; Grotzer, 2012). When something happens at one part of an ecosystem, it is not obvious where the original cause of the behavior originated. For example, a fish die-off might occur from runoff from a factory on the shore, or from a farm upstream that has slowly been adding nitrogen runoff to the river. Because of the time-delayed and invisible nature of many complex systems, behavior can be the hardest part for students to understand in a system (Hmelo et al., 2000).

Complex systems have multiple levels, such as the micro level, where parts interact, and the macro level, where overall system behavior can be observed. Alternative ideas about levels in complex systems are especially pernicious, because misunderstanding at one level can have adverse effects on understanding at other levels (Chi, 2000; Feltovich, Coulson, & Spiro, 2001). Level slippage (confusion between levels) is responsible for many deep misunderstandings about phenomena in the world (Wilensky & Resnick, 1999), and to understand complex systems students need to be able to shift through levels. Further, these multicomponent phenomena are extremely taxing for working memory. Students must be able to process simultaneous interactions that are often invisible, time delayed, and dynamic while working against assumptions gathered from their everyday experiences (Feltovich et al., 2001). Often, behavior at multiple levels may not be similar, and even when students understand micro and macro relationships they wrongly place causes within the system at the macro level (Penner, 2000, 2001). For instance, if a student sees an orderly line of ants, they may assume from this macro behavior that the ants are being directed and then make untrue assumptions about these micro parts. The organized line may suggest that the ants are themselves following orders or have a preference for whether the overall pattern (the line) exists, which they do not.

Ontological Categories

Finally, studies suggest that creating separate and distinct ontological categories for complex systems can help students develop deeper understanding about complex systems (Slotta & Chi, 2006). Students may misconceive complex systems as having incorrect properties because systems are understood by their membership within a generic system category that more accurately represents clockwork systems. Thus concepts inherit features of categories and concepts that are categorized into the wrong ontological category may wrongly take on the attributes of that category (Chi, 2005; Chi & Roscoe, 2002). For example, if a student believes that electricity is a substance instead of a process, he would believe that electricity can be stored in a battery since physical presence or mass is an attribute of a substance (Chi & Roscoe, 2002). Students who incorrectly attribute characteristics of categories fundamentally misunderstand the concepts.

Because students may not consciously encounter and experience complex systems at multiple levels, or correctly make connections between levels, they may lack a category for these systems and their emergent processes. Without an emergent category, students may have difficulty conceptually shifting complex systems' concepts into a correct category, making these misunderstandings robust (Chi, 2005; Chi & Roscoe, 2002). Simply telling a student of the existence of the category or its properties may not be enough to create this new concept. Emergent categories have interactions which are uniform, simultaneous, independent, continuous, and decentralized; while causal categories have interactions that are distinct, sequential, dependent, finite (meaning they terminate), and global (Chi & Roscoe, 2002). While a student may look at a list and see that categories are different, the learner may still not be able to make meaning. As discussed above, to understand an element such as emergence, students must attend to the collective interactions, and focus on the overall consequence of these interactions across time (Chi & Roscoe, 2002).

Studies show differences in how novices and experts construct solutions to complex system problems (Jacobson, 2000, 2001). Novices fail to use the correct ontological category by trying to make sense of an emergent process using a causal (or direct) category. This domain-general explanation of misunderstanding, where students categorize across ontological kinds, means it may be helpful to teach students about the causal structure that underlies emergent processes. Such an approach may enable students to recognize a variety of emergent processes (Chi, 2005). Novice ontological miscategorization can also help explain why alternative ideas are robust and how an instructional intervention that generalizes across domains might be effective (Chi, 2005).

Some research points to ways to effectively convey these system categories. Slotta and Chi (2006) found that directly teaching students about schemas led to increased learning about diffusion. In a subsequent study that explained ontology and emergent processes, students created deeper understandings of electrical current (Chi et al., 2012). Addressing students' ontological and epistemological beliefs is important because they may constrain (or aid) learners' ability to understand certain higher order concepts (Chi, 2005; Vosniadou, 1994; Vosniadou & Brewer, 1992). By definition, novices need to undergo radical conceptual change, and require curricula drawing attention to the network of beliefs and alternative ideas they have about the world that conflict with complex understandings (Jacobson & Wilensky, 2006).

In sum, to understand a complex system, students must correctly recognize and understand the behaviors of a variety of components that make up the system. This study's intervention conditions first aims to focus students on the more fundamental aspects of complex systems. A second goal is to help students recognize complex systems when they encounter them and correctly identify which type of system—complex or clockwork—they are investigating. It does not help students to theoretically know what a complex system is, and how it works, if they continue to miscategorize systems because they do not recognize them. This difficult cognitive task represents far transfer, where learners recognize underlying principles and are able to apply this understanding to new domains. To do this, students need to practice "building an interpretation" (Goldstone, 2006, p. 40) where their prior experience influences their perception and enables them to generalize by "rigging up a perceptual system to interpret a situation according to a principle, leaving this rigging in place for subsequently encountered situations" (p.41).

Simulations: Current Approaches & Studies

Computer modeling and computer-assisted instruction have facilitated progress in some of science's most difficult issues, including complex systems (Wilensky & Resnick, 1999). Simulations, or computer-based representations of phenomena, have engaged students to explore multi-level thinking, and studies have used simulations to allow people of all ages to engage in difficult topics, such as multilevel thinking and the concept of emergence (Wilensky & Resnick, 1999), as well as difficult causal issues within ecosystems (Grotzer et al., 2013).

The next section reviews two main strands of research that use simulations or computer-based instruction to help learners understand complex systems. One area of complex systems research uses simulations and agent-based models to help students understand complex systems with visualizations. A second area of research has used agent-based models in a variety of countries to help stakeholders better understand the complex systems they operate in, facilitate participation among these agents, and shape policy.

Agent-Based Models and Participatory Simulations in Education

Several classroom-based studies of computer-simulated learning environments demonstrate that simulations can help middle school through undergraduate-age students learn about complex systems. Studies have used agent-based models (e.g. NetLogo, StarLogo), where students are able to manipulate parameters and observe resulting micro-level interactions (Abrahamson & Wilensky, 2005; Colella, Borovoy, & Resnick, 1998; Resnick & Wilensky, 1998; Wilensky & Stroup, 1999); immersive simulations (e.g. EcoMUVE), where students move around in virtual environments (Grotzer et al., 2013); or participatory simulations (e.g. HubNet, Thinking Tags), which allow students to interact with each other in virtual worlds (Colella, 2000; Wilensky & Stroup, 1999). Studies typically target two forms of reasoning: *agent-based reasoning*, where students reason about properties and behaviors of elements within a system, and *aggregate reasoning*, where students reason about the properties and behaviors of the macro system (Levy, Kim, & Wilensky, 2004; Stroup et al., 2002). The next section discusses studies with several prominent agent-based and participatory simulations.

NetLogo/StarLogo. The first educational studies of computer-simulated complex systems such as traffic jams and ant behavior were conducted with an agent-based modeling program called StarLogo (Resnick & Wilensky, 1993). Although research demonstrated that students' decentralized thinking increased after experience with the simulation (Resnick, 1996), students often reverted to previous ways of thinking about complex systems when they applied their understanding to novel situations (Jacobson & Wilensky, 2006).

From these initial studies, Wilensky (1999) developed Net Logo, an agent-based modeling suite of simulations that allows students to manipulate complex systems. NetLogo allows students to actively manipulate elements at the micro-level and to observe the emergent effects of those manipulations at both the micro and macro levels (Jacobson & Wilensky, 2006). The agent-based approach has proven effective in many disciplines, where students demonstrate enhanced complex systems understanding after (1) exploring chemical reactions derived from behavioral rules of individual molecules (Stieff & Wilensky, 2003); (2) creating and testing individual-level models of predator-prey interactions (Wilensky & Reisman, 2006); (3) figuring out probability distributions from rules of elements (Abrahamson & Wilensky, 2004); and (4) deriving the ideal gas law from observing micro interactions (Wilensky, 2003; Wilensky, Hazzard, & Froemke, 1999). NetLogo simulations and accompanying curricula were designed to focus student attention on making connections between levels and understand emergent properties (Wilensky & Resnick, 1999).

ACT Model. The ACT project teaches middle school students about complex systems through aquaria using the Aquarium Construction Toolkit (ACT) (Vattam et al., 2011). The toolkit uses a Structure, Behavior, and Function focus of complex systems and allows students to design systems. *Structures* are how parts are physically related in a system, *Behaviors* are how parts are able to act, and *Functions* are the roles of these parts (Hmelo-Silver & Pfeffer, 2004) Previous research has shown that students have difficulty understanding the causal behaviors and functions of complex systems (Hmelo et al., 2000; Hmelo-Silver, Marathe, et al., 2007; Hmelo-Silver & Pfeffer, 2004). The ACT environment allows students to interact with a complex system and focuses their attention specifically on what is occurring at the structural, behavioral, and functional levels. Students are able to create models and make connections between parts of the system and label how they interact. Researchers report that students are also able to make connections between different levels of abstraction within the system (Hmelo-Silver, Jordan, Eberbach, Rugaber, & Goel, 2011) and express more behavioral and functional components of the system (Goel et al., 2010, 2013; Sinha et al., 2010; Vattam et al., 2011), which are signs of more expert thinking about complex systems. There is also some evidence that teaching complex systems with Structure, Behavior, and Function modeling in the ACT environment focuses students on the invisible components of complex systems as well as non-linear relationships (Honwad et al., 2010). Future research is now being done using MILA-S, a system that combines both the ACT modeling system and NetLogo to bridge the causal model students create with a NetLogo simulation (Joyner, Goel, & Papin, 2014).

EcoMUVE. The EcoMUVE project addresses issues with causal reasoning, which can cause learners to misconceive the properties of complex systems (Grotzer, 2012). EcoMUVE was designed by researchers at Harvard and is a multiuse virtual environment (MUVE) that allows students to explore two different ecosystems. For example, in one of the simulations, a fish die-off occurs and students are tasked with investigating the causes of the event. Students are given tools to explore and change both the microscopic level in the system as well as to explore the macroscopic environment because emergent features of complex systems occur across levels (Wilensky & Resnick, 1999). Learners are also able to move forward and backwards through time to experience the non-linear interactions that are important to the ecosystem. Research suggests this learning environment not only shifts students' causal understanding from more novice, event-based causes to more expert, process-based causes (Grotzer et al., 2013) but increases their ecosystem understanding (Metcalf, Tutwiler, Kamarainen, Grotzer, & Dede, 2013). While students participate by exploring within the environment of a complex system, they do not take the role of agents within the system, however.

HubNet. Only a few studies have explored agent-based participatory simulations to aid complex systems understanding. An early example is HubNet (Wilensky & Stroup, 1999), which allows students to take the roles of the micro-parts in complex systems in a variety of NetLogo simulations (Wilensky & Stroup, 2000a). For example, students can act as traffic lights trying to control gridlocked traffic with each student as a node in the system (Wilensky & Stroup, 2000b). In another activity, students take the role of molecules to better understand the interaction and movement within gases. These initial experiments suggested role-playing activities were both engaging and helpful for students, yet only anecdotal evidence was collected (Wilensky & Stroup, 2000a). HubNet is one of the first simulations where students can become agents participating in the model to experience how their micro actions turn into macro outcomes. The simulation has not been studied or updated in over a decade, however.

Thinking Tags. As computers have become smaller, technology has helped facilitate the participatory nature of simulations by making them mobile. One of the first mobile participatory simulations was created at MIT and involved the use of Thinking Tags (Colella et al., 1998). Thinking Tags are wearable, programmable devices that use infrared communication to make students agents within the simulation (Colella, 2000). For example, students can model the spread of a virus by becoming agents in the system. In one study, students used Thinking Tags as public displays to project students' beliefs while talking about genetic engineering (Yoon, 2008). Grade 9 students learned about the content of evolution while simultaneously using an evolutionary approach to understand complex systems. Methods included promoting variation, selection and interaction of ideas to help student ideas evolve. Through taking the roles of agents in this system, students both successfully functioned as a complex system as well as shifted their understanding of systems from clockwork to complex (Yoon, 2008).

These foundational studies highlighted several important factors for participatory simulations. First, results demonstrated that students were able to discuss, hypothesize and then test their ideas about the underlying system they represented (Colella, 2000). Second, students were able to create a shared and meaningful experience through the participatory experience. Third, students had different experiences within the simulation, and by making understanding overt and aggregating these different experiences, the simulation helped students collectively construct group understanding. Collaborative learning was accomplished through positive interdependence and by promoting interactions and group processing (Klopfer, Perry, Squire, & Jan, 2005).

Overall, participatory simulations can help learners visualize abstract concepts associated with complex systems (Wilensky & Stroup, 2000a) as well as directly experience what happens in a system (Colella et al., 1998). Through direct experience or modeling of the system, learners can develop understanding of the assumptions and develop connections between micro and macro behaviors (Wilensky & Resnick, 1999). Simulations can also serve as a shared representation that facilitates development of shared understanding and collaborative learning (Yoon, 2008). Although these simulations are a powerful way of allowing students to interact with complex systems, understanding and transferring understanding of complex systems has proven difficult (e.g. Grotzer et al., 2013; Jacobson, et al., 2011). Even though students may be able to develop more expert process-based explanations of causality, students still hold many alternative, incorrect ideas, such as focusing on event-based responses when explaining causality in complex systems (Grotzer et al., 2013; Hmelo-Silver, Marathe, et al., 2007).

Stakeholder Modeling

Research on agent-based participatory simulations of complex systems also models the actions and interactions of human agents and stakeholders to inform policy makers within complex systems (Pahl-Wostl, 2002). These simulations take a variety of approaches from using computers to complex board games to model systems. Simulations such as SAMBA-Week (Boissau & Castella, 2003), CORMAS (Bousquet, Bakam, Proton, & Le Page, 1998), and MAS (Bousquet & Le Page, 2004) allow stakeholders and policy makers to test their assumptions and use experiences to discuss and help guide policy making (Learmonth Sr. & Plank, 2015). Stakeholder modeling simulations can also be used to facilitate a shared and iterative decision-making process for creating resource management policy (D'Aquino, Le Page, Bousquet, & Bah, 2003). Studies using stakeholder simulations are discussed next.

Sylvopast. Sylvopast is a Role Playing Game as well as a Multi-Agent Simulation that was originally used to represent farmers and foresters as agents in southern France (Etienne, 2003). The simulation uses a companion modeling approach where stakeholders are interviewed and the variety of viewpoints are used to build a shared model. Over 32 games have been run and Sylvopast has been adapted to model fire hazards on the edge of forests (e.g. NimetPaLeFeu), as well as phenomena such as water usage, pollution, and disease in a village (e.g. AtollGame Simulator) (Barreteau, Bots, & Daniell, 2010). In all of these studies, stakeholders gave input throughout the iterative development process and simulations were used to increase knowledge, facilitate effective policy making, and support communication among actors.

Shadoc. Shadoc is a hydro-agricultural multi-agent simulation originally designed as a tool for simulating different scenarios around irrigation (Barreteau & Bousquet, 2000). Shadoc was created to allow learning by simulating instead of learning by doing, so institutions can test hypotheses before implementing them in the real world. Shadoc has had several experiments in the Senegal River Valley (Barreteau, Bousquet, & Attonaty, 2001; Daré & Barreteau, 2003; Lynam et al., 2002) as well as Thailand and the Philippines (Barreteau & Bousquet, 2000). The multi-agent simulation was designed with a companion modeling approach that allows input from stakeholders in the model. By discussing the assumptions of the model, stakeholders can (a) decide if their assumptions match the model's, (b) possibly alter their choices, and (c) use the model's outcomes during negotiation (Barreteau et al., 2001). From several case studies, researchers posit that as an agent-based model, Shadoc facilitated a common understanding of a problem because it was developed with and incorporated multiple viewpoints (Lynam et al., 2002). The model became a shared representation of a problem, which in turn facilitated negotiation. Through several implementations, researchers have also learned that participants in workshops have sensitivities to social hierarchies and these sensitivities affect their openness to participate in gameplay (Barreteau et al., 2001). Further, it is extremely important that the methodology of game development through involvement of stakeholders leads to an acceptance that the role-playing reality represents stakeholders' own social reality, which researchers confirmed through interviews (Daré & Barreteau, 2003).

CORMAS. CORMAS (COmmon-pool Resource and Multi-Agent System) is a multi-agent framework that has been used to simulate the interactions of a group of agents within a shared environment (Bousquet et al., 1998; Le Page, Becu, Bommel, & Bousquet, 2012). From this underlying framework, many scenarios can be built on top of it, such as herd mobility in Sahel (Bousquet, Barreteau, Le Page, Mullon, & Weber, 1999); fuelwood consumption and landscape dynamics in Burundi (Le Page, Bousquet, Bakam, Bah, & Baron, 2000); pine encroachment in southern France (Etienne, Le Page, & Cohen, 2003); and an irrigation water simulation in Bhutan (Gurung, Bousquet, & Trébuil, 2006). All simulations are based around natural resource management. Implementations often begin with a role playing game that stakeholders use to decide on rules for the system before constructing the computerized multi-agent simulation, which stakeholders then validate (D’Aquino et al., 2002).

A large focus of the CORMAS framework has been in companion modeling as illustrated in the Bhutan application (Gurung et al., 2006). In Bhutan, stakeholders were conflicted over water resources and a model was built to represent the situation. Stakeholders were invited to participate in a role-playing game and then semi-structured interviews were conducted to find out if the game represented their reality and what would need to be modified. This information was then used to create a multi-agent simulation using the CORMAS framework and several scenarios were proposed and tested with participants. Surveys showed that farmers felt the model was representative and that it helped them better understand the benefits of sharing water (Gurung et al., 2006). They also found that the model effectively facilitated discussion among the players, as well as increased knowledge and understanding of water sharing. Some participants even used information from the gameplay to alter when they released water. This goal of companion modeling was also labeled Self-CORMAS and further involved participants in earlier design stages so that the agent-based simulation could best serve as a mediating support for dialogue (D’Aquino, Le Page, Bousquet, & Bah, 2003).

Scaffolding Understanding of Complex Systems

Several computer-based simulation studies demonstrate that with the right guidance, students are able to develop a more sophisticated understanding of complex systems (Stieff & Wilensky, 2003; Vattam et al., 2011). In addition, role-playing participatory simulations can also increase awareness and understanding of different perspectives and stakeholders (Barreteau et al., 2001; D’Aquino et al., 2003). Although simulations offer powerful visualizations of complex processes and phenomena, students continue to encounter difficulties in learning about complex systems (Grotzer et al., 2013; Jacobson et al., 2011). Taken together, these studies point to a need to support individuals when learning about complex systems using simulations.

Scaffolding

Definition and History

Scaffolding is both a noun that refers to structures that are tailored to help learners until they can produce the behavior on their own, and a verb referring to the process of using scaffolds in a learning activity until independent performance is achieved (Pea, 2004). Scaffolding is the just-in-time support that allows students to gain skills in problem solving which unaided, would have been beyond their ability. Introduced by Wood, Bruner, & Ross (1976), its original conception referred to the scaffolding that occurs in the world in everyday learning situations between parents and their children, or between experts and novices; such situations are neither formal nor designed. Since this inception, the term *scaffolding* has been used for an increasingly diverse amount of applications with a large range of scaffolding types (Pea, 2004). Scaffolding is also increasingly used to refer to features of computer programs and less often for one-to-one scaffolding (Puntambekar & Hubscher, 2005).

Although not originally informed by Vygotsky, scholars have since used the zone of proximal development to inform and specify effective scaffolding, including through incorporating the learner’s need for social interaction into scaffolding (Pea, 2004). The Zone of Proximal Development represent the boundaries of activity within which a learner can succeed at a task when under more capable guidance (Vygotsky, 1978).

Scaffolding helps span the distance between a child's current ability level, and that which he or she can achieve but only with help.

Scaffolding is a critical component of student learning (Chi, De Leeuw, Chiu, & LaVancher, 1994; Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001) that makes accessible and manageable many topics that students would be unable to learn on their own. Scaffolding also makes learning more efficient (Hmelo-Silver, Duncan, et al., 2007). Good scaffolding shows students how and why to do individual tasks (Hmelo-Silver, 2006), by helping motivate them to understand why a task is important while reducing cognitive load created by their lack of procedural knowledge (Sweller, 1998). It includes diagnosis, calibrated support, and individualization. Support may consist of pre-stocked questions, dynamic support that adapts to student understanding, or tools that guide student thinking (Azevedo & Hadwin, 2005). By structuring tasks to focus students on those that are relevant to learning goals, scaffolding helps reduce cognitive load by removing distractions and reducing non fruitful pathways (Salomon, Perkins, & Globerson, 1991).

Scaffolding works by "enlisting student interest, controlling frustration, providing feedback, indicating important task or problem elements to consider, modeling expert processes, and allowing questions" (Belland, 2014, p. 507). These mechanisms help to engage and focus students by reducing cognitive load, and correcting mistakes while also demonstrating correct procedural knowledge. Reiser (2002, 2004) characterized scaffolding as having two competing mechanisms: structuring and problematizing. *Structuring* guides and supports learners in planning and performance to make learning easier, while *problematizing* helps shape performance and understanding by pointing students to important content and creating conflict, if needed, with current student beliefs.

Despite the broad usage of the term scaffolding, it is meant to differ in several ways from simple aids like calculators. First, scaffolding both simplifies and highlights complexity instead of just simplifying or facilitating a procedure (Belland, 2014). Relatedly, scaffolding can address complex knowledge and processes instead of just simple procedures because more knowledgeable mentors or computer-based instruction typically enact scaffolding. Within Computer Based Learning Environments (CBLEs) scaffolding is defined as “a layer of supportive features that lies on top of software and that acts on learners directly and straightforwardly” (Quintana et al., 2004, p. 341).

Some controversy exists over whether fading, defined as the removal of support as students learn, is necessary to be considered scaffolding (Belland, 2014; Pea, 2004), or whether some scaffolds support critical thinking and active learner engagement while not being removed. Technology scaffolds have become more prevalent in learning situations and are not always expected to be removed (Puntambekar & Hubscher, 2005). In this study, scaffolding is considered as supports for learning and do not necessarily fade over time.

Benefits

Research on scaffolding indicates many benefits for learners. Scaffolding can help build critical thinking skills, support student engagement in active and complex processes such as scientific inquiry, and allow mentors to teach students to use critical thinking abilities instead of just lecturing the content before a task (Linn, 2000). Scaffolding has been used for a variety of learning goals in CBLEs. It has been applied to improving higher order thinking abilities (Wood et al., 1976); content understanding (Azevedo, 2005; Linn, 2000); and metacognition (Azevedo, 2005; Quintana, Zhang, & Krajcik, 2005). Scaffolds for learning also improve skills such as argumentation (Belland, Glazewski, & Richardson, 2008), and motivation (Belland, Kim, & Hannafin, 2010).

Computer-based Scaffolding

For the past 20 years or so, computers and simulations have been proposed as a way to scaffold learning difficult topics. For example, science visualization technology was expected to aid learning through scientific inquiry (Edelson, Gordin, & Pea, 1999). Many have argued that software can support learning by providing structure for difficult tasks (Guzdial, 1994; Toth, Suthers, & Lesgold, 2002) and that learners could engage in activities that share key features of expert practice yet are either simplified or aided in such a way that they are carrying out key parts of the process (Lave & Wenger, 1991). In a push for science inquiry, facilitated with computer-based technology, Roschelle and colleagues (Roschelle, Pea, Hoadley, Gordin, & Means, 2000) argued that technology could aid fundamental characteristics of effective learning, ranging from active engagement including participation in groups and frequent interaction and feedback, to increased connections to real-world contexts.

Scaffolding Difficult Concepts

In the following section I discuss the problem of scaffolding in ill-structured environments. Studies demonstrate that differences in student outcomes can be attributed to scaffolding and how the scaffolding helps (or does not help) students learn from simulations (Honey & Hilton, 2011; Linn & Eylon, 2011). Given the difficulty of complex systems, scaffolding is crucial to help students learn about complex systems from simulations.

Ill-Structured Environments

Scaffolding helps students learning not only well-structured tasks such as algebra (Aleven & Koedinger, 2002; Koedinger, 2001; Lajoie & Derry, 2013), but also more open-ended investigations that require students to apply high levels of both domain knowledge and metacognitive skills. Numerous studies demonstrate that scaffolding can help students use simulations (Chiu & Linn, 2011; Honey & Hilton, 2011; Linn & Eylon, 2011; Linn, Lee, Tinker, Husic, & Chiu, 2006). Because these learning tasks are more ambitious than rote tasks, they consequently require greater support for learners (Quintana et al., 2004). Further, although open-ended learning environments such as simulations may help students visualize processes, these environments also pose many challenges to scaffolding (Pea, 2004; Puntambekar & Hubscher, 2005; Reiser, 2004). CBLEs with poor scaffolding can even be detrimental to student learning because they add confusing non-germane information that students must attend to (Azevedo & Hadwin, 2005). Ill-structured environments, such as complex systems simulations, pose challenges for traditional learning instruction. Spiro, Feltovich, Jacobson, and Coulson (1992) argue that neglecting these difficulties has led to predictable failures in learning, exhibited by, for example, oversimplification in student answers and the failure to transfer ideas into other domains.

To address these issues, Quintana et al. (2004) provide a framework for scaffolding inquiry projects in science. The framework focuses on the three interactive processes of sense making, process management, and articulation and reflection. Sense making takes place when students generate hypotheses, analyze data, collect observations, and carry out a variety of other scientific tasks. Process management refers to how students manage sense making tasks and make decisions about how to proceed in their investigations. Finally, articulation and reflection are how students review and evaluate and then communicate their findings (Quintana et al., 2004). These comprise tasks students must perform in scientific inquiry

More directly related to complex systems, Jacobson and Wilensky (2006) proposed five design principles for learning about complex systems with CBLEs. First, students should learn about complex systems through experience. Because important aspects of complex systems occur over different time scales of time and place, simulations and agent-based models are needed for students to experience these important elements and make them visible (Hmelo-Silver, Marathe, et al., 2007). Second, the organizing framework of complex systems needs to be made explicit because students do not just understand complex systems from observation (Goldstone, 2006; Jacobson, 2001). Third, students should be encouraged to collaborate, discuss, and reflect. Because knowledge and beliefs are constructed in socially mediated contexts (Brown, Collins, & Duguid, 1989), students need to collaborate and make sense of complex systems information together (Liu & Hmelo-Silver, 2010). Fourth, students should construct theories, models, and experiments, consistent with the tenets of scientific inquiry (Hmelo-Silver, Duncan, et al., 2007; Lederman, 1998) and working with complex systems models has proven an effective way to teach students (Abrahamson & Wilensky, 2005; Wilensky & Resnick, 1999). Finally, researchers should study learning trajectories for deeper understandings that students may develop (Jacobson & Wilensky, 2006).

Scaffolding Complex Systems

Scaffolding with simulations of complex systems has been shown to help students deepen their understanding of emergent processes in regards to electricity (Slotta & Chi, 2006). This study used direct ontological training for university undergraduate students to promote understanding of the emergent processes of electricity. Students with training showed improved performance on conceptual problems in electricity whereas control students showed no improvement. Undergraduate students who enrich their ontological understanding have also shown some improvement on transfer problem solving tasks (Jacobson et al., 2011). In the Jacobson study, two types of text-based scaffolding for complex systems ontologies were employed with a hypermedia simulation. Students who received the most scaffolding showed declarative knowledge gains. There was no difference between the two scaffolding groups for the more difficult problem solving tasks, which required students to explain, for example, how birds form flocks, or how termites store food.

Both self-monitoring scaffolds and ontological scaffolding may facilitate students' complex systems understanding in the context of participatory simulations. Self-monitoring scaffolds include both those that help students reflect on their progress and understanding, and scaffolds that help students plan next steps during inquiry (Quintana et al., 2004). A combination of process management and articulation and reflection scaffolds (McElhaney et al., 2015) shall be referred to as self-monitoring scaffolds in this study. Research demonstrates that students who plan and reflect on their understanding perform better than students who do not (Chi et al., 1989; Recker & Pirolli, 1995). Engaging in reflection can also help students improve their content understanding (White & Frederiksen, 1998). An example of a reflection scaffold is a "Checking Our Understanding" prompt, which encourages students to reflect on their understanding (Davis & Linn, 2000). An example of a planning scaffold can be seen in simulation ExplanationConstructor, which asks students to create questions to guide their investigations (Sandoval, 2003). This study investigates how self-monitoring scaffolding may help students learn about complex systems with simulations.

Ontological scaffolding may also help understanding and transfer by creating a framework from which students can organize complex systems concepts. Scaffolding with ontology training (Slotta & Chi, 2006) is meant to help students create a separate and distinct ontological category for complex systems (Chi, 2005). Chi's Framework (1992) suggests that students will make less faulty ontological categorizations if they have sufficient knowledge of the appropriate categories beforehand. Whereas ontology training suggested for addressing alternative ideas, such training may also help for either conceptual change or subordination of misconceptions as well (Slotta & Chi, 2006). By comparing and talking about the differences of several key components of complex systems (Jacobson, 2001; Jacobson et al., 2011), and making explicit the organizing framework of complex systems (Goldstone, 2006; Jacobson, 2001), students may be able to more accurately perceive and understand these components when encountered. For example, one study of ontological scaffolding placed NetLogo within hypermedia to explicitly visualize and explain complex systems to students (Jacobson et al., 2011). Students improved their declarative knowledge, and those with more expert complex systems ontologies did better on a transfer task (Jacobson et al., 2011). There are no studies to date that have investigated whether scaffolding with an agent-based participatory simulation can effectively help students better understand complex systems, however. Therefore it is important to understand what kinds of supports are most beneficial to understanding within this environment as well as which components of complex systems students find most difficult.

Purpose of Present Study

Because complex systems are inherently difficult, scaffolding student learning is integral to success. Core challenges to understanding complex systems, such as their hierarchical nature and multiple interacting levels, means a large burden on working memory for learners (Hmelo-Silver & Azevedo, 2006). Because learners have robust misconceptions (Chi, 2005), students will need help constructing a richer conceptual ecology embracing non-reductive & decentralized thinking, multiple causality, non-linearity, and randomness (Jacobson, 2000, 2001). A variety of agent-based models and simulations have shown both promise and difficulties in teaching students about complex systems.

The aims of this study were to investigate whether a combination of scaffolding and agent-based participatory simulation could help students' improve their understanding of complex systems components, and whether they could transfer their understanding to a new complex system. Specifically, this study asked the following research questions:

1) Can interactive instruction using an agent-based participatory simulation of the Chesapeake Bay watershed improve student understanding of complex systems?
   a) For what components of complex systems (e.g., decentralization, nonlinear action effects, and Agents) do students demonstrate improved or limited understanding?
   b) Can students transfer their understanding of complex systems to another context of architecture?
2) How does ontological scaffolding versus self-monitoring scaffolding during instruction using an agent-based participatory simulation of the Chesapeake Bay affect student understanding of complex systems?
   a) How does understanding of complex systems components compare for students receiving ontological scaffolding versus students receiving self-monitoring scaffolding?
   b) How does the ability to transfer understanding of complex systems to another context of architecture compare for students receiving ontological scaffolding versus students receiving self-monitoring scaffolding?

I hypothesized that students would show improvement for most components, although I expected their understanding of more difficult components (e.g., Agent Effects, Order) to show less improvement (Goh et al., 2012). Causal claims cannot be made about the transfer task but students were expected to display similar relative ability to transfer their understanding of components within an urban context. Finally, I hypothesized that given the difficulty of understanding complex systems concepts, the ontological scaffolding group would demonstrate a better understanding of these concepts after the intervention for both the non-transfer and transfer tasks.

Currently, very few studies have researched complex systems understanding in adults. Little is known about which components and which parts adults find difficult both within the domains in which they have learned them as well as transfer to new domains. Further, the use of agent-based participatory simulations is relatively limited to experiments without control groups and with small sample sizes. This study will build on these findings with experimental methods. Finally, given the difficulty students have in learning about complex systems a better understanding of which scaffolds helps students learn about complex system components would point to better future methods for teaching students.

CHAPTER 3: METHODS

Understanding complex systems in science is critically important to solving pressing problems in the world today. Given the inherent difficulty of teaching students about complex systems, and the lack of systematic knowledge about how post-secondary students acquire and use their understanding of complex systems, additional research in the educational setting is needed. This quasi-experimental study was designed to investigate the following overarching aims: (1) whether types of scaffolding within an intervention helped students improve their understanding of complex systems components through agent-based simulations and (2) whether scaffolding within an intervention helped students transfer their understanding of complex systems to another unrelated context.

In the following section, I first describe the study's research framework and methodology. I then describe the participants and the sampling design used to select and place students into one of two experimental conditions. Third, I describe data collection, including the instrumentation used to gather data, important characteristics of each measure, and the procedures for data analysis. Finally, I discuss limitations of the study as well as internal and external validity concerns.

Framework

The framework that was used in this investigation of student complex systems understanding is the Complex Systems Ontology Framework (CSOF) (Jacobson et al., 2011). The CSOF framework posits that novices and experts think about complex systems differently in regards to five different components (also known as ontological categories) of complex systems (see Table 1). Jacobson's ordering of ontological components builds on his earlier research (2001) demonstrating how novices wrongly apply certain clockwork systems attributes to complex systems and showing what more expert understanding looks like. Expert thinking means students recognize the correct attributes of components for appropriate systems. For example, a person may believe an ecosystem is a complex system, but also incorrectly believe that order from the system is imposed from the top-down, applying the incorrect clockwork attribute of Order to a complex system. Determining whether a learner actually understands a complex system means they must correctly recognized and understand how a number of components of the system operate. This framework is used to determine student understanding of complex systems in this study.

Table 1
Ontological Categories for Complex Systems

Ontologies	Types of Ontological Attributes	
	Clockwork	Complexity
Actions	Linear	Nonlinear
Order	Centralized	De-centralized
Causes	Single	Multiple
Agents	Predictable	Stochastic/Random
Processes	Static or Temporal Event	Equilibration or Emergent

Research Design

This study uses a 2x2 pretest-posttest quasi experimental design. Independent variables were whether students participate in a simulation and workshop intervention (within-subjects), and whether they receive either self-monitoring or ontological scaffolds for their treatment condition (between-subjects). Dependent variables were student understanding of adapted CSOF components in pretest, posttest, and transfer questions. This research design is optimal because randomized block sampling enables analyses indicating whether changes in student understanding were caused by treatment conditions.

This study also controlled for demographic variables. Before intervention, information was collected on student gender, age, college major, and weekly time spent playing video games. Although there is no literature suggesting that socio-demographic variables would affect outcomes, they were used to ensure statistically equivalent groups; exploratory analyses of descriptives confirmed similar gender, age, major, and video game use across all groups. Time spent playing video games was hypothesized to possibly contribute to how well students understood the simulation; this variable was used during randomized block sampling to ensure equivalence between groups.

Context & Participants

Sample

The sample for this study included 96 students from an architecture class focused on the interplay of architecture and larger systems. This class was a mid-level undergraduate course offered at a large tier-one research university and is required for architecture majors. The majority of students in this class were architecture majors (92%) with the other 8 students majoring in 7 different programs. The majority of the class was female (67%) and between 19 to 20 years old (73%).

The only criterion for selection for this study was enrollment in the host class. Therefore, although students were randomly assigned while controlling for demographic variables to treatment conditions, they were not randomly selected into the study. Access to the class was granted by the instructor and students were given information sheets with the option to have their data removed from the study, which no students chose to do. All undergraduate students (88%) and graduate students were included in this study, although graduate students did not participate in the transfer question because it was not a normal part of their class requirements.

Data Collection (Sources & Procedure)

Context

Next, I discuss the context of the intervention. First, I describe the simulation itself and gameplay during the simulation. Then I describe the workshops during which students received separate treatments before the simulation.

The Bay Game. The UVA Bay Game is a simulation in which players enact the role of stakeholders within a model of the Chesapeake Bay watershed ecosystem, an important example of a complex system. The simulation uses over 55,000 differential equations that support its extremely accurate behavioral fidelity (Plank, Feldon, Sherman, & Elliot, 2011). When tested with real world U.S. Geological Society [USGS] data from 2000 to 2008, the Bay Game simulation accurately accounted for 97% of the real world data. The Bay Game has a generalizable template using Java, R, PostGRES, and HTML 5. It can be run in any computer lab with internet access from a server. Full simulation gameplay, which takes about 5 hours, is considered to be ten rounds, with each round representing two years.

The simulation is participatory in that players are assigned the role of agents in the system such as crab fishermen, animal farmers, crop farmers, policy makers, land developers and regulators. Similar to role-playing games students become the characters in the simulation while also creating the system. Agent-based models simulate micro-level components and interactions and allow these parts to have local information and agency (Learmonth Sr. & Plank, 2015). The UVA Bay Game uses player decisions and interactions as well as nonhuman system components to influence system outcomes. Players witness the macro-level system outcomes as well as the individual (i.e. micro-level) interactions (Scholl, 2001). Players are grouped into teams by state, with states competing with each other for the best economic growth and ecological sustainability. Individual players attempt to improve the health of the ecosystem while also attending to their own economic needs. Players interact and negotiate with each other to develop an understanding of the different behaviors and functions of other students and nonhuman system components. For example, crop farmers need to decide whether to invest in high yield farming methods (more revenue and nitrogen runoff) or lower yield farming methods (lower revenue and nitrogen runoff). Impacting this decision are other stakeholders including policy makers, who decide whether or not to subsidize more environmentally friendly farming methods. Gameplay may help to promote student understanding of interactions between components and the emergent behaviors of the system as a whole that develop from these interactions.

In the UVA Bay Game simulation, players make decisions as they enact their roles as stakeholders in the watershed ecosystem. These decisions are entered into the simulation, and once all players have entered their decisions, the round ends. Then, players are given feedback on their individual and state results after each round on economic and ecological outcomes. This feedback includes information about a player’s net worth (taking into account cash, any equipment value, debt and interest on debt, for example) and Bay health using indicators such as nitrogen and phosphorus concentrations. Feedback also includes a presentation of decisions the player needs to make. Players compete by state for the greatest net income gains and the least contribution to nutrient runoff in the watershed. To support this competition, players are presented with an overall display of ranked state (regional) standings after each round. Here, players see the cumulative effects of their choices. This commonly sparks region discussions about what choices led to the most positive outcomes, what strategies might be reconsidered, and development of theories of why players' actions may have caused these outcomes. Because students playing the game are vested in succeeding as a group, and thus in making sense of the complex system together, students may support each other in the conceptual change process (Liu & Hmelo-Silver, 2010).

Player and regional decisions do not result in consistently predictable outcomes. This is complicated by the tension between economic and environmental needs at the individual, region, and system levels as well as by nonhuman system components such as weather that are not controllable. Flexible and adaptive responses by human stakeholders are essential for both the environment and the economy. Further supporting players' reflection, players can compare their outcomes to actual United States Geological Survey (USGS) data-based real world outcomes during the first five rounds of gameplay (equivalent of 10 years). The second set of five rounds begins after the current year simulating real world data.

Because of the setup of the simulation and need for students to learn from and communicate with each success in the UVA Bay Game relies on working with other students. In previous gameplays students often begin by learning about their roles and the current state of the watershed at individual computers (Plank et al., 2011; Rates, Mulvey, Carson, & Feldon, 2013). After students begin to understand their roles and who can help them with their goals they must reach out to policy makers for better financial incentives, students within their region to coordinate their strategy, as well as students in similar roles across regions to find out what strategies have worked for more successful participants. Therefore gameplay goals are aligned with those that foster student interactions (Wolfe, 1997), an important process in promoting conceptual change (Liu & Hmelo-Silver, 2010)

The interactive nature of the simulation has the potential to increase motivation in such a difficult subject by placing students within the context of what they are studying (Cordova & Lepper, 1996). This context is authentic and meaningful, with success requiring understandings of the system at both the micro and macro levels. The integration of cooperation within regions and competition between regions also may increase motivation. The simulation places complex systems within a real world problem of the Chesapeake Bay (as recommended by Brown et al., 1989), giving players a concrete example of a complex system as well as how it can affect their lives. Gameplay also models, visualizes, and confronts students with the macro effects of their micro decisions.

Treatment 1: Self-Monitoring Scaffolding. The self-monitoring scaffolding that was used for the Self-Monitoring groups consisted of consisted of process management, articulation, and reflection scaffolds. During the Self-Monitoring workshop students were fist given an explanation of how the game works and were then randomly assigned to practice roles for the duration of the workshop. Students worked in groups similar to those they would need to collaborate in within the simulation and asked to brainstorm strategies to succeed at gameplay. Because the simulation requires that students balance the parameters of making money individually as well as reducing pollution students were asked how they would do each of these separately, and then how they would optimize the needs of both parameters (See Appendix J). Students were then asked in small groups to plan out what information they'd need to know about the ecosystem as well as their own roles for the upcoming gameplay. Students both planned strategies for the simulation (process management) as well as discussed their ideas and understandings as a group (articulation). During the simulation, students were instructed with worksheets to think about their strategies and how to improve them (reflection, see Appendix H).

Treatment 2: Ontological Scaffolding. The ontological scaffolding that was used for the Ontological groups consisted of both the presentation of complex systems components as well as activities requiring students to apply these concepts to an ecological complex system. Components consist of emergence and the irreducibility of complex systems, non-linear action effects, decentralized order, adaptation, equilibration processes, and agent behavior. Students were taught each separate component as a group and for each component, students were given an explanation and a non-ecological example. For each example students asked questions and with the moderator brainstormed examples of these components they'd previously encountered. Then, in small groups (2-3 students), students were asked to discuss where in the simulation they might expect to encounter each component and to share their ideas with the class. Finally, students were also given an information sheet with these concepts as well as an assignment sheet with each concept. Students were then tasked with finding examples of each complex system component during the simulation that occurred later that week and filling out component examples on the assignment sheet (see Appendix H).

Instrumentation

A variety of instruments were used to collect data for this study. Demographic Data (see Appendix A) consisted of 8 questions designed to gather potentially important characteristics about students such as age, gender, or major. Identical pretest and posttest questions (see Appendix B) were posed to the students asking them to write short answer responses. Each question elicited understanding of a different complex systems component and one question was used to elicit understanding of three causation components. Each set of responses was only coded for the matching component the question was meant to elicit. Students were told the content of their responses would not affect their class grade but would be part of their participation grade. Finally, students responded to a longer transfer prompt (see Appendix C) in the form of a blog-post asking students to apply their understanding of complex systems to design a system (e.g., sewage, food, water, transportation) within a city.

Appropriateness. Because of the nature of complex systems, it is not appropriate to ask students multiple-choice questions. Complex systems understanding consists of several elements, their interactions, and the outcomes of these interactions, which are difficult to assess without more elaborate student responses. Therefore, data were collected through open-ended questions which first needed to be coded and then analyzed using quantitative methods.

Pilot Study. A pilot study was conducted a year earlier with a similar population taking the same class. This study was used to inform both instrument development as well as the study design. The pilot study uncovered issues with student response and implementation of the simulation. First, because of timing, there was severe attrition in posttest completion. Second, the length of time needed for the simulation was determined to be the entire class period. This initial study indicated that intervention and data gathering would need to take place over several weeks, and that pre and posttest completion should be a required part of the class. Finally, the format of the instrument used during the pilot study failed to gather rich data about student complex systems understanding. Because of this, the present study posed several short answer open-ended questions.

Measurement Characteristics.

Demographic Questionnaire. The demographic questionnaire consisted of 8 questions (see Appendix A). Seven of these questions were forced-choice responses while the final questions asked how many hours a week a student plays video games as a multiple choice question. The survey was meant to be relatively short and was completed electronically by the students before the intervention.

Pretest and Posttest Measure. Pretest and posttest measures were identical to ensure that response differences did not arise because of questions that measured different things (see Appendix B). Questions 3 through 5 measured causation and were taken directly from Grotzer and colleagues (Grotzer et al., 2013) and have been used in multiple studies of causation. Questions 6 and 8 were adapted from questions used in Jacobson’s (2001) initial study of novice/expert differences. The remaining questions were developed with the help of complex systems and science education experts. These questions were used to query students about their understanding of feedback loops as well as unpredictability within systems. All questions were short answer.

Transfer Question. All undergraduate students kept a blog as part of their normal classwork and blog assignments usually consisted of prompts with 500 to 700 word responses. The students' fourth blog prompt asked them to design a system within a hypothetical city related to either energy, water, food, transportation, or waste. Students were asked to design a system using both a clockwork systems model, as well as a complex systems model. This prompt was designed for students to apply their complex systems understanding from an ecosystem to a city. Further, this measure sought to determine whether students were able to talk about system type differences (clockwork vs. complex) in clear and distinct ways, representing distinct ontological categories.

Administration & Scoring of Measures. The demographic survey was administered a week before the intervention via Google Forms during class (see Appendix F). Students who were absent or failed to respond were emailed a separate link to the form. The pretest occurred during the first 25 to 30 minutes of four separate but concurrent workshops. Pretests were also administered electronically through Google Forms. The posttest was administered during class on the following week. The blog post prompt was then sent a few days later by email from the professor and students responded using WordPress to create blog posts within a week.

Procedures

Demographic Sampling & Randomization. At the start of class, the demographic survey link was projected on the class screen. Students were asked to answer all questions and those who did not respond were sent an email with the link the same day. Students were then randomly assigned as participants into one of four workshops using randomized block sampling on demographic variables (gender, major, and videogame experience).

Treatment Groups. Two workshops were assigned as Treatment 1: Self-Monitoring Scaffold groups and two were assigned as Treatment 2: Ontological Scaffold groups (see Appendix F). Each workshop was taught concurrently during the normal class period using a PowerPoint presentation (see Appendix J) to ensure consistency across workshops. In the Self-Monitoring condition, students were taught by two TAs and began class by spending 30 minutes completing the pretest questionnaire online. After this, students were given information about the Bay Game and the simulation that would take place 2 days later. Students were then asked to break into groups and develop strategies for how they might win at the game.

In the second condition, Ontological groups were taught by the professor of the class and the study author to ensure that information about complex systems was delivered consistently and competently by experts able to provide accurate answers to student questions. At the beginning of class, students in the Ontological groups took the pretest questionnaire for 30 minutes in the same manner as the Self-Monitoring groups. For the remainder of the class, students received ontological scaffolding that 1) taught about important complex systems components, 2) had students answer questions about and generate with examples of these components, and 3) attempted to explain where students might see these components within a virtual ecosystem represented by the UVA Bay Game.

After the initial questionnaire, all groups were given information sheets (see Appendix I) describing the important complex systems components, to ensure that both groups saw the same information. Further, both groups were given worksheets to be used during the simulation that Thursday (see Appendix H). Both groups were told not to share their responses.

Self-Monitoring groups were given a sheet with questions about what they liked and did not like about the game and which strategies they felt worked well. In contrast, the Ontological group was given question sheets asking them to list examples of the complex systems components they discussed during workshop. Of note, the Ontological groups actively discussed these topics and elaborated on what components of the Chesapeake Bay watershed represented these concepts.

The Self-Monitoring workshops were taught by two teaching assistants for the class and the Ontological workshops were taught by the class professor and the author because the Ontological workshop required content knowledge of complex systems. In order to help ensure that type of instructor did not play a role in student outcomes all instructors taught their workshops using two identical presentations. Further, because teaching assistants had less teaching experience the Self-Monitoring workshops were designed to be largely student led discussions and brainstorming and not dependent on teaching assistant content knowledge or teaching experience.

Gameplay. Gameplay took place in a large ballroom with groups set up with ten people to a table. This site allowed students freedom of movement to talk to other players in this largely interactive simulation. At the beginning of the gameplay session, students were given instructions about the goals of the game and were then largely left to ask questions and make their initial choices. Each round was punctuated by a 5-minute period when students waited to find out the results of their choices during gameplay. During this period, the presenter explained what the rankings and statistics meant on the main screen and explained to the group important changes in metrics and rankings. Five rounds of the simulation were completed, at which point final answers were locked in and the game was cycled to the end to see who won. At multiple points throughout the simulation, students were reminded to fill out their question sheets, which were collected at the end of the class period.

Posttest Questionnaire. At the start of class the following week, students were given the same questionnaire they took for the pretest. They were told that although these questions were the same ones they answered the previous week, it was important to respond a second time, even if their ideas had not changed. Students were told to write for 30 minutes and then class proceeded as normal.

Transfer Prompt. Students were emailed the transfer prompt (Appendix C) with instructions to complete the prompt within a week after the game play.

Data Analysis

Items and Rubrics for scoring were developed concurrently. The main source for complex system components came from the complex systems ontology framework (Jacobson et al., 2011, see Appendix D), adaptations made by Susan Yoon (Yoon, 2008; 2011; Goh et al., 2012), Tina Grotzer's work in causation understanding in complex systems (Grotzer et al., 2013; Grotzer, Tutwiler, Dede, Kamarainen, & Metcalf, 2011) and the author's previous work in developing a rubric to measure complex systems understanding in an ecosystem (Rates et al., 2013). During question development, I and a colleague determined which components we felt best represented student understanding of complex systems. For example, although Jacobson's work measures whether students focus on events vs. processes, Grotzer (Grotzer et al., 2011) developed more detailed causation rubrics that also measure whether students focus on non-obvious causes as well as distant causes, which represent more expert complex systems understanding.

For this experiment, several adaptations were made to the CSMM. First, following the lead of Susan Yoon and colleagues (Goh et al., 2012; Yoon, 2008; 2001) the levels for complex systems components were expanded from the novice expert binary levels to a more nuanced three levels. This choice was based on the author's previous work (Rates et al., 2013) where students showed more gradual understanding of complexity rather than an either clockwork or complex understanding. For example, students often gave a mix of centralized and decentralized order for an ecosystem, not one or the other. Levels were then developed using a combination of the above mentioned rubrics, and then tested on a subsample of student responses to make sure that coders agreed that these levels represented distinct, appropriate, and cohesive groups of students based on their component understanding. The three components used directly from the CSMM framework are Actions, Agents, and Order (see Appendix D).

The second set of adaptations involved altering the components of Causes and Processes. These were altered slightly to align with Tina Grotzer's work on Causation understanding in complex systems (Grotzer, 2012; Grotzer et al., 2013, 2011) because her work offers a more nuanced and elaborated understanding of the components of Causes and Processes. These two causation components were expanded to three components with two levels: Obvious vs. Non-Obvious, Local vs. Distant, and Event vs. Processes representing clockwork vs complex focus, respectively (see Appendix E). The rubric used for these three causation components was borrowed directly from a previously validated rubric developed by Grotzer, et al., (2011).

Through discussion and comparing the merits of the above mentioned rubrics, we determined the following components to best represent complex systems understanding: Causation: Event vs. Process focus, Causation: Non-Obvious vs. Obvious Causes, Causation: Local vs. Distant Causes, Order, Action Effects, and Agents (see Appendix E). The author then met with and discussed with an expert in complex systems understanding to adapt questions previously developed by Jacobson and colleagues (2011) to capture Order, Action Effects, and Agents components (see Appendix D).

Scoring Measures

The three causation components were scored using the same methods used by Grotzer and colleagues (2011; 2013). For the remaining three components, the author and the second rater developed rubrics for each component by first determining which characteristics of each component were salient and what represented low, medium, and high levels of understanding using previous rubrics in this field (Goh et al. 2012; Jacobson, 2001; Jacobson et al., 2011; Yoon, 208; 2011). Each rater then applied the rubric to ten responses, compared scores, and then adjusted the rubric when necessary to make sure that the three categories of responses represented distinct answers. We then repeated this procedure until we felt confident enough to move on to test inter-rater reliability.

To ensure inter-rater reliability, 20% of the items were coded by the author and the other rater. Both coders coded five complete sets of student data and compared answers and discussed coding interpretation after each set marking which we had disagreed on. This was then repeated until 20% of the data was coded, compared, and discussed for inter-rater reliability. A satisfactory inter-rater reliability score of above 80% was achieved for all rubrics (Table 2) and then the author coded the remainder of the data. The same rubric was used to code transfer responses. Both coders coded small sets of student responses, compared scores and discussed coding concerns. This was repeated until 20% of the data was coded and a satisfactory inter-rater reliability score of above 80% was achieved (Table 3). Both coders then coded separate sets of the remaining data.

Table 2
Inter-rater Reliability Scores for Pretest and Posttest Responses

Category	Alpha
Action Effects	.85
Agents	.94
Order	.91
Causation: Obvious	.88
Causation: Local	.92
Causation: Event	.93

Table 3
Inter-rater Reliability Scores for Transfer Responses

Category	Alpha
Action Effects	.83
Agents	.83
Order	.90
Causation: Obvious	.90
Causation: Local	.93
Causation: Event	1.00

Tests

Pretest Group Differences. Although participants were randomly assigned to groups pretest component scores were compared between treatment groups in order to ensure that no differences existed before the intervention. Because these scores violated normality Mann-Whitney tests were used to determine if there were significant differences. No significant pretest differences were found by treatment group (Table 4)

Table 4

Pretest Component Means by Treatment Group

	SM	OS			
	Pre (SD)	Pre (SD)	Mann U	Sig.	Z
Action	2.35(.74)	2.51(.55)	981.00	.18	.86
Agent	1.64(.78)	1.59(.82)	924.00	.37	-.41
Order	2.19(.76)	2.21(.71)	915.50	.49	.08
CS-Obv	.56(.24)	.55(.28)	1049.00	.40	-.25
CS-Local	.11(.21)	.18(.28)	902.00	.054	1.61
CS-Event	.16(.21)	.17(.21)	1038.00	.36	.36

Normality. All participant data were tested for normality to ensure inferential statistics could be used. Shapiro-Wilks test of normality for pretest and posttest variables were significant indicating non-normality for all pretest and posttest dependent variables (Table 5) as well as for all pretest and posttest dependent variables by treatment condition (Tables 6 and 7) and gain scores (Table 8) except for the category of Causation: Obvious/Non-Obvious (p = .053). Because all but one dependent variable violated normality, non-parametric tests were used to analyze all data.

Table 5

Tests of Normality: All Groups

	Shapiro Wilk Statistic	df	Sig.
Pre Action	.74	86	.01*
Post Action	.79	86	.01*
Pre Agent	.71	81	.01*
Post Agent	.79	81	.01*
Pre Order	.80	79	.01*
Post Order	.79	79	.01*
Pre Causation: Obvious Mean	.95	89	.01*
Post Causation: Obvious Mean	.95	89	.01*
Pre Causation: Local Mean	.67	89	.01*
Post Causation: Local Mean	.71	89	.01*
Pre Causation: Event Mean	.77	89	.01*
Post Causation: Event Mean	.80	89	.01*

Note. *Indicates Significant Violation of Normality ($p<.05$)

Table 6

Tests of Normality: Self-Monitoring Group

	Shapiro Wilk Statistic	df	Sig.
Pre Action	.75	44	.01*
Post Action	.79	44	.01*
Pre Agent	.73	41	.01*
Post Agent	.79	41	.01*
Pre Order	.79	39	.01*
Post Order	.81	39	.01*
Pre Causation: Obvious Mean	.95	45	.05
Post Causation: Obvious Mean	.95	45	.03*
Pre Causation: Local Mean	.59	45	.01*
Post Causation: Local Mean	.72	45	.01*
Pre Causation: Event Mean	.73	45	.01*
Post Causation: Event Mean	.80	45	.01*

Note. *Indicates Significant Violation of Normality ($p < .05$)

Table 7
Tests of Normality: Ontological Group

	Shapiro Wilk Statistic	df	Sig.
Pre Action	.69	42	.01*
Post Action	.79	42	.01*
Pre Agent	.70	40	.01*
Post Agent	.77	40	.01*
Pre Order	.80	40	.01*
Post Order	.77	40	.01*
Pre Causation: Obvious Mean	.94	44	.03*
Post Causation: Obvious Mean	.93	44	.01*
Pre Causation: Local Mean	.73	44	.01*
Post Causation: Local Mean	.71	44	.01*
Pre Causation: Event Mean	.79	44	.01*
Post Causation: Event Mean	.82	44	.01*

*Note. *Indicates Significant Violation of Normality (p<.05)*

Table 8
Tests of Normality: Gain Scores

	Shapiro Wilk Statistic	df	Sig.
Action	.85	84	.01*
Agent	.82	81	.01*
Order	.82	79	.01*
Causation: Obvious	.94	89	.01*
Causation: Local	.86	89	.01*
Causation: Event	.92	89	.01*

*Note. *Indicates Significant Violation of Normality (p<.05)*

Descriptive and Non-Parametric Tests.

Research Question 1a. Descriptive tests were used to explore differences between student pretest and posttest scores (Research Question 1a). Because all but one component violated normality, Wilcoxon signed-rank tests were used to determine if there were significant differences between pretest and posttest scores for all components.

For all three Causation components analyses differed from those by Grotzer and colleagues (2011; 2013). In their original study, all student responses to the prompt

"What might have caused the fish die off?" were pooled together and analyses were run on this entire set of responses. However, students are allowed to write as many responses as they like and verbose students were therefore given more weight within these analyses. To give all students equal weight, an average score for each student's total number of responses was used for all analyses.

Research Question 1b. Descriptive tests were used to explore differences between components and system types for Far Transfer responses.

Research Question 2a. A Wilcoxon signed-rank test was used to determine if there were significant differences between pretest and posttest component scores for each separate treatment group. A Mann-Whitney test was used to determine if there were significant differences between treatment conditions for gains in component understanding. Gain scores were calculated by subtracting pretest scores from posttest scores in both treatment groups.

Research Question 2b. A Mann-Whitney test was used to determine if there were significant differences by treatment condition for individual component understanding. Overall component scores were then created by aggregating all component scores for each participant. A Mann-Whitney test was used to determine if there was a significant difference for the mean number of complex systems components used by treatment condition on the far transfer item.

Effect Sizes

Effect sizes were calculated for all variables using the following equation recommended by Rosenthal (1991) to convert z-scores into effect sizes:

$$r = \frac{Z}{\sqrt{N}}$$

where N is the total number of observations compared.

Coding

All student responses were first coded for whether their responses demonstrated either clockwork or complex systems understanding for each causation component, or whether responses represented one of three levels of complex systems understanding for Order, Action Effects, or Agents. Qualitative coding was conducted after quantitative analyses to better understand why certain changes occurred among student responses. After determining which student scores changed from pretest to posttest student responses were grouped by identical numeric changes (e.g., those who changed from a score of one to two were grouped separately from those whose scores changed from two to three). Groups were then read holistically to look for emergent themes and trends to describe similarities of pretest scores, posttest scores, and changes in scores. Coding focused not only on explaining significant quantitative changes, but also movement in scores that may have canceled out changes (i.e., if a large group of students improved understanding of a component while another group exhibited reduced posttest scores.) If patterns emerged student responses were then coded individual for its presence to help determine the magnitude of the effect.

Validity and Trustworthiness of Data

To ensure validity and trustworthiness of data, several methods were employed. First, almost all parts of the experiment were audio recorded. All four workshops were audio recorded as well as the Bay Game intervention. The lecture before the simulation that deals with complex systems as well as after in which students review what they had done were also recorded. These were done in case inconsistencies were found in the data between each pair of treatment groups. Although identical Power Point presentations were used for each pair of groups, if we found different outcomes for these group pairs the audio data may offer some reasons for this discrepancy.

Both treatment groups were split into two separate classrooms to capture whether differences were due to the condition or something about the room, presenter, or group. Before comparing treatment conditions on outcome variables, within group comparisons were conducted to ensure that both classrooms of Self-Monitoring groups and both classrooms of Ontological groups did not differ on any important outcome variables. This was done to help ensure that changes in student outcomes are due to treatment condition instead of any other causes.

Limitations

There are several limitations of the design of this study. First, although participants were randomly sampled into groups, the pool from which they were chosen was a single class within the architecture school. Although there were a variety of students within this group, this limits the generalizability of the sample studied. Another limitation is the dosage of the intervention. Although the time was expanded greatly from the original pilot study of 1 day, results may be limited by the length of time students had to interact with the simulation.

Role of Researcher & Ethical Concerns

As the main researcher in this study, I had two roles. First, I collected data. Students were briefly introduced to me at the start of the semester and told that data would be collected later in the semester to better understand whether they were learning complex systems content. Before data collection began, students were informed again of this data collection and that 1) data would be used to improve the class and 2) their responses would be confidential. During class, I sat in the back of the room with the TAs of the class and did not interact with students. My second role occurred during the intervention when I taught a workshop. I introduced myself to the group and explained that I would be helping teach one of the four workshops in order to prepare students for the simulation that week (all other TAs were out of country that week). Students were informed that their responses would be kept confidential and that they could have their data removed from the study without consequence (no students made this request).

Ethical concerns in this study were also minimized as much as possible. First, I collected as little sensitive information as possible which was anonymized and stored on a secure server. Second, interventions and data collection occurred during classroom times. Students were not asked to do more work than was already part of their class.

CHAPTER 4: RESULTS

Introduction

The results are organized by research questions below. First, changes for students on component scores from pretest to posttest question are discussed. Then, overall descriptions of student responses to the transfer question are shown to understand which components students were able to apply in the architectural (city systems) context. Finally, comparisons are made between the Self-Monitoring treatment condition and Ontological Scaffolding treatment condition to see which conditions best helped component understanding. Finally, these conditions are compared to see if they contributed to transfer.

Overall Component Differences between Pretest and Posttest Scores

The first research question to be analyzed was: For what components of complex systems do students demonstrate improved or limited understanding? First, descriptive statistics and student examples are shown for each component individually. Significance testing is discussed overall, and then student examples are provided for components that demonstrated significant changes.

Descriptive Statistics

Because the components Action Effects, Agents, and Order are interpreted on the same scale, I discuss these first and then move on to the three causal components of Non-Obvious, Distant, and Process Causes. Although both sets of components use different scales, they both represent a range of more novice understanding (describing complex systems using clockworks system characteristics) to more expert understanding (describing complex systems and their properties using complex system characteristics). For Action Effects, Agents, and Order, student descriptions were rated as either 1) Novice, 2) Medium, or 3) Expert understanding while for the Causal characteristics they were rated as either 0) Novice or 1) Expert.

Action Effects. On average, students demonstrated a medium-expert understanding of Action Effects during the pretest (M = 2.43, SD = .65), and decreased after the intervention by .17 points (M = 2.26, SD = .69) (Table 9). Most student responses represented the highest level of understanding in the pretest by both agreeing that large effects can come from small causes while also explaining how this can happen through cascading (nonlinear) effects or chain reactions. During the pretest, 57% of students (Table 10) gave expert level responses similar to the following:

> Since so much of the world is interconnected at various levels, it makes sense that a small change in one element of a system would immediately affect other elements that they have relationships with. This develops into a chain reaction, as each element responds to changes occurring in the many elements around it. (Participant 31)
>
> Small changes can cause large effects in the ecosystem. This holds true for the process of food chains. If an organism at the bottom of the food chain goes extinct, then the next organism that relies on that which died out either has no food or has to compensate by eating too much of another organism in which that goes extinct. Both possibilities then effect the next two levels in either direction and so on and so forth. (Participant 11)

In these responses students gave clear reasons for how small causes might turn into large effects.

Table 9

Component Differences between Pretest and Posttest Scores

	Pre (SD)	Post (SD)
Action Effects	2.43(.65)	2.26(.69)
Agent	1.61(.80)	1.81(.78)
Order	2.20(.73)	2.18(.74)
Causation: Obvious vs. Non-Obvious	.55(.26)	.59(.23)
Causation: Local vs. Distant	.15(.24)	.18(.27)
Causation: Event vs. Process	.16(.21)	.21(.25)

Table 10

Percent of Student Responses by Level

	Pretest			Posttest		
	1	2	3	1	2	3
Action Effects	8.6%	39.8%	51.6%	13.8%	46.0%	40.2%
Agent Actions	58.0%	22.7%	19.3%	41.6%	36.0%	22.5%
Order	18.6%	43.0%	38.4%	19.5%	42.5%	37.9%

Many students in the pretest (40%) and the posttest (46%) gave responses that fell into the second level. Students in these responses did not demonstrate that they understood how such large effects would occur, as seen in the following examples:

> I believe that small changes can lead to large effects in the ecosystem, and that this is mostly observable over a period of time (not instantaneous). The slightest change in a system could cross the boundary between what an organism can live and thrive in and what it would quickly die in, and the death or life of many of these organisms would impact the death and life of other organisms dependent on them. (Participant 27)

> It's True, small changes can lead to large effects. this is true because everything i connected in the ecosystem. EX: food chain. (Participant 62)

Whereas these students may understand how large effects might grow from small causes they did not give enough information in their responses to show more than agreement.

Very few students showed a novice level of understanding (9% in the pretest and 14% in the posttest, Table 10). These students gave responses that either explicitly disagreed with large effects growing out of small causes, or felt that these could only happen through an aggregation of several small causes. For example, one student responded as follows:

> I think that one sole small change will not lead to a large effect, but that many of the same small changes together will. An ecosystem is huge and full of many connections, one person turning off the faucet while brushing their teeth, will not lead us to conserving massive amount of water over night. But if everyone decided to make the same change in their lives, I could see it leading to potential change on the larger scale of the ecosystem. (Participant 57)

This student denied that non-linear effects might happen, but felt that only through aggregating many small actions could a large effect occur. Although small causes can aggregate into large effects, this student is incorrect to state that this is the only way for large effects to occur. These responses were not common.

Agents. On average, students began with a novice-medium understanding of Agents on the pretest (M = 1.61, SD = .80), and increased by 0.2 points after the intervention (Table 9). In both pretest and posttest responses, students understood Agents the least of the three components. This component requires students not only 1) to understand that although it is possible to understand rules of behavior, one cannot completely predict behavior but also that 2) actions cannot be reliably predicted due to randomness or chance factors in the environment. Student responses on the pretest were largely at the lowest level (58% of responses) with around 20% of students in the mid-level and 20% in the high-level categories. By the posttest, a shift occurred out of the lowest level with the highest gains in the mid-level of the component (an increase of 13.3% of students) and only a slight increase of the highest level of understanding for this category (3.2%) (Table 10). This means that most students who improved went from indicating that they believed the actions of agents in a complex system are largely predictable to understanding that they are not wholly predictable. There was little increase in explanation of how Agent actions are not predictable in student responses. For example, the pretest asked students if they could predict the movement of a single fish based on the movement of the school of fish. The majority of students gave Level 1 responses similar to the following: "you could predict the movement of an individual fish based off of knowledge of how larger groups of fish swim about in various instances. Essentially extrapolating behavior from a greater population" (Participant 89); "If you know the single fish's location and the path of movement of surrounding fish, yes I think so. Again, he will probably follow at least a similar path to whoever moved before him" (Participant 21); and "Yes. As there is only one thought process to consider, you could predict that they will react to an object in a certain manner, or tend to swim towards one side more often" (Participant 71). These responses showed that students largely felt the individual in the system is predictable and future behavior can be calculated with enough knowledge.

Students who gave responses that fell within the second (medium) level gave responses that showed they believed one could not predict an agent's future movements: "Their behavior might follow a certain pattern but I do not think it is possible to completely say what a fish definitely will or will not do" (Participant 38); "Yes you could, with a reasonable amount of error. You could track the path of the school, but the fish might weave in and out within that school and that individual motion would be almost impossible to track" (Participant 20); and finally

> I think it depends on the time to predict the movement of an individual fish with enough knowledge. If for example there is food provided to the fish you could predict that the fish would move to this area. Or if there is cold water coming from one side of the water side then you might predict it would move away. In

> other words, I think that in some situations we might predict the movement of an individual fish but I do not think that in general that is possible. (Participant 46)

These students indicated that prediction is not fully possible but they did not give enough information to show that they understand randomness or chance factors needed to demonstrate the highest level of understanding (level 3).

Only a few students demonstrated the highest level of understanding as exemplified by the following responses: “No, because an individual fish may have changed a lot due to the environment it is put in. Thus, having enough knowledge of the individual fish is not enough to predict the movement” (Participant 16); “No because the movement of a single fish can be affect not only by the qualities of the fish itself but also largely depends on the whole system of the living space that the fish lives in” (Participant 29); and “No. The movement of an individual fish cannot be predicted. There are always too many possibilities that people cannot control” (Participant 36). These students demonstrated that they not only understood that movement and actions of agents cannot be fully predicted, even with enough knowledge, but also that unpredictability is due to randomness or chance factors within the environment.

Order. On average, students began with a medium understanding of Order (M = 2.20, SD = .73), which stayed virtually the same in the posttest, decreasing by .02 points (Table 9). The average student response (about 43%) started and stayed at a mid-level, which meant that students gave a mix of both top-down and bottom-up examples for how ants organize themselves in the search for food. For example, the following responses represented this mid-level of understanding in describing how ants find food:

> They probably have sense to know where there are picnics or garbage to eat. It is not a coincidence to have 30 ants in one area around a leftover sandwich. I assume in the colony they have hierarchies where certain ants are assigned to food

> duty. I often see ants carrying food in teams of two or three so they most likely hunt and come back to the ant holes and share what they got with the rest of the ants. (Participant 32)

> I do not think there is an order to it initially. I think ants go about searching for food. Finally when food is found they report to the colony and an order is created to retrieve the food. (Participant 10)

Both pretest and posttest scores for the highest level of understanding of Order also stayed around 38% (Table 10). Students representing this level of understanding stated how ants find food in a bottom-up way exclusively. For example,

> I suspect it begins as a random search (perhaps with a rudimentary procedure involved), so initially, many ants will search unsuccessfully. But when one finds food, they have a mechanism for communicating its location (perhaps with a pheromone trail?) such that it can guide the behavior of other ants who have not yet found food. If, for example, something like a pheromone trail overrides an ant's initial search procedure, so that it follows a trail if it crosses one, eventually a large number of ants could end up following the trail between their hive and the food. (Participant 50)

> I think ants go about finding food in an order. The order is emergence and basically come naturally. Because there is no one control the ants, or lead the ants of finding food in an order. The ants basically are trying to keep the same distance with one another, not to be so close and not to be so far, thus that causes ants go finding food in an order. (Participant 24)

In these responses, Order was not described with either leaders or a chain of command but in a bottom-up and emergent way.

Relatively few students (19%) spoke of ants finding food in a novice way by exclusively describing a top-down search, such as the following:

> I believe there is an order in the way that ants collect their food. Maybe there is a queen ant in a colony that gives the instruction on how to collect the food. (Participant 75)

> There seems to be an order in which ants go on to finding food. I am not exactly sure how it works, but I am sure that it is not random. There might have an "alpha" in their crew that leads them to specific places and tells them what to do. Like any other creature that is abundant on earth, there has to be some kind of leader. (Participant 15)

In these examples, students demonstrated that they have a difficult time conceiving how order could arise without a leader.

Obvious vs. Non-Obvious Causes. The item assessing this component asked whether students would attribute the causes of an effect in a river (a fish die off) to causes that were easily perceptible or if they would go beyond these to think about less tangible causes. Responses to this question consisted of causes described in very few words. Non-obvious causes students gave were largely variations of disease (e.g., viruses, bacteria, a sickness spreading in the pond); pollution (e.g., air pollution, water pollution due to a factory); poor water quality (e.g., less oxygen available, eutrophication); and runoff (e.g., nutrients from agricultural runoff, increased runoff from adjacent lands). Obvious causes students gave were about population increase (e.g., spawning and dying, overpopulations leads to a shortage of food); predators (e.g., new fish predator, over fishing); low food supplies (e.g., lack of food, loss of food supply); visible pollution (e.g., oil spill, trash in water), weather (e.g., hurricanes, drought), and water issues such as changing tides or lack of vegetation. Before the intervention, a little over half of the causes that students gave for a fish die-off were non-obvious (M = 0.55, SD = 0.26) with a slight improvement after the intervention (M = 0.59, SD = 0.23) (Table 9). This meant that students gave slightly more non-obvious responses than obvious responses throughout.

Local vs. Distant Causes. Students relied heavily on using local causes to explain the fish die-off. Responses to this question consisted of causes described in very few words. Local causes focused on animals (e.g., fishing, predators); disease (e.g., bacteria, viruses, a sickness spreading in the pond); food (e.g., loss of food, food shortage); pollution (e.g., chemical water pollution, toxins); weather (e.g., red tide, storm); and water issues such as changes in river current or salinity. Distant causes students gave were mainly about pollution (e.g., pollutants from a factory, careless pollution by people living nearby) and runoff (e.g., runoff from nearby factories, runoff from adjacent lands) that happened outside the river. On average students gave distant causes only 15% (*SD* = 24%) of the time during the pretest, which increased to 18% (*SD* = 27%) in the posttest (Table 9). A large number of students (33% in the pretest and 26% in the posttest) listed only local causes, resulting in large standard deviations and overall means that skewed right. The change in ratio of local to distant causes occurred because the average number of distant causes given by students increased from 0.53 distant causes per person in the pretest to 0.62 distant causes in the posttest per person, while the average number of local causes per person in the pretest (*M* = 3.30, *SD* = 1.77) essentially stayed the same (*M* = 3.29, *SD* = 1.86).

Event vs. Process Based Causes. Students began with a relatively small average of process-based causes (*M* = 16%, *SD* = 21%) but made a small increase to 21% (*SD* = 25%) of responses consisting of process-based causes after the intervention (Table 9). A large number of students (25% during pretest and 24% during posttest) gave only event based causes, resulting in large standard deviations and overall means that skewed right. Responses to this question consisted of causes described in very few words. The event-based causes students gave were largely about pollution (e.g. oil spills, dumping of waste); disease (e.g., disease from bacterial infection, virus killing fish); animals (e.g., over hunting, a predator has killed the fish); low food supplies (e.g., lack of adequate food, lack of nutrition); and weather (e.g., extreme tidal change, storm). Process-based causes that students gave also focused on similar topics, but students talked about these as either occurring over longer periods of time, or in regards to balance within a system. For example, some students talked about increased soil levels eventually destroying vegetation" (Participant 9) or "Fertilizer run-off creating too many plants, starving the fish for oxygen" (Participant 3). These were not one-off events but longer-term processes within the system.

Significance Testing

A Wilcoxon Signed Ranks test was used to investigate whether students made improvements from their pretest to posttest component scores (Table 11). Student understanding of Agents significantly improved by 0.2 points (z = 2.18, p = .02) and understanding of Causation: Event vs. Process significantly improved by .05 points (z = 1.70, p = .045) while student understanding of Action Effects decreased by .17 points (z = -2.43, p = .01). The effect size for the increase in Agents understanding is r = .17 and for Causation: Event vs. Process is r = .13 while the decrease in Action Effect understanding is r = -.19. Although all other components improved from pretest to posttest, changes were not significant.

Table 11
Significant Component Differences between Pretest and Posttest Scores

	Pre (SD)	Post (SD)	Wilcoxon Z	Sig.	Effect Size R
Action	2.43(.65)	2.26(.69)	-2.43	.01*	-.19
Agent	1.61(.80)	1.81(.78)	2.18	.02*	.17
Order	2.20(.73)	2.18(.74)	-.03	.45	.00
C: Obv.	.55(.26)	.59(.23)	.97	.17	.07
C: Local	.15(.24)	.18(.27)	.95	.17	.07
C: Event	.16(.21)	.21(.25)	1.70	.045*	.13

Note. * indicates Wilcoxon Signed Ranks test was significant (p<.05)

Next I discuss what changes occurred for the components of Action Effects and Agents, and give examples of changes that students made. Components that did not exhibit change are not discussed.

Action Effects. Because the mean of Action Effects started high (*M* = 2.43, *SD* = .65) it might have been expected that an increase in understanding would have been more limited than the other components, but I did not expect that this component would decrease. To make sense of this, I conducted several further analyses to explore what might have changed for the worse about student understanding and student responses.

For the 27 student responses that showed a decrease in student understanding, results fell into two patterns. First, the majority of students (18) dropped one level from more expert non-linear understanding (level 3 out of 3) to a mix of understanding (level 2 out of 3). Further analysis revealed that these 18 students did not show misconceptions in their posttest responses, but instead exhibited shorter and simpler responses than in their pretest answers. The following are three examples of these shortened posttest responses: "I believe so. Everything in the world is somehow related. A change in one thing can have effect on others and so on" (Participant 87), "yes, this happens because of chain reactions and feedback loops" (Participant 54), and "yes, small changes do lead to large effects in the ecosystem, because ecosystem for most times acts as a complex system rather than a clockwise system. The impact is non-linear" (Participant 24). In all three of these responses, students failed to demonstrate that they understand how or why they might happen, a necessary characteristic, which they all demonstrated in their pretest essays. In other words, students whose scores decreased initially wrote more words and went further to demonstrate their understanding, an indication of possible test fatigue.

The other theme that arose from the qualitative analysis showed four other students who dropped either 1 or 2 levels for what was coded as an “additive” misconception. This occurred when students responded that non-linear effects could occur, but only through the accumulation of several small effects either through time or by number. For example, one student responded that “Yes. Many slight effects can create a large effect. Even if there is no notable change in the system after a small change, as time goes on, these changes build up to become very apparent” (Participant 73). Another student said, “Carbon emissions are one example. While each individual automobile may be producing only a small amount of emissions the sum of all those small parts actually adds up to something quite large” (Participant 19). Neither of these are incorrect ideas, but they did not represent the non-linear effects that are created through cascading effects, which the rubric coded for. Students may have understood how these occurred, but they do not provide evidence of understanding.

Agents. The significant improvement of student understanding of Agents largely came from students who initially believed that the actions of agents in a complex system are largely predictable but later understood that actions are not wholly predictable (Table 11). For example, one student responded to whether one could predict the movement of an individual fish in the pretest that “With enough knowledge of a fish's general path, food sourcing, and “comfort zones” you could potentially predict the path of a fish” (Participant 96), an example of a novice response. After the intervention, this student said, “you cannot predict the movement of the individual because it is less predictable than an entire school. Emergence of the pack does not exist here.” Here the student now believes that an agents’ actions are less predictable. Another student initially felt that

"Yes, you could predict the movement of an individual fish if you studied its past behavior, defense mechanisms, diet, preferred environment, etc." (Participant 69) while after the intervention said:

> If you knew the past behavior, priorities, necessities, habitat, tendencies, etc. of a species of fish you could to some degree predict where they would travel to in relation to time. You could not predict the more subtle and spontaneous movements of a single fish though. If you knew they had a school they travelled with you could predict that they would join them.

This student also demonstrated a change in understanding agent actions as unpredictable, but still did not go far enough to explain how chance factors or unpredictable environmental factors cause this unpredictability. Similar changes in student responses, from a novice to a medium level response, were largely responsible for the significant improvement in understanding this component.

Event vs. Process-Based Causes. Similar to the other causal components, this change in proportion occurred not because the number of event-based causes per student decreased from pretest to posttest (M = 3.01, SD = 1.46 to M = 2.98, SD = 1.36) but because students increased the overall number of process-based causes they gave from pretest to posttest (M = 0.60, SD = 0.77 to M = 0.79, SD = 0.94). Students wrote about relatively more process based causes such as "Overpopulation lead to a shortage of food, and these fish starved" (Participant 78) and "nutrients allow for excessive algae growth, and such growth depletes the water from oxygen, leaving fish with conditions not supportive of life" (Participant 4).

Far Transfer

The second part of the first research question asked the following: Can students transfer their understanding of complex systems to another context of their architecture course? Blog-post responses were coded for whether students demonstrated an understanding of or used a complex systems component in describing a system within an architectural context. Components that were represented in clockwork ways were not coded because the goal was for students to demonstrate an understanding of the more difficult complex systems level of each component. In the following section, descriptive statistics are described for overall components; then examples of student responses to the transfer question illustrate how students represented each of these components.

Descriptive Statistics

On average, students demonstrated an understanding of Order and Action Effects more often than Agents, Non-Obvious and Distant Causes on the transfer item (Table 12). Due to the nature of the task, all students talked about the process of a system and therefore this was represented in all transfer responses. The Order component (Table 12) was written about by the most students (51.3%) and Action was mentioned by almost as many (48.7%), while Non-Obvious causes (24.4%), Distant Causes (21.8%) and Agents (29.5%) were all written about in the transfer topic by less than a third of students. Twelve students in the sample were graduate students and therefore were exempt from the transfer question, and 6 students failed to turn in a response.

Table 12
Transfer Frequency for Components

	N	# of Responses	% of Responses
Action	78	38	48.7
Order	78	40	51.3
Agent	78	23	29.5
Causation: Non-Obvious	78	19	24.4
Causation: Distant	78	17	21.8
Causation: Process	78	78	100

Students were given the option of writing about energy, food, transportation, waste, or water for their transfer response. By far the most popular topic to write about was food (41%), followed by water and energy (14.1%), waste (11.5%) and transportation (10.3%, Table 13). Seven students (9%) talked about systems generically and did not choose one of the given choices.

Table 13
Transfer Topic Frequency

	Frequency	Percent
Food	32	41.0%
Energy	11	14.1%
Water	11	14.1%
Waste	9	11.5%
Transportation	8	10.3%
No Topic	7	9.0%
Total	78	100%

Different complex system components were represented more often depending on the topic that students wrote about (Table 14). Overall, students who wrote about Transportation talked the most often about Agent Effects (62.5%), those who wrote about Food talked about Order the most (65.6%), and those who wrote about Water systems wrote about Action the most (63.6%). Distant Causes were somewhat represented when writing about Food (40.6%), and in general students did not write about Non-Obvious Causes very much.

Table 14
Percent of Components Present by Topic

	Action	Agent	Order	Causation: Non-Obvious	Causation: Distant	Causation: Process
	Percent	Percent	Percent	Percent	Percent	Percent
Energy	45.5%	27.3%	54.5%	9.1%	9.1%	100%
Food	43.8%	34.4%	65.6%	31.1%	40.6%	100%
Transportation	37.5%	62.5%	50%	25%	0%	100%
Waste	55.6%	0%	44.4%	22.2%	11.1%	100%
Water	63.6%	27.3%	18.2%	27.3%	18.2%	100%
No Topic	57.1%	14.3%	42.9	14.3%	0%	100%

Finally, students who chose Food as a system for their transfer response wrote about more components (*M* = 3.16, *SD* = 1.13) than those who chose other topics (Table 15, while those who failed to pick a topic demonstrated the least understanding of complex systems components (*M* = 2.29, *SD* = .95).

Table 15
Average Number of Components by System Type

	N	Mean	Std. Deviation
Energy	11	2.45	1.13
Food	32	3.16	1.22
Transportation	8	2.75	.89
Waste	9	2.33	.71
Water	11	2.55	1.04
No Topic	7	2.29	.95

The following section discusses examples of how components were represented in transfer topics.

Action Effects. The component Action Effects was highly represented in almost all of the systems students chose. Students discussed this component the most in the design of a water system (63.6%). The following are some examples of designs demonstrating an understanding of these non-linear effects:

> Landa goes ahead and describes the process in which a system like this works alone and just triggers one thing to another, eventually leading them to a greater output: "A trigger of one energy form sets off a flow in another which, in turn, triggers a release of a flow in the first; the insertion of more parties creates a chain of trigger-flow interactions that may go in a series, in parallel or both…. The trigger-flow interactions specifically create an interdependent reproduction among the participating dissipative structures. It interlocks a series of separately reproductive systems into a single, interactive reproductive system" (De Landa 77). These small changes would result in a more sustainable output later in time. (Participant 15)

> On the other hand, a complex approach would involve a web of solutions that are independent of each other. These small changes would turn into big outcomes. (Participant 8)

> A healthier ecosystem will create a feedback loop of improved water quality; once the river become a public water source, restrictions on boat traffic will improve health of the river, allowing water habitats to grow, increasing natural filtration, improving water quality. (Participant 9)

> As the price tag on fresh water goes up, the local economy begins to suffer and there is a decrease in state revenue, and federal financial aid must be sought in order to keep up this rather linear system. This also has ramifications for social equity, with poorer areas in both urban and rural environments less likely to receive quality freshwater or to have systems that can collect and distribute a freshwater supply efficiently. (Participant 27)

> If one of these steps were to suddenly fail, a pressure pump, a transportation car or even if the lake were to suddenly pollute the whole process would be affected. As Author Donella H. Meadows states in his work "Thinking in systems"; "Reinforcing Feedback loops are sources of growth, explosion, erosion, and collapse in systems" (155), meaning that if these failures were to occur and reinforced either negative or positive effects could occur. For example the failure of a pressure pump in a specific building would result in no water on the fourth floor of such specific building in which no citizen would be able to take a shower, go to the bathroom, clean their home, etc. Which would result in the over accumulation of dirt and waste and further more beginning of these citizens to search for new water sources, such as friends apartments, common bathrooms, etc. (Participant 48)

In all of these instances, participants wrote about how small causes could lead to large effects and in some cases explained why these were important to consider within the design of these systems.

Agents. Students who chose to design a transportation system often demonstrated an understanding that agent actions are unpredictable (63%) (Table 14). The following are a few examples of students representing an understanding of Agent effects as they talk about designing a transportation system in a city.

> Patterns may also emerge from interactions within the city. For example, if taxi drivers notice that they are getting many calls from a certain location on a particular day or time, then they will likely drive by the area at that time in hopes of finding customers. Vice versa, if customers know that many taxis often drive down a particular street, then they will gravitate towards that street in hopes of finding quick transportation. This system is reliant upon the needs and behaviors of many variables and is highly variant and reactive. (Participant 69)

> Essentially, within a city, there are hundreds of thousands of different systems and they all are effected by the occupants of the city uniquely and therefore effect the city in different ways. (Participant 35)

> One of the main problems of city transportation is that, especially in big cities like NYC, there are millions of drivers, pedestrians, and bicyclists who each have an individual agenda and are constantly fighting for space on the road. This individualistic nature makes road behavior unpredictable and chaotic. (Participant 37)

These students demonstrated an understanding of the unpredictability of agent actions and that emergent outcomes may happen due to the many chance factors within these systems.

Order. Students who chose to design an agricultural system were the most likely to mention that organization came from a bottom-up process (66%) (Table 14). The following are a few examples of students representing an understanding of order coming from bottom-up organization as they write about designing an agricultural system in a city.

> Fifteen years ago in my home city in Shijiazhuang, you could see individual farmers selling products from their own land in the city on streets. People viewed themselves as part of the city organism instead of the dominator. The food supply was a local closed web with the participation of multiple factors. There was no

> leading factor so not a single factor can destroy the whole system. Also, the detrimental side effects were reduced because the food is locally served without much transportation. (Participant 14)

> The first modification I want to make in city food chain is to localized the food production and efficiently reapply the by-products which are often treated as pure waste in system. The urban roof-top farmer is one practical option. Individuals, communities or neighborhoods could cultivate in nearby living space. And the community garden or personal farmers in one hand can greatly improve food quality, providing fresh and organic healthy food to citizen, in another hand, can reduce the energy needed for transportation (Participant 24)

> The management of this system should be bottom-up, or rather, it should be dictated by the source farms. Local markets and grocery stores should only stock produce that is seasonally available and produced by regional farmers, rather than shipping products across the country or even greater distances. All homes should be outfitted or have easy access to composting facilities. A weekly/biweekly collection should take place to guarantee that people actually use the system (no one *actually* wants compost sitting in a bin for years outside of their house). I believe that in the implementation of these three basic management principles, the food system will run itself sustainably in a closed cycle. (Participant 26)

In these examples, students demonstrated an understanding that order in agricultural systems in cities can be emergent through the individual actions of people such as in garden rooftops, local markets, and using more regional farmers instead of single large farms.

Students who chose to design an energy system for a city were also highly likely to mention that order came from a bottom-up process (54.5%; Table 14). The following are a few examples of students representing an understanding of order as they talk about designing an energy system in a city.

> Different parts that form the city interact with each other and display certain kinds of overall order. Because the city is not an artificial machine that functions perfectly with everything working together with a certain goal, it is really important to think carefully about the different systems in the city that influence people's everyday life. (Participant 36)

> Urban energy system can also be viewed in a complex system, which resembles the ecosystem. Compare to the top-down approach in clockwork system, a

> complex system is a decentralized bottom-up approach, where sub-systems can give rise to a more complex system. In this case, each member of the community is both producer and consumer of the renewable energy liberated by technology- electromagnetic (photovoltaic materials), thermal (radiant solar collectors and geothermal systems) and kinetic (turbines for harnessing the wind and the tides). As a result, sources of energy become diverse and sustainable. The flow of energy shifts from a directional stream into a field of intense, dynamic lateral connections. (Participant 99)

In these examples, students demonstrated that Order can be emergent through the individual actions of people such as in buying solar panels or installing their own turbines.

Causation: Non-Obvious. The focus on non-obvious causes was also not well represented in almost all of the systems that students designed, with only 24% (Table 14) of student responses mentioning causes that were not visible by the naked eye. One system where more students were able to represent this component (22%) was in designing a waste system (Table 14). The following are some examples of these designs:

> It is inherent in our nature to think about problem solving in a linear path, as if we wanted to reach from point A to point B right away. What if there is a third point C and is a much better choice than B? If we had taken into account the different possible variables in our problem, maybe we would have saved energy and time rather than trying to think for a second or third solution. Every problem we confront, either day to day or design struggles, has multi-faced components. They all belong to a complex system, where the whole is more than the sum of its parts. (Participant 45)

> The top-down approach of the major waste management systems maintaining and regulating the inputs and outputs on the large scale works wonders for individual neighborhoods. However, what is not discussed is what exactly can be recycled and made into useful resources. There is no dialogue between the waste management companies and the community about new ways of recycling nor the expansion of the list of recyclable materials. (Participant 55)

Participants, when they did write about non-obvious causes, usually focused on solutions and the non-obvious problems they attempted to remedy by emphasizing what was being overlooked. Students noted that these problems remained because the real causes were not readily perceived or acted upon in these systems.

Causation: Distant Causes. The focus on distant causes was not well represented in any of the systems that students designed. The one system where almost half of students were able to represent this component (41%) was in designing a food system (Table 14). The following are some examples of these designs:

> And then there is another centralized stock-feeding base thousands of miles away. This is, in reality, the practice of most cities in developed and some rising undeveloped countries. Yet it is not necessarily the smart choice as transportation of food generated huge cost and equally huge pollution to our city. (Participant 14)
>
> The whole process from food growing to final consumption of citizens is always pictured as a linear web. Or from another conventional view of energy, food that is grown outside the city or even sometimes across the world is brought to tables in city by planes, trucks and railways. All of these transportation require an enormous amount of energy and then release similar amounts of harmful toxins into the atmosphere. (Participant 24)
>
> The transportation of produce from farms to the city is particularly important, noting efforts to reduce carbon emissions and footprints during the entire process. The main way to help mitigate these environmental impacts is to source local – within 100, 150 miles. This limitation helps to reduce the number of large scale, mass production farms that serve the city. (Participant 26)
>
> Food is grown (or raised) outside the city, sometimes nearby, but often halfway across the world. These resources are then transported to the city in planes, trains, and automobiles, all of which consume enormous amounts of energy and release similar amounts of harmful toxins into the air as they crawl across our counties, states, and countries. (Participant 31)

In nearly all of the agricultural responses that mentioned distant causes of problems, transportation of food was mentioned. This suggests that some systems make it easier for students to focus on more distant causes. No students discussed distant causes for transportation systems, and barely any discussed distant causes for energy, waste, or water systems.

Change in Component Understanding by Treatment Condition

The second research question asked: How does understanding of components of complex systems compare for students receiving self-monitoring scaffolding versus students receiving ontological scaffolding? A Mann-Whitney test was first used to determine if there were significant differences for individual component scores between treatment conditions to ensure equivalence between groups. There were no significant differences for any pretest components (Table 4). To investigate if students showed improvements on component scores within treatment conditions, a Wilcoxon Signed Ranks test was used for each condition separately (Table 16). No components for the Self-Monitoring group changed significantly from pretest to posttest (Table 16). The Ontological group showed significant improvement for Agents by 0.23 points ($z = 1.79$, $p = .04$) and Process vs. Event Causes by .09 points ($z = 1.81$, $p = .04$) while there was also a significant reduction of Action Effects score by 0.18 points ($z = -1.97$, $p = .03$). The effect size for the increase in Agents understanding was $r = .20$ and for Causation: Event vs. Process is $r = .19$ while the decrease in Action Effects understanding was $r = -.22$. All other component changes were not significant.

Table 16
Comparisons of Pretest and Posttest Scores by Treatment Condition

	Self-monitoring				Ontological			
	Pre (SD)	Post (SD)	Z	Sig.	Pre (SD)	Post (SD)	Z	Sig.
Action	2.35(.74)	2.20(.76)	-1.49	.07	2.51(.55)	2.33(.61)	-1.97	.03*
Agent	1.64(.78)	1.80(.73)	1.33	.12	1.59(.82)	1.82(.84)	1.79	.04*
Order	2.19(.76)	2.05(.76)	-1.47	.09	2.21(.71)	2.31(.70)	1.53	.10
C: Obv	.56(.24)	.59(.25)	.69	.25	.55(.28)	.59(.22)	.67	.25
C: Lcl.	.11(.21)	.17(.25)	1.59	.06	.18(.26)	.20(.29)	.15	.45
C: Evt.	.16(.21)	.17(.19)	.48	.32	.17(.21)	.26(.30)	1.81	.04*

Mean gain scores were used to determine if there was a difference for change in scores from pretest to posttest. Because these scores violated normality (Tables 4 & 5) a non-parametric Mann-Whitney test was conducted to determine if there were significant differences between treatment groups on gains for each component. Only one component, Order, showed a significant difference between treatment groups (z = 2.17, p = .02) with the Self-Monitoring group showing reduced understanding (M=-.18, SD=.76), while the Ontological group showed improvement (M= .18, SD=.71), an effect size of r = .24 (Table 17).

Table 17
Mean Gain Score Differences by Treatment Type

	SM	OS			
	Gain (SD)	Gain (SD)	Mann U	Sig.	Z
Action	-.19(.82)	-.24(.77)	837.00	.34	.43
Agent	.17(.17)	.23(.83)	808.50	.45	.12
Order	-.18(.76)	.18(.71)	581.00	.02*	2.17
CS-Obv	.02(.28)	.02(.29)	982.00	.48	.07
CS-Local	.07(.29)	.00(.30)	894.50	.20	.84
CS-Event	.02(.25)	.08(.29)	886.50	.19	.89

The trend found between treatment conditions was that there was a significant difference on gain scores for the Order component. Interestingly, this occurred because there was a non-significant decrease in understanding of Order for the Self-monitoring group while there was a non-significant increase of understanding for the Ontological group. This appears to have happened because more students fell one level of understanding in the Self-monitoring group (23.1% as opposed to 10% in the Ontological group). For example, the following Self-monitoring students went from a medium understanding of Order (a mix of bottom-up and top-down causes of order for ants finding food) to more novice top-down responses.

> **Pretest:** ants travel in colonies to hunt for food & the ants mimic each others' behaviors and movement patterns

> **Posttest:** the ants follow a leader and mimic each other's behaviors as they search for food. (Participant 8)

> **Pretest:** I think there is no particular order to how ants find food. I think they look for it and when they come across it they attack. But if there are multiple options I think they just go with whatever will be the most beneficial to them. If someone left out a bunch of cookies in one area, compared to a few cookie crumbs, I think the ants are more likely to go to the source that will benefit them most.
> **Posttest:** There is probably order. Food is such a necessity that ants would not leave that to randomness. They probably search for it in terms of what would benefit them the most. (Participant 57)

Students also decreased one level from a high level of bottom-up understanding to a medium level of bottom-up and top-down:

> **Pretest:** I believe that ants go about finding food by means of organized excursions that collect food and bring it back to their primary dwelling where the queen resides. I believe that the order is instinctual and that, for the most part, even what may seem to be a lone and wandering ant is most likely fulfilling its role in this complex system of hunting and gathering.
> **Posttest:** I believe that there is a stringent and organized method in ant colonies' food collection. I believe that the order is instinctual and that different ants are bred to perform different roles to benefit the system as a whole. (Participant 43)

> **Pretest:** I think it is sort of like the flocking example we have seen in class. One ant stumbles upon food (they wander aimlessly until then) which leads other ants to the source until there is a group of them feeding off of one location. It is fairly random but instinctual.
> **Posttest:** one ant stumbles upon food, brings some back to the ant hill, returns to where the food was first found and other ants follow, slowing gathering. However, the first ant does not stay the leader; once an ant has found the source of food, they are just as knowledge able as the first ant and thus are equal again (Participant 71)

> **Pretest:** Ants use their senses to locate food sources (sight, smell, etc.), then they release pheromones along the path to the food so that the rest of their colony can locate the food. They also probably learn by experience of knowing where food is frequently found. Natural selection has also played a role in only allowing the ants capable of finding food to survive and reproduce.
> **Posttest:** Ants have an order that ha come from instinct, trial & error, natural selection. Through evolution, ants have developed the most efficient system for locating food sources that is highly dependent on their senses and pheromones. (Participant 69)

The opposite trend happened in the Ontological scaffolding group, which had a larger number of students increasing their understanding by one level (32.5% as opposed to 15.4% for the Self-monitoring group). The following are examples of improvement from novice to a medium level of understanding for the Ontological group:

> **Pretest:** I honestly do not know if ants have a sense of smell or not, but I do know that when one ant finds a source of food, it brings its little bastard friends with it on a second trip and this huge conga line starts where they continuously go to the food source and bring it back.
> **Posttest:** There is some kind of order to it. One ant finds the food source and it's been proven that things almost always take the path of least resistance, therefore ants shuffle in line towards the food. (Participant 65)
>
> **Pretest:** I think there is an order. There is a leading ant and the rest of the group follows it.
> **Posttest:** I think there is an order. The order comes from the system in the ant group. Ants have a system in the group when they try to find food. (Participant 99)
>
> **Pretest:** I think ants find food as a colony, maybe delegating specific group of ants to find this food. Therefore I think there is an order and it comes from the ants themselves. They probably try to create colonies near large sources. They also work together to conquer large sources of food like large decaying insects.
> **Posttest:** They find food through what seems like a random search but once food it spotted, they use their senses to communicate with each other about collaboration. They are then able to form order to line up and collect the food. This order comes from their ability to adapt and a linear system. (Participant 91)
>
> **Pretest:** I am not sure about how ants find food but when they sense it they form a single path and follow only the ant at the front. When one gets lost, it seeks for a different path and all the ants right behind him follow him
> **Posttest:** I think there is an order but I am not sure how it exactly works. From my observations, when a group of ants capture food nearby, they organize in a single line and form a path leading to the food. Apparently, the each individual ant only follows the one in from of him and when one gets lost and forms a new path to the food all the ants behind him follow him. (Participant 45)

And for the Ontological group examples of a medium level of understanding to a more expert level:

> **Pretest:** I speculate that ants go about finding food through their sense of smell. They can track the food down by smelling it and find their way back to the colony

by retracing their own scent. The first ant can notify other ants who will follow the trail and set up at pathway between the food and the colony. The simple rules of the for the ants would be to follow the scent of the ants in front of them, collect the food, and return to the colony following the scent along the way.
Posttest: The ants search for food is random, but once they find something an ordered system is created to retrieve the food and bring it back to the ant hill. A lone ant stumbles onto some food source and brings some of it back to the hill leaving a trail of scent for the other ants to follow to get to the food and back to the hill. The order comes from the ants' simple rule to follow the scent. (Participant 13)

Pretest: one or a small number of ants goes out using some sort of sense most likely smell, to scout food, then once it finds it it goes back to get additional ants to help collect and transport the food back to the ant hill to consume. Ants often work as teams carrying food or supplies
Posttest: scouts spread out from the ant hill individually, when they find a food sources they send a pheromone signal back to alert the rest of the ants, who then come to help collect the food in a system similar to an assembly line. (Participant 9)

Pretest: There is some order. Every ant will leave a specific kind of chemical, which other ants can trace, on its path. When an ant finds some food and returns to the hive, other ants will follow its path to the food.
Posttest: They leave chemicals along their paths. Individually random, but some order in the whole (Participant 85)

Treatment Type Differences for Transfer

The second part of the second research question asked the following: How does the ability to transfer understanding of complex systems to another context of architecture compare for students receiving Ontological scaffolding versus students receiving Self-monitoring scaffolding? To determine if there were differences on transfer between conditions, a Mann-Whitney test was used to compare mean differences for each component (Table 18). Although the Self-Monitoring condition earned higher means for all components, there were not significant differences between conditions.

Table 18
Transfer Task Differences by Treatment Type

	SM (SD)	OS (SD)	Sig.	Z	U
Action	.51(.51)	.46(.51)	.42	.44	720.50
Agent	.30(.46)	.29(.46)	.58	.04	755.00
Order	.54(.51)	.49(.51)	.41	.46	718.50
CS: Non-Obvious	.30(.46)	.2(.40)	.22	1.04	681.00
CS: Distant	.24(.44)	.2(.40)	.41	.51	722.00
CS: Process	1.00(0)	1.00(0)	1.00	0.00	758.50

A Mann-Whitney test, using overall sum scores, determined that there were no significant differences by treatment group, although descriptively, the Self-Monitoring group had a higher mean number of components mentioned (M = 2.89, SD = 1.10) than the Ontological group (M = 2.63, SD = 1.11).

Summary

Overall, students in both scaffolding conditions demonstrated a small significant decrease in understanding of the component Action Effects from pre-to posttest and a small significant increase of understanding of the components Agents and Event vs. Process based Causation. The ontological scaffolding group had the same significant increases in Agents and Events and decrease for Action. The self-monitoring group demonstrated only non-significant similar trends for all components except Order. There was a significant difference between treatment groups for the component Order with a small, non-significant increase in understanding for the ontological group and a small, not significant decrease in understanding for the self-monitoring group.

Overall, nearly half of the students were able to demonstrate understanding of the components Action Effects and Order in a different domain (an architectural setting), with the Agent Actions, Non-Obvious Causes, and Distant Causes appearing less frequently. Whether students demonstrated understanding of a component varied depending on what type of system they wrote about, however. For example, students who wrote about transportation more readily showed an understanding of Agent Actions, while only those who wrote about food showed an understanding of Distant Causation. There was no difference between treatment groups on the ability to transfer this understanding.

CHAPTER 5: DISCUSSION

In this chapter I return to the original research questions and discuss findings. I then explore how this work contributes to the literature, describe limitations of the study, and suggest future directions for research.

School science standards as well as science education researchers (Jacobson & Wilensky, 2006) have called for students to learn complex systems (Achieve Inc., 2013; National Research Council, 1996, 2012). Previous studies have examined difficulties students have in learning complex systems (Assaraf & Orion, 2005; Hmelo-Silver, Duncan, et al., 2007; Jacobson, 2001; Resnick, 1996; Stroup & Wilensky, 2000; Wilensky & Resnick, 1999) for a variety of age groups.

The results of this dissertation build upon previous research (Goh et al., 2012; Grotzer et al., 2013; Jacobson et al., 2011; Yoon, 2008, 2011), and address limitations of previous studies. Despite the number of studies investigating how to help students understand complex systems with simulations (Barreteau & Bousquet, 2000; Boissau & Castella, 2003; Grotzer et al., 2013; Jacobson et al., 2011; Vattam et al., 2011), none of these place students in the role of agents that are a part of and create the systems under investigation. Studies that have put students in the role of agents either have not focused on student understanding of complex systems components (Colella, 2000) or have done no experimental investigations (Wilensky & Stroup, 2000a). The present study explicitly investigates whether participating in and experiencing being an agent in a complex system simulation helps students better understand system components. Extending other research that investigates how to support understanding of simulations and complex systems (Jacobson et al., 2011; Slotta & Chi, 2006), this study contributes to the literature by comparing the effect of self-monitoring and ontological scaffolds to help students understand an inherently difficult topic. Finally, this study builds upon a view that learning encompasses transfer (Bransford & Schwartz, 1999; National Research Council, 2000) by addressing whether students can transfer their understanding of components outside of the domain of the simulation.

Student Understanding of Complex System Components

This section examines the first research aim of whether an agent-based participatory simulation intervention could help students understand complex system components. Results are discussed in the context of previous literature.

Change in Understanding of Complex System Components

Action Effects. Most students began with a medium-high understanding of Action Effects, and a significant decrease in understanding occurred after the intervention (Appendix K). Interestingly, there are conflicting findings from previous research about how difficult students find this component. Small studies of undergraduate understanding indicated none of them understood how small causes can lead to big effects (Jacobson, 2001); after a hypermedia intervention with another sample of undergraduates, this was the only component on which participants did not improve (Jacobson et al., 2011). In contrast, a study in grades 8-12 found that this was the easiest category for students to understand (Goh et al., 2012). The findings from this study found that overall, undergraduate students found this category to be the least difficult and they also did not improve their understanding, possibly because of their initially high scores.

The assessment for Action Effects required participants to demonstrate not just a type of understanding (i.e. non-linear vs. linear) but explain how they believed this understanding works. Students wrote shorter and less involved responses on the posttest, and scores significantly decreased, despite the treatment. A possible reason for why students demonstrated worse understanding of Action Effects after the intervention may have been that the intervention did not help students understand how small causes can create large effects. Students began with a medium-high understanding of Action Effects and fell to a medium understanding after the intervention. During the simulation students worked together as a large group, made their own choices during rounds, and then saw these summed effects displayed for both territorial groups, and the Bay as a whole. It may have been that students interpreted the overall effect on the system as an aggregated effect of everyone's equally weighted choices.

There were two main ways students could have explained how small causes create large effects. The first is that small causes can spread through systems through growing chain reactions or cascading effects. For example, if a species of fish dies, and then several species of predators that depend on that fish die, and then the ecosystem collapses, and thus a relatively small initial change can grow into a much larger, non-linear effect. The second is that a small cause does not have a large effect on its own, but many small causes add up to creating a large cause. For example, a single individual who wastes water is unimportant, but if everyone acts like that person, the effect becomes devastating. In the first example, a small cause can lead to a large effect; in the second example, many small causes lead to a large effect. These two understandings are not mutually exclusive, and a student who believes the latter does not necessarily disagree with the former unless explicitly stating so. However, students tended to respond with answers that focused only on the aggregation of small causes. Therefore the item used to elicit student responses may not have fully captured whether students understood non-linear effects and how they may emanate from small causes.

Both the intervention and the simulation might be improved for future studies. First, given the sharp decrease in student response length, and their tendency to skip the second part of the question, future development of items should not have multiple questions embedded in a single item. Second, because students were able to give multiple reasons for how large effects occur that other than cascading growth and chain reactions, items should be adjusted to ensure students focus on these processes. Finally, during the simulation, discussion should be focused at different points to elicit students' beliefs about causes of the system effects. This may mean directly asking about whether effects are occurring from everyone making small changes or if key stakeholders are having a non-linear effect on the system. It may also benefit students to disaggregate their individual effects on the system so they can see exact impacts of their actions. Students may find that making a large change may have small impacts, or that possibly small but important individual changes affect the Bay disproportionately compared to other changes.

Agents. Students understood the Agents component the least well of these three components but notably, made small but significant improvements (Appendix K). One possible explanation for these results may have been the unpredictability that students witnessed during the simulation. Because students take the roles of agents in the simulation, they were able to personally experience how random changes in the environment changed their own behaviors. Students may also have experienced how their own actions may not always have had the intended or hoped for effect.

These findings are somewhat in keeping with previous research findings. Jacobson's original study of undergraduate novices (2001) showed that most of their responses viewed agent actions as completely predictable, while a later study showed they could improve their understanding (Jacobson et al., 2011). A study of middle school understanding for the predictability of the effects of agents (slightly different than agent actions) found this to be the most difficult category for students to understand (Goh et al., 2012). The findings from this study extend these middle school findings to show that even at the undergraduate level, this appears to be the most difficult component for students to understand.

Changes in the design of the simulation may help facilitate improved student understanding. Discussion between rounds might make emergent behavior and randomness within the system tangible by focusing on why students made choices they made and whether the choices of others were as predicted. Focusing students on the chance factors in the environment that may have altered their decisions or led to new behaviors may help focus students on the inherent randomness that exists within the system.

Order. Overall, student understanding of Order remained at a medium level throughout the study (Appendix K). Previous research has shown that Order is a difficult component for grade 8-12 students (Goh et al., 2012) and that even gifted students have difficulty with bottom-up order ideas such as evolution and self-organization (Jacobson

& Archodidou, 2000; Settlage, 1994). Similarly, students had a moderate understanding of bottom-up order and did not improve in this college-age sample.

During the simulation students encountered bottom-up examples of organization (e.g., students were not told what to do but self-organized however they saw fit) while also experiencing top-down organization (e.g., regulators could give tax incentives for different behaviors from players) (Appendix K). Order in the simulation, as in the real world, comes from a mixture of top-down and bottom-up processes that are not explicitly addressed during the simulation. Although students may understand both types of organization, the simulation did not explicitly highlight either type for students.

Thus modifications may help students to explicitly address what types of organization they see and how they might be occurring in the simulation. There are multiple instances of top-down organization from a variety of regulators as well as bottom-up organization from individual students. Discussing and comparing these in between rounds or adding prompts within the simulation may help focus students on what these may have in common or how they interact.

A final pattern that developed was that student responses that fell into the expert range either specifically mentioned the use of pheromone trails or a variation of how ants might use chemicals to signal other ants. Although neither treatment condition instructed students about ants and food gathering behavior, students who appear to have increased their content knowledge with more specific terms were more able to demonstrate expert understanding of bottom up organization. This points to the importance of domain specific content knowledge for students to have concrete material to apply and think through how their more domain general understanding of complex systems components function in the transfer context. Although this study did not focus on increasing domain specific content knowledge to aid transfer students would most likely benefit from a combination of domain general complex system component understanding and domain specific content knowledge in the transfer context to apply these higher level concepts to.

Obvious vs. Non-Obvious Causes. Students' responses did not significantly shift for this component (Appendix K). Previous research has not investigated whether older post-secondary students attend to non-obvious causes more than obvious causes but several studies have focused on middle school understanding of non-obvious causes. In one study, 8^{th} grade students had difficulty focusing on nonobvious causes in a unit on pressure (Basca & Grotzer, 2001). However, there is some limited evidence that discussion of non-obvious causes might benefit which causes students attend to. In other studies, 6^{th} grade students had difficulty focusing on nonobvious microbial causes of decay (Grotzer, 2009) and demonstrated mixed abilities to focus on nonobvious causes related to pressure (Grotzer, 2003).

In a study related to ecosystems, Grotzer and colleagues (2011; 2013) investigated the same fish die-off question used in this experiment as well as coding scheme. Students surprisingly focused on significantly more non-obvious causes in both pretest and posttest responses (Grotzer et al., 2013, 2011). After a two week intervention, the number of obvious causes decreased significantly while the number of nonobvious causes given stayed about the same. Similarly, participants in this study proposed more non-obvious causes on average, with 55% of pretest and 59% of posttest causes being non-obvious. However, the results from Grotzer's 2013 study showed a changing ratio due to a reduction of obvious causes from pretest to posttest while the number of nonobvious causes stayed about the same. In contrast, in the current study, the ratio changed because the number of obvious causes that students gave stayed the same while the number of non-obvious causes given increased.

A few conclusions can be drawn from this. First, the findings from this study support previous work done on nonobvious causes for middle school aged students. This is unsurprising for two reasons. First, there is no reason to believe that as students get older, their focus would move away from nonobvious causes towards obvious causes. Second, the criteria for coding an obvious cause was that it is visible to the naked eye. Although this is probably a good metric for younger students, it may not be as appropriate for postsecondary adults. For example, chemicals are considered nonobvious because we cannot see them when added to water. However, to claim that chemicals would not be obvious to an adult as a possible cause for the death of fish in a river rings false. Although chemicals are not physically visible, they are salient within our culture as part of the broader discussion about pollution and health for many decades now.

Nonobvious causes are by definition causes that are hidden from view and without their consideration, a person would have an incomplete understanding of how a system works (Basca & Grotzer, 2001). Within ecosystems, causes are often nonobvious and absent these, an accurate understanding of system dynamics is not possible. There is evidence to suggest that the default assumption students often make is to construct causal reasoning from obvious perceptible causes (Grotzer, 2005, 2009) and that even adults are unlikely to look for further causes when obvious ones already exist (Grotzer, 2012). This is important because if we get stuck on a more obvious but incorrect cause, we may neglect to consider less visible but more important causes. Encouragingly, the results from this study support that students beyond middle school do attend to non-obvious causes.

During the simulation, students were largely left to discover how the system works through their own trial and error. They also learned by asking questions of moderators and discussing with peers what they tried. Students were by definition likely to encounter obvious causes within the system and only through further searching, discussion, and trial and error were they able to learn about non-obvious causes for behavior in the system. Because the simulation neither highlighted all possible causes for students nor were discussions specifically focused on getting students to think through all possible causes, students may have settled for more obvious causes and then moved on to understanding other parts of the simulation.

Although the increase from pretest to posttest in non-obvious causes was not significant, this positive trend might be improved with a more explicit discussion of nonobvious causes during the simulation. A focus on pushing students to think beyond the initial, possibly more obvious causes they suggest might help focus students to think about nonobvious causes. Still, students have shown that they already attend to nonobvious causes, and problems for systems thinking are not that students think about obvious causes, but that they fail to think about non-obvious causes. An incomplete understanding would also exist if students gave only nonobvious causes while ignoring obvious causes. Therefore the goal for understanding is to make sure both types of causes are considered, which our findings show to be true, even before the intervention occurred.

Local vs. Distant Causes. This component assessed whether participants focused on causes that were physically close to the effect (a fish die-off) or further away from the effect (Appendix K). Because we have limited information when we assess causal connections, and because most of this information is often local and immediate, people often limit the causal models they create to interpret systems and events (Grotzer, 2012). This default of attending to local causes prevents students from having full understandings of issues in ecosystems such as acid rain and global warming whose causes are necessarily far away. It is this “Action at a distance” mindset that we want to cultivate for better systems thinking because the exclusive focus on easier to comprehend local causes often prevents students from looking to potentially important distal causes. Further, this effect is shown in adults (Grotzer, 2004) as well as children (Lesser, 1977) and infants (Spelke, Ann, & Woodward, 1995).

This study found that students relied heavily on using local causes to explain the fish die-off. During the simulation, students were not told which causes have which effect on the system. Because of this students may have focused on the more immediate causes around them. Given the short amount of time for the simulation, students may not have had time to search for more distant causes. During the pretest, very few students talked about distant causes and improvement in the posttest occurred because more distant causes were given while the number of local causes stayed about the same. In a study of middle school students, from which this measure was adapted, Grotzer and colleagues (2011) found students included significantly more local explanations than distant explanations in their pretest. This number turns out to be quite similar to this study’s findings with an average of 3.45 local causes given per student and .59 distant causes given in the pretest. This suggests that student focus on distant vs. local causes remains about the same for both age groups.

Furthermore, these findings converge with other studies of middle school students. In one pilot study researchers also found students gave more local than distant causes for complex ecological phenomena and were able to improve the number of distant causes they gave after an attention at a distance intervention (Gramling, Solis, Derbiszewska, & Grotzer, 2014). Interestingly, students assigned local causes as being more important than distant causes. In a different study of elementary through middle school age students they also gave more local responses yet when asked did not express a preference for either (Grotzer & Solis, 2014). Their findings point to factors that enable increased distal responses as prior knowledge in general, prior knowledge of science concepts, as well as prior mechanisms knowledge.

The increase in distant causes for this study from pre to posttest was not significant, but it was in the right direction. This study converges with previous work and extends the pattern of local and distant causal thinking found in elementary and middle school students to those in post-secondary education. Though we did not query whether there was a difference in whether students found distant or local causes more important, there was a definite focus on more local than distant causes in students' responses.

Students might have improved their focus on distant causes with prompts built into the simulation to focus students on alternative causes. This might also be accomplished during discussion between rounds by having students brainstorm causes for either improvement or degradation of the system and then categorizing whether these were local or distant causes. Students could then be challenged to generate further distant causes and discuss why they might be important or why it might always be important to stop and think about what distant causes might be affecting any system.

Event vs. Process Based Causes. This component assessed whether students focused on causes that were events, or if they were able to focus on the more long-term processes that eventually led to the effect (a fish die-off) (Appendix K). The distinction between these within the framework of ontological categories (Ferrari & Chi, 1998) is important because a focus on causes as events represents a clockwork way of thinking, while a focus on process represents more expert complex systems understanding (Jacobson, 2001; Jacobson et al., 2011). Without an understanding and focus on the causal forces that occur in complex systems, students will only focus on dynamics when events occur (Grotzer, 2012).

Students in this study began with a small number of process causes and significantly improved by increasing this number while the number of event causes remained the same, shifting the overall proportion. These results confirm several other findings from the literature examining student focus on processes. First, a previous study from which this protocol was adapted found that middle school students also heavily favored event-based explanations over process based explanations for a fish die off (Grotzer et al., 2011; 2013). In that study, using a simulation meant to help students improve understanding causal understanding in complex systems, the only significant change found for student responses was a reduction of event based causes given after the intervention. Although the population was younger than in this study, the mean number of process based causes given for these students of 1.41 started much higher than in this sample (*M* = .60, *SD* = .77).

Similar results have been found for other age groups measuring a focus on processes. A small group of undergraduate students were shown to focus less on processes in complex systems than experts (Jacobson, 2001) and after a hypermedia intervention undergraduate students were able to focus more on processes over events, though the size of this increase was not given (Jacobson et al., 2011). Similarly, middle school students also demonstrated a more novice event-based focus when learning about genetic engineering and complex systems, which increased through a 10-day workshop (Yoon, 2008). More recent work measured data from grade 8-12 students (*N*=44) and measured how difficult different complex systems components in biology were for this age group to understand (Goh et al., 2012). Results showed that students found understanding complex system processes to be one of the most difficult components, after Order and Agent Effects.

Overall these studies show that students of all ages have difficulty focusing on processes in complex systems and that through a variety of interventions (hypermedia, interactive workshops, or participatory simulations), students are able to move their focus and explanations towards this ontological category. The results from this study show that these students were also firmly entrenched in an event-based focus when enumerating ideas for why a fish die-off might have occurred. However, they did significantly improve their focus on the processes behind this effect after the intervention.

Because students take the role of agents within this simulation during rounds, they witness the behind the scenes processes that lead up to the events at the end of rounds.

After each round ended, students saw the results of the processes as sudden changes in bay health and their own finances. Because of this incremental updating, students took part in the processes within the ecosystem and then witnessed the events that arose from these causes. This back and forth might possibly explain why students improved their understanding,

Although students did improve their focus towards a more complex systems process view, it should be noted that this was a small effect. Future scaffolding might improve understanding by focusing students during the simulation on what causal processes they believe are giving rise to the results in between rounds. Both through reflection and group discussion students might be directed to focus on which processes are having which effects in the system and how these effects are manifested.

Transfer of Component Understanding

This section looks at how well students transfer their understanding of components of complex systems to another domain. First, I will discuss what student responses looked like and then compare these to a previous study of transfer for complex systems.

The components Order and Action Effects were the most understood by students matching pretest and posttest findings. For the transfer question used in this study (Appendix C) students were allowed to choose the system they would design or alter for a city, with food being the most popular system by a large margin. There was a large amount of variability for how often a component was mentioned depending on the system a student chose to write about. For example, no students who chose the topic of waste expressed understanding of Agents, while students who wrote about energy mentioned this component frequently.

This suggests at least two possible scenarios for transfer. First, there is the possibility that certain systems better facilitate students' understanding of certain components of transfer. For example, the majority of students who talked about food gave bottom-up examples of order. Students talked about the need for bottom-up organization of individual farming and local farms to counteract negative effects from more top-down industrial farms. They also gave many responses for distant causes by talking about the negative local effects of transportation and distant farms unconnected from the community. Similar understanding of bottom-up order, however, occurred much less often (18% of responses) when students discussed designing a water system for a city.

A second explanation would be that students have more prior knowledge of different systems, or parts of systems, which is then represented in variation of their understanding of components in each system. One could imagine that in talking about bottom-up order for water systems, that individual water catchment systems is no more difficult to understand or design than individual farm plots. However, less than a quarter of students who wrote about water systems demonstrated understanding of this complex systems type of organization. This may be a reflection of greater prior knowledge (more knowledge of types of agricultural systems) or simply more exposure (greater salience of agriculture in day to day life or past experience).

Students demonstrated differing abilities to talk about different components overall, with half of students talking about Order and Action, although there was variation in understanding of components by type of system. This warrants further exploration because previous research in learning progressions (Goh et al., 2012) suggests an order of difficulty for complex systems component understanding for students. Whereas Goh et al. found Order to be the second most difficult topic for high school students, Order was the component students in this study most readily demonstrated their understanding for in this transfer question. However, within Order, there was great variation depending on which system students chose to talk about.

Student Understanding of Complex System Components by Treatment Condition

Students received two different scaffolding treatments meant to help them better understand complex system components. The group in the self-monitoring condition took part in scaffolds meant to help them both plan and reflect on their understanding of the simulation of the Chesapeake Bay watershed and on which factors they felt were important. The group in the ontological scaffold condition took part in scaffolds meant to explicitly teach them about complex system components in ecosystems.

Two interesting trends developed between scaffolding treatment conditions. First, the significant gains in Agents and Causation: Events vs. Processes, as well as the significant decrease in Action Effects occurred only in the ontological scaffolding group. Although the self-monitoring scaffolding group showed similar trends in five of the six components, these gains were not significant from pretest to posttest. Further, although these gains were significant for the ontological group, they were not significantly different between groups. The increase in two components is not surprising, as other research demonstrates that ontological scaffolding can help students make sense of simulations of complex phenomena (Chi & Slotta, 2006; Jacobson et al., 2011). The ontological scaffolding may have helped students develop a framework about Agents and Process-based causes that they may have used to interpret the phenomena of the simulation.

Results suggest that self-monitoring prompts may not have the same benefit for Agents and Process-based Causes. Guiding students to plan and reflect upon their understanding within the simulation may not be adequate to help students engage in knowledge building about complex systems. It is important to note, however, that these effects were small and that for the other components, except Order, no significant differences exist. There are a few possible reasons for this. First, scaffolding may not have helped students engage in beneficial processes for learning. Students in one treatment may not have self-monitored, and in the other they may not have learned much about ontological components. Second, they may have engaged in these processes but they weren't enough to help students make sense of the simulation. Finally, they may have indeed engaged in these processes and learned from the simulation but the assessments were not sensitive enough to distinguish this. For all three of these cases, future research is needed to provide more information to rule out these possibilities.

The second trend found between treatment conditions is that there was a significant difference on gain scores for the Order component which overall did not significantly change. This is because there was a non-significant decrease in understanding for the self-monitoring group while there was a non-significant increase of understanding for the ontological group. This largely happened because more students decreased one level of understanding in the self-monitoring group while the ontological group had a larger number of students increasing their understanding by one level (mainly from a medium level of understanding to an expert level of understanding).

Because the Bay Game is a coupling of multiple systems (aquatic ecosystems, human systems, etc.) and order comes from a mix of top-down and bottom-up organization. Students are presented with bottom-up examples of order (e.g. all players have local goals and organize on their own) as well as top-down aspects represented by regulators. For example, if a farm regulator in a region wants to encourage more green farming she subsidizes this type of farming and tries to control how farmers will grow their crops. Although both scaffolding conditions encounter these types of Order only the ontological group discussed and was reminded to pay attention to bottom-up types of organization. Although they did not significantly improve their understanding, there were positive trends of improvement. However, when students were not explicitly taught this in the self-monitoring condition they appear to have shifted their focus in the opposite direction towards top-down organization.

Similar to Resnick and Wilensky's assertion of the centralized mindset (1999) and Jacobson's findings (2001) that novices focus mainly on centralized order the self-monitoring students appear to have shifted towards this top-down way of thinking. In contrast, the ontological scaffolding students actually increased their focus on bottom-up order. This component is suggested to be one of the most difficult components for high school students to understand (Goh et al., 2012) and although both treatment conditions started at a mid-level of understanding they soon diverged. The bias towards a centralized way of thinking may have been partially reinforced for the treatment that was not guided towards focusing on bottom-up order due to the prevalence of top-down regulators within the simulation. The ontological scaffolding condition, may have focused student attention on more examples of this organization during the intervention.

Given the differences between these treatment conditions and the tendency towards the centralized mindset in the literature, explicit scaffolding of bottom-up organization for all students seems necessary. Students appear to naturally attend to simpler top-down instances of organization and need to be redirected to pay attention to the more diffuse and complex bottom-up instances in the simulation. This might take the form of group discussions around the different types of organization students are noticing as well as their characteristics.

Differences between Treatment Groups on Transfer

There were no differences for transfer based on treatment types. This is largely to be expected as there was only a small difference between treatment groups for their gain in understanding of components after the intervention. Because the transfer task was not given before the simulation, no causal claims can be made about the effect of the simulation on transfer. However, because students had difficulty with several components (Agent Actions, Non-Obvious Causes, and Distant Causes) during the posttest transfer task, the experience of the simulation was unable to bring these students up to a more expert understanding regardless of where they started from. Because both scaffolding groups showed no differences in ability to transfer their understanding, this demonstrates just how difficult certain components of complex systems understanding are for transfer. This may mean that a simulation that does not simulate multiple domains and therefore does not allow students to practice transfer of their understanding may not be enough. It may also mean that although ontological scaffolding was helpful for students to significantly increase their understanding a small amount, that other types of scaffolding may be necessary for transfer.

Limitations

One of the largest limitations of this study is the amount of time students had for the scaffolding workshop as well as for the simulation intervention. Both occurred in classes that are 75 minutes long and after taking the pretest in the workshop and getting logged in and set up for the simulation participants had only about 50 minutes for workshop discussion as well as the simulation. Given that this was an ongoing class this was a generous amount of time for the instructor to give but this severely limits both the dosage as well as time for reflection, which is one of the most important activities for conceptual change (Davis & Linn, 2000).

A limitation for generalizability is the sample used in this study. All students were selected because they attended an architecture class teaching systems thinking for architecture. Students were largely in their early twenties, female, and undergraduates. Further, students self-selected into this class. Therefore generalizations from this experiment are limited to similar populations from which this data was gathered. Further, because the focus of the class was systems thinking in architectures student understanding may be higher than the general population. Therefore, pretest scores of component understanding may not be representative of other students of the same age.

Although no experiment runs perfectly, one large problem arose during the simulation. During the last 15 minutes of the simulation intervention, a glitch in the simulation caused one group’s results to display incorrectly. Although group selection was randomized separately from randomization for treatment groups, this issue may have caused some students to have an even shorter dosage than the rest of the class. Students continued to play the game aware that their results were probably not accurate.

Finally, a main limitation for understanding systems thinking has to do with how student understanding is elicited. One major difficulty is that systems themselves are nonlinear although we must speak, and write, in a linear way. This means that students are asked to explain, in a linear way, systems without a beginning, middle or end and with constantly changing interactions at multiple time scales. This is a challenging task, and one that is even harder when asked to do it in short answer form. However, without some structure, students may wander in their responses and avoid talking about the specific components we want to know about. One solution would be to first ask more open ended questions and then to narrow students to either short answer or multiple choice responses (Metcalf, Tutwiler, Kamarainen, Grotzer, & Dede, 2011). While this may be more ideal than just short answer questions, it requires considerably more time and good will from the students, a problem found during the posttest responses in this study. Further, it is not necessarily clear how to combine student responses from more open ended essays and more narrow multiple choice questions, especially if students give conflicting responses.

Implications

There are three broad categories of implications for this study. The first category deals with the effectiveness of the simulation as well as representation of components. The second category discusses the effectiveness of scaffolding agent-based participatory simulations of complex systems. Finally, I discuss difficulties with assessing understanding of complex systems.

Effectiveness of Simulations

Based on the overall pattern of results, participatory agent-based simulations may not significantly help students understand complex systems, even with scaffolding. While in this instance the Bay Game is a simplified version of a very complex ecosystem, it is still complex and students still have a lot of information to attend to. Even when explicitly scaffolded to pay attention to complex system components, students may be too occupied with understanding the system as a whole to do so. The complexity of the simulation may also prevent students from recognizing instantiations of components when they encounter them. Further, the goals of the simulation may not be commensurate with focusing on complex system components. That is, during the simulation, students are told to learn about their roles, learn how their actions affect the system, and learn strategies to improve their intended effects. These goals may focus students away from understanding complex system components as students focus more narrowly on their own individual situations. Therefore, students may need to experience a variety of roles in agent-based participatory simulations in order focus more widely on the system. Because it is cognitively challenging to focus on the dual tasks of gameplay and reflecting on the system, it may be more effective to allow students to have a variety of experiences and for these experiences to contribute to a broader overall understanding of the system.

Alternately, students might simply require more time than was available in this study to orient themselves to the simulation before being able to focus on complex system components. Students may eventually come to understand the system's underlying behaviors, but only after they have first made sense of the structural features for their given role. This is supported by the mainly positive though non-significant change in student understanding for most components in this study. This possibility points to the need not only for more time with the simulation but also for debriefing and reflection after the experience which is a component of self-monitoring that was not used in this study.

Improving complex systems understanding may also depend on the system that is represented within the simulation. Student responses for the transfer question largely reflected the same difficulties they demonstrated in their pretest and posttest responses. However, there were intriguing differences in component understanding depending on which type of system students wrote about (e.g., those who wrote about water systems more often understood Action Effects). Certain complex system components, such as Order or Agents, may be more salient and readily understood depending on the type of system represented within a simulation. This may be due to inherent characteristics of specific systems that make certain components more easily recognizable or intelligible. Therefore, it may be that any simulation is more effective at improving understanding of system components depending on which type of system is represented in the simulation. If true, using a variety of simulations or specific simulations that use systems that match the components to be taught would be preferable to extended time with one simulation.

Alternately, differences in component understanding in systems may be a reflection of greater prior knowledge or salience of the topic for students. Although students increased understanding of some components without directly being taught domain specific content students would almost certainly benefit from a combination of domain specific content knowledge and domain general complex systems focused instruction.

Finally, because students made small but significant improvements in understanding for some but not all components this suggests that experience and not just visualization may be important for helping students learn about specific complex systems components. Experiencing the needs and choices of agents that lead to Order from bottom-up organization may be more effective than just seeing the order occur.

Effectiveness of Scaffolding

Although ontological scaffolding caused small but significant improvements for a few components, scaffolding did not seem to matter overall. It is possible that scaffolding might have the potential to help but was applied incorrectly. For example, some students were given worksheets to help them focus on complex systems components during gameplay, but perhaps informative packets or access to experts to field questions would have been more effective. Although students received passive guidance in the form of worksheets during the simulation, they still needed to choose to use these scaffolds to monitor and reflect on their understanding. Many may have not chosen to do so, and designing scaffolds that actively engage students in these processes may increase their effectiveness in helping guide students in these metacognitive tasks.

In the specific instance of Order the type of scaffolding did have an effect on student understanding. In this case students who might naturally have a bias towards a centralized mindset showed lower understanding after interacting with a simulated complex system while those with ontological scaffolding showed a positive though non-significant increase in their understanding. This suggests that for components that students find counterintuitive that simply more experience with a complex systems not only didn't improve understanding but might allow students to further miscategorize the complex system as having properties of a clockwork system. This supports Chi's conjecture of the importance of ontological training and the need to create distinct ontological categories, especially for components that may be counterintuitive.

Effectiveness of Assessment

Because complex systems are characterized by numerous parts and changing interactions, and because these may happen over a variety of time periods, behaviors of these systems are difficult for students to talk about. During this intervention, many of the measures used to capture student understanding revealed limitations. Other researchers have attempted to deal with this issue by first giving student more open ended questions, and then focusing them with multiple choice questions in an attempt to not lose nuance in student understanding while also making sure students address specific components being researched (see Metcalf et al., 2011). In this study, similar problems arose. Questions were short answer (a compromise between essay and multiple choice) but still did not elicit the correct focus from students. In other words, student responses were sometimes vague, or did not fully answer the question that was asked.

Because of these difficulties, scholars in this area need to find a better way to assess complex thinking. Students may understand parts of systems in a non-linear way, and the process of writing out linear explanations or being encouraged to do so may prove too difficult or even contradictory for students. Other researchers have collected multiple outcome measures (e.g., concept maps, interviews, essays) (see Assaraf & Orion, 2005; Yoon, 2011) to provide students a variety of ways to express their complex systems understanding. How these data sources are combined and whether it is practical to collect and analyze this variety of data, at multiple time points, with a larger number of students needs to be further studied.

Future Research

The findings from this study point to several productive areas for future research. Further studies using agent-based participatory simulations are needed. Although this study showed that students made small improvements in their understanding of some components, further learning may follow from increased dosage, curriculum development within which to better situate the simulation, or more effective scaffolding. The current study shows some promise for some components. These suggestive effects could be confirmed and expanded with either studies incorporating the findings from this one, or with a combination of agent-based simulations such as NetLogo and agent-based participatory simulations such as the UVA Bay Game.

Adjustments to the simulation as well as how gameplay is conducted need to be studied (Appendix K). An important aspect for gameplay is between round group discussions. Although ontological scaffolding prior to gameplay helped students better understand some components, timing of scaffolding needs to be investigated. In game group discussions may also be just as important (Liu & Hmelo-Silver, 2010) as well as post-intervention reflection (Davis & Linn, 2000) and combinations of scaffold timing may prove more effective in helping students better understand complex systems components.

Further research should be conducted to determine what types of scaffolding are effective within agent-based participatory simulations as well as how these should be implemented. Process management may be more important during a simulation as students navigate the complex system while reflection after a simulation is ineffective without this. Therefore a combination of types of scaffolding may be needed.

Research should also be conducted to better understand component difficulty in context. Although there are beginning attempts to measure which components are more difficult (Goh et al., 2012) this may vary depending on the context in which students are discussing these components. Therefore component difficulty needs to be measured in a variety of contexts in order to more accurately inform both which components might need more pedagogical support as well as which environments these components might best be presented to students in. The importance of domain specific content knowledge also needs to be investigated.

Both the items used in this study as well as the rubric need refinement. To more completely elicit the indicators measured by the rubric, items should align more with the rubric. For example, when eliciting understanding for Action Effects, items should require students to explain the role of randomness and chance factors in systems. There were also a variety of components, such as feedback loops, that were elicited but not analyzed in this study. Expansion of the items and associated rubric should incorporate these complex systems components.

Although there is some convergence between this study and previous findings for which components are most difficult, little is known about why students find particular components difficult or what they find effective in helping them understand these concepts. Qualitative studies to better understand why students have difficulties with individual components as well as what they find difficult or effective with this simulation are needed. Interviews with students could help determine both what they find difficult about complex system components and what they find effective in learning about these components. Additionally, other types of data such as concept maps and essays should be collected and analyzed as students often do not know why topics are difficult. Only with an understanding of what students specifically do not understand, why these components are difficult, and when students need the most help in learning about them can the correct scaffolding be designed and implemented.

Overall this study demonstrates that agent-based participatory simulations and experiencing complex systems can help students learn certain complex systems components. It adds evidence to the need for ontological scaffolding and Chi’s theory of ontological categorization and Jacobson’s delineation of complex and clockwork systems. Finally, it points to the need to better understand complex system components in context and whether the types of systems they are understood in may affect student ability to transfer their understanding.

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APPENDICES

Appendix A

Demographic Questionnaire

In order to create groups for the gameplay on Thursday (Oct. 23rd) we need the following information. If you are not comfortable answering any question (besides the first three questions which will be necessary for assigning groups) you may indicate this.

1. What is your name?
2. What is your UVA email address?
3. What is your gender?
4. How old are you?
5. Are you a graduate or undergraduate student?
6. What is your Major/area of study?
7. What year in school are you?
8. How many hours a week do you play video games?

   0 hours a week
   1-4 hours a week
   5-10 hours a week
   11-20 hours a week
   More than 20 hours a week

Appendix B

Pretest & Posttest Questionnaire

1. Name:____________________
2. ID:_________________________
3. You're walking by a river and realize there are a large amount of dead fish on the shore.
4. Please make a list of possible causes for the fish die off.
5. What information might you need to help explain why the fish have died?
6. How do you think ants go about finding food?
7. Is there any order to this or is it random? If you believe there is order where does it come from? If not, how might it work?
8. The butterfly effect was written about by Ray Bradbury in 1952. It proposes that small changes can lead to large effects. Do you believe that small changes can lead to large effects in ecosystems? If so how might this happen and what might be the mechanisms? If not why is it unlikely that small changes can cause large effects in ecosystems?
9. Please give an example of a positive feedback loop in a complex system and explain why? Do the same for a negative feedback loop in a complex system and explain why.
10. What happens to the complex system if you remove the positive feedback loop in the previous question from a complex system and explain why this effect/non-effect might happen? What happens if you remove the negative feedback loop from a complex system and explain why this effect/non-effect might happen?
11. Could you predict the movement of a school of fish if you had enough knowledge about the individual fish? If yes explain how. If not, explain why not.
12. Could you predict the movement of individual fish with enough knowledge?

Appendix C

Blog Transfer Question

The goal for this week's blog post is to apply your understanding of complex systems, and their distinction from more mechanistic or "clockwork" approaches to systems to a situation other than the Bay Game. Use the example of a city needing to provide for its needs with energy, water, food, and waste – choose one of these systems and describe how you might improve it:

Prompt: How would you design a system for the efficient provision of services in a city using a complex systems model? How would you do this using a clockwork model?" Be sure to talk about which factors you would focus on, how it would be implemented, how it would be managed, how long you would need in order to know if it was successful and what would you measure for this success.

As with all blog posts, your post should be 500-700 words. Use the lessons from the bay game, the class lectures and discussions, as well as the readings to demonstrate your understanding of these types of systems. The choice of a specific topic within the range of urban systems is up to you, so please apply this blog to an issue that is of great interest to you. Be specific in your reference to the characteristics of the systems.

Appendix D

Complex Systems Coding Rubric (Jacobson et al., 2011)

Belief Category	Coding	Characteristics	Examples for Rater Training
Understanding	Reductive	Whole is sum of parts	Try to Understand a forest by analyzing the parts of the plants, animals, and insects.
		Isolated parts or step-wise sequences	
		No mention of part or agent interactions	
	Non-Reductive	Whole is different than sum of parts (new patterns or structures)	A traffic jam, looked at from above, propagates backwards, even though cars in a traffic jam speed up, slow down, change lanes, stop, but rarely go backwards
		Interaction between parts or agents	
Action Effects	Linear	Interaction between parts or agents are proportional small action -> small effect, Large action -> large effect	The movement of pool balls when hit easy or hard by pool stick.
	Nonlinear	Interactions between parts or agents are not proportional: Small action -> Large effect; Effects of actions may not be repeatable	Small temperature changes in Pacific ocean (El Nino) lead to heavy rains in South America and can cause droughts in southeastern Asia, India, and southern Africa and unusual weather in North America
Order	Centralized	Linear physical interactions between parts of system	Gears in a mechanical clock
		Agent or part has a power or force that imposes order on the system	King Controls his Country
		Chain of command or authority links controlling agent or part to other agents or parts of system	Planned socialist economies
	De-centralized	Interactions distributed across parts or agents results in an ordered system	Ecosystem of a rain forest
		Interactions may be linear or nonlinear	Goods and services in a city
			Weather
Agents	Predictable	Actions of parts or agents may be predicted based on knowledge of rules or characteristics of the part or agent	The movement of pool balls when hit easy or hard by pool stick.
			Movement of gears in a clock or machine
	Not Predictable	Actions of parts or agents cannot be predicted based on knowledge of rules or characteristics of the part or agent	Weather
		Randomness or chance factors	Flip of coins or shuffling of cards
Processes	Event	System is an "event" with a beginning, middle, and end	Going to school to get an education or a credential
			Playing jacks or soccer
	Equilibration—emergent process	System is an on-going, dynamic process	The ongoing, dynamic interaction of electron bonds when hydrogen and oxygen interact to form water
		System self-organizes through information flows and feedback	Interactions of plants, animals, insects, and environment in an ecosystem such as a forest.

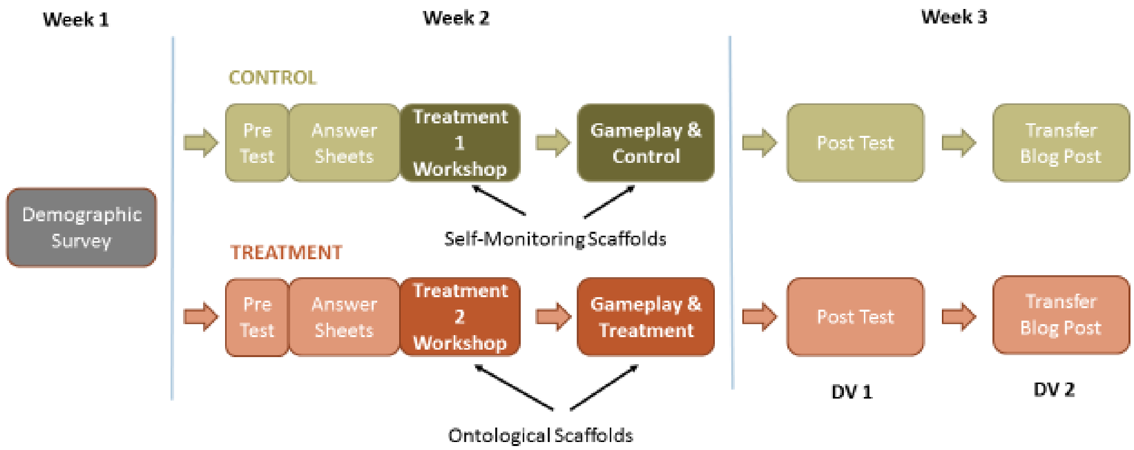
Appendix E

Final Coding Rubric

Category	Description	Level 1	L1 Examples	Level 2	L2 Examples	Level 3	L3 Examples
Causation: Obvious vs. Non-Obvious	Causes that can or cannot be seen with the naked eye.	Can be seen with the naked eye.	People dump trash into river; No food for fish	Cannot be seen with the naked eye	Low oxygen; High toxin levels;	X	X
Causation: Local vs. Distant	Location of where causes originate	Causes originate where effect is located	Bacteria spreads in the river; Over fishing	Causes originate away from effects	Toxins in water from factory upstream; runoff from nearby farms	X	X
Causation: Event vs. Process	Whether a cause is a specific moment in time or ongoing	Causes are discrete events	Lack of food; Predator; Low tide	Cause are processes in a larger pattern, longer period of time; refer to balance.	Farm toxins leak into river over time; overfishing slowly ruins health of river	X	X
Order	Organization of system	Top-down; Chain of Command; Individual leaders impose order	The queen orders the ants to find food; Ants follow direction from leaders	A mix of top-down and bottom up order	Ants randomly look for food, when it is found they order other ants to bring it back	Bottom-up: Multiple groups create order; Local Interactions	Ants randomly search for food; When ants find food they leave a pheromone trail and other ants follow the trail when they find it
Agent Actions	Predictability of actions of agents in system	Actions of agents are predictable	You could predict the movement of a fish if you knew about the school	Actions of agents are not predictable	You cannot predict the movement of a fish	Actions of agents are not predictable due to chance factors/randomness	You cannot predict the movement of a fish because of random environmental variables
Action Effects	The relationship between actions and effects	Small actions create small effects; Large effects only from large causes or many small causes	Small changes by individuals only make a difference if everyone does it	Large effects possible from small actions; Do not explain how	Butterflies can cause storms across the world	Small actions can lead to large effects; Explain through cascading chain reactions	The dying of this organism will begin a chain of events leading to loss of food higher up in the food chain disturbing the balance of the ecosystem

Appendix F

Study Design



Appendix G

Logic Model

SITUATION	INPUTS	STUDENT ACTIVITIES	OUTPUTS	OUTCOMES
• To be scientifically literate students will need to understand complex systems (Jacobson & Wilensky, 2006; Achieve Inc. 2013) • However, complex systems are difficult to learn (Hmelo-Silver et al., 2007) • Participatory Simulations (Grotzer et al.., 2013) and Scaffolding (Slotta & Chi, 2006) may help.	Scaffolding Workshops • Presentation • Instructor Support for Students Bay Game Intervention • Simulation • Group Discussion • Worksheets	• Gameplay • Role-Playing • Negotiation • Discussion • Brainstorming • Reflection • Generate Questions	• Student Pretest & Posttest Assessments • Gameplay Worksheets • Transfer Blog Post • Observational Notes/Audio Recordings	• Increased Complex Systems Component Understanding • Transfer of Complex Systems Understanding

Appendix H

Self-Monitoring Gameplay Form

Name:______________________________ Computing
ID:______________________________

At different points during gameplay, when you have free time (e.g. after you've made your choice for that round), please attempt to fill in this sheet as best as you can.

Successful Strategies you've seen?

____
____
____
____
____

Biggest mistakes you've made? (Explain/give details)

____
____
____
____
____

Biggest mistakes you think other people are making? (Explain/give details)

____
____
____
____
____

What don't you understand as you're playing? (Explain/give details)

____
____
____
____
____

Anything new you've learned? (Explain/give details)

____
____
____
____

Ontological Scaffolding Gameplay Form

Name:______________________________ Computing

ID:______________________________

At different points during gameplay, when you have free time (e.g. after you've made your choice for that round), please attempt to fill in this sheet as best as you can.

Examples of **Feedback Loops** during gameplay? (Explain/give details)

Examples of **Decentralized Order** during gameplay? (Explain/give details)

Examples of **Unexpected Behavior** during gameplay? (Explain/give details)

Examples of **Emergence** during gameplay? (Explain/give details)

Examples of **Non-Linear Effects** during gameplay? (Explain/give details)

Examples of **Multiple Drivers** during gameplay? (Explain/give details)

Appendix I

Take Home Fact Sheet

Complex Systems Components

If you were wondering, here are some of the components of complex systems we are studying:

1.) Whole vs. Parts
   a. Complex systems are more than the sum of their parts. For example, in a traffic jam the parts of the traffic jam are the cars which are moving forward. However, at the “macro” level is the traffic jam which “emerges” and spreads backwards on the highway.
2.) Non-Linear Actions
   a. In complex systems actions may be linear (small causes have small effects) or non-linear (small causes may have large effects) and occur further away in time or space. Because of feedback loops small changes may be amplified throughout a system.
3.) Decentralized Order
   a. In complex systems order may be decentralized and order results from these interactions across the parts, as opposed to a top down actor (such as a president or prime minister) imposing order on the system. For example, in a free market system order arises from people buying and selling goods and prices shifting accordingly due to supply and demand.
4.) Adaptation
   a. In complex systems parts adapt to their changing environment. For example, in an ecosystem if a predator eats a species of fish, and that fish dies off another species may take its place and the predator may then adapt its diet to this new species.
5.) Processes
   a. In complex systems processes do not have a beginning, middle, and end. The system is an ongoing and dynamic process with constant interactions between parts. Further, these interactions of parts at the micro level give rise to a macro level that may look different as was seen in the traffic jam example in part 1.
6.) Predictability
   a. In complex systems it is impossible to predict what happens at the micro-level due to randomness and chance, even though the parts follow simple rules. However, at the macro level, even though things aren’t predictable there may be somewhat reliable conditions. For example, you may not know when it will rain, but it’s fairly predictable that it will rain in the spring.

Appendix J

Self-Monitoring Example Activity

In your small groups (2-3)
How will you balance the 2 factors of Bay Health & Making Money?
What are some ways of developing strategies?
What information do you need to know about the ecosystem?
What information do you need to know for the different roles?

Self-Monitoring Workshop

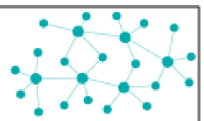
At different points during gameplay, when you have free time (e.g. after you've made your choice for that round), please attempt to fill in this sheet as best as you can.

1. Successful Strategies you've seen?
2. Biggest mistakes you've made? (Explain/give details)
3. Biggest mistakes you think other people are making? (Explain/give details)

Gameplay Worksheet

Ontological Scaffolding Example Activity

Order



Within an ecosystem, where do you think order comes from?

What about in a business? A clock?

Centralized vs. De-centralized Order

- Centralized
  - There are linear interactions between parts
  - An agent has power to impose order on a system (top-down)
  - Chain of command that links controlling agents
- Decentralized
  - Interactions across parts create order (bottom-up)
  - Linear & non-linear interactions

What are some examples of de-centralized order in the Chesapeake Bay Watershed?

Ontological Workshop

At different points during gameplay, when you have free time (e.g. after you've made your choice for that round), please attempt to fill in this sheet as best as you can.

1. Examples of **Feedback Loops** during gameplay? (Explain/give details)
2. Examples of **Decentralized Order** during gameplay? (Explain/give details)
3. Examples of **Emergence** during gameplay? (Explain/give details)

Gameplay Worksheet

Appendix K

Overall Results

Comp.	Pre	Post	Understanding	Representation in Game	Future Work

Action Effects	2.43	2.26 (-.17*)	• **Medium-High**
			• Small, significant decrease
			  • *Due to item elicitation issue*
				• Make choices, see impacts
				  • Aggregated (environment & economic impacts)
				  • Individual (individual economic state)
					• **Simulation:** individual impacts
					  • Individual summary scores of own contribution and causes
					• **Gameplay**: Discuss cause and effect

Agents	1.61	1.81 (.2*)	• **Medium-Low -> Medium** • Small, significant improvement • *Experience being agents, making choices*	• Students are agents, experience own choices, see other's choices • Experience chance factors/randomness (hurricane)	• **Simulation:** Representation of chance • **Gameplay:** Discuss choices, changes, and randomness

Order	2.2	2.18 (-.02)	• **Medium**
			• No Improvement
			• Treatment differences
			  • Ontological improved
			  • Self-monitoring got worse *(Possible centralized mindset)*
				• Bottom up = player interactions and agreements, local goals, conflicting choices with group
				• Top-down =regulators, group decisions
					• **Simulation:** Visual organizer of groups
					• **Gameplay:** Discussion and categorization of organization

Non-Obvious	.55	.59 (.4)	• **Medium (Good Balance)** • No Improvement	• Chemical pollution	• **Gameplay:** List and categorize causes during discussion • Is this based on a real percentage or an arbitrary goal?
Distant	.15	.18 (.3)	• **Low** • No Improvement	• Adjacent regions impact on own region	• **Simulation:** Highlight origin of effects, how much students impact region vs. neighbors

Process	.16	.21 (.5*)	• **Low -> Medium-Low**
			• Small, significant Improvement
			  • Gameplay over prolonged time period
			  • Focus on changes & balance
				• Students play through many events, begin to see patterns
				• Balance of components experienced, highlighted
					• **Gameplay:** Have students discuss balances, processes, make connections between events and underlying systemic causes