Understanding Complex Systems: Some Core Challenges
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Complex systems have a hierarchical nature and have multiple interacting levels (Wilensky & Resnick, 1999). In complex systems, the aggregate nature of the system is not predictable from isolated components but occurs through the interaction of multiple components. For example, the human body is composed of multiple sub-systems and may be understood anatomically and physiologically. Only with experience and expertise do we come to understand how different levels of a complex system are related. There are some deep principles that underlie many complex systems, some of which Jacobson and Wilensky (this issue) discussed, such as structure-behavior-function (SBF) and emergence (see Goldstone & Sakamoto, 2003, for others). What differentiates these complex systems from complicated systems such as pulley systems is the heterogeneity of components and their multiple levels of organization. For example, a pulley system is made up of several pulleys, perhaps of different sizes and orientation, but they are fundamentally the same. Compare this to an artery, which is composed of at least three different kinds of cells and networks of fibers, all different components that together form the blood vessel.

Many complex systems can be viewed as emergent or causal depending on the point of view one is taking. The human circulatory system is a good example. It is a subsystem of the human body. Many different kinds of cells form the tissues of system. The blood is composed of several different kinds of cells suspended in
plasma (the structures). Together they transport oxygen and nutrients, fight infections, and clot (functions). These cells are transported in arteries and veins. The arteries have several layers of cells that differ in structure and function. The tissues combine to form the organs, which work together as a system. The heart pumps the blood through the body by creating pressure differentials that drive movement (behaviors). This system interacts with other systems in the body. If the respiratory system is not exchanging a sufficient amount of air, the circulatory system initially compensates by pumping more blood around the body. Thus, at one level, the system is emergent; that is, the cells combine to produce a complex system. At another level, structure-behavior-function representations can also be used to describe the system in causal terms. Similar kinds of analyses could describe other complex systems such as ecosystems.

Understanding and reasoning about complex systems places a huge burden on working memory resources and is often counterintuitive (Feltovich, Coulson, & Spiro, 2001; Narayanan & Hegarty, 1998). In addition, education about complex phenomena often ignores the phenomena themselves and instead has learners focus on memorizing the names of the parts of the system (American Association for the Advancement of Science, n.d.). Thus, it is not surprising that most people understand complex systems as collections of parts with little understanding of how the system works (Hmelo-Silver, Marathe, & Liu, 2004; Hmelo-Silver & Pfeffer, 2004).

Despite the difficulties in learning about complex systems, these are foundational for many areas of learning and offer the potential to integrate across many disciplines. For example, understanding aquatic systems can integrate biology, chemistry, physical science, and social science (e.g., considering the effect of humans on the environment). Learning about complex systems and how to support learning about complex systems are key research issues for the learning sciences, and we have identified a host of challenges that learning scientists must come to terms with if we are to help students understand particular complex systems and the notion of complex systems in general.

COGNITIVE CHALLENGES ASSOCIATED WITH UNDERSTANDING COMPLEX SYSTEMS

One of the major issues affecting students’ ability to learn about complex systems is their cognitive, metacognitive, and self-regulatory processes. Several researchers have recently argued that students’ ability to learn about complex systems and other challenging topics (Azevedo, in press-a; Quintana, Zhang, & Krajcik, in press; White & Frederiksen, in press) is to a great extent dependent on the deployment of such processes to plan, sustain, and reflect on the complex mechanisms underlying learning about complex systems. The majority of current research on learning about complex systems is based on the implicit assumption that students
not only have these skills, but that they are motivated and can effectively make decisions regarding their learning and the instructional context. But these assumptions are faulty (Azevedo, in press-b). We need to reconsider these assumptions and to examine their role in fostering students’ learning about complex systems.

There are developmental issues related to the use of cognitive, metacognitive, and motivational skills required to sustain learning in specific contexts. For example, younger students (i.e., middle school and high school) are not usually motivated to engage in the learning of complex systems (e.g., Azevedo, Cromley, Winters, Moos, & Greene, 2005). Younger students do not always plan, set goals to drive their learning, or activate relevant prior knowledge to anchor new learning to their emerging understanding (e.g., Vye et al., 1998). We believe that studying the use of metacognitive processes in understanding complex systems is critical to understanding how we can facilitate learning about complex systems, as learners must engage in monitoring multiple activities during such learning—their emerging understanding, the aspects of their learning context (e.g., available instructional resources, peer, teachers, other contextual agents), and also their conceptual growth.

Besides learning mechanisms, there are reasoning skills that must be deployed concurrently to support learning about complex systems. Recently, de Jong and colleagues (2005) identified and listed key factors necessary for effective discovery-based learning environments (e.g., NetLogo) to foster students’ learning about particular complex systems. Learners need generic knowledge about the nature of models (physical, formulas, three-dimensional, etc.), domain knowledge, general skills (including cognitive and metacognitive skills and motivational strategies), and scientific reasoning skills, such as hypothesis generation, experimentation, data collection, data analysis, and communication of results. Without such background understandings, it is difficult, if not impossible, for a learner to learn about a complex system through simulation and modeling. This suggests that the field must strive for explanations of the roles these underlying mechanisms (cognitive, metacognitive, and motivational) and scientific skills (e.g., online inquiry, scientific reasoning) play in supporting learning about complex systems. Such understanding is required for us to be able to design and analyze the results of large-scale, classroom studies where these mechanisms relating individual, collaborative, and situational factors are more complex than in a lab.

SCAFFOLDING WITH COMPUTER-BASED LEARNING ENVIRONMENTS CAN SUPPORT LEARNING ABOUT COMPLEX SYSTEMS

Jacobson and Wilensky (this issue) argue for the importance of experience with complex systems, and we agree. But discovery alone is not sufficient. Students
need scaffolding to guide their exploration and experience (Azevedo, in press-b; Hmelo-Silver, 2006). The widespread use of open-ended learning environments offers the potential to foster students’ learning about complex systems (Azevedo, Cromley, & Seibert, 2004). However, due to the complex nature of learning about these environments, we believe it is necessary to support students’ learning by providing embedded scaffolds designed to support certain learning and inquiry processes (Lajoie & Azevedo, in press). It is important to determine what types of scaffolds and other learning aids are needed to support students’ learning of complex systems and to study these systematically.

There are many challenges for scaffolding learning about complex systems. We need to better understand what aspects of learning to scaffold, such as schemas and strategies, and how scaffolding should be applied. As well, we need to consider important issues such as how or even whether to adjust scaffolding to the needs of individual learners and how scaffolding can support collaborative learning about complex systems. Most recent computer-based learning environments use “blanket scaffolding” (Putambekar & Hubscher, 2005, p. 7) to support student learning (i.e., the same scaffolding is available to all learners) rather than providing ongoing diagnosis, calibrated support, and tailored feedback (e.g., Anderson, Corbett, Koedinger, & Pelletier, 1995). According to contemporary views of software-realized scaffolding (Hmelo-Silver, 2006; Pea, 2004; Putambekar & Hubscher, 2005), all students tend to receive the same scaffolding from embedded scaffolds (e.g., procedural scaffolds, advisors, or pedagogical agents), with individualized scaffolding needed to support their learning provided by other agents in the learning environment (e.g., peers, teachers). This contemporary form of scaffolding, used in most computer-based learning environments, “violates” aspects of the original more individualistic conception of scaffolding—scaffolding is mostly fixed, rarely faded, and generally brought into play at the initiation of the learner rather than a more knowledgeable other (Wood, Bruner, & Ross, 1976; cf. Pea, 2004; Putambekar & Hubscher, 2005, for a recent review). This is based on certain as yet unsubstantiated assumptions about students’ ability to deploy the key metacognitive and self-regulatory skills necessary to learn about complex systems in a particular learning context (Azevedo & Hadwin, 2005). For example, why would we assume that students know when to choose a metacognitive prompt or a strategic prompt? Do they know that they do not know something at that point in time? Do they know how to create subgoals and plan their learning accordingly? In addition to providing strategic help, as most software-realized scaffolding does now, scaffolding can also be used to promote schema development (e.g., Hmelo-Silver, 2006), but this approach has not been applied in the complex systems domain. As such, we argue that more research is necessary to understand when, how, and why to scaffold learning about complex systems in the context of computer-based learning environments.
The recent study of complex systems comes from several fields with different underlying assumptions, goals, methodologies, and analytical methods. Though we can begin to appreciate the benefit of a multidisciplinary approach to research in complex systems, we need a rich theoretical and empirical base from which to understand the challenges and opportunities associated with such an approach. We argue that there is a dire need to amalgamate diverging theoretical frameworks to analyze the complexities in learning about complex systems. Some current theoretical frameworks include complexity science (Jacobson, 2001; Wilensky & Resnick, 1998), structure-behavior-function theory (Goel et al., 1996; Hmelo-Silver & Pfeffer, 2004), conceptual change (Vosniadou, 1994), knowledge integration (Linn & Hsi, 2000), and self-regulated learning (Azevedo & Cromley, 2004). In addition, there is also a need to collect multiple data sources and use mixed methods to triangulate between qualitative data and quantitative data. There is also a growing need to determine what types of data provide appropriate evidence of students’ understandings of complex systems. We argue that different types of data are necessary to have a full understanding of the complexities related to learning about complex systems. For example, there are data related to the topic (e.g., changes in knowledge structures), one’s participation in scientific inquiry process (e.g., changes in participatory involvement), learning mechanisms (e.g., cognitive, metacognitive, motivational, self-regulatory), scientific inquiry processes (e.g., hypothesis generation, experimentation, evaluating data, reasoning strategies), and the transfer of these skills to other domains and tasks.

Another important issue is related to the types of studies being conducted. What are the strengths and weaknesses of our current research methodologies? For example, do we need year-long classroom studies focusing on a few students in an unstructured classroom environment, or can we have small-scale laboratory experiments. What is the range? How long does it take to change one’s conception of a complex system? These factors related to the study of complex systems are themselves interrelated. It is worthwhile to remember Ann Brown’s (1992) idea that laboratory and classroom experimentation can be mutually informative. For example, Liu, Hmelo-Silver, and Marathe (2005a, 2005b) first conducted proof-of-concept work in the laboratory to see whether the SBF representation affected student learning from hypermedia. This set of laboratory studies demonstrated effects on both outcomes and processes of learning about a complex system and sets the stage for classroom studies. But a key issue for classroom research will be helping teachers understand complex systems and how to support student learning (e.g., Azevedo, Winters, & Moos, 2004).
SUPPORTING STUDENTS’ LEARNING OF COMPLEX SYSTEMS

Once we have an understanding of how students learn about complex systems, we can explore how to best prepare teachers to support students’ learning. Research on how children learn about complex systems, including significant developmental and learning trajectories, can be used to inform teacher thinking about student learning. But despite government mandates (National Council for Accreditation of Teacher Education, 2002), teachers are not being prepared to handle such learning. Teachers need to understand how to use guided discovery approaches such as problem and project-based learning (Barron et al., 1998; Blumenfeld et al., 1991; Hmelo, Holton, & Kolodner, 2000; Hmelo-Silver, 2004; Krajcik et al., 1998; Vick, Azevedo, & Hofman, 2005). With technological advances, educators have become inundated with computer-based learning environments such as simulations, hypermedia, and other Web-based learning environments that may have the potential to facilitate students’ learning of complex systems in such areas as science, math, and social studies. Unfortunately, teachers are not being trained how to support students’ learning with such technology-based environments. Such environments, we think, are especially important to learning about complex systems, so it is especially important for teachers to have the skills needed to support learning of complex systems from simulation and modeling software (Lajoie & Azevedo, in press; Corno & Mandinach, 2004).

This challenge has several parts, and we need to answer numerous questions about the potential impact of hypermedia and modeling environments on learning before these environments can be productively infused in the classroom (Azevedo, in press-b; Mandinach & Cline, 2000). We need to understand the kinds of pedagogical content knowledge needed to help teachers productively use computer-based learning environments to teach about complex systems, which includes understanding how students learn about complex systems. This information can then be used to inform practices in teacher preparation programs to better foster their students’ learning with such open-ended learning environments.

CONCLUSION

Learning about complex systems is hard. It is hard because of the domains themselves, which span and integrate a vast range of subject matter. It is hard because there are many systems concepts that we have never directly experienced or that violate our intuitions. It is hard because learning about these systems challenges cognitive, metacognitive, and social resources. The learning sciences is at an early stage of understanding how people think about complex systems (e.g., Hmelo-Silver & Pfeffer, 2004; Jacobson, 2001) and how they learn about such systems (e.g.,
Azevedo, in press-b; Charles & D’Appolonia, 2003; Wilensky & Resnick, 1999). Whereas Jacobson and Wilensky (this issue) outline a number of challenges in learning about complex systems, here we have highlighted a number of issues that the field should better understand if we are going to support students’ learning about complex systems. Understanding these issues requires that learning scientists identify and carry out a broad research program regarding how students and teachers learn about complex systems. From the emerging theoretical and empirical bases, we can more readily help a new generation learn about complex systems and the dynamic roles they play in our world.

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