

## **Embodied Perspective Taking in Learning About Complex Systems**

FIRAT SOYLU

*University of Alabama, USA*

fsoylu@ua.edu

NATHAN HOLBERT

*Columbia University, USA*

holbert@tc.columbia.edu

COREY BRADY

*Vanderbilt University, USA*

corey.brady@vanderbilt.edu

URI WILENSKY

*Northwestern University, USA*

uri@northwestern.edu

In this paper we present an approach to learning design that leverages *perspective taking* to help students learn about complex systems. We define perspective taking as projecting one's identity onto external entities (both animate and inanimate) to predict and anticipate events based on ecological cues; to automatically sense the affordances of objects in the environment and take advantage of these affordances; and to understand the mental states of other individuals, an ability crucial for socialization and communication. We introduce one key construct, "phenomenological connectors," which are essentially activities that encourage embodied perspective taking across micro and macro levels of a system. Phenomenological connectors enable learners to step inside a system at various levels, thereby having first-person experiences of multiple agents and components, as they attempt to make sense of that system. We consider agent-based model-

ing activities as exemplars of this design approach. We argue that agent-based models (ABMs) present unique perspective taking challenges and learning opportunities, to learners. Informed by the learning design approach proposed, we present a curricular agent-based modeling unit on Particulate Nature of Matter (PNoM) and present data from the implementation of this unit in two 10<sup>th</sup> grade science classes. The discussion of data focuses on how students make sense of their first-hand experiences in a diffusion of odor experiment, where students collectively act as sensors to track the diffusion of odor, by building and reasoning with agent-based models, and taking perspectives of different agent- and aggregate-level elements of the system.

**Keywords:** perspective taking; embodied cognition; complex systems; agent-based modeling; particulate nature of matter

When I observed phenomena in the laboratory that I did not understand, I would also ask questions as if interrogating myself: “Why would I do that if I were a virus or a cancer cell, or the immune system?” Before long, this internal dialogue became second nature to me; I found that my mind worked this way all the time.

(Salk, 1983, p. 7)

The purpose of this paper is to discuss how embodied approaches to cognition can illuminate children’s learning about complex systems in STEM domains. We propose a learning design approach that harnesses insights about the role of bodily interaction and perspective taking to help children learn about complex systems. We consider perspective taking as a core human ability that is tightly related to action, social interaction, verbal behavior, and a wide range of cognitive abilities. We provide an evolutionary account for how perspective taking relates to other human abilities, and we bridge this view with approaches to perspective taking in learning about complex systems. To help communicate how the ideas presented here can be applied in classroom contexts, we present a curricular unit on the Particulate Nature of Matter (PNoM), which was developed as a model-based inquiry curriculum for the NSF-funded ModelSim project, and discuss findings from the implementation of this unit in two 9<sup>th</sup> grade chemistry classes.

The study of complex systems has gained attention over the last several decades, leading to new insights and findings, as well as changing conceptual frameworks in both physical and social sciences (Jacobson & Wilen-

sky, 2006). Complex systems approaches enable the study of how structures and agents that make up a system interact, leading to non-linear causal relations and events across multiple levels of structure, organization, and time scales. Boosted by rapidly developing computational modeling tools, complex systems frameworks have shifted ways of thinking in many domains that are critical to daily life of individuals: for example, educational practice, research, and policy (Jacobson, Kapur, & Reimann, 2016; Maroulis et al., 2010; Wilensky & Resnick, 1999), economics (Foster, 2005), psychology and neuroscience (Bullmore & Sporns, 2009; Chialvo, 2010), and medicine (Ahn, Tewari, Poon, & Phillips, 2006; Barabási, Gulbahce, & Loscalzo, 2011).

The shift from linear, centralized, and reductionist approaches to dynamic and complex systems approaches is also changing K-12 classrooms. There is now a large body of research on how novice learners and experts think about complex systems (e.g., Goldstone & Wilensky, 2008; Hmelo-Silver & Pfeffer, 2004; Jacobson, 2001; Wilensky & Resnick, 1999) and how learning environments and activities can be designed to help students learn about and recognize features of complex systems in a wide range of curricular domains (Brady, Holbert, Soylu, Novak, & Wilensky, 2015; Klopfer, Scheintaub, Huang, Wendel, & Roque, 2009; Levy & Wilensky, 2009; Wilensky & Reisman, 2006; Yoon, 2008). However, making complexity accessible is not always an easy feat. Incorporating invisible and dynamic phenomena at one level (e.g., the motion and collisions of gas particles), with events that are observable and accessible to first-person experience at another level (e.g., feeling pressure when pushing the handle of a bicycle pump) constitutes a challenge for many learners. Students often gravitate towards centralized, deterministic, and static explanations for complex phenomena, as opposed to decentralized/emergent, probabilistic, and dynamic ones (Blikstein & Wilensky, 2009; Hmelo-Silver & Pfeffer, 2004; Wilensky & Resnick, 1999). Computational modeling is recognized as one effective way of providing students with enriched inquiry experiences that can enable construction of an interconnected and personally-relevant understanding of how complex systems work across multiple levels (Brady et al., 2015; Sengupta, Kinnebrew, Basu, Biswas, & Clark, 2013).

One important concept in complex systems is “emergent levels,” that is, levels of a phenomenon that arise from the interactions of elements at lower levels. Wilensky and Resnick (1999) argue that confusion about the casual relations between events at different levels underlie many misunderstandings about patterns and phenomena across a wide range of science domains. By documenting and studying the experiences of three learners building

computational models about different phenomena, they exemplify how constructing agent-based computational models can help with exploring and developing an enriched understanding of multi-level phenomena. For example, they show how understanding the emergence of Maxwell-Boltzmann distribution (aggregate-level) from an initial state of particles with same speeds can happen by focusing on the non-linear (i.e., not head-on) collision of two particles with the same speed, which leads to each particle exiting the interaction with different speeds (particle-level). They also show how constructing an agent-based model can facilitate understanding counter-intuitive aggregate phenomena (as in the transformation of a particle system, in which initially all particles have the same speed, and over time, the *average speed* decreases with time while the *total energy* is conserved).

Perspective taking has been proposed as a fundamental strategy in understanding agent-level interactions in a complex system (Ackermann, 1996; Stroup & Wilensky, 2014; Wilensky & Reisman, 2006). More generally, perspective taking is seeing a situation from another agent's perspective. Taking the perspective of an agent involves looking at a system from the agent's perspective, which provides an intuitive access to possibilities of interactions with and affordances of other elements of the system. For example, Wilensky and Reisman (2006) demonstrate how learners assume the perspectives of agents in ecosystems (e.g., a firefly) while constructing computational models of various complex biological phenomena (e.g., the synchronous flashing of groups of fireflies). Assuming the perspective of, for example, a firefly, pushes the learner to think about how one firefly might behave, in such a way that when many more fireflies engage in similar behavior, a collective, synchronous flashing emerges, even without a central controller. By articulating in code the simple behaviors of the firefly, the learner might construct an agent-based computational model where many more fireflies, behaving in similar ways, can act together. This allows testing if the hypothesized perspectives and the related behaviors lead to the expected, emergent, aggregate-level phenomenon—synchronous flashing—and, if not, requires iterative reflection on the behaviors of the firefly and further testing in the computational model. Wilensky and Reisman (2006) call this an “embodied modeling approach.” It is embodied because it encourages learners to bring insights from their daily bodily experiences into their understanding of complex systems. Other learning design efforts leveraging perspective taking and facilitating use of bodily knowledge include *participatory simulations* (Wilensky & Stroup, 1999b). In these activities, each student plays the role of an agent in a complex system and interacts with other agents and elements of the system. Participatory simulations

can be connected with agent-based modeling activities using the NetLogo language and platform (Wilensky, 1999), through the networked HubNet system (Wilensky & Stroup, 1999a) which enables groups of learners to connect with a simulation as agents. Participatory simulations (networked models) further facilitate perspective taking by providing individuals with agency and control of one of the agents in the system, while providing the group with a shared experience of aggregate-level emergent phenomena at the same time. This not only requires thinking about what it would be like to be one of the agents in the system, but also acting as one of the agents.

Tomasello, Kruger, and Ratner (1993) distinguish between visuospatial perspective taking (e.g., as assessed by the Piagetian “three-mountains” task; Piaget & Inhelder, 1969) and a broader form which refers to “all the attempts of one person to understand or perceive a situation in the way that another person understands or perceives it” (p. 510). Both forms of perspective taking seem to play a role in learning. For example, Modell (2007) showed that visuospatial perspective taking experiences improve learning performance in domains with complex spatial representations. The broader definition provided by Tomasello et al. refers to a *theory of mind* activity, where one person sees a situation from another’s perspective, considering inter-subjective, sociocultural, and situational factors. They define this form of learning as “learning in which the learner is attempting to learn not from another, but through another” (p. 496). Learners were found to engage in this form of perspective taking while learning in a wide range of science domains (e.g., Ackermann, 1996; Lindgren, 2012; Nemirovsky, Tierney, & Wright, 1998; Wilensky & Reisman, 2006). In this paper we attend to this broader form of perspective taking and look at its role in learning about complex systems.

Perspective taking has been leveraged in many spaces and contexts; among them, virtual environments provide unique affordances for engaging in perspective taking activities. One of these affordances is the ability to control a virtual agent, which not only allows seeing the virtual world of the agent from the agent’s perspective, but also affords acting on the environment, which is a unique phenomenon and is usually not part of our perspective taking experiences outside of virtual contexts (i.e., we do not control other people’s bodies when we assume their perspectives). There is evidence that engaging with a virtual world from the first-person perspective of an agent can improve learning outcomes, compared to modes of engagement from third-person perspectives. For example, in a study where learning outcomes of a training program for safety procedures in a hazardous manufacturing environment were compared, Lindgren (2012) found that

embodied experiences, which involved engaging with the work environment from a first-person compared to a third-person perspective, resulted in better learning outcomes.

One possible disadvantage of virtual environments is the limited modes of bodily interaction (usually limited to interacting with a mouse, a keyboard, and a screen). However, virtual environments can integrate with real-life, physical contexts, which can allow for unique and rich perspective taking experiences that would not be possible in one form of learning environment alone (virtual or physical). For example, Moher (2006) developed distributed simulations embedded into third to sixth grade classroom environments, covering a wide range of topics from ant colonies to astronomy. These simulations provided opportunities for learning both through bodily motion in the physical space and through perspective taking during interactions with virtual agents dispersed through the physical space.

While perspective taking involves shifting and converging one's experience towards another entity's phenomenal field, its opposite involves detaching one's perspective from any one particular entity, and looking at a situation from a view above—a bird's eye, aggregate perspective. These two states of experiencing a system—taking the perspective of a particular entity in the system and taking the aggregate perspective—can be complementary in facilitating learning. Ackermann (1996) defines deep learning and cognitive growth as an “on going dance” (p. 5) between “diving-in,” which refers to the act of projecting oneself into different elements of a situated experience, and “stepping-out,” or taking a “god's eye view,” where the learner assumes the viewpoint of an external observer to make sense of what has happened from a distance. She considers both diving-in and stepping-out as essential aspects of deep learning. Many educational designs have attempted to leverage Ackermann's “diving in” and “stepping-out” strategy. For example, role playing activities, where learners switch between perspectives of particular elements of the system and the aggregate view, have been shown to improve learning outcomes in math and science domains (Duatepe-Paksu & Ubuz, 2009; Resnick & Wilensky, 1998). Similarly, Stroup and Wilensky (2014) point to two crucial aspects of learning about complex systems; aggregate and agent-based reasoning, and they argue for the complementarity of these two types of reasoning, which they call “*embedded complementarity*.”

In this paper, we explore why perspective taking is important for understanding complex systems and illuminate the nature of perspective taking; its evolutionary origins, neural mechanisms, and its relation to bodily processes that support action. We approach perspective taking as a participatory

activity that constantly takes place in our interactions with the world. We argue that:

- (1) Understanding a complex system involves taking perspectives of the different agents (both animate and inanimate) of a system across micro and macro levels and interpreting the outcomes of agent-based interactions at these levels (Ackermann, 1996; Stroup & Wilensky, 2014; Wilensky & Reisman, 2006).
- (2) Perspective taking abilities evolved in response to environmental pressures, and they support not only communicative skills, but also (and originally) action and tool use. These systems were later adapted during evolution of cognitive skills. Perspective taking is therefore tightly related both to bodily, contextual experiences that support action and to evolutionarily newer cognitive skills, such as language and metaphorical thinking.
- (3) Perspective taking involves simulation of the sensorimotor and affective states of others (see Decety & Grèzes, 2006 for a review). For example, watching a friend trying to pull a Jenga block without causing the tower to collapse activates partially overlapping sensorimotor circuitry in the observer's brain, as if the observer were also engaging in the same action. These transient brain states are shaped based on previous experiences within the system, and they help predict future behaviors of the agents, and possible emergent outcomes (Soylu, 2016). While students' daily experiences can provide the experiential ground for understanding a complex system, students may not have the rich experiential repertoire needed to take perspectives of elements of a system at the micro-level. Providing students with contextualized, bodily experiences across micro and macro levels can facilitate learning about complex systems. We call such activities, which provide embodied experiences that link perspectives of agents across different levels, *phenomenological connectors*.

We fashion a view of perspective taking in the design of learning environments that underscores the potential importance of embodied experiences both at the agent (micro) and aggregate (macro) levels. We make this case by first exploring views and findings on perspective taking across different forms of cognitive activity, such as social interaction, language, and tool use. We then review evolutionary approaches and neuroscience findings on perspective taking to provide a theoretical foundation for new strategies for embodied educational design. Next, we put forth a new design construct, which we call *phenomenological connectors*. Phenomenological connectors

refer to activities that provide students with opportunities to take on perspectives of and have direct perceptuo-motor experiences with elements at both the agent and aggregate levels of a system. Informed by the framing of embodiment presented in the first part of the paper, we consider use of agent-based modeling (ABM) in learning about complex systems (Jacobson & Wilensky, 2006; Klopfer et al., 2009; Wilensky & Reisman, 2006; Wilkerson-Jerde, Wagh, & Wilensky, 2015) as an exemplar of this design approach. We argue that these model-based learning environments present unique perspective taking challenges and opportunities for the learner. For example, understanding a complex system (see Jacobson et al., 2016 for a review of approaches to learning about complex systems) requires switching between the perspective of individual agents in the system as well as viewing the system at the aggregate level to link agent-level interactions with emergent, aggregate outcomes. Finally, we provide a specific example of the phenomenological connectors approach by describing the design and implementation of, and the classroom data generated from, a curricular ABM environment to support learning about the Particulate Nature of Matter and key mechanisms of the Kinetic Molecular Theory (KMT).

## PERSPECTIVE TAKING AND THE EVOLUTION OF COGNITION

Action understanding—interpreting and making sense of the actions of others—is a crucial skill for coordination and collaborative goal-oriented behavior of groups of individuals. Primates have a specialized system for understanding the actions of other individuals, allowing them to mentally simulate an observed actor’s behaviors (Rizzolatti, Fadiga, Gallese, & Fogassi, 1996). But going beyond action understanding, this system also allows the simulation of the *mental* state of another individual during social interaction.

The existence of a cortical mechanism in the monkey brain that activates motor areas during observation of goal-directed actions in others suggests that skills like action understanding, imitation, and perspective taking are not purely cognitive: rather, they involve a sensorimotor simulation system (Gallese & Sinigaglia, 2011). A growing body of evidence for a similar mechanism in the human brain (Grezes, Armony, Rowe, & Passingham, 2003; Mukamel, Ekstrom, Kaplan, Iacoboni, & Fried, 2010) provides further support for the simulation theory. The sensorimotor simulation system allows us to simulate the sensorimotor and affective states of an observed individual and to make sense of social situations (Gallese & Goldman,



1998). Embodied evolutionary theories of human communicative behavior provide an integrated account for how seemingly distinct skills like action understanding and imitation, tool use, verbal language, and abstract thinking are all grounded in our ability to take perspectives of other entities and simulate lived experiences (Arbib, 2002; Fogassi & Ferrari, 2007; Gentilucci & Corballis, 2006; Rizzolatti & Arbib, 1998).

The evolutionary move from the ability to imitate to gesture-based communication made it possible for humans to express intentions by engaging in symbolic actions (Corballis, 2010). For example, pretending to throw a spear might serve to invite someone to go hunting. This requires a first level of abstraction where the action represents a communicative meaning instead of being an actual goal-directed hunting behavior. This type of communication (and what might follow, e.g., going hunting together) requires multiple levels of (recursive) perspective taking activity. First, the communicator has to execute the action expressed while simulating the mental state of the other party (e.g., my friend is in listening mode, trying to understand what I am communicating). The listener then has to simulate the action observed to interpret its meaning (a first level of mental simulation), based on the assumption that the performing party intends to be communicative (involving a second level of mental simulation). Understanding the meaning of the action observed, and confirming that it is in fact being executed for a communicative purpose, requires evaluation of both environmental cues (e.g., time of the day, location), and historical and cultural background (past history with the observed individual, culture and rituals of the tribe, etc.). Furthermore, because communication is a time-pressured activity, comprehension has to happen in a situational continuity, which makes it possible to predict, for example, whether the observed action is communicative, merely based on what took place previously. The development of the vocal system allowed humans to associate actions (like throwing a spear) or qualities (e.g., physical, emotional or mental states) with specific vocalizations. Use of the vocal system for communicative purposes allowed both a multimodal means of communication (including gestures and facial expressions along with vocalizations), and also the development of a complex grammar (Studdert-Kennedy, 2002).

**Tools use and the social brain.** In a limited definition, tool use can be described as use of an external physical entity to enhance human manipulative capabilities. While other animals show a limited ability to use tools (e.g., use of a stick to retrieve food), humans are unmatched in making and using tools and in learning from others how to use them (see Arbib, 2011 for a review on evolution of language and tool use). Tool use requires walk-

ing upright to free up hands, and depends on changes in the sensorimotor systems that allow for fine motor movements and hand-eye coordination. In addition, tool use requires identification of tools and activation of previously-learned motor programs for specific tasks. Chao and Martin (2000) propose that our ability to identify tools might depend on the re-activation of sensory and motor experiences attributed to the object viewed. This suggests that identification of a tool involves re-activating sensorimotor circuits characterizing the activity that would take place during the interaction with the tool, and that the *embodied semantics* of objects around us emerge from our history of interactions with them. We simulate possibilities of interactions with objects when we merely see them, and our previous interactions with these objects shape our immediate perceptions of them. In this sense, identification of an object does not consist so much in retrieving physical attributes of an object category stored in the memory and comparing it to the perceived stimulus; rather, identification of the tool occurs as visual features of the object trigger perceptuomotor programs created either during previous direct interactions or through observations of another individual interacting with it. Gibson (1986) originally framed this mechanism with the concept of *affordance*. The affordance of a tool is an emergent theme in the coupling of the individual's unique skills and bodily structure with features of an external physical entity. In other words, affordance is what an individual can do, and is habituated to do with a physical object.

Social learning, most importantly imitation learning, played an important role in the dissemination of tool use across human cultures (Arbib, 2011; Tomasello et al., 1993). The ability to learn how to use tools—including both how to recognize them and how to retrieve perceptuomotor programs to use them effectively—might have constituted a strong selection pressure for early humans (van Schaik, Deaner, & Merrill, 1999). In addition, findings showing that early hominids, such as *Homo Habilis* (meaning “handy man,” for its unprecedented tool use skills), having what we now consider to be speech areas (based on cranial cavities), have provided evidence for verbal skills being built on systems that originally evolved to support using and disseminating knowledge of tools (Rizzolatti & Arbib, 1998). Overall, the human body and brain have evolved to allow tool use, to learn about how to use tools from others, and to disseminate this knowledge. We make sense of using tools within a social context, and perspective taking is the fundamental strategy for learning how to use tools.

Considering the evolutionary origins of unique human skills, related to social cognition, verbal language, and tool use, provides us with an expansive picture of perspective taking. We argue that understanding why per-

spective taking and situated, bodily activities can help with learning about complex systems requires adopting the presented evolutionary and embodied approach. Perspective taking uses a core simulation system, which evolved to support a wide range of human competencies. The argument that embodied simulations are the source of semantics (Gallese & Lakoff, 2005; Soylu, 2016) implies that negotiated symbols (symbolic actions) within a socio-cultural context emerge from the crystallizations of social action-situations that are repeated and reused within that socio-cultural context. Functioning as social agents in complex social groups requires the ability to effortlessly take the perspectives of others. Perspective taking is also a prerequisite for imitation learning and verbal communication.

To this point, we provided an embodied account of perspective taking and discussed importance of perspective taking for different domains of cognition, including social interaction, language, and tool use. In the remainder of the paper we shift our attention to how we can harness what we know about embodied perspective taking for innovations in learning design.

## CONNECTING EMBODIED PERSPECTIVE TAKING WITH LEARNING DESIGN

Because research indicates that action, movement, and gesture can support learning in a variety of educational contexts (Cook, Mitchell, & Goldin-Meadow, 2008; Lindgren & Johnson-Glenberg, 2013) it is not surprising that many educational interventions have begun to incorporate action and gestures in novel ways, where physical interaction leads to development of sensorimotor schemas, which later supports formation of more formal forms of understanding. Designs that fall into this category may involve adding bodily interactions to more traditional educational practices (e.g., concrete math manipulatives; Carbonneau, Marley, & Selig, 2013), using physical motion or gestures as control mechanisms for visualizations and games (e.g., Johnson-Glenberg, Birchfield, & Megowan-Romanowicz, 2010; Lindgren & Johnson-Glenberg, 2013), or leveraging gestural and action metaphors for complex concepts and phenomena for which most people have little everyday experience (Antle, Droumeva, & Corness, 2008; Howison, Trninic, Reinholz, & Abrahamson, 2011).

*Embodied design* is a term first introduced to the Learning Sciences by Abrahamson (2009), who later described it as “a pedagogical framework that seeks to promote grounded learning by creating situations in which students can be guided to negotiate tacit and cultural perspectives on phenomena under inquiry; tacit and cultural ways of perceiving and acting” (Abrahamson, 2013, p. 224). This term is instrumental in avoiding a common fal-

lacy with the conceptualization of embodied learning; the idea that bodily mechanisms simply augment conceptual processing, providing a larger benefit for some activities or conditions than for others. Rather, the embodied cognition orientation asserts that *all* cognition is embodied regardless of the activity, concept, or process under inspection. What we strive for, as educational designers, is to design learning environments that are compatible with the mechanisms underlying the learning process. In this sense, “embodied design” is not design that activates embodied learning; it is design that resonates with the way we learn, which is always already embodied.

### **Embodied Modeling: Perspective Taking and Learning about Complexity**

The theory of embodied cognition offers a wide design space, which includes both direct bodily interaction as well as other forms of engagement, such as perspective taking. A core mechanism of the embodied mind is our ability to activate sensorimotor states that are not part of our immediate perceptions or actions (no external stimuli, no overt action). This mechanism undergirds a wide range of skills, including understanding and imitating actions of others; having an immediate sense of the affordances of objects around us by way of simulating interactions with them; and engaging in verbal communications. We propose *perspective taking* as a construct that connects these diverse skills. Here, perspective taking refers to our ability to assume the perspective not only of another individual, but also of non-human or even inanimate entities, to predict their behaviors and to envision potential ways of interacting with them.

Our natural tendency toward perspective taking in understanding new domains has been previously harnessed by *constructionist* approaches to learning and design (Abelson & diSessa, 1986; Papert, 1980; Papert & Harel, 1991). For example, in the Logo programming language users are encouraged to draw shapes and objects by controlling a digital Turtle through simple commands (e.g., “forward 60”, “right 90”). Learners are encouraged to “play Turtle,” that is, to “think like the Turtle,” or to take on the perspective of the Turtle by projecting themselves onto the Turtle. Because of its accessibility through this kind of perspective taking, Papert (1980) describes the Logo Turtle as *body syntonic*. One can use knowledge of how one’s own body moves in physical space to reason about how to command the Turtle to draw shapes. Taking on the role of the Turtle makes it possible to understand geometric shapes and patterns in a body syntonic way, and it allows for new body-oriented definitions. For example, a traditional definition

for an equilateral triangle would be “a polygon with three equal-sized edges and vertices.” Alternatively an equilateral triangle can be defined in Logo as the trace the Turtle leaves behind while following the command, “repeat 3[ forward SideLength right 120 ].” This essentially tells the turtle to take a fixed number of steps forward (the length of each side), then turn 120 degrees right, repeating these steps three times. With this definition, an equilateral triangle becomes the path created by a set of programmable actions that the Turtle will follow. In other words, the triangle becomes an artifact created by movement through two-dimensional space. In their book, *Turtle Geometry*, Abelson and diSessa (1986) provide an in-depth exploration of how this alternative representation, based on movement, can provide new entry points into basic and advanced concepts in both traditional geometry and differential geometry.

Taking the perspective of the Turtle and moving it using programming commands allows for a new type of formalism that puts the body and movement at the center. Extending this one-to-one relationship between the learner and Turtle, StarLogo (Resnick, 1996, 1997; Wilensky & Resnick, 1999) and NetLogo (Wilensky, 1999) were developed to enable the learner to command not just one Turtle, but a multitude all at once. This shift, from perspective taking of one Turtle to many *agents* allows for the exploration and descriptions of a class of phenomena known as complex systems—systems that can be very difficult to predict or explain, and that emerge from the interaction of many simple and easily understandable individual agents.

Leveraging the unique affordances of agent-based modeling tools such as NetLogo, Wilensky and Reisman (2006) proposed an embodied modeling approach to provide learners opportunities to build and explore models of various phenomena such as predator-prey population relations or the synchronized flashing of fireflies. In this embodied modeling approach, systems are not described by aggregate outcomes or perceived behaviors of the whole, but rather through the articulation of rules of interaction among different individual elements or agents that *generate* these aggregate phenomena. Engaging in this form of modeling requires putting oneself in the place of the agent and thinking at the level of the agent, rather than at the level of the system. Indeed, using the HubNet (Wilensky & Stroup, 1999a) module of NetLogo, a group of learners can enter a simulation together, directly taking on the role of agents in a *participatory simulation*. These group role-playing activities particularly harness the perspective taking aspect of embodied modeling (Wilensky & Reisman, 2006); individual participants gain insights into agent behaviors, while the group as a whole collectively produces the emergent outcomes of the system they are modeling.

The general goal of such embodied, agent-based modeling approaches is to help learners construct a decentralized and emergent understanding of the complex phenomena exhibited by a system encompassing multiple levels. Wilensky and Reisman (2006) offer two reasons for providing opportunities for learners to take the perspectives of agents in the phenomena studied while at the same time observing aggregate level changes. First, this embodied modeling approach offers feedback to learners at both the individual and the aggregate level. And second, learners are better able to understand the rules at the individual level (as opposed to an aggregate formula) because “students will often try to make sense of a given rule set by assuming the perspective of the individuals within the model and using their imaginations” (Wilensky & Reisman, 2006, p. 186). Assuming the agency of an actor embedded in the system is proposed as a powerful aspect of the embodied modeling approach: “When their knowledge of the individual biological elements is combined with their knowledge of their own embodiment, their own point of view, they are enabled to think like a wolf, a sheep, or a firefly” (p. 203).

Why does assuming the role of an agent situated in a system (agent-based thinking) facilitate our understanding of a complex phenomenon? How does it tap into the way our minds work? First, agent-based thinking is a theory of mind activity where the learner imagines how it would be to be, for example, a firefly (Wilensky & Reisman, 2006). As was discussed earlier, embodied simulation of the sensorimotor and introspective (e.g., intentional and emotional) states, either of another individual or the self, is a central mechanism in human cognition. In this sense, adopting an agent-based perspective resonates with the usual way we make sense of our world. As discussed earlier, the embodied simulation system reactivates transient bodily states, shaped by previous experiences, to help make sense of actions and internal states of an “another” entity. Yet, our repertoire of previous experiences can limit or expand the extent with which we can look at the world from another entity’s perspective.

In previous studies, children were reported to indulge in anthropomorphic thinking in an effort to make sense of non-human agents’ behaviors in science domains (Ackermann, 1999; Dickes & Sengupta, 2012; Kapon & DiSessa, 2012; Nemirovsky et al., 1998). This form of anthropomorphic thinking involves ascribing intentionality to the agents, and explaining agent behavior based on human-like mental and intentional states. This is similar to what Dennett (1987) described as the *intentional stance*—one of the approaches (“stances”) humans adopt to understand and predict the behavior of unfamiliar entities. Adopting an intentional stance involves explaining

and predicting an entity's behavior by assuming that the entity's behaviors are governed by its beliefs, and intentional and mental states. Anthropomorphic approaches (intentional stances) also help children explain how agents interact with one another and are affected by each other's behaviors. From this perspective, agents react to other agents' behaviors not by following a set of predetermined rules, but by perceiving the behavior, triggering specific human-like mental and intentional states, and responding with human-like (re)actions. For example, Kapon and diSessa describe how an eighth grader accounts for the elasticity (springiness) of various solid objects when compressed with force. In one specific case, a heavy object is put on a flexible surface. When the student is asked if the surface exerts force on the object, the student responded "Yes, but not enough to maintain its original shape, so it's preventing the fishing weight from completely destroying it or altering its shape, I guess, but it's not ... it doesn't have enough strength, I guess" (p. 279). Here the force interactions between the surface and the object are described as a form of a struggle, where the surface tries to maintain its original shape, but does not have enough strength to do so. In another example, the same student explains the behavior of spring compressed by hand as follows: "Yeah. It [the spring] wants to return to its original. I'm trying to think of a word to explain that [pause] state, I guess. It wants to return to the way it was" (p. 280). Children use similar strategies in reasoning about behaviors of computational artifacts (e.g., robots, agents in a simulation). Even though they very well know that these are not living entities, in reasoning about the behaviors of these computational artifacts, children treat them as social agents with mental lives and with control of their behaviors (Ackermann, 1999). When studying complex systems, the anthropomorphic approach allows the use of perspective taking abilities to interpret agent-based behaviors, and facilitate understanding of emergent, aggregate outcomes (Dickes & Sengupta, 2012). Apart from scientific reasoning, we argue that approaching objects as animate beings relates to our core need to understand affordances of non-human entities and predict their behaviors based on perceptual cues. In this sense, anthropomorphic thinking also relates to tool use and, as Nemirovsky et al. (1998) have pointed out, "projecting anthropomorphic qualities on tools nurtures the weaving together of logical necessity and empirical evidence" (p. 166). While taking perspectives of other people is ordinary for learners (though it poses its own challenges), taking the perspective of an air molecule while learning about gas laws is considerably harder, given the lack of overlapping bodily states and experiences (e.g., what it is like to be an air molecule). The learning design approach presented here addresses this challenge.



Perspective taking in an agent-based environment also involves imagining how the agents in a system might perceive the affordances of other objects within the ecology of the system in which they are embedded. That is, the agent-based perspective involves developing a sense of the affordances of other objects in the system, from the viewpoint of an individual agent. Therefore, the projection of agency onto a sheep in an agent-based model also involves seeing the model's world through the eyes of that sheep (Wilensky & Reisman, 2006). From the sheep perspective, *grass* affords *eating*, even though this is not the case for most people. Therefore, taking on the perspective of another entity also involves a shift in looking at the affordances of the objects in the world where the target entity exists. This requires assuming the body (or the physical structure) of the target entity, imagining that body's interactions with other objects in the environment, and developing intuitions about what those objects can afford, given the body and situatedness (referring to the narrative that frames the interactions) of the target entity.

To ground our discussions thus far and to further the previous work done using agent-based modeling in STEM education, in the next section we present a curricular activity that is informed by the embodied approach we have presented. This activity is part of a larger unit, which includes agent-based computational models as well as virtual models coupled with physical computational tools. Each of these artifacts is embedded in a carefully constructed sequence of science inquiry activities (Brady et al., 2015), meant to encourage students to connect prior experiences in the physical world to complex abstract phenomena through a series of perspective taking and other “embodied” activities. The artifacts presented here were developed as part of the ModelSim project—a 4-year project focusing on the design and scaled implementation of technology-rich ABM science curricula to address challenging topics in the physical and biological sciences.

### **LEARNING DESIGN ARTIFACTS: SCIENCE INQUIRY WITH AGENT-BASED MODELING**

The design approach presented here distinguishes itself from previous efforts to leverage perspective taking in learning about complex systems, by mixing computational modeling with a situated role-playing activity, where students play the role of an element of a system in a physical experiment, provide data input for the computational model, and acquire bodily experiences about what it might be like to be that element of the system. The

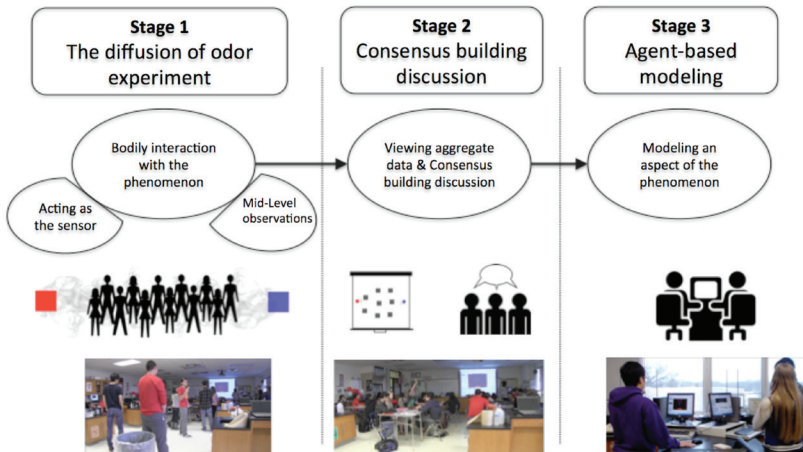


central theme here is that students are given opportunities to take perspectives of and have direct perceptuomotor experiences with elements that exist at both agent and aggregate levels of particle systems. These activities aim to develop a holistic understanding of the Particulate Nature of Matter (PNoM), characterized by an ability to project one's identity into elements of systems at different levels. We call such activities *phenomenological connectors*, since they provide bodily experiences that help bridge first-person phenomenology of the learner both at the micro and macro levels of the system (see Brady et al., 2015 a for more detailed description of these activities and the underlying design approach). The activities, the teacher guides, and the computational models for this project are publicly accessible in the ModelSim project website (<http://modelsim.tech.northwestern.edu/>).

In addition to describing the activity, we also present data from the implementation of the PNoM unit in two 10<sup>th</sup> grade science classes, with 24 students in each class, in a north-Chicago suburban public school. Written informed consent from parents and assent from students were obtained before the study. All procedures were in accordance with the ethical standards of the institutional research board and with the 1964 Helsinki declaration. The data presented below includes observation notes and video recordings from classroom sessions, student answers on in-class assignments, and student-created artifacts.

### **Modeling the Diffusion of Odor: Being the Sensor**

**Activity Description.** This activity serves as the introduction to the PNoM unit, which builds on earlier work, involving students in modeling the behavior of gas particles in a box (Wilensky, 2003) and engages learners with the phenomenon of the diffusion of an odor throughout a room. The data presented here were collected during three classroom sessions of this activity.



**Figure 1.** The diffusion of odor activity.

In the first stage of the activity (Fig. 1), students are organized in pairs, with one member acting as a “smell sensor” and the other as recorder. After the sensor-students have distributed themselves throughout the classroom, a mint fragrance is released at two locations. One of the mint fragrance sources is on a hot plate, while the other has been cooled, leading to differential speeds of diffusion from the two sources. Using number gestures (from one to three) each sensor-student signals her individual, location-specific readings of smell intensity, communicating this information to her recorder-partner, who enters this data into the modeling system shared by all students in the classroom. As time passes, sensor and recorder pairs continue to enter data, characterizing their perception of odor intensity over time (Fig. 2). The diffusion of odor activity is distinguished from other data-generating modeling activities, in that, instead of using electronic sensors, students themselves act as the sensors. In this way, this activity exemplifies a unique mixture of the *bifocal modeling* approach, which involves students collecting data using sensors and building computational models of the same phenomena to match the behavior of the model with the data they collected (Blikstein, 2014), in addition to a *participatory simulation*, where each student role-plays an agent in the system (Wilensky & Stroup, 1999b).

In the second stage of the activity a visualization is produced, which aggregates the individual “sensor” data to show how the odor has been detected throughout the classroom over time. This provides evidence to fuel a whole-class discussion of what mechanisms might account for patterns observed in the diffusion phenomenon (Fig. 3). Thus, in the first stage, stu-

dents make local observations about how the odor might be diffusing, by paying attention to the smell intensity reported by their peers adjacent to them. These observations constitute a mid-level, between the agent and aggregate levels (Levy & Wilensky, 2008). They do not provide complete information about what is happening at the aggregate, class-level, but they provide intuitions to learners about the aggregate level outcomes based on local observations. The visualization in the second stage provides a more complete picture of how the smell intensities reported across the class have changed over time.



**Figure 2.** Students signal their current sense of smell level by gesturing numbers to their partners, who record the data on network-connected computers.

In the third stage of the activity, student pairs work to construct a runnable ABM to describe or explore one testable aspect or hypothesis that they have chosen, related to the shared diffusion experience. For instance, one group might attempt to reproduce and explain the general pattern of spread from one or both odor-releasing locations; another might investigate possible reasons for fluctuations observed in specific sensor readings over time; and a third might conduct an experiment about a possible mechanism, such as temperature, for the varying rate of spread for each odor. As the different groups develop their models, they post their works-in-progress to a shared “gallery” of experiments, which enables them to monitor, reflect on, and comment on each other’s work in real time.



**Figure 3.** The class reflects on the aggregate data collected during the diffusion experiment. The changes in odor level reported by each student-sensor over time are projected on the screen.

**Classroom findings.** All stages of the activity relied heavily on students' experiences with projecting themselves into components of the system. In this section we show how these acts of perspective taking, specifically "acting like a sensor," served as a *phenomenological connector* for exploring the emergent nature of the diffusion phenomenon. Acting as a sensor raises questions about how a sensor works, which in turn leads to questions about the nature of what is being sensed: the gas particles. After reviewing the visualization of the aggregate diffusion experience data, the teacher initiated a class discussion to highlight interesting features of the data and to engage students in hypothesis generation. Early in this discussion, students began discussing diffusion of the odor in terms of the behaviors and characteristics of particle movement.

T (Teacher) - So what can you say, what is your conclusion based on what you see so far?

Chen (Student) - Hot stuff is smelly!

T - Hot stuff is smelly? [Laughing] Ok, any other reasons why that might happen do you think?

Chen - The heat probably makes the molecules faster and the smell spreads to the room faster and more further than the one that was not heated.

Chen<sup>1</sup> is obviously already aware of some relationship between heat and the motion of particles. In addition, this nod to particle motion early in the

<sup>1</sup> This is a pseudonym, as are all the names presented in this paper.

discussion, rather than vague abstractions such as “hot stuff is smelly,” will serve as an interesting anchor throughout the discussion.

As the discussion progresses, the teacher draws the students’ attention to fluctuations in the readings reported by the sensor-students.

Teacher (T) - There is someone who goes two to one, interesting. Who is two to one there? What happened there [Madeline]?

Madeline - I thought the smell got stronger but then realized it didn’t

T - It is interesting. (laughing) You were a little bit too anxious and jumped on that?

Madeline - Could it happen that the smell went down?

(Multiple students) - yeah

T - And why would the smell go down though?

George - Less molecules?

T - Less molecules, good. Less molecules moving through the air at that particular moment, absolutely. Ok let’s keep going. So again we get a three and a one, Is that you [Neil], three to one? Interesting. What made you go to three to one ?

Neil - I just moved my head towards to the board and couldn’t smell it

T - Perhaps the number of molecules like [George] was saying, maybe there is less of them. Let’s keep going, let’s see. Two and then finally look at this source here. And he was right on top of that odor or molecules right there, and then eventually never beyond that.

Madeline - Did any of the molecules come from the one right in front of me at all or is all from there (pointing to the hot plate)

T - That’s a good question. Alright [Madeline’s] question was; were those molecules, when we say smell, did any of those molecules come from here, or do you suppose that was all from the front of the room? Is that possible, could it be possible?

George - I think a lot of them comes from other the one (hot plate) but some of it is from here.

T - And why would that happen?

George - Because it was a lot faster

T - With more kinetic energy? Good

T - Alright so again, where are the molecules, and where is the source coming from? Do we have all the answers to this?

George - Probably not

While the teacher initially seemed interested in engaging students in discussions of data collection and the possibility of a sensor malfunction (“too anxious”), one student shifts the discussion back towards a possible particle-level explanation. Taking on the perspective of a sensor allowed students to experience the irregular, non-linear nature of diffusion—non-linearity that is hidden in aggregate-level equations and visualizations of the phenomenon. Because students situated their perspective at the micro level, the “uniformity” and “smoothness” of aggregate level models were not dominant in their conceptualizations. Rather than wave off the inconsistencies in observation as a “bad sense of smell” or the human nose as an inadequate sensor, students looked for particle-level explanations of this “noisy” non-linearity. Specifically, students articulated the notion that the nose functions as a detector of *the number of particles present at a given moment*—as indicated by students’ frequent use of phrases like “less molecules” and “a lot of them.”

The above excerpt also highlights the students’ attention to the nature of the directionality of particle movement. These themes are picked up in two subsequent discussions. In the first, occurring immediately after the excerpt above, students adopt the sensor perspective to attempt to make sense of how the placement of the sensors might impact how they have visualized the phenomenon.

Teacher (T) - So if we had to come up with a statement about how the molecules diffuse, what would you say?

Dai - They move in all directions

T - Is it this way this way or this way? What do you think Liu?

Liu - I think everywhere. It looks like it is going straight down there, in the middle because that’s where we all were.

T - So if you think about where sensors were located, is this the best setup?

Liu - Most of are at the center, and there some on the sides

T - It looks like we look like a tree, coming up and branching out a little bit. Do you think it would change if had more sensors?

Liu - Well the pattern wouldn’t change but we would be able to see, we would get more data.

Here students fall back into an aggregate discussion of particle motion, describing particle diffusion simply as “moving in all directions” and “everywhere.” However, one student also shifts back into a sensor-perspective and states, “it looks like it’s going straight down there, in the middle because that’s where we all were.” Even though the student still believes that the molecules might move in “all directions” and expresses that she expects “the pattern wouldn’t change,” she is able to articulate that the location of the sensors make us “able to see” the pattern itself.

In the following class period, students continued to question the specifics of that pattern. After the teacher chose (not originally part of the unit) to introduce students to the equation-based Graham’s Law (i.e., the rate of diffusion is inversely proportional to the square root of gas density), the class had a follow-up discussion to relate this description of the aggregate diffusion phenomena, characterized by a formula, to their recorded observations from the diffusion experience that had taken place in the previous class session.

Teacher (T) - How do you suppose this [Graham’s Law] relates to what we did yesterday with the HubNet simulation... Explain the pattern of that, of the way that the gas molecules traveled [silence] Did they all go up, and nobody smelled it? How did it actually travel?

Alvin - Kind a moved like out. I don’t know how to describe it. If it was like a small circle then it started to get larger [gesturing an expanding sphere].

T - Any abnormalities do you think in that pattern?

Mira - Me! [The student who smelled the odor towards the very end of the experiment]

Mira - I couldn’t smell it like until the last 10 seconds.

T - So she was kind of an anomaly, right? Everyone around him smelled it. Does that necessarily mean that there is something wrong with our sensor?

Zoe - Yeah probably [laughs]

T - Be nice... Or could you have any other possible reasons as to why Mira who is right by the plate did not smell it, like we think she should.

Mira - I probably have an awful sense of smell.

T - Ok could have an awful sense of smell. But let’s assume that the sensor is working just fine, it must have been because you eventually smelled the odor, that peppermint odor. Any other possible reasons as to why?

How would you make a prediction about that or a conclusion about that?

Ayla - May be like the molecules went around her?

T - How would it be possible for them to diffuse around her?

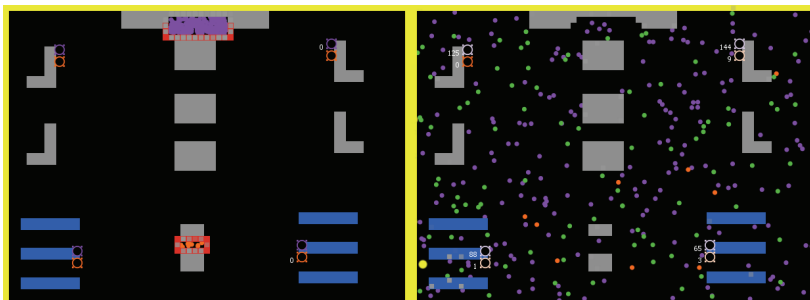
Ayla - Maybe it was like too low so she couldn't smell them... Again the possibilities are endless, but what if the gas molecules then came off the table because she was so close, hit her more so down here [showing her waist line], maybe toward the belly area and never went up to the nose, and then it worked its way this way [pointing to the head level]

Mira - That's a possibility. I am not like putting the blame but it might also be like the air currents that went around me [pointing to the air vents]

While students were tempted to resort to abstractions such as “how smell works” or to explain away strange data as an “anomaly,” through both the teacher’s efforts and students focusing on first-person experiences of individual student-sensors, they began to ask what these experiences might mean for both particle and aggregate level phenomena. Consequently, their explanations do not end at the aggregate (“it was like a small circle then it started to get larger”), but instead begin to include how particles might collide with tables in the room, might move in three dimensions at different rates (“too low so he couldn’t smell them”), and might be impacted by the movement of other particle’s in the room (air currents), etc.

In the third stage of the activity, students used a *sandbox* agent-based model (Brady et al., 2015) to model one aspect of the diffusion experiment they chose. In the sandbox modeling environment they used for this work, learners can add, remove, speed up, and slow down particles that move according to the Kinetic Molecular Theory (KMT) as well as add obstacles with which the particles collide (see Fig. 3). In this stage, learners formulated and explored hypotheses about how particle-level dynamics might lead to emergent aggregate-level outcomes observed frequently by switching between the agent and aggregate-level perspectives. A key bridging notion here is the perceptuomotor experiences of students moving their heads, smelling the scent, assessing its intensity, and recording its strength. By acting as the sensor, they associated the aggregate level perceptuomotor experience with the particle-level representation of the phenomenon. Inferences about the diffusion of particles, based on sensor readings in the model, are thus grounded in an intuitive and self-referential (body syntonic) understanding of how a sensor might work. The sensor is a component that exists across both stages of the activity (scent diffusion experiment & modeling), and the experience of taking on the role of the sensor functions as a *phenomenological connector* between the two levels (aggregate & particle-level).





**Figure 4.** Two states of the diffusion sandbox experiment developed by one of the student groups. According to the students, the gray and blue objects are intended to represent furniture (desks, lab benches). The purple and orange squares, with a circle at the center, represent sensors. The image on the left shows the state of the model before the odor particles (purple and orange colored dots) are released from their red “containers” into the classroom. The image on the right shows the state of the system after the odor particles have been released.

During later class discussions as well as subsequent modeling activities, students frequently drew on both the diffusion experiment and the modeling activity. For instance, they talked about sensors “smelling” odors, providing additional support for the idea that students’ first-person experiences are intermingled with their understanding of the functioning of the sensor. One student group summarized their findings from the modeling experiment they constructed, as follows:

If molecules in one jar are heated and the molecules in another jar are cooled, then the heated molecules will be smelled/detected first. After testing this in the simulation, it was found that in twenty seconds, the heated particles hit the sensors (on average) 11.25 times compared to 4.25 times for the cooled molecules. In our peppermint experiment, the people in the front/nearest to the heated peppermint were the ones to smell it first and strongest. The people nearest to the cooled molecules couldn’t smell anything for a long time. This shows that the heated molecules are smelled stronger/first because they are faster and more able to maneuver quickly around a room

Students’ experiences in the diffusion experiment and experiencing this phenomenon from the sensor’s perspective led them to discover several cen-

tral properties of complex systems more broadly. In the post activity questions, when asked what led to fluctuations in the reported peppermint odor levels, some students focused on intrinsic aspects of olfactory experience, for example, habituation: “The sensors may develop sensory adaptation, they grow accustomed to the smell,” and “Human error or building up of a tolerance for the smell.” Others explored extrinsic factors, for example the location of the sensors: “The people in the middle had the most fluctuation because the hot gas was far away but it diffused and moved towards them but the cold gas didn’t come to them and was less concentrated than the hot gas,” or time: “As the molecules spread apart, the smell may be strong at first then weaken as they move, until more molecules are diffused.” Students also encountered and explored the concept of *equilibrium*, another central feature of complex systems. For example, when asked what interesting patterns they had observed during the diffusion experiment and the modeling activity, one student said, “Over time, the heated molecules and the cold molecules started having about equal amount of contact with the sensors. I believe that the molecules reached equilibrium; the random collisions and transfer of energy between the heated and cold molecules led to equilibrium.”

In the examples from the classroom session we presented multiple instances where students’ interpretations of aggregate level phenomena seamlessly involve particle-level events. We argue that students naturally weave together aggregate- and particle-level events in their explanations, drawing on their first-hand experiences of functioning as a sensor and thinking about how a sensor interacts with elements of the system across the two levels. Connecting the two levels based on first-person experiences allows students to explore complex systems notions like fluctuations, stability, equilibrium, and feedback loops, and to think about complex phenomena like diffusion in non-linear terms.

### **Phenomenological Connectors**

Earlier in the paper we defined a phenomenological connector as an activity that provides embodied perspective taking experiences both at the agent (micro) and aggregate (macro) levels, in an effort to allow learners to associate events across the two levels based on first-person experiences. Depending on the phenomenon studied, the elements at a particular level may not easily lend themselves to perspective taking experiences (e.g., the learner might have a hard time imagining how it is to be that specific part of

the system). For example, in the Modeling the Diffusion of Odor example, the sensor, an inanimate electronic object, is one that does not easily lend itself to perspective taking. However, by designing an activity where the students act as sensors we open up opportunities for first-person identification with sensors, while at the same time, by looking at the projected aggregate image, they also monitor the aggregate perspective at the same time. This pairing allows students not only to conceptualize the diffusion of odor as a phenomenon emerging from the behaviors and movements of gaseous particles, but also an olfactory experience that they can personally relate to.

The term phenomenological connector points to the key notion that the learners' first-person phenomenology is the bridge that allows them to relate different levels of the system. This idea can be implemented in many other domains of science where initially hard-to-comprehend or abstract phenomena at each level can be made accessible to students by facilitating first-hand experiences at each of these levels, followed by discussions to share and compare these experiences. A key design element here is how the learners are encouraged to switch their perspectives among the different elements of the system—to experience two different levels of the system simultaneously, and to place these perspectives in dialogue with and in relation to one another.

First-hand experiences with the sensor at one level, which allows seeing and experiencing the system from the sensor's perspective, also supports easier access to the other level. Acting as the sensor gives direct access to understanding the affordances of a sensor. As previously noted, our perception and thinking about the affordances of a tool are informed by the simulation of possible interactions with that tool, which is in turn shaped by previous experiences. The bodily experience of acting as a sensor also grounds conceptual ideas about how a sensor functions and how particles behave during their interactions with a sensor, which then is generalized to how gas particles behave during diffusion.

In addition to having perspective taking experiences across the two levels, the diffusion activity allowed students to step out of the "shoes" they were wearing and look at the phenomenon studied and their experiences from an outsider's perspective. This is what Ackermann calls "diving-in and stepping-out";

People cannot learn from their experience as long as they are entirely immersed in it. There comes a time when they need to step back, and reconsider what has happened to them from a distance. They take on the role of an external observer, or critic, and they revisit their experience "as if" it was not theirs.

They describe it to themselves and others, and in so doing, they make it tangible and shareable. (Ackermann, 1996, p. 5)

During the discussions that took place after the diffusion experiment, students reviewed what had happened during the entire duration of the experiment and talked about different ways to explain the emerging patterns in the diffusion phenomenon. Similarly, after the modeling activity, each group posted their models in the online gallery and commented on one another's models. This was followed by another whole class discussion. While the experiment and the modeling activity allowed them to "dive-in", these two activities allowed them to "step-out" and look at the collective experience of the class and the tangible outcomes, from a third-person perspective.

One point to take note of here is that acting as a sensor can yield to emergence of a human-like notion of how a sensor works. As we discussed previously, this resonates with anthropomorphic ways with which children interpret behaviors of agents and artifacts (both physical and computational) in science domains (Ackermann, 1999; Dickes & Sengupta, 2012; Kapon & DiSessa, 2012; Nemirovsky et al., 1998). However, obviously, the actual functioning of such a sensor (how the electronic circuitry would interact with molecules and provide an aggregate measure of the detected substance), is markedly different from the functioning of a "human sensor." A description of a sensor requires taking a mixture of what Dennett (1987) calls a *physical* stance and a *design* stance. The physical stance appears when the behaviors of an entity are explained based on its physical constitution and laws of physics that govern it. In the design stance, the behaviors of the entity, which is a designed artifact (e.g., robot, computational agent), are explained based on the pre-programmed rules and heuristics that the entity is constructed to follow. As sensors are designed computational artifacts, and as interactions between sensors and particles can be modeled by the laws of physics and chemistry (in particular, the KMT), students would be expected to transition from an intentional stance (the anthropomorphic approach) to a mixture of physical and design stances in their explanations. In this study we did not focus on how this transition takes place in the long term. However, how this transition happens in students as they learn about and interpret complex systems should be the subject of future studies.

## CONCLUSION

Our goal in this paper was to contribute to previous efforts to leverage perspective taking to facilitate learning about complex systems. To answer

the question, “Why is perspective taking important for learning?” we delved into the evolutionary origins of three foundational human abilities—verbal language, social cognition, and tool use—and we argued that perspective taking permeates these three domains and is essential to each of them. Then, we reviewed the embodied simulation theories of cognition to provide an account for how perspective taking makes use of sensorimotor and affective systems and is inherently related to situated action.

Next, we discussed the implications of the presented embodied approach to perspective taking for learning about complex systems. Previous studies on learning about complex systems (e.g., Ackermann, 1996; Wilensky & Reisman, 2006) emphasized the importance of experiences where the learner switches between micro and macro levels of a system to make sense of how the simple behaviors of a multitude of agents lead to emergent outcomes at the aggregate level. We argued that perspective taking in agent-based modeling activities can be enriched by allowing the learners to take the role of elements of the system studied, where students act as components of the computational model and provide data input to the model based on their bodily experiences in real-life experimental contexts. In such designs, students function as components embedded within the system, instead of interacting with it from a third-person, experimenter’s perspective. This allows learners to acquire first-person bodily experiences and develop intuitions about agent-level interactions that otherwise are not within the realm of first-person experience. We argue that activities that provide situated, bodily experiences both at the agent- and aggregate-levels provide students with intuitions and personally relevant experiences to the system they study, and facilitate associating the events and interactions at the agent-level with emergent outcomes at the aggregate level.

We called such activities that link agent- and aggregate-levels of a system through immersed, bodily activities *phenomenological connectors*. The feature that distinguishes these activities from previous efforts that leverage perspective taking (Wilensky & Reisman, 2006) and use real-life data (Blikstein, 2014) in ABM is providing opportunities for the students to use their bodies as elements of the system they are studying and to use their perceptuomotor experiences as input data for the ABM.

We presented an example activity, in which students act as sensors in a diffusion of odor experiment. The smell intensity indicated by the students is fed into the model to aggregate and visualize the data and to characterize how odor diffuses, provoking discussions about how the initial temperatures of the odor containers affect diffusion patterns. Particle-level phenomena are often perceived as abstract and hard to understand for students. The

experience of acting as a sensor pushes students to think about how particle-level interactions might have affected their first-person experiences of smelling odor, linking imagined particle-level interactions with observed aggregate-level phenomenon. The data collected from the implementation of the diffusion of odor activity across two 10<sup>th</sup> grade science classes demonstrate how students draw on their experiences as sensors to first explain patterns of diffusion in the aggregate data and then to construct agent-based models of the diffusion phenomenon.

## References

- Abelson, H., & diSessa, A. (1986). *Turtle geometry: The computer as a medium for exploring mathematics*. MIT press.
- Abrahamson, D. (2009). Embodied design: constructing means for constructing meaning. *Educational Studies in Mathematics*, 70(1), 27–47. <http://doi.org/10.1007/s10649-008-9137-1>
- Abrahamson, D. (2013). Toward a taxonomy of design genres : Fostering mathematical insight via perception-based and action-based experiences. In *Proceedings of the 12th International Conference on Interaction Design and Children* (pp. 218–227). <http://doi.org/10.1145/2485760.2485761>
- Ackermann, E. K. (1996). Perspective-taking and object construction: Two keys to learning. In Y. Kafai & M. Resnick (Eds.), *Constructionism in Practice: Designing, Thinking, and Learning in a Digital World* (pp. 25–37). Lawrence Erlbaum, Mahwah, NJ.
- Ackermann, E. K. (1999). Enactive representations in learning: pretense, models, and machines. *Learning Sites: Social and Technological Contexts for Learning*, (October), 144–154.
- Ahn, A. C., Tewari, M., Poon, C. S., & Phillips, R. S. (2006). The limits of reductionism in medicine: Could systems biology offer an alternative? *PLoS Medicine*. <http://doi.org/10.1371/journal.pmed.0030208>
- Antle, A., Droumeva, M., & Corness, G. (2008). Playing with the sound maker: do embodied metaphors help children learn? In *Proceedings of the 7th international conference on Interaction design and children* (pp. 178–185). <http://doi.org/10.1145/1463689.1463754>
- Arbib, M. (2002). The mirror system, imitation, and the evolution of language. In K. Dautenhahn (Ed.), *Imitation in Animals and Artifacts* (pp. 229–280). MIT Press.
- Arbib, M. (2011). From Mirror Neurons to Complex Imitation in the Evolution of Language and Tool Use. *Annual Review of Anthropology*, 40(1), 257–273. <http://doi.org/10.1146/annurev-anthro-081309-145722>
- Barabási, A.-L., Gulbahce, N., & Loscalzo, J. (2011). Network medicine: a network-based approach to human disease. *Nature Reviews. Genetics*, 12(1), 56–68. <http://doi.org/10.1038/nrg2918>

- Blikstein, P. (2014). Bifocal modeling: Promoting authentic scientific inquiry through exploring and comparing real and ideal systems linked in real-time. In A. Nijholt (Ed.), *Playful User Interfaces* (pp. 317–352). Springer. [http://doi.org/10.1007/978-981-4560-96-2\\_15](http://doi.org/10.1007/978-981-4560-96-2_15)
- Blikstein, P., & Wilensky, U. (2009). An atom is known by the company it keeps: A constructionist learning environment for materials science using agent-based modeling. *International Journal of Computers for Mathematical Learning*, *14*(2), 81–119. <http://doi.org/10.1007/s10758-009-9148-8>
- Brady, C., Holbert, N., Soylu, F., Novak, M., & Wilensky, U. (2015). Sandboxes for Model-Based Inquiry. *Journal of Science Education and Technology*, *24*(2–3), 265–286. <http://doi.org/10.1007/s10956-014-9506-8>
- Bullmore, E., & Sporns, O. (2009). Complex brain networks: graph theoretical analysis of structural and functional systems. *Nature Reviews. Neuroscience*, *10*(3), 186–98. <http://doi.org/10.1038/nrn2575>
- Carbonneau, K. J., Marley, S. C., & Selig, J. P. (2013). A meta-analysis of the efficacy of teaching mathematics with concrete manipulatives. *Journal of Educational Psychology*, *105*, 380–400. <http://doi.org/10.1037/a0031084>
- Chialvo, D. R. (2010). Emergent complex neural dynamics. *Nature Physics*, *6*(10), 744–750. <http://doi.org/10.1038/nphys1803>
- Cook, S. W., Mitchell, Z., & Goldin-Meadow, S. (2008). Gesturing makes learning last. *Cognition*, *106*(2), 1047–1058.
- Corballis, M. C. (2010). Mirror neurons and the evolution of language. *Brain and Language*, *112*(1), 25–35. <http://doi.org/10.1016/j.bandl.2009.02.002>
- Decety, J., & Grèzes, J. (2006). The power of simulation: Imagining one's own and other's behavior. *Brain Research*, *1079*(1), 4–14. <http://doi.org/10.1016/j.brainres.2005.12.115>
- Dennett, D. (1987). *Then intentional stance*. The MIT Press.
- Dickes, A. C., & Sengupta, P. (2012). *Learning Natural Selection in 4th Grade with Multi-Agent-Based Computational Models. Research in Science Education* (Vol. 43). <http://doi.org/10.1007/s11165-012-9293-2>
- Duatepe-Paksu, A., & Ubuz, B. (2009). Effects of drama-based geometry instruction on student achievement, attitudes, and thinking levels. *The Journal of Educational Research*, *102*(4), 272–286. <http://doi.org/10.3200/JOER.102.4.272-286>
- Fogassi, L., & Ferrari, P. F. (2007). Mirror neurons and the evolution of embodied language. *Current Directions in Psychological Science*, *16*(3), 136–141.
- Foster, J. (2005). From simplistic to complex systems in economics. *Cambridge Journal of Economics*, *29*(6), 873–892. <http://doi.org/10.1093/cje/bei083>
- Gallese, V., & Goldman, A. (1998). Mirror neurons and the simulation theory of mind-reading. *Trends In Cognitive Sciences*, *2*(12), 493.
- Gallese, V., & Lakoff, G. (2005). The brain's concepts: the role of the sensory-motor system in conceptual knowledge. *Cognitive Neuropsychology*, *22*, 455–79. <http://doi.org/10.1080/02643290442000310>
- Gallese, V., & Sinigaglia, C. (2011). What is so special about embodied simulation? *Trends in Cognitive Sciences*, *15*(11), 512–519. <http://doi.org/10.1016/j.tics.2011.09.003>



- Gentilucci, M., & Corballis, M. C. (2006). From manual gesture to speech: A gradual transition. *Neuroscience & Biobehavioral Reviews*, *30*(7), 949–960.
- Gibson, J. J. (1986). The theory of affordances. In *The Ecological Approach to Visual Perception* (pp. 127–136). Lawrence Erlbaum Associates.
- Goldstone, R., & Wilensky, U. (2008). Promoting Transfer by Grounding Complex Systems Principles. *Journal of the Learning Sciences*, *17*, 465–516. <http://doi.org/10.1080/10508400802394898>
- Grezes, J., Armony, J. L., Rowe, J., & Passingham, R. E. (2003). Activations related to “mirror” and “canonical” neurones in the human brain: an fMRI study. *Neuroimage*, *18*, 928–937.
- Hmelo-Silver, C. E., & Pfeffer, M. G. (2004). Comparing expert and novice understanding of a complex system from the perspective of structures, behaviors, and functions. *Cognitive Science*, *28*(1), 127–138. [http://doi.org/10.1016/S0364-0213\(03\)00065-X](http://doi.org/10.1016/S0364-0213(03)00065-X)
- Howison, M., Trninic, D., Reinholz, D., & Abrahamson, D. (2011). The Mathematical Imagery Trainer: From Embodied Interaction to Conceptual Learning. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1989–1998). ACM. <http://doi.org/10.1145/1978942.1979230>
- Jacobson, M. (2001). Problem Solving, Cognition, and Complex Systems: Differences between Experts and Novices. *Complexity*, *6*(3), 41–49. <http://doi.org/10.1002/cplx.1027>
- Jacobson, M., Kapur, M., & Reimann, P. (2016). Conceptualizing debates in learning and educational research: Toward a complex systems conceptual framework of learning. *Educational Psychologist*, *1520*(September), 1–9. <http://doi.org/10.1080/00461520.2016.1166963>
- Jacobson, M., & Wilensky, U. (2006). Complex systems in education: scientific and educational importance and implications for the learning sciences. *Journal of the Learning Sciences*, *15*, 11–34. [http://doi.org/10.1207/s15327809jls1501\\_4](http://doi.org/10.1207/s15327809jls1501_4)
- Johnson-Glenberg, M., Birchfield, D., & Megowan-Romanowicz, C. (2010). Semi-virtual embodied learning-real world stem assessment. In L. Annetta & S. Bronack (Eds.), *Serious Educational Game Assessment: Practical Methods and Models for Educational Games, Simulations and Virtual Worlds* (pp. 225–241). Rotterdam.
- Kapon, S., & DiSessa, A. (2012). Reasoning through instructional analogies. *Cognition and Instruction*, *30*(3), 261–310. <http://doi.org/10.1080/07370008.2012.689385>
- Klopfer, E., Scheintaub, H., Huang, W., Wendel, D., & Roque, R. (2009). The simulation cycle: Combining games, simulations, engineering and science using StarLogo TNG. *E-Learning*, *6*(1), 71–96. <http://doi.org/10.2304/elea.2009.6.1.71>
- Levy, S. T., & Wilensky, U. (2008). Inventing a “mid level” to make ends meet: Reasoning between the levels of complexity. *Cognition and Instruction*, *26*(c), 1–47. <http://doi.org/10.1080/07370000701798479>



- Levy, S. T., & Wilensky, U. (2009). Crossing levels and representations: The connected chemistry (CC1) curriculum. *Journal of Science Education and Technology, 18*(3), 224–242. <http://doi.org/10.1007/s10956-009-9152-8>
- Lindgren, R. (2012). Generating a learning stance through perspective-taking in a virtual environment. *Computers in Human Behavior, 28*(4), 1130–1139. <http://doi.org/10.1016/j.chb.2012.01.021>
- Lindgren, R., & Johnson-Glenberg, M. (2013). Emboldened by embodiment: Six precepts for research on embodied learning and mixed reality. *Educational Researcher, 42*(8), 445–452. <http://doi.org/10.3102/0013189X13511661>
- Maroulis, S., Petry, H., Stringer, M. J., Gomez, L. M., Amaral, L. A. N., Wilensky, U., ... Works, H. I. (2010). Complex Systems View of Educational Policy Research. *Science, 330*(32), 38–39. <http://doi.org/10.1126/science.1195153>
- Modell, H. I. (2007). Helping students make sense of physiological mechanisms: the “view from the inside”. *Advances in Physiology Education, 31*(2), 186–92. <http://doi.org/10.1152/advan.00079.2006>
- Moher, T. (2006). Embedded phenomena: supporting science learning with classroom-sized distributed simulations. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 691–700*. <http://doi.org/10.1145/1124772.1124875>
- Mukamel, R., Ekstrom, A. D., Kaplan, J., Iacoboni, M., & Fried, I. (2010). Single-neuron responses in humans during execution and observation of actions. *Current Biology, 20*(8), 750–756. <http://doi.org/10.1016/j.cub.2010.02.045>
- Nemirovsky, R., Tierney, C., & Wright, T. (1998). Body motion and graphing. *Cognition and Instruction, 16*(2), 119–172.
- Papert, S. (1980). *Mindstorms: Children, computers, and powerful ideas*. Basic Books, Inc.
- Papert, S., & Harel, I. (1991). Situating constructionism. *Constructionism, 36*(2), 1–11.
- Piaget, J., & Inhelder, B. (1969). *The psychology of the child*. New York: Basic Books.
- Resnick, M. (1996). Beyond the Centralized Mindset. *Journal of the Learning Sciences, 5*(1), 1–22. [http://doi.org/10.1207/s15327809jls0501\\_1](http://doi.org/10.1207/s15327809jls0501_1)
- Resnick, M. (1997). *Turtles, termites, and traffic jams: Explorations in massively parallel microworlds*. Cambridge: MIT Press.
- Resnick, M., & Wilensky, U. (1998). Diving into complexity: Developing probabilistic decentralized thinking through role-playing activities. *The Journal of the Learning Sciences, 7*, 153–172.
- Rizzolatti, G., & Arbib, M. (1998). Language within our grasp. *Trends in Neurosciences, 21*(5), 188–194.
- Rizzolatti, G., Fadiga, L., Gallese, V., & Fogassi, L. (1996). Premotor cortex and the recognition of motor actions. *Cognitive Brain Research, 3*(2), 131–141.
- Salk, J. (1983). *Anatomy of reality*. New York: Columbia University Press.

- Sengupta, P., Kinnebrew, J. S., Basu, S., Biswas, G., & Clark, D. (2013). Integrating computational thinking with K-12 science education using agent-based computation: A theoretical framework. *Education and Information Technologies, 18*(2), 351–380. <http://doi.org/10.1007/s10639-012-9240-x>
- Soylu, F. (2016). An embodied approach to understanding: Making sense of the world through simulated bodily activity. *Frontiers in Psychology, 7*(December), 1–10. <http://doi.org/10.3389/fpsyg.2016.01914>
- Stroup, W. M., & Wilensky, U. (2014). On the embedded complementarity of agent-based and aggregate reasoning in students' developing understanding of dynamic systems. *Technology, Knowledge and Learning, 19*(1–2), 19–52. <http://doi.org/10.1007/s10758-014-9218-4>
- Studdert-Kennedy, M. (2002). Mirror neurons, vocal imitation, and the evolution of particulate speech. *Mirror Neurons and the Evolution of Brain and Language*.
- Tomasello, M., Kruger, A. C., & Ratner, H. H. (1993). Cultural learning. *Behavioral and Brain Sciences, 16*, (April), 495–552. <http://doi.org/10.1017/S0140525X0003123X>
- van Schaik, C. P., Deaner, R. O., & Merrill, M. Y. (1999). The conditions for tool use in primates: implications for the evolution of material culture. *Journal of Human Evolution, 36*(6), 719–741.
- Wilensky, U. (1999). NetLogo. <http://ccl.northwestern.edu/netlogo/>. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
- Wilensky, U. (2003). Statistical mechanics for secondary school: The gaslab multi-agent modeling toolkit. *International Journal of Computers for Mathematical Learning, 8*(1), 1–41. <http://doi.org/10.1023/A:1025651502936>
- Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a fire-fly: Learning biology through constructing and testing computational theories—an embodied modeling approach. *Cognition and Instruction, 24*(2), 171–209.
- Wilensky, U., & Resnick, M. (1999). Thinking in levels: A dynamic systems approach to making sense of the world. *Journal of Science Education and Technology, 8*(1), 3–19.
- Wilensky, U., & Stroup, W. (1999a). HubNet. Evanston, IL: Center for connected learning and computer-based modeling, Northwestern University.
- Wilensky, U., & Stroup, W. (1999b). Learning through participatory simulations: network-based design for systems learning in classrooms. In *Proceedings of the 1999 Conference on Computer Support for Collaborative Learning* (p. 80).
- Wilkerson-Jerde, M., Wagh, A., & Wilensky, U. (2015). Balancing Curricular and Pedagogical Needs in Computational Construction Kits: Lessons From the DeltaTick Project. *Science Education, 99*(3), 465–499. <http://doi.org/10.1002/sce.21157>
- Yoon, S. a. (2008). An evolutionary approach to harnessing Complex Systems Thinking in the Science and Technology Classroom. *International Journal of Science Education, 30*(1), 1–32. <http://doi.org/10.1080/09500690601101672>

**Acknowledgements**

This material is based upon work supported by the National Science Foundation award, DRL-102010, “Enabling Modeling and Simulation-Based Science in the Classroom,” Northwestern University. The authors thank Michael Novak for contributing to the design of the instructional materials, Arthur Hjorth and Bryan Yu Guo for assisting with data collection, and Sharona Levy for providing feedback on a draft of the manuscript.