Spinners, Dice, and Pawns: Using Board Games to Prepare for Agent-Based Modeling Activities

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INTRODUCTION

Computational models and simulations can be powerful tools to help learners understand a wide variety of natural phenomena (National Research Council, 2011). However, in order to construct understandings of target phenomena—especially those that emerge from the complex interactions of a large number of entities—it is important for learners to also understand a model's simplifying assumptions, including the rules that govern the behavior of individual computational agents (Jacobson & Wilensky, 2006; Son & Goldstone, 2009; Wilensky & Reisman, 2006; Wilensky & Resnick, 1999). For example, in a model of a predator-prey ecosystem (e.g. Wilenksy & Reisman, 2006; Wilensky & Resnick, 1999) learners ideally understand that the model represent simplified ecosystems with two or three types of organisms; that these organisms reproduce asexually based on some fixed probability; that encounters between predators and prey are determined by chance discrete movements on a two-dimensional plane; and that simulations advance in fixed step-by-step time intervals (ticks).

In this paper we consider the use of specially designed board games as a way to prepare elementary school students to explore computational agent-based models. We have designed these games to closely resemble their computational counterparts in certain key respects. For example, for a wolf-sheep predation model, we designed an activity in which game pieces represent wolves and sheep that move on a board based on the flick of a spinner (rather than a pseudo-random number generator). These games aren't necessarily intended for playing more than a few times—their fun is quickly replaced by the tedium of moving many pieces and keeping track of things like energy levels on a score sheet. But then one of our learning objectives is to help children appreciate why computers are useful tools for scientific modeling—they can make thousands upon thousands of precise computations in the blink of an eye and keep track of vast arrays of data. Other goals include introducing learners to the world of complex systems and the rules that govern their behavior, foregrounding the role of randomness, and promoting productive collaboration in investigations of scientific phenomena through computational modeling.

Our hope is to build on both conceptual and social resources of game play to scaffold learners' understanding of agent-based computational models. In this paper we discuss both our learning objectives and game designs in more detail. We also elaborate on a theoretical framework based on the use of *transitional forms* (e.g. specially designed board games) to help learners make use of conceptual and social resources of board game play in the context of agent-based modeling. This research is preliminary. We present observations from a pilot test of our board games and computational modeling environment with eleven elementary school children in a summer workshop in a research laboratory.

BACKGROUND

Board games and the study of complex systems have a rich history dating back to Thomas Schelling's pioneering work on dynamic models of segregation (Schelling, 1971). To explore the relationship between individual preferences for neighbors and the resulting size and scale of segregation that can result from those preferences, Schelling created models to simulate effects at population levels. These models consisted of simple rules that would govern the movement patterns of individuals in a community. At the outset of this work, Schelling used a pencil and paper to 'run' his models, drawing X's and O's to denote different types of individuals and then erased and redrew the individual based on the rules of the model, tracking how the distribution of X's and O's changed at each step. Schelling quickly realized the haphazard nature of this approach and moved to placing coins on a checkerboard to more easily explore the space (Aydinonat, 2006). Schelling's "checkerboard" model has been credited as one of the first uses of the agent-based modeling methodology being applied to social sciences (Epstein & Axtell, 1996). Although perhaps not a board game in the strict sense, Schelling's work highlights the idea of board games as complex systems in which simple but formal rules result in game trees of staggering complexity (Gobet, de Voogt, & Retschitzki, 2004; Salen & Zimmerman, 2004).

Board Games as Vehicles for Learning

Research on learning through game play is not new. For example, Fine (1983) studied players of pen-and-paper role-playing games and observed many instances of players learning through their interaction with and advancement in the role-playing game subculture. Additionally, traditional board games such as chess have long been used as a context for studying cognition (Chase & Simon, 1973; Gobet et al., 2004). However, the recent rise in the size of mainstream gaming culture has resulted in a renewed interest in the study of games as a medium for teaching and learning (e.g. Gee, 2003). One feature of board games that make them especially compelling environments for learning is the transparency of the core mechanisms and rules that underlie the game (Zagal, 2006). Because the game is physically enacted and officiated directly by its participants, there is no opportunity for game mechanics or rules to be hidden from the players. This is in direct contrast to video games where underlying mechanisms are often unknown. This aspect of board games has also made them constructive environments for studying computational thinking in non-computer-based contexts. Berland and Lee (2011) observed and analyzed students as they played a collaborative board game to develop and identify computational thinking practices learned and deployed in situ. They found that the board game served as a medium that supported the players learning and internalizing the rules of the game as well as creating new rules and shared understanding of the game in a socially distributed way.

Games have also proven to be a productive backdrop for the study of both cultural and cognitive processes. Adopting a situative perspective of cognition (Greeno, 1998; Hutchins, 1995; Lave & Wenger, 1991), knowledge is viewed as "distributed among people and their environments, including the objects, artifacts, tools, books, and the communities of which they are a part" (Greeno, Collins, & Resnick, 1996, p. 17). Games can provide "a representational trace of both individual and collective activity and how it changes over time, enabling the researcher to unpack the bidirectional influence of self and society" (Steinkuehler, 2006, p. 97). In her study investigating the relation between sociocultural and individual cognitive structuring, Nasir (2005) used dominoes as a context to study the development of strategic and mathematical skills in players of different levels of expertise.

Making Sense of Complex Systems

Despite the ubiquity of complex systems in our world, research has found that complex systems are generally difficult for people to learn (Hmelo-Silver & Pfeffer, 2004; Jacobson & Wilensky, 2006; Penner, 2000; Resnick, 1996; Wilensky & Resnick, 1999). In their work on student understanding of complex systems, Wilensky and Resnick found that young learners are often predisposed to attribute emergent phenomena to what they call a "deterministic-centralized mindset" (Resnick, 1996; Resnick & Wilensky, 1998; Wilensky & Resnick, 1999). In this mindset, individuals who witnesses a pattern emerge from the interaction of individuals will credit a non-existent leader or centralized conductor for observed behavior. Another source of confusion stems from slippage between individual and aggregate levels of a system, which results in individuals attributing characteristics of an aggregate population to an individual or vice-versa (Wilensky & Resnick, 1999).

In a study of younger learners' understanding of complex systems, Levy and Wilensky (2008) asked sixth-grade students to explain what happens when students in a gym class are asked to spread-out for calisthenics. The purpose of this line of inquiry was to gain insight into how young learners make sense of emergent phenomena they have experienced that can be explained at the individual level as well as the aggregate level. In analyzing the responses, the researchers noted that students regularly created a "mid-level" view of the system consisting of pairs or small groups of students that they used to make sense of both the larger phenomena and individuals' roles in bringing about the aggregate pattern. The researchers also found that students whose explanations began with attention to individual agents and worked their way up to aggregate level features via a constructed mid-level showed evidence of more sophisticated reasoning about complex system. Based on this work and other work with computational agent-based modeling environments, Wilensky has proposed a learning trajectory that begins with a focus on individual agents and progresses to aggregate level characteristics of a complex system (Levy & Wilensky, 2008; Wilensky, 2003; Wilensky & Papert, 2010).

Agent-based Modeling for Teaching Complex Systems

To introduce concepts of complex systems to younger learners, agent-based modeling has proven to be an effective approach (Centola, Wilensky, & McKenzie, 2000; Wilensky, 1997, 1999a; Wilensky & Reisman, 2006). Agent-based modeling is a paradigm in which large numbers of agents are encoded with specific rules and operate in parallel, allowing for both individual and population behaviors to be observed and measured. NetLogo (Wilensky, 1999b) is a constructionist agent-based modeling environment that makes it easy to construct, run and explore the rules that govern complex phenomena. NetLogo has successfully been used to introduce students to emergent complex systems phenomena including predator-prey interactions (Wilensky & Reisman, 2006), chemical reactions at the molecular level (Stieff & Wilensky, 2003), and the emergence of probability distributions from agent-level stochastic events (Abrahamson & Wilensky, 2005).

STUDY OVERVIEW

We pilot tested the use of board game play as preparation for computational agent-based modeling as part of a study with eleven elementary school children (ages 8-11) recruited from suburban schools in the United States Midwest. As compensation for participating in the study, children received a \$5 gift card to an ice cream shop. For this study we analyzed four hours of video data taken from the first group of children consisting of three girls (2 sisters) and one boy. The children participated in a series of workshops held in a research laboratory over a period of consecutive weeks. For each workshop the children began by playing a board game designed to mirror the mechanisms of a corresponding agentbased model. After one or two complete rounds of game play, children moved on to the computational modeling environment. After each task, we conducted a group interview in which we asked the children to compare the two activities and to explain which version they preferred and why.

The Agent-Based Board Game

The focus of the first workshop was a wolf-sheep predation model (Figure 1). The board game version of this model consists of a board, pieces representing wolves and sheep, and a spinner. Players either take on the role of sheep or wolves. The objective of the sheep is to survive and not be eaten by wolves, while the objective of wolves is to eat all of the sheep. During game play, the wolf team keeps track of the current energy levels for each of the wolves (at each wolf turn, the wolves lose one energy point). If a wolf and sheep happen to occupy the same square, the sheep token is removed from the board and the wolf's energy is restored. For each move, the players spin the spinner to determine the direction of movement for their pieces. In a given turn, all of the pieces move in the same direction, requiring a player to use the spinner only one time. This rule is a substantial departure from the computational model in which each agent moves independently. A second change we made to the board game was to add a "?" wedge to the spinner. This outcome allows players to choose a direction of movement for their population. While this rule is not present in the agent-based model, we added it to create a more enjoyable board game experience. As we discuss below, these differences provided an interesting opportunity for reflection.

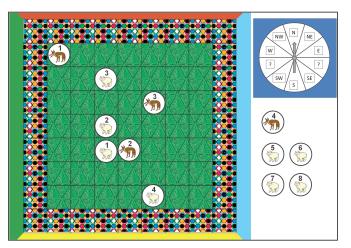


Figure 1. The wolf-sheep predation board game.

NetTango Modeling Environment

In the second phase of the workshop, children used a computational modeling environment called NetTango (Horn & Wilensky, 2012) that we designed to run on an interactive tabletop surface (Figure 2). The tabletop allows multiple users to simultaneously manipulate digital content using direct touch input. NetTango uses the NetLogo Java API as a modeling engine, allowing it to run existing NetLogo models with minimal modification.



Figure 2. NetTango running its version of the wolf-sheep predation model.

NetTango presents users with a world window that provides an animated visual depiction of the model being simulated. Children can move and resize this window using standard multi-touch pinch and drag gestures. A control toolbar enables users to play, pause, rewind, and fast-forward simulations. Finally, similar to NetLogo, the environment provides a set of control widgets to adjust model parameters (e.g. sheep reproduction rate).

CONCEPTUAL RESOURCES OF BOARD GAME PLAY

A central premise of this work is that conceptual resources of board game play can serve as useful building blocks for agent-based modeling activities. By conceptual resources we refer to knowledge schemes situated in the sociocultural context of board game play. Our approach is informed by Saxe's notion of form-function shifts (Saxe, 1994; Saxe, 1999) in which cultural forms such as those found in board game play can be appropriated and repurposed by individuals to serve new cognitive functions. These functions can, in turn, propagate through social groups through a process of sociogenesis. Building on this framework, our goal is to help learners to draw meaningful parallels between game play and agent-based modeling in order to map conceptual resources from one domain to the other. Here we use games that are specifically designed to facilitate a shift of resources for a particular agent-based model in general, although there are more general-level concepts that apply to a broad selection of agent-based models. In our workshops we combined these *transitional games* along with guided reflection to make the connection between the two activities more explicit.

The value of such an approach is suggested by the parallel representational structures of board games and computational models. For example, many board games make use of a grid of squares that directly corresponds to the two-dimensional array of patches underlying many agent-based models. The semantics of game pieces and their interactions on the board also parallel computational agents acting out rules in a simulation. For example, game pieces that are "captured" are removed from the board while agents that have "died" no longer appear in the visual representation of the world. These semantics provide a ready vocabulary for making sense of modeling activities, provided that they can be applied in the new situation.

Another familiar concept of board game play is the notion of formal systems of rules that govern the interactions between pieces and their movement on the board. The behaviors of agents in a computational model are, of course, also determined by formal systems of rules—in this case the rules are specified in computer code such as NetLogo. The major difference between the two activities is that in the case of board games, the players themselves are responsible for enacting the rules (and often times negotiating and arguing over the meaning of rules with other players in the game). Our goal in the use of transitional board games is not only to emphasize the existence of formal rules governing agent-based models in general, but also to make the board game rules as similar as possible to the specific computational model being introduced. Just as rules give each board game its own particular flavor and personality, so too do the rules define the essence of an agent-based models. Ideally, board game play provides a fun and familiar context in which learners, through the enactment of rules, can develop a more thorough understanding of particular models.

Related to rules, board games also provide an opportunity to introduce new or potentially unintuitive aspects of agent-based models. For example, many computational models make use of an implied torus topology in which agents *wrap* from one side of the screen to the opposite side. This behavior is not obvious when the model runs and may be an entirely new behavior to the players. To introduce this aspect of the world, we imposed this same rule on our board game, thus forcing players to confront this wrapping movement as they played the game. Players initially had difficulty with this concept especially in the case of a game piece being in the corner and having to wrap both horizontally and vertically in the same move. As game play progressed, players became more comfortable and fluent with this aspect of the game, as they required less assistance to correctly "wrap" a game piece when it crossed over the edge of the board. By having players enact this rule in the shared space of the board game, the correct behavior and logic is negotiated and reinforced by the group.

Randomness as a Driving Force

Another central feature of both agent-based models and board games is the role of randomization to simulate stochastic processes and avoid predictability outcomes. In board game play, the randomizers are physical (spinners, dice, shuffled cards, etc.) and their role in the game is both explicit and accessible to the players. In computational agent-based models randomization may be less obvious than in board game play, but no less important for the functioning of the system. In having players use the spinner to determine the movement of the game pieces, we hoped to make clear to the participants the central role that randomness plays in these models of complex systems. In our post-tabletop interview, we asked the children to compare the board game to the tabletop model:

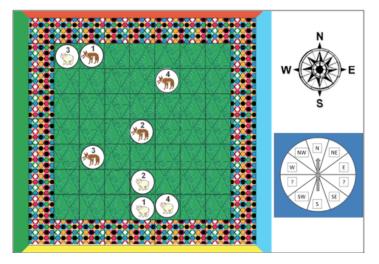
Interviewer: So do you think the model is more interesting than the board game? Which one do you think is more interesting? Laura and Dennis: The model Diana: The model Laura: The model, because it moves. Interviewer: Because it moves? Well, the board game moves too. Emily: But, you have to spin your move. Dennis: because there is no spinning thing in the model. Interviewer: So why does the spinner make it less interesting? Emily: because you have to go to certain direction, instead of you can go whichever direction you want, because the wolves are kind of like chasing after you [Diana: but Emily...] so you have to go in the direction of the wolves if you get spun in the direction of the wolves.

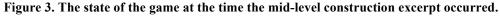
Diana: But Emily though, but Emily! It is the same thing in this game (pointing at the tabletop), I mean you cannot control where your sheep go here either. They go where they want.

In this exchange, we see Diana pointing out that the tabletop model in fact does have a control mechanism that is analogous to the spinner in the board game. Her comment highlights the central role that the randomization mechanism plays in both environments. To do so, they draw on the conceptual resource of the spinner in the board game context and apply it to the new tabletop environment.

Designing for the Developmental Trajectory

The progression from board game to computational model potentially reinforces the developmental trajectory proposed by Levy & Wilensky (2008) in which reasoning about individual agents precedes reasoning about aggregate-level phenomena. By enacting and monitoring population dynamics through game play, learners consider individual agents, sub-groups of agents (mid-level constructions), or the population as a whole. By providing a "?" wedge on the spinner, we gave students an opportunity to make strategic in-game decisions (play is not governed entirely by chance). Often strategic movement decisions are not made by studying the placements of all the pieces in aggregate or by focusing on one piece individually, but instead by focusing on small clusters of agents. The following conversation occurred after the sheep team spun a "?", meaning they could choose what direction to move their flock. The state of the board is displayed in Figure 3.





Diana: (on sheep team): Question mark. We should probably move...

Laura: (on sheep team): this way (pointing to the cluster of sheep and gesturing east), we should move east

Dennis: (on wolf team): uh-uh-uh (disapproving sound - he points to sheep 3 at the top of the board who would be eaten if they choose east) Diana: oh yeah, we should move, ummm Emily: (on wolf team): well, if you move north, you have a better chance of getting eaten, if you move south you have a better chance of getting eaten Laura: well, one of the wolves is going to die anyways Diana: let's move, ummm Laura: which makes it better to sacrifice our piece

The sheep team focus on the cluster of sheep at the bottom of the board and propose a direction that is best for the group at the expense of the individual. This is an example of the sheep team constructing a mid-level group. Here, they treat the three sheep (sheep 1, 2 and 4) as a single entity and propose a direction based on what is best for the unit as a whole. After a member of the wolf team (Dennis) points out how a move to the east will sacrifice sheep 3, the sheep team reconsiders, but still discusses whether or not sacrificing that one sheep will be the best course for the team. This mid-level construction was not just created by the sheep team, but instead shared across the teams. When the player from the wolf team (Emily) makes a comment about north and south being risky choices, the comment is in reference to the sheep team's constructed mid-level cluster as a move north or south does not put the lone sheep (sheep 3) in any greater danger. The small population and slow progression of the board game gives the players opportunities to think about the relationship between the individual, a subset of a breed, and the whole population.

SOCIAL RESOURCES OF BOARD GAME PLAY

Our interest in board games considers more than the physical artifacts of play—spinners, dice, game pieces, and the like. While these objects are important, we are equally interested in the social aspects of game play that surround these artifacts and give them meaning. Interactive tabletops afford social interaction by virtue of both form factor and use within learning settings in which group engagement is valued (e.g. classrooms and museums). Snibbe and Raffle's (2009) principle of social familiarity capture this idea well: "media should augment and reinforce existing collocated social behaviors" (p. 1449). For example, video game play in homes is a socially familiar practice in which kids self-organized into a diverse array of learning arrangements(Stevens, Satwicz, & McCarthy, 2007). By having board games play an introductory role to agent-based modeling and complex systems, we hope to provide leaners with useful social resources to support productive collaboration around the tabletop. Our previous research on family game play around a tabletop surface in a natural history museum suggests that families can adapt social aspects of game play to negotiate goals and to maintain group engagement (Horn et al., 2012). However, in the museum, we presented visitors with a video game—it consisted of multiple levels, correct actions were animated with stars, and so on. It is far from certain that children engaged in modeling activities will similarly adapt social practices of game play to maintain productive collaborative engagement, even when agent based modeling is directly preceded by board game play.

Turn-Taking: Leveraging Board Game Social Resources to Explore Agent-Based Models

In this section, we present a brief analysis of the social practices of board game play as the students in our study moved from game play to computational modeling. We focus on turn taking in particular, an aspect of game play in which children coordinate shared sequential access to an activity. We see turn taking as advantageous because, at its best, children silently and efficiently transfer control of access with little disruption to the activity itself (Cole, 1995; Inkpen et al., 1995; Inkpen et al., 1997). However, as might be expected turn taking was not necessarily an obvious way to engage with the modeling activity. However, through the use of appropriate cues (that we term transitional forms), we argue turn taking practices can be spontaneously evoked on the part of the students.

In the board game, turn taking behavior was evident as players fluidly alternated between the wolf team and the sheep team. What was notable, however, was the role of the spinner as not only a randomizer for the movement of agents on the board, but also as an embodied representation of sequential control (turn taking). On each turn, children would first flick the spinner to determine the direction of movement for their agents. They would then move their tokens and assess outcomes such as "eating" sheep and updating wolf energy levels. Because of its central role in the game play, the spinner was a convenient mechanism for players to indicate the transition from one turn to another (Figure 4)¹.



Figure 4. Players used the physical spinner to both indicate the current team and the transition of turns from one team to the other.

After playing the board game, the children moved on to the tabletop modeling activity. However, in the modeling activity the notion of a "turn" manifested itself at a different level. In the board game, turns correspond to the movement of agents on the board, whereas in on the tabletop, a turn is a single, complete run of a model. On the tabletop, at each turn, the children would adjust environment parameters, reset the model, and then run the simulation. The simulation could be controlled with the on-screen control panel that included play and pause buttons as well as fast forward, rewind, and reset buttons (Figure 5).



Figure 5. The graphical control panel widget

¹ Board game play can be described as a distributed cognitive system (Hutchins, 1995) consisting of various physical artifacts (board, game pieces, spinner), the players themselves, the rules of the game, and the associated social practices of game play.

The social practice of turn-taking was immediately apparent to the players after having played the board game. The following excerpt takes place at the beginning of the tabletop activity, when the interviewer is introducing the task to participants:

Interviewer: basically, we are going to run the model here (pointing at the graphical control panel) and you are going to see what happens and then I want you guys to change it around (pointing at the setting bars) and make predictions about what is going to happen after... Emily: so we should each have a turn, not everybody at once.

While the children identified the turn-taking practice as a way to interact with the model, it was not immediately apparent how turn taking should be coordinated. In the first session the children apparently believed that the graphical toolbar was fixed in place—they never moved it from its default location on one corner of the tabletop. During the session the girl who was the closest to the toolbar dominated its use. The other children would frequently reach across the table to press one of the buttons. However, in the second session, the children realized that the graphical toolbar could be moved around the screen and a conflict ensued over who should "own" the toolbar and where it should be positioned on the table. In this session, the graphical toolbar took on a role similar to that of the spinner, both in the sense of representing participant control (whose "turn" it was) and allowing access to resources of the activity. However, the children seemed to lack consensus on turn taking protocols for sharing resources. This conflict led us to redesign the toolbar for the third session. Here we introduced a physical object (reminiscent of the spinner) that the children had to place on the table to make the graphical toolbar appear (Figure 6).

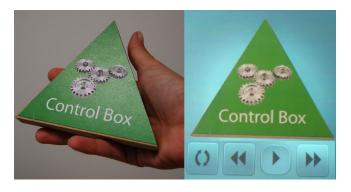


Figure 6. The tangible toolbar token is a triangular wooden block that children must place on the screen to make the toolbar widget appear (right).

The introduction of this new controller resulted in a qualitative shift in the turn taking protocols using during the investigation of the agent-based model, resulting in children spontaneously adopting turn taking protocols that were similar to the board game setting. The physical control box could be passed between players and its position could be used to denote whose turn it currently was in a socially familiar way. This resulting shift in model interaction is more fully explored in (Olson, et al., 2011).

CONCLUSION AND FUTURE WORK

In this paper we have presented a brief argument for the use of designed board games to introduce learners to agent-based modeling activities. We proposed that there are well-established conceptual and

social resources of board game play that can potentially be evoked in modeling activities through the use of transitional forms (specially designed board games and other physical and digital objects that draw parallels between the two activities). This work is still in progress; more research will be necessary to understand the process and pace with which conceptual and social resources of board games can be appropriated for computational modeling.

REFERENCES

- Abrahamson, D., & Wilensky, U. (2005). ProbLab goes to school: Design, teaching, and learning of probability with multi-agent interactive computer models. *Proceedings of the Fourth Conference of the European Society for Research in Mathematics Education. San Feliu de Gixols, Spain.*
- Aydinonat, N. E. (2006). An interview with Thomas C. Schelling: Interpretation of game theory and the checkerboard model. *Economics Bulletin*, 2(2), 1–7.
- Berland, M., & Lee, V. R. (2011). Collaborative Strategic Board Games as a Site for Distributed Computational Thinking. *International Journal of Game-Based Learning*, 1(2), 65–81. doi:10.4018/ijgbl.2011040105
- Centola, D., Wilensky, U., & McKenzie, E. (2000). Survival of the groupiest: Facilitating students' understanding of the multiple levels of fitness through multi-agent modeling-The EACH Project. *International Journal of Complex Systems*.
- Chase, W. G., & Simon, H. A. (1973). Perception in chess. Cognitive psychology, 4(1), 55-81.
- Epstein, J. M., & Axtell, R. L. (1996). *Growing Artificial Societies: Social Science from the Bottom Up* (First ed.). A Bradford Book.
- Fine, G. A. (1983). Shared fantasy: Role-playing games as social worlds. University of Chicago Press.
- Gee, J. P. (2003). What Video Games Have to Teach Us About Learning and Literacy (1st ed.). Palgrave Macmillan.
- Gobet, F., de Voogt, A. J., & Retschitzki, J. (2004). Moves in mind: The psychology of board games. Psychology Pr.
- Greeno, J. G. (1998). The situativity of knowing, learning, and research. American psychologist, 53(1), 5.
- Greeno, J. G., Collins, A. M., & Resnick, L. B. (1996). Cognition and learning. Handbook of educational psychology, 77, 15–46.
- 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.
- Hutchins, E. (1995). How a cockpit remembers its speeds. Cognitive science, 19(3), 265-288.
- Jacobson, M. J., & Wilensky, U. (2006). Complex systems in education: Scientific and educational importance and implications for the learning sciences. *The Journal of the Learning Sciences*, 15(1), 11–34.
- Lave, J., & Wenger, E. (1991). Situated learning: Legitimate peripheral participation. Cambridge Univ Pr.
- Levy, S. T., & Wilensky, U. (2008). Inventing a "Mid Level" to Make Ends Meet: Reasoning between the Levels of Complexity. Cognition and Instruction, 26(1), 1–47. doi:10.1080/07370000701798479
- Lotka, A. J. (1925). Elements of physical biology. Williams & Wilkins company.
- National Research Council. (2011). *Learning Science Through Computer Games and Simulations*. Committee on Science Learning: Computer Games, Simulations, and Education, Division of Behavioral and Social Sciences Education. Washington D.C.: The National Academies Press.
- Olson, I. C., Atrash Leong, Z., Wilensky, U., & Horn, M. S. (2011). It's just a toolbar!: using tangibles to help children manage conflict around a multi-touch tabletop. *Proceedings of the fifth international conference on Tangible, embedded, and embodied interaction* (pp. 29–36).
- Penner, D. E. (2000). Explaining systems: Investigating middle school students' understanding of emergent phenomena. *Journal of Research in Science Teaching*, *37*(8), 784–806.
- Resnick, M. (1996). Beyond the centralized mindset. The Journal of the Learning Sciences, 5(1), 1–22.

- Resnick, M., & Wilensky, U. (1998). Diving Into Complexity: Developing Probabilistic Decentralized Thinking Through Role-Playing Activities. *Journal of the Learning Sciences*, 7(2), 153–172. doi:10.1207/s15327809jls0702_1
- Salen, K., & Zimmerman, E. (2004). Rules of play: Game design fundamentals. The MIT Press.
- Saxe, G. B. (1999). Cognition, development, and cultural practices. In T. E. (Ed.), *Culture and Development. New Directions in Child Psychology*. SF: Jossey-Bass.
- Schelling, T. C. (1971). Dynamic models of segregation. Journal of mathematical sociology, 1(2), 143–186.
- Son, J. Y., & Goldstone, R. L. (2009). Contextualization in Perspective. Cognition and Instruction, 27(1), 51–89. doi:10.1080/07370000802584539
- Steinkuehler, C. A. (2006). Why Game (Culture) Studies Now? *Games and Culture*, 1(1), 97–102. doi:10.1177/1555412005281911
- Stevens, R., Satwicz, T., & McCarthy, L. (2007). In-Game, In-Room, In-World: Reconnecting Video Game Play to the Rest of Kids' Lives. *The John D. and Catherine T. MacArthur Foundation Series on Digital Media and Learning*, -, 41–66. doi:10.1162/dmal.9780262693646.041
- Stieff, M., & Wilensky, U. (2003). Connected chemistry—incorporating interactive simulations into the chemistry classroom. *Journal of Science Education and Technology*, 12(3), 285–302.
- Vygotsky, L. (1978). Mind in society: The development of higher psychological processes. Harvard Univ Press.
- Wilensky, U. (1997). What is normal anyway? Therapy for epistemological anxiety. Educational Studies in Mathematics, 33(2), 171–202.
- Wilensky, U. (1999a). GasLab: An extensible modeling toolkit for connecting micro-and macro-properties of gases. Modeling and simulation in science and mathematics education, 1, 151.
- Wilensky, U. (1999b). *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.
- Wilensky, U., & Papert, S. (2010). Restructurations: Reformulating Knowledge Disciplines through New Representational Forms. In I. Kallas (Ed.), *Proceedings of the constructionism 2010 conference*. Presented at the Constructionism, Paris.
- Wilensky, U., & Reisman, K. (2006). Thinking Like a Wolf, a Sheep, or a Firefly: 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.
- Zagal, J. P. (2006). Collaborative games: Lessons learned from board games. *Simulation & Gaming*, 37(1), 24–40. doi:10.1177/1046878105282279