FEATURE ARTICLES

Education as a Complex System: Conceptual and Methodological Implications

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Education is a complex system, which has conceptual and methodological implications for education research and policy. In this article, an overview is first provided of the Complex Systems Conceptual Framework for Learning (CSCFL), which consists of a set of conceptual perspectives that are generally shared by educational complex systems, organized into two focus areas: collective behaviors of a system, and behaviors of individual agents in a system. Complexity and research methodologies for education are then considered, and it is observed that commonly used quantitative and qualitative techniques are generally appropriate for studying linear dynamics of educational systems. However, it is proposed that computational modeling approaches, being extensively used for studying nonlinear characteristics of complex systems in other fields, can provide a methodological complement to quantitative and qualitative education research approaches. Two research case studies of this approach are discussed. We conclude with a consideration of how viewing education as a complex system using complex systems' conceptual and methodological tools can help advance education research and also inform policy.

Keywords: computer applications; educational policy; experimental research; organization theory/change; policy analysis; qualitative research; research methodology; secondary data analysis

Scientific study of the behavior of complex physical and social systems over the past three decades has led to significant insights about the world that classical approaches tended to oversimplify or to ignore (Bar-Yam, 2003). However, the application of complexity perspectives to education research is at a relatively early stage, although use of conceptual perspectives from complex systems is increasing (e.g., Jacobson & Wilensky, 2006; Wilensky & Jacobson, 2014). For example, Bereiter and Scardamalia (2005) noted this influence in the use of complexity concepts in the education research literature: "*self-organization and emergence* … [in] mainstream educational psychology … [make it] increasingly apparent that there are no simple causal explanations for anything in this field" and "learning itself, at both neural and knowledge *levels*, has *emergent properties*" (p. 707; italics added).

We are also seeing suggestions that complexity perspectives provide important ways to understand more deeply educational change and have the potential to inform educational policy (Mason, 2008). Lemke and Sabelli (2008) have noted that the "education system is one of the most complex and challenging systems for research" (p. 128). They recommend combining conceptual perspectives about complex systems with computer modeling capabilities to inform policymakers about proposed interventions and their potential impact.

The main purpose of this article is to consider education as a complex system and to discuss conceptual and methodological implications. We review two recent studies for which complexity conceptual perspectives and methods allowed insights that may not have been revealed by conventional education research techniques. We conclude with a consideration of how using complex systems' conceptual and methodological tools can help advance education research that also informs policy.

Education as a Complex System

Scientific views of complex systems (sometimes referred to as the field of *complexity*) primarily come from research in the physical sciences, mathematics, and computer science (Gell-Mann, 1994;

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Table 1
Components of the Complex Systems' Conceptual Framework for Learning With Examples

Complex Systems Conceptual Perspectives	Complex Systems Example	Learning or Educational Example
Complex Systems Focus Area: *Collective Behaviors of a System*		
Agents or elements in system	Ants foraging for food	Neurons in the brain Students in a classroom
Self-organization	Birds flocking	P-prims forming coordination classes Children forming groups on playground
System levels	Micro level of chemical interactions, macro level of chemical system equilibrium	Individual student cognition, collaborative learning activities Vygotskian learning from interpersonal interactions that are internalized
Sensitivity to initial conditions and nonlinearity	Butterfly effect	Gap in academic performance of low and high SES children increases from kindergarten to high school Cognitive activation in initial learning influences subsequent learning
Emergence	Classic "V" formation of flocking of individual birds	Collaborative interactions of students leading to convergence in problem solutions Emergence of conceptual understanding in conceptual change: "aha" moments
Complex Systems Focus Area: *Behaviors of Individual Agents in a System*		
Parallelism	Numerous biological cells typically interact via a variety of protean signals	Numerous brain cells activated during problem-solving tasks Collaborative learning activities
Conditional actions	If a wolf is hungry and sees a sheep, then the wolf tried to eat the sheep	If a student is engaged they have greater persistence and greater subsequent learning
Adaptation and evolution	The wing coloration of the peppered moth changed (evolved) from mainly whitish/mottled to mainly darkish brown from pre- to post-industrial age Great Britain	Young children often have "flat earth" mental models, primary school age children often have synthetic "hollow earth" mental models, and older students have "globe earth" mental models

Source. Reproduced from Jacobson, Kapur, and Reimann, 2016.

Holland, 2006; Kauffman, 1993; Wolfram, 2002) and the social sciences (Byrne, 2013; Mason, 2008; Sawyer, 2005).[1] To consider what it means to view education as a complex system, Jacobson, Kapur, and Reimann (2016) have proposed a *Complex Systems Conceptual Framework for Learning* (CSCFL), which consists of a set of conceptual perspectives that are generally shared by complex systems relevant to education (see Table 1).

The CSCFL organizes these conceptual perspectives in two focus areas: *collective behaviors of a system* and *behaviors of individual agents in a system*. Key conceptual perspectives in the first focus area are: (a) interactions of individual agents or components of the system that often may be described in terms of simple rules; (b) feedback interactions between agents that may occur within or across system levels; (c) self-organization of agents in a system that typically result from the two previous conceptual perspectives; (d) sensitivity to initial conditions or chaos, where there is an amplification of initial state differences in a system (often based on positive feedback interactions) that may contribute to major behavioral changes in a system; and (e) emergence, regarded by many scientists as the most important complexity construct (Bar-Yam, 2003; Gell-Mann, 1994; Holland, 2006; Kauffman, 1995; Mitchell, 2009). There is also a somewhat counter-intuitive aspect of emergence, which is described by Jacobson et al. (2016) as the:

> formation of collective properties at a macroscopic level of a system from simple behaviors of the parts, with those properties frequently are not found in the parts. For example, in a traffic system the macro-level formation of a traffic jam propagates *backwards* even though the individual cars at the micro-level general move *forward* as they speed up or slow down, with some lateral lane changes—but rarely do the cars move backwards in traffic. (p. 211)

This example includes conceptual perspectives (a) – (d) of *complex collective behaviors of a system* while also illustrating key features of *emergence*, which are that the whole of a complex system is not merely the sum of parts (i.e., cars move forward), but are also often different than those parts (i.e., the traffic jam goes backwards) in key and perhaps even surprising ways (Casti, 1994).

Our reading of the complex systems and education literature is that, in general, the conceptual perspectives in the CSCFL focus area *complex collective behaviors of a system*, such as nonlinearity and emergence, have been emphasized. However, conceptual perspectives in the focus area *behaviors of individual agents in a system* have received less attention, even though educational systems, in common with complex systems, "involve many components that adapt or learn as they interact" (Holland, 2006, p. 1). Holland proposes several important characteristics of how individual elements or agents behave, of which three are currently included in the CSCFL as being the most relevant for educational systems: (a) parallelism, (b) conditional actions, and (c) adaptation and evolution.

Parallelism is exhibited when agents in a complex system have simultaneous interactions with each other by sending and receiving signals. For example, students on a playground will be doing a variety of things simultaneously while talking and listening to each other (sending and receiving signals), some riding a swing or perhaps pushing a friend, others throwing a ball back and forth, playing hopscotch, and so on.

Conditional actions are how an agent might respond to received signals, often described with rules such as IF a certain signal is received, THEN act in a certain way. For example, if a soccer ball is close to a player (i.e., an agent in the system), then they would try to kick it, unless IF the player is the goal keeper THEN they would try to catch or deflect the ball. An important characteristic of complex systems is that the combination of relatively simple agent rules, and the parallelism of many agents simultaneously acting based on these rules, can result in very complex and dynamically changing behaviors.

Adaptation and evolution is a particularly important conceptual perspective in complex systems, of relevance to educational systems in that the agents themselves change over time; that is, they learn.[2] Gell-Mann (1994) has described learning as changes in an agent's internalization of perceived regularities in their environment which, in turn, increases the agent's potential for adaptive behavior in their environment. For example, students in a classroom may be regarded as agents in an educational complex system who, at a given time, have certain internal cognitive structures and affective knowledge related to a subject, and who, over time at school, will (hopefully) construct (i.e., evolve) new or modified cognitive structures from their learning activities.

In closing this section, we note that Jacobson et al. (2016) do not claim that the CSCFL's currently included complexity conceptual perspectives are exhaustive. There are, of course, many, many more complexity concepts—such as autocatalytic systems (Kauffman, 1995), activation and inhibition (Bar-Yam, 2003), bifurcations (Mitchell, 2009), and so on—that can also have relevance for understanding various aspects of education as a complex system. Still, we believe the CSCFL includes a reasonable core of complexity conceptual perspectives relevant to educational and learning systems, and that these can be useful analytical tools for education researchers. For example, they can provide a principled way to reconcile the long-running debate between cognitive and situative theories of learning (Jacobson et al., 2016). In the next two sections, we consider how the CSCFL also has relevance for research and methodological issues concerning educational complex systems.

Complexity and Research Methodologies for Education

We now shift our focus from the CSCFL to considering implications for methodologies used for education research and to inform policy about educational systems. But first it is important to establish how areas of education research and policy are connected so that complexity perspectives can be valuable analytical tools to each. One key way is that the information flows available to inform policy decisions are constrained by the types of methodologies that have been developed and validated by education and social sciences researchers.

Broadly speaking, existing methodological approaches for education research fall into two main categories: quantitative and qualitative (Firestone, 1987). Quantitative approaches (including experimental and quasi-experimental) are pervasively used in education research (Kapur, Hung, Jacobson, & Voiklis; Suthers & Hundhausen, 2003). Rooted in a positivist philosophical tradition, quantitative methods typically seek to establish causal or quasi-causal explanations of design or intervention effects versus control or comparison conditions. In contrast, qualitative approaches have a phenomenological philosophical basis that seeks to describe and to understand educational contexts and environments. Although there are education researchers who exclusively use one or the other of these methodologies, since the late 1980s it has become increasingly common for education researchers to use the different, but complementary, types of information generated by these two methodological perspectives in order to understand the educational issue being investigated (Firestone, 1987).

However, there is an important question that must be asked. Are the existing quantitative and qualitative methodologies—whether separate or in combination—in fact sufficient for providing appropriate information and understandings of the dynamics of educational systems viewed from the complexity perspectives outlined in the previous section?

Unfortunately, the answer is no. Most mathematical tools commonly used in quantitative research (e.g., differential equations and statistical modeling) are linear tools that work by breaking a system into its components or parts, studying the parts individually, and then adding the parts together to form the whole. However, emergent phenomena in an educational complex system generally have nonlinear properties, which cannot be analyzed by adding up the parts because the patterns at the macro-level of a complex system generally have different properties to the constituent parts at the micro-level of the system. Holland (1995) argues, "Nonlinearities mean that our most useful tools for generalizing observations into theory—trend analysis, determination of equilibria, sample means, and so on—are badly blunted" (p. 5).

There is another important limitation to quantitative and qualitative approaches: they are best suited to explaining and understanding what has already emerged (Epstein & Axtell, 1996). For example, opinions, norms, convergence in group discussions may be viewed as intra- or inter-personal patterns. Once these emerge, then quantitative methods may explain aggregate-level relationships and qualitative methods may provide rich descriptions of these opinions, norms, or group interactions. However, as Kauffman (1995) observes, the same trajectory of interactions may not have occurred, even if there had been similar initial conditions. In order to understand emergent phenomenon in complex systems of education (and other domains) more fully, it is necessary to study and explain the patterns that actually unfolded, as well as the space of possible trajectories that could have unfolded.

For policy purposes, the space of possible trajectories for an educational system is of particular importance, as we discuss further below. However, it is clear that the two predominately used methodological approaches available to education researchers and policy makers have fundamental limitations for understanding two key components of the CSCFL—nonlinearity and emergence—in complex systems of education.

We certainly acknowledge that quantitative and qualitative approaches each have value for the study of linear characteristics of educational systems in education research, as well as approaches that integrate or blend these methods (Firestone, 1987). However, complex systems have regions where system behaviors are both linear and nonlinear. Jacobson and Kapur (2012) have argued that there is a "dialectical co-existence of linearity and non-linearity in terms of feedback interactions within and across levels of the system so that collective properties arise (i.e., emerge) from the behaviors of the parts, often with properties that are not exhibited by those parts" (p. 310). While currently used quantitative and qualitative techniques are generally appropriate for studying the linear dynamics of educational systems, it is important to ask what techniques are appropriate for studying the nonlinear dynamics of educational complex systems.

Jacobson and Kapur (2012) note that scientists conducting research into nonlinear dynamics in other complex systems areas (e.g., physics, biology, economics) have been developing and using a range of computer modeling techniques. They also propose that modeling methods such as agent-based models (ABMs) can function as a methodological complement to quantitative and qualitative approaches.

Briefly, there are two main types of computational modeling: agent-based models (ABMs) and equation-based models (EBMs) (Parunak, Savit, & Riolo, 1998). These two approaches have a similar goal, which is to create a computer model of a system, but they differ in two fundamental ways. First, they use different assumptions to define relationships between entities in the model. EBMs typically use quantitative formalisms such as algebraic or partial differential equations to express how entities in the system are related over time. In contrast, ABMs use algorithmical formalisms to represent the behaviors of the individual entities (i.e., agents) such as wolves eating sheep or teachers interacting with students, and then "turns them loose to interact" (Parunak et al., 1998, p. 10).

Second, ABMs and EBMs differ fundamentally in terms of their respective direction of focus on levels.[3] ABMs are often referred to as being "bottom up" in that they algorithmically model the behaviors of agents or component elements at a particular level of the system and then allow a focus "up" at emergent behaviors at a higher level. In contrast, EBMs are often viewed as being "top-down" in that they start at a higher system level but use equations to model component behaviors at a lower system level.

EBM methods are best suited if the interest of the modeler is at a macro-level of a system where the aggregate properties are reasonably well understood to the degree that they can be captured by equations and then used to explore different "what-if" scenarios, such as a reduction in tax revenue during a recession that leads to a reduction in a school district's budget and options such as increasing class size or reducing extra-curricular activities to balance the budget. In these examples, the macro-level relationships between tax revenue, school budget, class size, and extra-curricular activities might be linear. However, EBMs do not consider micro-level interactions such as specific individuals who are out of work and thus pay few or no taxes, individual school staff having to make decisions about whether to purchase a greater number of chairs and other classroom supplies for larger classes or cut popular extra-curricular classes such as art, music, and sports, and so on. In general, if the behavior of a system is linear, then normalized assumptions about micro-level behaviors that contribute to the macro-level properties (such as we described) may be sufficient to generate a model that can be useful for certain types of education research or policy decisions.

However, what if the micro-level interactions and possible emergent properties at the macro-level are not necessarily well-understood, or cannot be anticipated because of nonlinearity in the educational system of interest? In such circumstances, ABM approaches can be effective because they can focus on micro-level interactions—for which there is often quantitative and/or qualitative data to inform the specification of agent-based rules—and then to allow model runs (i.e., turn them loose to interact) to explore various possible outcomes. This will, in turn, likely generate macro-level system behaviors that may or may not have been anticipated, as well as information about interactions between micro- and macro-levels of the system. It is also possible to explore the model through multiple runs in order to gain insights into possible trajectories of what could have unfolded (Kauffman, 1995), such as by identifying attractors in a high dimensional space that may influence system behaviors (Gleick, 1987).

We also note that ABM methods are increasingly being used not only in the natural sciences (Wilensky & Rand, 2015) but also in economics (Arthur, Durlauf, & Lane, 1997; Testfatsion, 2006), business (Rand & Rust, 2011), sociology (Squazzoni, 2012; Watts & Strogatz, 1998), and socio-cultural psychology (Axelrod, 1997; Epstein, 2006), to name a few areas. Grounded in complexity theory, ABM provides important theoretical and empirical insights into the dynamics of complex systems in the social sciences (Eidelson, 1997) .

We believe that ABMs, when integrated with quantitative and qualitative methods, can potentially reveal insights about the dynamics of complex systems of education across the range of levels and time scales, such as those discussed by Lemke and Sabelli (2008), which may not be possible through the use of any single methodology. We view the integration of complexity modeling with quantitative and qualitative methods as overlapping and complementary (see Figure 1), with each method providing analytical tools for gaining different types of insights into the dynamics of the educational system issue being explored, while also providing analytical focus when used together (as suggested by the Venn diagram overlap in the center of Figure 1). Further, we are beginning to see examples of education and education policy research in which modeling methods such as ABMs are being productively used as an important complement to quantitative and qualitative approaches, which are discussed in the next section.

Studying Education as a Complex System: Two Research Case Studies

In this section we have selected two research case studies to illustrate the use of complexity conceptual perspectives and computer modeling tools. We believe that certain findings may not

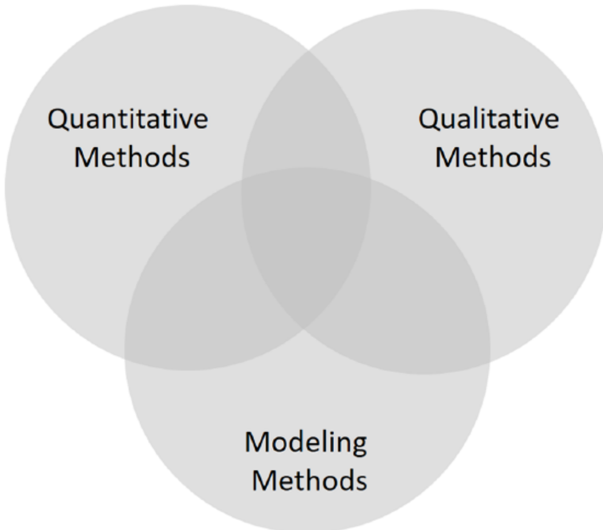

FIGURE 1. *Quantitative, qualitative, and modeling methods areas of overlap and distinctiveness.*

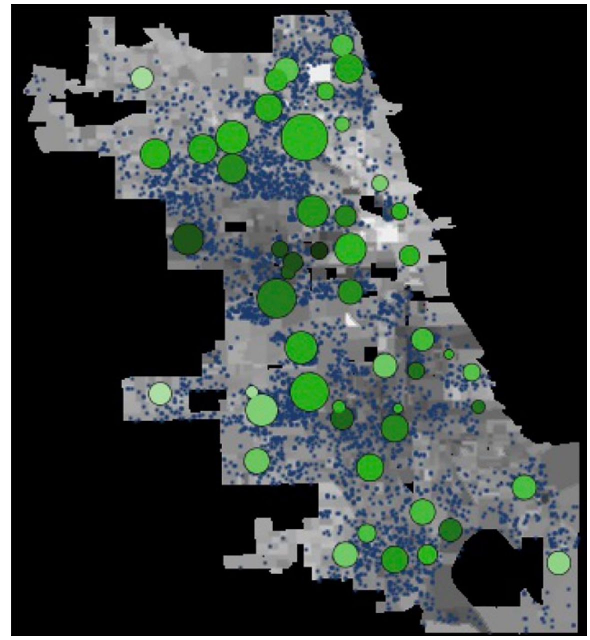

FIGURE 2. *Visualization from an agent-based model of school choice in Chicago, Illinois.*
Note. Small dots represent students, large circles represent schools, circle size represents academic performance, and background shading shows high and low poverty areas respectively (dark gray, high; light gray, low).
Source. Reproduced from Maroulis et al. (2014), licensed under CC BY 4.0.

have been identified with more commonly used quantitative and qualitative education research methods and analytical perspectives. We discuss these two programs of research in turn.

Our first research case study is the work of Maroulis, Bakshy, Gomez, and Wilensky (2014) that involved the use of ABMs to study initiatives to provide parents with school choice in the United States. Briefly, proponents of school choice reform argue that competition introduced by allowing parents to select the schools their children attend will lead to better schooling and incentives for school reform. In contrast, opponents of this type of reform claim resources are drained away from schools and that school quality is thus hurt, not helped, by such a reform. Research into this issue, since the 1990s, has employed standard quantitative and qualitative methods, but studies have provided inconclusive and even conflicting findings.

Maroulis et al. (2014) investigated this policy debate by creating ABMs of a school district's transition from a local neighborhood school catchment area system to a school choice system. The agents in the system were schools and students. School agents varied in terms of the quality and building capacity of existing schools, and in that new schools entered the system by imitating top existing schools. Student agents varied in their ability and background, and the researchers ranked schools according to achievement and geographic proximity. The academic achievement of the student agents combined individual traits and the value-added by the quality of the school they attended. Real data from Chicago Public Schools was used to initialize the model (see Figure 2).

The use of these ABMs helped identify dynamics—such as CSCFL conceptual perspectives of micro-macro levels, nonlinearity, and emergent properties—that had not been revealed in previous quantitative and qualitative research. Specifically, model runs demonstrated that the timing of new schools entering the system was a critical factor. The overall system improves because new schools entering the system imitate the top existing schools. However, a high emphasis on achievement at the schools led to new schools entering the system earlier, which resulted in lower achieving new schools. Thus, there was a paradoxical mismatch between macro-level and micro-level behaviors of the system in that increasing the emphasis on school achievement at the household level did not generally lead to increasing achievement at the district level. From a policy perspective, results of using ABMs suggest that the critics of school choice reform were correct that school achievement in the overall system would not rise. However, the reason proposed by the critics—draining of resources away from existing schools—was not actually the causal factor; rather, it was the timing of new schools entering the system.

This ABM also provided other school choice policy insights, such as the unintended transfer of top students to private schools where vouchers issued by the government were used to pay for the private schooling, which was an emergent property of the changes in the Chicago Public School system (Maroulis et al., 2010). Another unexpected dynamic of the Maroulis et al. (2014) model was that being a top-rated school (based on the mean achievement levels of its students) was an unstable (i.e., nonlinear) state: the top-rated school attracted many new students, some of whom did not achieve as highly, thus bringing down the school's achievement rating, so that another school became a top-rated one. This unexpected insight from their modeling has policy implications for the domain being modeled. Many choice schools avoided this issue by being selective, but if school choice is really implemented in the so-called free market form that advocates sketched out, then this instability will become a reality. That is, if students and parents really have choice and base that choice on the level of achievement by students at a school, then the

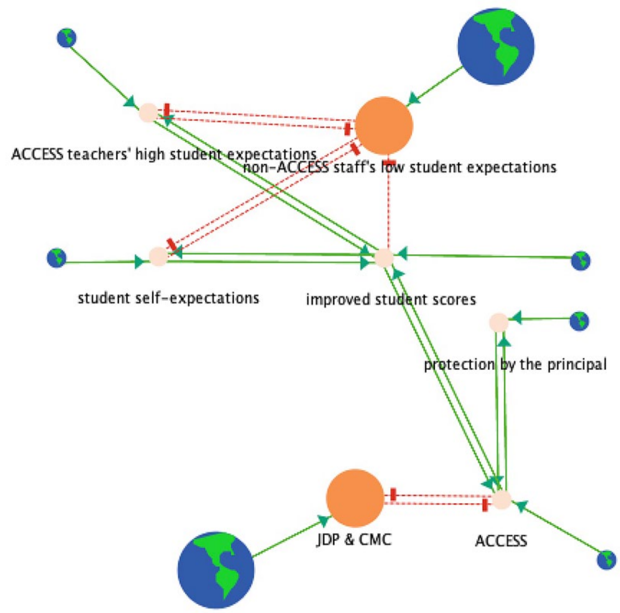

FIGURE 3. *A multi-mediator model of two purposeful perturbations involved in a successful school-wide reform. Source.* Reproduced from White and Levin (2016).

highest achieving school will get the most applications from a range of students which, if they have to accept all or a random selection of those students, will lead to that school no longer being a top-school. Or, to put it differently, what makes a school a top-school is precisely its selective admissions policy, which in fact is counter to a free choice model.

Our second case study involves the work of White and Levin (2016) and Levin and Datnow (2012), which used computer simulation models based on complexity theory to better understand and guide educational change initiatives. In a study at a continuation high school (a school of last resort for students having difficulties in regular high schools), several conceptual perspectives from complex systems, such as self-organization, feedback loops, equilibrium, nonlinearity, and emergence, were used to guide the implementation of a reform to provide access to higher education for these students. These complexity concepts were also used as a means for understanding the ways that the reform unfolded, and to provide a guide (i.e., inform policy) for implementing similar reforms in other high schools.

Changing a stable complex system (i.e., one at equilibrium) requires a perturbation to how the agents interact with each other in order to shift to a different stable state. In their research, White and Levin developed the concept of a "purposeful perturbation," a change in the everyday operation of education that both makes sense locally and moves the stable educational system away from the status quo, through a "tipping point" or nonlinear change, and then to a new desired stable state in which the educational reform becomes routine practice (i.e., a new equilibrium emerges). Several of these purposeful perturbations that were identified in the school reform design experiment research were captured in agent-based models by White and Levin (2016), within a modeling framework called multi-mediator modeling (MMM).

One of the MMM models they developed is shown in Figure 3. The labeled circles represent the key concepts in the model, and the globes represent the impact of everything outside the model on the concepts in the model. Arrows with solid lines show the positive impact that one concept in the network has on another concept, and dotted barred lines show the negative impact that a concept in the network has on another.

This model captures the initial effort of teachers involved in the reform (called ACCESS) to raise student expectations of their own capabilities for success in college-level academic work. This effort by teachers was opposed by the students' low self-expectations, which unfortunately were further reinforced by the low expectations of these students held by other staff members at the school. Still, the expectations of the students were raised in a nonlinear way, in part by the ACCESS teacher expectations and in part by the improved college placement test scores of the students. However, the ACCESS change alone did not lead to a school-wide implementation of the reform. It was found that protection from the principal of the school was needed along with the improved student scores over time in order to reach a tipping point, after which the ACCESS reform replaced the previous status quo programs at the school.

The White and Levin research demonstrates how conceptual perspectives from complex systems can inform and help analyze the changes in the school practices over time related to a reform initiative. The multi-mediator models provided runnable representations of the key agents (e.g., teachers, students, school staff) and factors changing the school environment (e.g., ACCESS reform) that resulted in outcomes from various runs of these models that aligned in key ways to the qualitative research findings. In particular, the ability to model the tipping-points—the nonlinear changes—that were found illustrates our assertion of how computer modeling of complex systems can synergistically be combined with more standard education research methods, such as, in this example, a qualitative design experiment.

These two projects represent proof-of-concept research that illustrates how the use of computer modeling, in particular ABMs, in conjunction with complexity conceptual perspectives such as those from the CSCFL, can provide useful and sometimes unique research and policy insights about educational complex systems. Also, these two projects demonstrate that complexity-based computer modeling approaches can provide analytics and information that go beyond traditional quantitative and qualitative education research approaches. As Jacobson and Kapur (2012) suggest, these projects use modeling methods to complement and extend traditional education research methodologies, not to replace them. Future work is now needed to further develop and validate modeling approaches that will meet the needs of education researchers and policy makers.

For those who are interested in exploring and extending approaches such as those we have discussed, then we recommend consulting other research in areas that have employed modeling approaches and conceptual perspectives from complex systems. For example, Mitchell (2009) provides a balanced discussion of the conceptual and methodological issues related to research involving complex systems in a wide range of areas in the physical and social sciences. Wilensky and Rand (2015) discuss both general techniques for developing agent-based models as well as an historical overview of computational modeling and a range of case examples. But given these are still early days in the use of such approaches for education research, we recommend examination of high quality research in other social sciences fields that have used various computational modeling approaches (e.g., Epstein, 2006; Epstein & Axtell, 1996; Testfatsion, 2006). Overall, we believe such modeling approaches can be effectively adapted and employed in education research and can inform educational policy as well.

Conclusion

Viewing education as a complex system has important implications both for education research and for educational policy (Lemke & Sabelli, 2008). Combining new conceptual tools, such as the Complex Systems Conceptual Framework for Learning (CSCFL), with new methodological tools for complex system analysis, especially agent-based modeling, can provide education researchers with new insights into the dynamics of complex educational systems. We also believe these complexity oriented conceptual and methodological tools can inform educational policy by showing different possible futures that various efforts at systemic educational reform might follow, especially as these tools allow ways of examining the often-nonlinear dynamics of educational complex systems. We hope this overview of conceptual perspectives and computer modeling methods will stimulate further awareness of these approaches among education researchers and policy makers as they engage the wide range of critically important challenges in 21st-century education.

NOTES

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[1]For further background about the field of complexity, Mitchell (2009) provides an excellent overview of key conceptual perspectives about complex systems and their application in many areas of science.

[2]Some complexity scientists make a distinction between a *complex nonadaptive system* and a *complex adaptive system* (Holland, 2006). The former refers to a complex system where the agents in the system do not change over time, such as atoms in a chemical molecular system. The latter refers to a complex system with agents that change (i.e., evolve) over time, such as a genotype change in DNA that results in a phenotypic change in the traits of the organism or how it behaves in its environment. The changes in the individual agents in a complex adaptive system may also be described as the adaptation of these agents to their current and changing environments. The adaptation and evolution of agents is the main distinguishing conceptual perspective between an adaptive complex system and a nonadaptive complex system.

[3]We view the notion of levels in a system as being relative, and so regard a macro-level as meaning a higher, less granular level, and micro-level as meaning a lower, more granular level.

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