## Title
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# Developing a conceptual framework to explain emergent causality: Overcoming ontological beliefs to achieve conceptual change

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## Abstract

One approach to conceptual change suggests that ontological barriers may impose beliefs that contribute to learners' misconceptions and misunderstanding of many science concepts. Overcoming this hurdle requires ontological training, which we argue may be possible using concepts and behaviors related to the discipline of complexity. We investigated the difficulties related to learning complex systems concepts, specifically systems exhibiting emergent causal processes. Results showed that all students acquired the following three concepts: Multiple Levels of Organization, Local Interactions, and Probabilistic Behavior. However, all but one student remained unable to develop and use a sophisticated understanding of the concepts of Nonlinearity and Randomness. This suggests that these latter concepts may be the most deeply rooted and robust of the ontologically based misconceptions. Further research is required to investigate if this tendency toward "causal determinacy" may be modified using other types of interventions.

## Introduction

Beliefs are thought to have substantial affects on how we interact with and interpret the world. Recent studies in fields such as theories of self (Dweck, 1999) and epistemological beliefs (Hofer & Pintrich, 2002) suggest that these ways of thinking also may affect learners' ability to perform certain tasks or construct certain types of knowledge. It is therefore reasonable to propose that ontological beliefs may play a significant role in learners' misunderstanding of concepts whose mechanisms are unfamiliar or completely unknown.

Chi, Slotta and deLeeuw (1994) put forward the argument that robust misconceptions associated with the learning of certain key science concepts[1] may be the result of assigning these concepts to incorrect ontological categories. It is possible also that lacking knowledge of a specific ontological category limits learners' ability to construct explanatory frameworks for a certain class of science concept.

The ontological category at the heart of this inquiry is that of emergent causal processes. It describes the behavior of phenomenon that rely on the interactions of multiple agents, all operating under the same constraints, without centralized control, influenced by flows of information with feedback loops and selection mechanisms, which generate multiple levels of organization within a system. The nonlinear and probabilistic nature of these complex systems is responsible for the seemingly magical transformations that occur between levels of the system. Put simply, emergence is characterized as the higher-level system's behavior, which arises, but cannot be predicted, from the behavior of individual lower-level entities in the system.

## Conceptual Challenges of Emergence

Although we know a lot about emergent causal processes, we continue to be challenged by why these concepts pose obstacles to learners. Duit, Roth, Komorek and Wilbers (1998), and Penner (2000), among others, have studied what students learn about complex systems when provided with different types of models. From their work we know that it is possible to learn some aspects of emergent behaviors, but these studies have not articulated the dimensions nor have they looked at the potential for transfer of this explanatory framework to achieve conceptual change.

Although students may be exposed to the behaviors and functioning of complex systems in general course work (e.g., diffusion of gases), it appears that many do not understand the concepts deeply; and they do not transfer these explanations to other instances of emergence (Jacobson, 2000). In fact, Jacobson's work shows that novice learners do not correctly attribute emergent causation to explain the behavior of complex systems whereas experts in fields such as biology and economics do so readily. Therefore we know that it is possible to use this as a generic framework as a generic to explain novel emergent phenomena. Additionally, Jacobson's results provide evidence to support the claim that expertise in certain fields may be built on a deep understanding of this emergent ontological category.

[1] Conceptual change difficulties reported in learning some important science concepts such as electricity in physics (Chi, Feltovich, & Glaser, 1981; White, 1993), gas laws and equilibrium in chemistry (Wilson, 1998), and in the biological sciences such concepts as diffusion, osmosis (Odom, 1995; Settlage, 1994), and evolution (Anderson & Bishop 1986; Brumby, 1984; Jacobson & Archodidou, 2000).

Lastly, there are powerful computer models to facilitate the acquisition of complex systems, however, the literature tells us that certain beliefs appear to limit how readily learners "see" and correctly explain the model's behaviors (e.g., Resnick & Wilensky, 1997). For instance, Resnick (1994) identifies the tendency to attribute centralized control to self-organizing behaviors of multi-agent computer models in StarLogo™. But we do not know the impact of simulations and modeling of different types of complex systems on understanding of emergent behaviors. Nor do we know if all aspects of emergence as demonstrated by these models of complex systems are equally challenging to novice learners.

Our interest in this paper is to take a modest step toward addressing some of these gaps in understanding how knowledge of emergent causal processes, as demonstrated in multi-agent simulations, may affect learning of certain science concepts. More specifically, we seek to identify and describe which emergent behaviors can be learned through simple simulations and modeling of emergent systems and which are more problematic for learners.

In the following sections we will describe the mixed method longitudinal case study of nine science students who participated in five, one-on-one, one-hour long inquiry-based sessions using simulations designed with StarLogo™. We will also describe the coding taxonomy (Complex System's Taxonomy – CST) which we developed to analyze the transcribed audio data collected.

## Material and Methods

### Sample

We recruited science students, between the ages of 17 and 18, in their freshmen year at a pre-university English college in Quebec (equivalent to grade 12). From this cohort we selected nine case studies using a purposeful sampling strategy (Creswell 2002). A major criterion for selection was the students' level of motivation and persistence[2].

The students' ages and academic experiences guaranteed that their formal knowledge of complex systems and emergent processes was limited or non-existent. However, we administered a pre-test to establish a baseline of their entry-level knowledge of these concepts (these data are not discussed in this paper).

### Instruction

The treatment consisted of five, 60 minute one-on-one inquiry-based sessions. Each session was comprised of two major components: (a) StarLogo computer simulations, and (b) cognitive scaffold in the form of coach/interviewer. The simulations were selected based on the ratings of four subject matter experts. The criteria were that the simulations should demonstrate emergent causal processes, and may in fact exhibit other behaviors of complex dynamic systems. The resulting treatment consisting of three simulations, and one tutorial, (Slime - session 1; FreeGas – session 2; StarLogo programming tutorial – session 3; no simulation – session 4; Wolf-Sheep – session 5) selected from a bank of over 12 other existing StarLogo simulations that also were judged appropriate for grade 12 science students. The simulations finally selected also have a prior history of providing learners with opportunities to learn about concepts of complexity (e.g., Resnick & Wilensky, 1997). This should not suggest that each simulation presented the same level of affordance for learning complexity concepts, however, they all held the potential to demonstrate some level of the more anticipated behaviors (i.e., non-isomorphic multiple levels of organization, decentralized control, randomness, nonlinearity, probabilistic behavior, and dynamic homeostatic behaviors). A question of interest that emerged from the observations was the differential effects of the different types of complexity represented in the simulations (i.e., the tightly coupled organization modeled in Slime simulation, versus the dissipative systems of FreeGas, and the somewhat in-between system modeled in Wolf-Sheep). Lastly, we also did not know the impact of presentation sequence but decided to keep this constant across learners to reduce the variability among cases although it prevented us from learning more about this question.

### Procedure

Over the period of five one-hour sessions, spanning a 7-week period each of the nine learners met individually with the coach in a research lab and worked with the simulation assigned for the session (see above). As they explored the assigned simulation, learners were asked to describe their observations related to the behaviors of the agents (i.e., slime mould, gas molecule, turtle, wolf-sheep) and construct and articulate possible explanations for these behaviors. The literature suggests that these causal explanations would reveal the underlying component beliefs/mental models (deterministic "clockwork" component beliefs used by novice learners versus nondeterministic "emergent" component beliefs used by experts) used to interpret these phenomena (e.g., Chi, et al, 1994; Jacobson, 2000). These statements could then be coded and triangulated with data collected relating to shifts in component ontological beliefs that forms part of a larger study (Charles, 2003).

Based on the literature (e.g., Resnick, 1994) we anticipated that learners would be able to identify and describe behaviors common to complex dynamic systems during their sessions. Therefore the ability to

[2] Learning Approach Questionnaire (LAQ) created by Donn (1989) was used to assess motivation. We selected participants with high internal motivation to ensure persistence with the task over course of this longitudinal study.

comply a list of the structural similarities between the simulations was viewed as the high level objective of this experience. At the conclusion of each session learners were asked to attempt to produce a list of behaviors exhibited by the simulation. If necessary they were reminded of the list complied from their previous sessions. Lastly, they were provided with a list of concepts, which may be related to either complex or simple systems and asked to construct a concept map. These data are not described in this paper.

**Data collection, coding, and analysis**

We collected direct observational data (audio and video tapes of the instructional activities), written documents (students' responses at the pretest and posttest), and interview data. A coding scheme entitled Complex Systems Taxonomy (CST) was developed to determine students' conceptual understanding of the various aspects of complex systems. Adapted from Jacobson (2000), it reflects concepts presented by Holland (1995), Bar-Yam (1997), and others. This "fine grain" overly represented coding scheme was used purposefully to ensure that all articulated observations of systems' behaviors could be coded (see Appendix for complete CST). Post analysis results allowed for narrowing of the taxonomy for future use.

## Results

One of the major themes constructed from the categories to emerge from the interviews was that the different simulations facilitated the acquisition of different aspects of complex systems. The results in Table 1 represent the total responses aggregated across students. It displays the percentage of responses within each complex systems component.

Table 1: Distribution of responses (percentages) within Complex Systems Taxonomy (CST) for each simulation.

| CST Concept | Simulations | | |
|---|---|---|---|
| | Slime | FreeGas | Wolf-Sheep |
| **ML** | 49.1 | 35.2 | 32.5 |
| **LI** | 22.4 | 25.1 | 35.3 |
| **OS** | 2. 8 | 14.0 | 8.6 |
| **PR** | 11.4 | 19.3 | 13.4 |
| **RB** | 5.1 | 3.0 | 2.3 |
| **TA** | 4.20 | 0.26 | 0.19 |
| **FL** | 1.10 | 0.43 | 2.90 |
| **DE** | 0.68 | 1.20 | 0.70 |
| **SR** | 0.74 | 0.00 | 0.13 |
| **DC** | 1.30 | 0.68 | 1.40 |
| **DI** | 0.32 | 0.00 | 0.38 |
| **NL** | 0.00 | 0.15 | 0.38 |
| **PA** | 1.40 | 0.26 | 1.00 |

**ML** is Multiple Levels of Organization, **LI** is Local Interactions, **OS** is Open Systems, **PR** is Probabilistic Behavior, **RB** is Random Behavior, **TA** is Tags, **FL** is Flows, **DE** is Dynamic Equilibrium, **SR** is Simple Rules, **DC** is Decentralized Control, **DI** is Diversity, **NL** is Nonlinear, **PA** is Pattern Recognition

To answer the question *what difficulties might students experience with learning the concepts involved with emergent causal processes* we analyzed the data both at the level of students and at the level of emergent causal process concepts. Thereby producing the two levels of analysis reported below.

**Student level analysis**

Figure 1 illustrates the combined scores on the CST for each student across all sessions. On this basis students could be classified into four groups:

• *Sophisticated Emergent Causal Processes (ECP) Identifier* (CST score > 75). This describes Greg who is considered an outlier at the high end.

• *High Moderate Emergent Causal Processes (ECP) Identifier* (CST score between 60 and 70). This describes Mitch, Sidney and Sam.

• *Moderate Emergent Causal Processes (ECP) Identifier* (CST score between 40 and 50). This describes Walter and Norman.

• *Novice Emergent Causal Processes (ECP) Identifier* (CST score between 30 and 40). This describes Emilie, Penny, and Monique (an outlier at the low end).

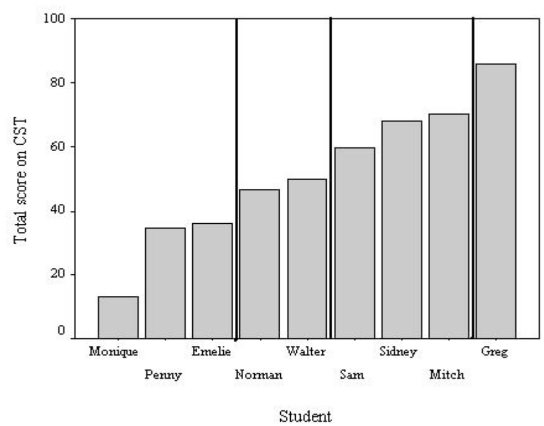


Figure 1: Student's understanding of Complex Systems concepts over three simulations.

**Concepts level analysis**

The results of Table 2 show the number of statements (relative to each student's total number of statements) that were coded (using the CST) into each Complex Systems concept. Thus, it allows us to make a provisional decision on whether each student observed and therefore discussed the Complex Systems concepts. If one arbitrarily, takes a value of 1 as the cutoff point, we can provisionally conclude that all students including the three Novice ECP Identifiers (Monique, Emilie, and Penny) observed and discussed the concepts of "multiple levels of organization", "local interactions", and "probabilistic causes". All the other students also observed and discussed the concept of "random behavior". The major difference between the Moderate ECP Identifiers (Norman and Walter) and the High ECP Identifiers (Sam, Sidney, and Mitch) was in the general strength of their responses. On the other hand, the Sophisticated ECP Identifier (Greg) not only had a greater response to the latter concepts, he also observed and discussed more concepts, namely "flows" and "dynamic equilibrium"

Table 2: Relative number of statements made by each student coded into Complex Systems concepts over three simulations.

| CST Concepts | Novice ECP | | | Moderate ECP | | High-Moderate ECP | | | Sophisticated ECP |
|---|---|---|---|---|---|---|---|---|---|
| | Monique | Emilie | Penny | Norman | Walter | Sam | Sidney | Mitch | Greg |
| ML | 6.7 | 21.0 | 15.7 | 16.1 | 20.9 | 22.3 | 30.8 | 26.0 | 25.8 |
| LI | 3.0 | 8.5 | 8.8 | 11.3 | 13.0 | 17.5 | 17.1 | 20.6 | 25.7 |
| OS | 0.0 | 2.2 | 3.6 | 2.7 | 4.1 | 4.1 | 2.4 | 5.4 | 12.1 |
| PR | 2.6 | 2.3 | 3.6 | 5.8 | 6.7 | 7.3 | 10.8 | 11.6 | 13.0 |
| RB | 0.0 | 0.5 | 0.9 | 3.1 | 1.0 | 2.5 | 3.7 | 2.7 | 2.4 |
| TA | 0.4 | 0.4 | 1.1 | 1.6 | 1.1 | 0.8 | 0.4 | 1.5 | 1.3 |
| FL | 0.2 | 0.0 | 0.0 | 0.4 | 0.0 | 0.1 | 0.4 | 0.2 | 1.2 |
| DE | 0.5 | 0.1 | 0.2 | 0.1 | 0.6 | 0.3 | 0.4 | 0.6 | 1.0 |
| SR | 0.1 | 0.0 | 0.2 | 0.1 | 0.0 | 0.4 | 0.4 | 0.0 | 0.4 |
| DC | 0.1 | 0.6 | 1.9 | 0.2 | 0.3 | 1.3 | 0.5 | 0.3 | 0.3 |
| DI | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 0.4 | 0.0 | 0.4 |
| NL | 0.0 | 0.0 | 0.1 | 0.1 | 0.2 | 0.0 | 0.1 | 0.2 | 0.5 |
| PA | 0.0 | 0.0 | 0.4 | 0.0 | 0.8 | 1.8 | 0.1 | 0.1 | 0.9 |

ML is Multiple Levels of Organization, LI is Local Interactions, OS is Open Systems, PR is Probabilistic Behavior, RB is Random Behavior, TA is Tags, FL is Flows, DE is Dynamic Equilibrium, SR is Simple Rules, DC is Decentralized Control, DI is Diversity, NL is Nonlinear, PA is Pattern Recognition

The interpretation that concepts, which had low counts on the CST scheme (e.g., random behavior, nonlinear effect, decentralized control, dynamic equilibrium), suggests that students did not observe them is not the only conclusion to be drawn from these data. It may indicate that learners readily recognized the behavior described by the concept and chose to focus instead on other concepts that were more challenging or interesting. It may also indicate that the simulation did not offer sufficient affordances for learning that concept.

## Discussion

Chi and colleagues (e.g., Chi et al., 1994; Chi 2000) have long proposed that ontological training will remove ontological barriers, which they speculate create the misunderstandings observed when learning certain scientific concepts. Our study shows that not all of these identified barriers are equally daunting. In fact, our study confirmed that using the selected intervention, it was possible to hurdle two of the barriers (Multiple Levels and Local Interactions) identified as problematic by Chi (2000). Our results also suggest that two (Nonlinearity and Random Behaviors) of a possible six complex systems concepts are either not affected by this intervention with its relative affordances for learning complex systems concepts (i.e., non-isomorphic multiple levels of organization, decentralized control, probabilistic behavior, and dynamic homeostatic); or, that these concepts represent a deeper level of entrenched beliefs and require some other type of intervention or condition before substantial change will be observed. The more important of these two is randomness because it is an addition to the list of barriers identified by Chi (2000).

### Adding to the list of Ontological Barriers - "Causal Determinacy"

One of the ontological barriers not identified by Chi (2000) is the attribution of causal determinacy (i.e., difficulty in acquiring the concept of random actions). This current study shows that, possibly because of weak affordances of the simulations, students experienced difficulty with the notion of randomness. Klopfer and Um (2000) in a study of fifth and seventh grade students using StarLogo in a scaffolded learning environment called "Adventures in Modeling" also demonstrated that students experienced difficulties with learning the concept of random events; although in the latter portion of their 14 sessions intervention, students were able to grasp this concept.

The evidence from the study reported here and from the larger study (Charles, 2003) is that all the learners at some level were challenged by randomness. In fact, it was the main stumbling block for Greg who otherwise acquired an understanding of all the emergent causal processes without exceptional cognitive struggle. For example, Greg when provided with an ontological prompt during session 1, answered with an explicit statement describing the Slime mould model as being deterministic. His view was that the computer program limited the options and therefore the outcome was determined a priori, therefore predictable.

Greg: Yeah, I think it's more of a deterministic system. Because like even looking at the way that this is set up there was a minimum number of turtles that you could have and I think it starts off as a system that has a plan and that all the other variables just act on whether like it's your plan ... so you have a deterministic system.

What this suggests perhaps is that even though learners accept the randomness of some happenings, as indicated in their answers to the question about ants foraging, at a deeper level they struggle to accept the lack of some means of predicting future outcomes (even by infinitesimally small or remote means). This deep level understanding is further confounded by the limitations of the programmed environment of the simulations, which indeed may confirm beliefs that there is some level of predictability because random number generations machines are behind these calculations. This is the level of discussion that Greg, Mitch and Sidney all at some point conducted with the coach.

How then did any of the learners show signs of acquiring a deeper level understanding of this concept? The evidence suggests that Greg was the only case to describe random actions at the deeper level of understanding as an element of true causal indeterminacy and "noise". He appeared to accomplish this as a consequence of both cognitive scaffolding and his domain knowledge. During the final interview session, one year after the intervention, Greg was asked to explain his concept map. In this discussion, he elaborated on the role played by random actions in the behavior of systems. This required him to reflect and in doing so he referenced his course work from biology and how the "noise" of random events creates the "possibilities" of the future states.

Greg: ...so that creates um, randomness, and that creates possibilities, also. That if there were no random events, then you wouldn't have those possibilities. Um, but all these chance events, they, when they get absorbed into the complex system, they have very little effect. It's like throwing a pebble into a river. Sure, you might course the river in a one in billion chance or something, but chances are it does nothing. It's not going to affect the flow of the river in any way. Uh, so, what that means is that complex systems, they follow more rules of probability, and they, they... so nothing is for sure I guess, there is always the element of chance involved. But they're [complex systems] by and large more predictable than simple systems.

The attribution of causal determinacy is a key obstacle to understanding emergent causal process for most learners. This arises either because of the learners' component beliefs, as in the instantiation of the case study Norman, or because of the confounding of concept and programming limitations as demonstrated by Sidney, Mitch and overcome by Greg. The contention may come as no surprise to those investigating the cognitive processes involved in reasoning about uncertainty (e.g., Shauhnessy, 1992). Metz (1998) points to the spurious causal attributions that result from misunderstanding of randomness and probability. What is surprising is that this same barrier also may account for a major difficulty in learning emergent causal processes such as evolution. This contention is supported by research from Zaïm-Idrissi, Désautels, and Larochelle (1993). In their study working with 15 biology students (master's level) they concluded that the majority of the sample held deterministic forms of reasoning about the topic of evolution. Furthermore, they uncovered several inconsistencies in the belief systems of the study's participants, primarily, the conflict between deterministic and probabilistic reasoning.

Therefore, it is possible that this causal determinacy attribution may be one of the most widely interconnected beliefs that affect other related beliefs such as probabilistic causes, and even decentralized control. It may well fit Chinn and Brewer's (1993) description of the evidentiary supporting schema. They state: "It appears, then, that well-developed schemas are not necessarily entrenched. The key is whether the schema is also embedded in evidentiary support and is used to support a wide range of other theories and observations that the person believes" (p. 17). Future research is required to try and untangle the possible confounding of the simulations' weak affordances and the students' ontological belief about randomness.

## Conclusions

Using the complex systems' taxonomy, the results of this inquiry show that all nine case study students had little difficulty developing an understanding of three emergent causal processes: Multiple Levels of Organization, Local Interactions and Probabilistic Behavior. However, the emergent component concepts of Nonlinearity and Randomness were challenging for all. In fact, only one student, Greg, was capable of demonstrating a deep conceptual understanding of these concepts. Furthermore, his understanding grew with maturation over time, with experience from complementary content areas, and cognitive scaffolding from the coach/interviewer. Greg's persistent attempts to reason with these concepts and explain phenomena using these notions (e.g., explaining evolution of a species as dependent upon random events) may also account for his ability to acquire this knowledge.

The results of our study also show that the affordances for learning aspects of emergent causal processes, and concepts of complexity, offered by multi-agent simulations and modeling are highly related to the type of complex system represented and also to the students' background understanding of science. In particular more learners had difficulty learning with representations (simulations) of dissipative system complexity (FreeGas) compared to those using representations of tightly coupled organization models of complexity (Slime).

In summary, this investigation provides evidence that it is possible, using simple simulations and scaffolding, to facilitate the learning of some aspects of an emergent causal explanatory framework. However, other components of emergence, which are linked to non-deterministic (i.e., randomness) and nonlinear conceptions are not easily acquired and may represent the more deeply entrenched ontological beliefs. Further research is needed to examine these specific aspects of emergent causal frameworks and the effectiveness of other types of instructional simulations and tools.

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## Appendix

| COMPLEX SYSTEM CODING TAXONOMY |
|---|
| 1. Local interactions. |
| 2. Simple rules |
| 3. Decentralized control |
| 4. Random behavior |
| 5. Tags |
| 6. Flows |
| 7. Internal models |
| 8. Diversity/ variability |
| 9. Modularity |
| 10. Pattern formation |
| 11. Open/closed systems |
| 12. Multiple Levels |
| 13. Probabilistic |
| 14. Nonlinearity |
| 15. Criticality |
| 16. Dynamic equilibrium |
| 17. Adaptation |
| 18. Selection |
| 19. Time scale. |
| 20. Multiple causality |