What are the Levers by which a Complex Systems Approach may Empower Learning?

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Abstract

This study examined middle school students' learning of the gaseous phase in chemistry through an emergent complex systems perspective as compared with learning through a normative disciplinary view. Building and adding onto previous research, We examine the contribution of design components (computer models and physical laboratories) to leverage learning in a novel learning environment based on complex systems approach.

As schooling turns to increasingly more digital experiences of learning, it is important to assess whether vital contributions of earlier approaches to science learning are lost in the process. We explore the contribution of physical experiences with laboratories and computational model-based complex-systems approach to learning a chemical system. The study compares junior-high school students' learning of the gaseous phase in chemistry in three modes: with computer models using a complexity approach (M), with a normative disciplinary approach that includes laboratories (L), and with computer models using a complexity approach that includes laboratories (ML). Learning is tracked for relevant science concepts, such as pressure, and systems ideas, such as emergence and randomness.

Extending previous research, we focus on agent-based modeling a more recent complex-systems approach to modeling systems, and we study a more nuanced set of learning outcomes.

Keywords: Complex systems, Conceptual learning, Systems thinking, Laboratories, Model-based Learning.

Introduction

Understanding the structure of matter and its properties is central to everyday knowledge of many phenomena and to our ability to address vital engineering and science challenges. Although much effort has been expended in teaching the topic in schools, many students display difficulties in understanding chemical systems (Ben-Zvi et al., 1986; Nakhleh, 1992; Dori & Hameiri, 2003; Johnstone, 1991; Nussbaum, 1985; Talanquer, 2007; Treagust et al., 2003; Adadan et al., 2009; Ozmen, 2011). The main sources of difficulty touch upon the small scales at which the micro-world, the causal substrate, operates and the systemic nature of such phenomena ((Johnstone, 1993; Gilbert & Boulter, 2000; Authors, 2009). For brevity, hence we use the term "micro" even though molecules' actual sizes are at the submicroscopic level). In discussing complex systems, "micro" as opposed to "macro" signifies an arbitrary level of individuals.This raises the need for representation and visualization methods to help students understand the particulate level of matter. A visual, dynamic and linked representation that brings micro- and macro-levels closer and helps attend to the multiple, parallel and interacting nature at the micro-level is provided through agent-based modeling (ABM) platforms, such as NetLogo (Wilensky, 1999). ABM is an extensively used computational modeling paradigm, which simulates dynamic systems by simulating each of their many autonomous and interacting entities (named agents) (Holland, 1995; Kauffman, 1995; Bar-Yam, 1997). By experimenting with agent behaviors and interactions, we view how collective behavior results from individual behaviors and interactions.

A number of researchers have examined the relative efficacy of learning with laboratories and with computerized models. Combining laboratories and models has been found to be more effective than using only models (ML > M) (Jaakkola et al., 2010) or only laboratories (ML > L) (Zacharia & Olympiou, 2012; Donnelly et al., 2012). When combining labs and models students were better able to take charge of the inquiry process and its decisions; while with laboratories alone students focused more on the actions needed to reach a correct solution (ML > L) (Donnelly et al., 2012). Zacharias & de Jong (2014) claim that not every combination of laboratories and models promotes learning with respect to the separate modes, and make the case for a more nuanced effort in attending to different implementation features. Similar to the current study, Liu (2006) has compared learning the Gas Laws with each mode and in combination, finding that the combined condition promoted greater learning than each of the separate modalities (ML > M = L). However the author acknowledges that a problem with the experiment is the longer duration of the combined condition, which could explain the greater learning.

Research Questions

We explore learning in one of three modes: complex-systems based curriculum with computer models (M), normal curriculum with laboratories (L), and their combination (ML) comparing:

RQ1: *Conceptual learning overall*: How does conceptual change concerning the gaseous phase compare in the three learning environments?

RQ2: *Conceptual learning by science concept*: How does conceptual change regarding specific science concepts – pressure, diffusion, temperature, density, Kinetic Molecular Theory (KMT) and Gas Laws – compare between the three learning environments?

RQ3: *Conceptual learning by system components*: How does conceptual change regarding specific complex systems perspective - micro level, macro level, transition between the micro and macro levels, randomness - compare between the three learning environments?

Method

Research Approach and Design

We have used a mixed methods approach combining quantitative analysis of questionnaires and qualitative analysis of interviews. The research was planned as a non-randomized three-group comparison quasi-experimental pre-test-intervention-post-test design. This study is based upon the questionnaire data.

Participants

124 seventh grade students participated in the study: 76 males, 48 females. In all classes, the teachers have an undergraduate degree in science education and several years of teaching experience. Research went through the Ministry of Education approval process. All participants' parents completed consent forms.

Procedure

Before and after the activities, spaced 2-3 weeks apart, students completed identical content knowledge questionnaires during 30 minutes. The three groups engaged with the learning materials over identical spans of time: 12 45-minute lessons, separate or double periods.

Learning Environments

The M and ML groups used the [name with-held] curriculum (Authors, 2010) that was designed with an emergent perspective, encouraging students to investigate the micro-level and emphasizes how the macro-effects result from interactions between particles at the micro-level and included model exploration activities. The M group did not experience laboratories and demonstrations. The L group experienced lectures, textbook, laboratories and a very short demonstration of a computer model.

Data Collection Tools

The main data collection tool in this study was a content knowledge questionnaire. The questionnaire is based on that used in previous research on learning Gas Laws and KMT (Authors, 2009b) and diffusion (Odom & Barrow, 1995).

Analysis

Students' answers to the questionnaire items were coded by science concepts and by systems reasoning. The multiple-choice answers were coded as correct or incorrect. Overall learning gains were computed as (post-pre)/pre to account for initial differences between the students and to assess students' growth with regards to their initial understanding. Specific learning gains were computed as the (post-pre) to prevent distortion resulting from small denominator numbers.

Validity and Reliability

The items were evaluated by five experienced science teachers, to ensure content-alignment to normal curriculum and appropriate level. The construct and criterion validity of the content knowledge questionnaires was reviewed by five science teachers, two of whom taught the [name with-held] curriculum, three who taught with the normative curriculum. All confirmed that the test items were appropriate for examining the issues studied in the two learning environments. The questionnaires were coded by the researchers and the participating teachers. Comparison of the independent scores and codes yielded 97% agreement on 2,208 items.

Findings

The findings are presented in Appendix 1.

Conceptual learning overall: Students' scores rose in all three groups, but to a different extent, showing a distinct effect of combining models and labs: L-29% (45), M-38% (35) and ML-78% (50). ANOVA comparison shows significant variance between the three groups, $F(2, 121)=16$, $p<.001$, partial $\eta^2=0.21$, due only to ML's larger gain, not to any M-L differences.

Conceptual learning by science concept: ML > M=L for temperature, density, KMT and Gas Laws. ML > L with no other differences for diffusion. M > L for KMT. Pressure is learned similarly in all groups.

Conceptual learning by system components: ML>M=L The combined mode is more effective than each of the separate modes, that are similar in their effects for the micro-level viewpoint, a coordinated emergent view and probabilistic reasoning. ML>L for reasoning about the macro-level, all other comparisons similar.

Discussion and conclusions

In previous research (Samon & Levy, 2013), we show that learning about chemical systems is strongly enhanced through complex systems approach. In this research we examined what are the relative contributions of physical experiences with laboratories and demonstrations and a computational model-based complex-systems approach to learning a chemical system?

A distinct and strong advantage was found for learning about the gaseous phase through a computational emergent perspective (a tripling of learning gains) one that emphasizes micro-to-macro reasoning about systems combined with physical experiences. Surprisingly, no differences were found in learning between a complex-systems model-based approach and a more normative approach employing laboratories. Our explanation for this phenomenon is that the computer models provide a powerful representation of the micro level, which is necessary for a basic understanding of chemistry. Laboratories provide first-hand experience of the macro-phenomena that anchors and grounds further learning of how imperceptible micro-level objects and interactions produce them. Without such grounding and bridging, the explored phenomenon is contained within the digital world, usually simplified and less accessible to multiple modes of perceiving and action. Without such bridging between computation and the physical world, we are replicating old learning results, rather than using technology to promote a deeper understanding.

Given the surge in the use of computer models for learning science, many times replacing lab-based physical experiences, we find the results of this study as providing cause for pause. When replacing labs with models, we may not have noticed any changes to learning, as students learned similarly in both conditions. However, we have not utilized this transition to *enhance learning considerably* by using a *combination* of complexity-based computational model exploration with the more familiar laboratory experiences in a connected way.

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Appendix 1

Table: Questionnaire Scores and Learning Gains, Descriptive and Inferential Statistics

			Descriptive									Inferential			
			Laboratory			Models			Laboratory-Models						
		# items	Pre M(SD)	Post M(SD)	LG (%)	Pre M(SD)	Post M(SD)	LG (%)	Pre M(SD)	Post M(SD)	LG (%)	F (p) L/LM/M	F (p) L/M	F (p) L/LM	F (p) M/LM
Overall		26	42.65 (14.25)	54.2 (18.4)	28.8 (45.3)	52 (12.1)	68 (7.1)	37.5 (35.4)	44.43 (11.9)	75.53 (15.1)	78.1 (49.7)	16**[1,2] (0.00)	1.05 (0.31)	25.57** (0.00)	15.86** (0.00)
Science concepts	Diffusion	4	40 (26)	49 (29)	9 (32)	41.5 (30)	51.5 (22)	10 (40)	41.5 (22)	67.5 (25.5)	26 (31)	3.34 (0.39)	0.0 (0.99)	6.07** (0.01)	4.132 (0.46)
	Pressure	5	54 (29)	72 (23)	18 (31)	70 (29)	92 (16)	22 (32)	60 (27)	88 (23)	27 (24)	1.2 (0.32)	0.23 (0.59)	2.267 (0.14)	0.75 (0.39)
	Temperature	4	24 (28)	49 (29)	25 (26)	18 (24)	155 (18)	36 (23)	36 (25)	73 (20)	38 (27)	6.02* (0.03)	3.8 (0.54)	6.85** (0.01)	0.85* (0.03)
	Density	10	39 (19)	53 (21)	14 (24)	49.5 (16)	64 (14)	14.5 (26)	41 (16)	70 (22)	29 (23)	6.0* (0.03)	0.24 (0.62)	10.29** (0.00)	6.4** (0.01)
	KMT	9	40 (16)	48 (23)	8 (29)	46.5 (14.5)	67 (13)	14.5 (22)	40 (16)	77.5 (19)	37 (22)	17.3** (0.00)	4.74* (0.03)	29.01** (0.00)	13.09** (0.00)
	Gas Laws	11	49 (21)	62 (23.5)	13 (24)	54 (12)	64 (7.3)	10 (32)	55 (20)	78 (18)	23 (18)	5.13** (0.00)	0.61 (0.43)	4.7* (0.03)	15.85 ** (0.00)
Systems thinking	Micro	6	42 (21)	43 (23.5)	1 (30)	47 (20)	56 (12)	9 (23)	40 (20)	72 (24)	32 (27)	19.94** (0.00)	1.78 (0.18)	28.5** (0.00)	15.84** (0.00)
	Macro	8	49 (24)	59 (23)	10 (23)	58 (21)	76 (10)	18 (24)	52 (20)	77 (18)	25 (21)	5.2** (0.00)	2.06 (0.16)	10.82** (0.00)	2.09 (0.15)
	Emergence	11	44 (17)	61 (23)	17 (25)	53 (12)	68 (11)	15 (13)	50 (17)	78 (18)	28 (18)	5.7 (0.07)	0.08 (0.78)	6.7** (0.01)	12.75** (0.00)
	Probabilistic	3	37 (29)	52.5 (34.5)	15.5 (38)	62.5 (32.5)	74 (26)	11 (34.5)	35 (27)	73 (27)	38 (39)	6.3* (0.03)	0.23 (0.63)	7.95** (0.00)	9.78** (0.00)

[1] * marks significance of p<.05; ** marks significance of p<.01

[2] Shading of significant differences