Promoting Learning Transfer by Constructing Computational Models of Complex Systems in Science among Middle School Students

Janan Saba
University of Haifa
janansaba3@gmail.com

Hagit Hel-Or
University of Haifa
hagit@cs.haifa.ac.il

Sharona T. Levy
University of Haifa
stlevy@edu.haifa.ac.il

קידום העברה של למידה על ידי בניית מודלים חישוביים של מערכות מורכבות במדע בקרב תלמידי חטיבת הביניים

ג'נאן סאבא
אוניברסיטת חיפה
janansaba3@gmail.com

חגית הל-אור
אוניברסיטת חיפה
hagit@cs.haifa.ac.il

שרונה ט' לוי
אוניברסיטת חיפה
stlevy@edu.haifa.ac.il

Abstract

The paper concerns synergy between science education, complex systems and, computational thinking (CT) through constructing computational models using Much.Matter.in.Motion (MMM) platform. It focuses on transferability of complexity-based structure, which underlies MMM, across different domains. The complexity-based structure suggests that a system can be described and modeled by defining entities, their actions, and interactions. We compared learning of seventh-grade students using MMM with students' learning following a normative curriculum using textbooks. Results show: the experimental group successfully promoted their conceptual learning, systems understanding, and CT; they showed relatively high degrees of near and far transfer, with a medium effect size for far transfer; Independent contributions of learning CT and learning systems on learning transfer; conceptual understanding indirectly impacts transfer.

Keywords: Complex Systems, Computational Thinking, Modelling, Transfer.

Background

The paper focuses on how the synergy between science education, complexity and, computational thinking (CT) may impact learning transfer.

In this research, middle school students modeled systemic phenomena with the Much.Matter.in.Motion (MMM) platform (Levy, Saba, Hel-Or, 2019). MMM (Figure 1) is a block-based modeling platform that enables students to learn chemistry and physics through constructing a wide range of computational models in these domains. It targets learning science and developing CT through the lens of complex systems (Saba et al., 2021). One of MMM's distinct innovations is the common complexity-based structure expressed in the coding interface. Modeling based on complexity-based structure allows separating the code for different populations and decomposing the code for each population into three components: properties of population's entities, their actions, and their interactions with each other and with macro-level boundaries and fields.

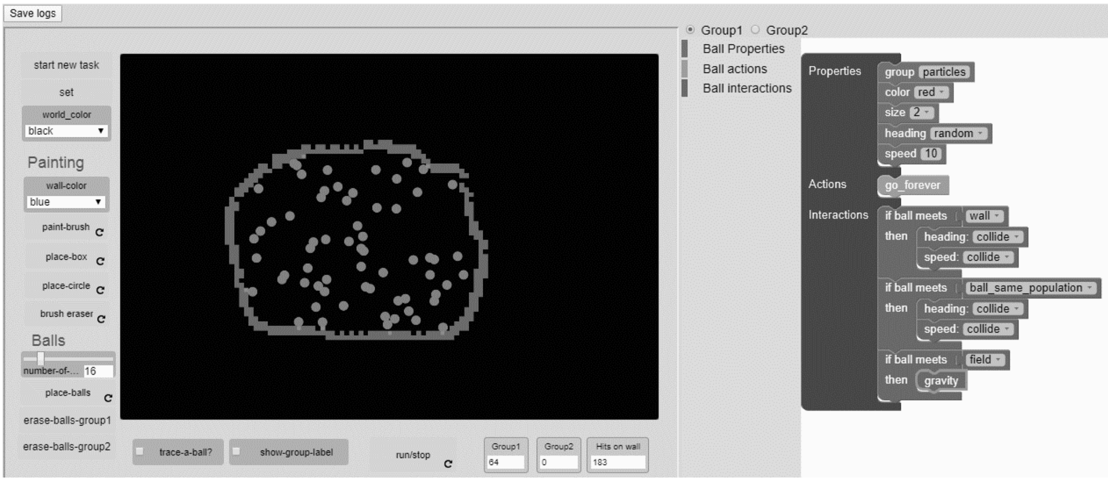


Figure 1. The Much.Matter.in.Motion (MMM) interface: left half - NetLogo MMM; right-half-coding block.

Learning transfer is a central construct in this study. It is the ability to use knowledge learned in one context within a new context (Bransford, Brown & Cocking, 2000 p. 51). Several studies have demonstrated the difficulties in achieving transfer of learning (Thorndike, 1906), a deep understanding of the source problem is required before transferring to the target domain, which in educational settings does not usually happen within short durations as the source domain has just been learned (Lobato, 2006; Marton, 2006; Chi & VanLehn, 2012).

The topic of learning transfer in the context of schools is rarely researched (Fuchs et al., 2003; Terwel et al., 2009; Rosholm et al., 2017). Moreover, only scant research has explored transfer through the perspective of complex systems (e.g. Goldstone& Son, 2005).

In this study, near and far transfer is explored in schools, in the context of students' computational modeling in science.

This paper aims to explore how learning by constructing models with MMM contributes to promoting CT, conceptual understanding of the knowledge domain, and systems understanding; and how these processes, in turn, support the transfer of the complexity-based structure across different domains.

Computational thinking

Computational Thinking (CT) encompasses the ability to solve problems, design systems, and understand human behavior in ways that are related to the ideas behind computation. It includes decomposing difficult problems into smaller and easier ones that can be solved, the use of recursive thinking, pattern finding, and abstraction (Wing, 2006). One conventional view of teaching CT is based on having students learn programming skills through using computer-based platforms (e.g. Scratch, Resnick, et al., 2009). However, several studies in educational STEM address the impact of integrating CT into learning within the STEM domains. The learning process focuses on enhancing both CT and conceptual understanding through introducing computational modeling tools for complex systems (e.g CTSiM, Basu et al., 2014; DeltaTick, Wilkerson-Jerde et al., 2015).

Complex systems are composed of many elements, which interactively self-organize in coherent global patterns (Epstein & Axtell, 1996; Holland, 1998; Bar-Yam, 2003). Although these studies use modeling tools for enhancing both CT competences and conceptual understanding through the lens of complex systems, the computational modeling tools are restricted to a specific science-content.

Construction of models

Model construction simplifies the phenomenon of interest based on the future use or the goal of the model; and can serve as an explanatory tool (Gobert & Buckley, 2000). In this study we adopt the agent-based modeling approach (ABM) for construction models of complex systems which relies on complexity theory (Bar-Yam, 2003). The ABM approach represents systems through their participating entities, assigning them behaviors and interactions. Running the simulation has these entities act and interact. As a result, an emergent collective pattern can arise bottom-up. We selected this viewpoint in the present research because of its generativity both in science and in helping students relate micro and macro levels (Wilensky & Resnick, 1999; Levy & Wilensky, 2009).

Transfer of learning

In this study, we explore near and far transfer. Near transfer occurs between two similar contexts. However far transfer occurs between two superficially dissimilar contexts but abstractly related (Barnett & Ceci, 2002); Gentner, 1983; Hummel & Holyoak, 2003; Klahr & Chen, 2011; Day & Goldstone, 2012).

The failure to transfer learning is a well-known problem. Some researchers go so far as to deny the existence of far transfer (Barnett & Ceci, 2002; Denning, 2017), other researchers find a very limited degree of far transfer (Sala and Gobet, 2017). Chi &VanLehn (2012) have in fact defined this problem by using two terms: (1) surface features which refer to the perceived concepts, or entities that have an explicit description in a problem; so that transfer by surface similarity is based on reminding and knowledge application; (2) deep structure that also indicates the procedures for solving a problem which often cannot be directly recognized. Transfer fails when the two problems have dissimilar surface features but a similar deep structure (Gick & Holyoak, 1983; Chi &VanLehn, 2012). Transfer by structural similarity takes place by matching between the relations within systems in two dissimilar contexts, which involved different objects and features (Gentner, 1983; Hummel & Holyoak, 2003; Klahr & Chen, 2011; Day & Goldstone, 2012).

With respect to transfer of learning about complex systems, distinct advantages have been found when using an agent-based approach (ABM) to complex systems. ABM approach can increase learning transfer by having students interpret the entities and relationships in computer simulations. Especially when these interpretations are idealized, the set of relations in one setting can be used in dissimilar situations, thus promoting the transfer of deep principles of complex systems across domains (Goldstone & Wilensky, 2008; Goldstone & Sakamoto, 2003).

Research question

This study presents research conducted on learning the topic of gases in chemistry through constructing computational models. The following research questions guide this exploration.

RQ1: *Learning through constructing models*.

How does constructing models of complex systems on the topic of gases with MMM promote students' conceptual learning, systems understanding, and computational thinking compared with normative instruction of the subject?

RQ2: Learning *transfer*.

How does near transfer and far transfer of learning compare between students who model gas behavior with MMM and students who experience normative instruction of the same subject?

What aspects of the complexity-based structure are associated with students' knowledge transfer when comparing near transfer with far transfer?

RQ3: *Path analysis*.

How do conceptual learning, systems understanding, and computational thinking contribute to knowledge transfer when engaging in learning using MMM?

Methods

The study is a quasi-experimental, pretest-intervention-posttest-control comparison group design**.** We compared the conceptual learning, systems understanding, and CT by 26 seventh-grade students using the MMM platform with 24 students' learning following a normative curriculum using textbooks. In addition, near and far transfer are quantitatively and qualitatively compared between both groups. The study extended over four 1.5-hour sessions.

Data sources

Both groups answered two identical pre-and post-test questionnaires:

(1) Gases questionnaire tests for conceptual learning, systems understanding. It consists of 18 multiple-choice items. Systems understanding is analyzed with the same items testing both macro-level and micro-level explanations.
(2) Computational Thinking questionnaire consists of six items (two multiple-choice, four open-ended). It includes a pseudocode of MMM-constructed models.

Both groups answered the post-test far transfer questionnaire. Questionnaire items require a far transfer of the complexity-based structure learned in the context of gas particles to the collective behavior of ants inside an ant-hill (Figure 2).

Regarding near transfer, the "aquarium problem" from the CT questionnaire was selected, and pseudocode for an MMM-constructed model is presented. It requires transfer of the complexity-based structure when learning about gas particles inside a container to solving a computational problem related to the collective behavior of fish inside an aquarium (Figure 2). Effect size was manually computed: squared Z-value of Mann Whitney, divided by (N – 1).

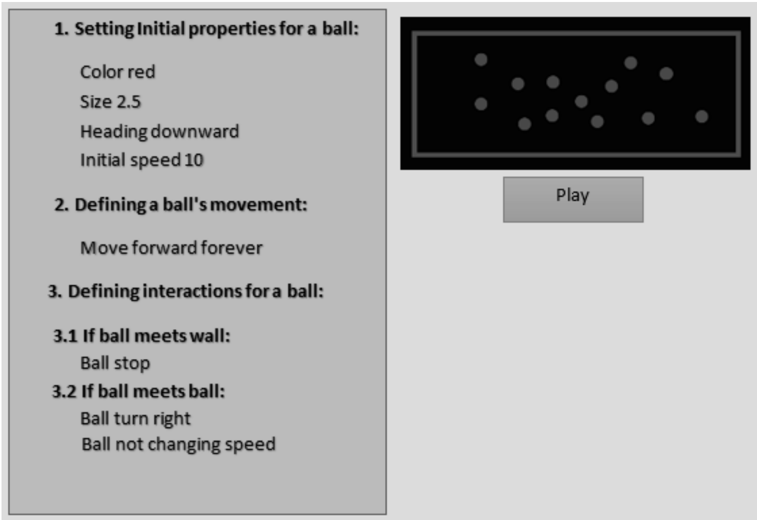
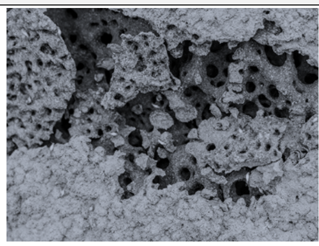
Near transfer question: the "aquarium problem"	The following model describes an aquarium that contains 13 fish of the same type and size. In this model each ball is a fish that lives inside the aquarium. A computer program that describes the properties of the fish and how each fish moves within the aquarium is displayed on the left.  **1.** When you click the "Play" button, what do you think will happen? **2.** Toxic material was poured into the aquarium and covered the internal walls. As a result, any fish that comes to the wall will die and stop its movement. **3.** When you click the "Play" button, what do you think will happen? 4. What would you change the program in Section 3.2, to allow fish to stay alive for a longer period?
Far transfer question: the "ants problem"	The world of ants Inside an ant nest, there are rooms of different sizes, as in the figure. Ants walk in random paths for food. When an ant collides with another ant, it slows down its speed.  1. Ant 1 enters the room, Describe a possible trajectory of the ant in the room. 2. Another 100 ants enter the same room. Describe in words a possible trajectory of Ant 1 trajectory. What will happen to its speed? 3. Describe what has changed since the entrance of 100 ants into the room? 4. All the 111 ants move to a neighbor room which is twice larger. Describe what is changing due to moving all ants to a larger room?

Figure 2. Near transfer question from the CT questionnaire, and far transfer question from the far transfer questionnaire.

Findings

Conceptual knowledge, Systems understanding and computational thinking.

Table 1 summarizes the quantitative analysis of conceptual knowledge, systems understanding of the gases questionnaire and CT of the CT questionnaire.

Conceptual Knowledge. Results show that both groups displayed learning, however, a higher score was obtained by the experimental group. Repeated Measure ANOVA shows a significant time effect ($F(1,48)=74$,$p<0.01$) from pre- to post-test. The interaction between time and group ($F(1,48)=0.13$,$p<0.05$) shows the superior learning of the experimental group.

Systems Understanding. Results shows that both groups have significantly enhanced their understanding of the different systems components (Micro, Macro, Micro/Macro). Repeated Measure ANOVA shows a significant time effect (Micro: $F(1,48)=15.92$,$p<0.01$; Macro: $F(1,48)=19.56$,$p<0.01$; Micro/Macro: $F(1,48)=45.85$,$p<0.01$) from pre- to post-test. The specific component that contributes to this result is the micro-level reasoning regarding the systems. The interaction between time and group at the micro-level ($F(1,48)=6.47$,$p<0.05$) shows the superior learning of the experimental group.

Computational thinking. Findings reveal that both groups increased their CT score from pre-test to post-test, however the experimental group showed a much greater increase than the comparison group. Repeated Measure ANOVA shows a significant time effect ($F(1,48)=50.70$, $p<0.01$) for both groups. The interaction between time and group is significant ($F(1, 48) = 23.10$, $p<0.01$) favoring the experimental group.

Table 1. Conceptual understanding before and after experiencing either the MMM learning unit or the normative learning unit (comparison $N = 24$, experimental $N = 26$).

			Pretest (%)		**Post-test (%)**		**Statistical tests[3]**					
							Time			**(time x group)**		
	Component	Number of items	Comp[1] M (SD)	Exp[2] M (SD)	Comp M (SD)	Exp M (SD)	F(1,48)	p	η_p^2	F(1,48)	p	η_p^2
Science concepts	Overall	18	49 (13)	53 (14)	63 (13)	80 (11)	**75**	**0.000**	0.61	**0.13**	**0.011**	**0.13**
Systems components	Micro	6	40 (19)	49 (20)	45 (17)	71 (15)	**15.92**	**0.000**	0.25	**6.47**	**0.014**	**0.12**
	Macro	3	54 (32)	53 (27)	71 (28)	83 (24)	**19.56**	**0.000**	0.29	1.72	0.196	**0.04**
	Micro/ Macro	9	55 (18)	58 (26)	72 (21)	85 (14)	**45.85**	**0.000**	0.49	2.55	0.117	**0.05**
Computational Thinking	Overall	6	14 (18)	24 (22)	20 (21)	56 (26)	**50.01**	**0.000**	0.51	**23.10**	**0.000**	**0.32**

[1] Comparison group
[2] Experimental group
[3] Repeated Measure ANOVA

Transfer of learning

The quantitative analysis of near and far transfer (Table 2) reveals a significant high degree of transfer for the experimental group in both near and far transfer with respect to the comparison group. However greater effect size was found for the far transfer compared with near transfer.

Table 2. Quantitative analysis of near and far transfer items of the experimental group versus the comparison group.

	Number of items	Comparison group *Mdn*	Experimental group *Mdn*	*U*	*P*-value	Effect size η^2
Near transfer	3	11	62	95.5	**0.00**	0.23
Far transfer	4	31	50	161	**0.003**	0.36

For the qualitative comparison, students' responses were coded according to the complexity-based structure used in MMM. Table 3 describes our coding table based on the complexity-based structure and examples of students' responses to the two transfer problems. Table 4 illustrated the number of students who used each variable within their responses to the two transfer problems.

Table 3. Coding students' responses to the two transfer problems based on the complexity-based structure. The examples are excerpts from the students' answers to the questionnaires.

Complexity-based structure			Near transfer fish problem example	Far transfer ants problem example
Category		**variable**		
Properties		Speed	*I would decrease the initial speed of the fish.*	*It [Ant 1] can go anywhere and its speed will remain constant.*
		Heading	*The fish moves randomly until it hits a wall; it will collide; and if it hits a fish it will turn right and decrease speed.*	*Ant 1 moves randomly inside the room.*
Interactions	Interaction with wall	Mentioned	*I think the ball collides with a ball and turns right and then collides with the wall.*	*The more ants in the room, the greater the density; they will collide more with the wall and with other ants.*
		Speed	*Some of the fish will hit the wall and stop*	*The ant walks randomly and collides with the wall as a result, it changes direction at the same speed.*
		Heading	*The fish move. When they collide with the wall they change their direction and speed; if a ball hits a ball, it will turn right and stay at the same speed.*	*It [Ant 1] moves until it collides with a wall and then it changes direction and continues on it way.*
	Interaction with another entities	Mentioned	*I think the fish first meet each other and then, after they reach the wall, they die.*	*Because the room is larger, it [Ant 1] will collide less often with other ants.*
		Speed	*I would change the speed of the fish. if they [fish] collide with other fish their speed will decrease.*	*Each time Ant 1 collides with the other ants it will slow down, and its speed will decrease until it stops.*
		Heading	*They [fish] collide with each other so they turn right but in all cases their speed does not change.*	*The ant will collide more frequently with other ants and as a result its speed will become much smaller, and change direction.*

Table 4. Students' responses to the near and far transfer problems based on the complexity-based structure, comparison of the experimental group and comparison group.

The complexity-based Structure			Experimental group (N=26)		Comparison group (N= 24)	
			Near transfer[1] (%)	Far transfer[2] (%)	Near Transfer (%)	Far transfer (%)
Properties		Speed	19	54 [3]	0	54
		Heading	58	92	51	71
Interactions	with other entities	Mentioned	15	54	25	0
		Speed	85	30	29	21
		Heading	73	8	20	4
	with wall	Mentioned	19	8	17	0
		Speed	65	8	20	8
		Heading	30	15	8	8

[1] Near transfer problem - the "aquarium problem"
[2]Far transfer problem– the "ants problem"
[3]Grey shade- represents cells in which more than half of the students mentioned the variable.

Experimental group. Results show that in the near transfer problem, students were based on the two main categories of the complexity-based structure. In the properties category, the main focus is on the heading of the fish when they moved inside the aquarium. Most of the students referred to interaction with another fish in their response expressing changes in both the speed and the heading. The interaction of the fish with the edge of the aquarium, the students referred only to changes in fish's speed. In the far transfer items, most of students' responses focused on the Properties category by referring to heading and speed of the ants. Regarding interactions, students only mentioned the interactions with other ants.

Comparison group. Results show that students' responses relied mainly on describing the properties category in both near and far transfer problems. In the near transfer problem, the focus is on the heading of the fish. However, in far transfer, students relied in both heading and speed of the ants.

The effect of students' conceptual knowledge, systems understanding and CT on Learning Transfer.

Figure 3 describes the following hypotheses: conceptual knowledge, systems understanding (the micro-level for its significant contribution) and CT each affect students' transfer of learning; increased CT enhances conceptual knowledge; increased CT and increased conceptual knowledge both contribute to systems understanding. Results of path analysis (Figure 4) show the direct effect of the two variables - post-test micro-level and post-test CT on the transfer score ($R^2 = 0.4, F(2,23) = 4.86, p = 0.01$). Significant results were found for both the post-test micro-level score (β = 0.64, p = 0.012) and for the post-test CT score (β = 0.41, p = 0.03). An indirect effect of the post-test Gases score on the transfer score was also found ($R^2 = 0.5, F(2,23) = 11.17, p = 0.00$) by affecting the post-test micro-level score (β = 0.73, p = 0.000. This analysis reveals that science conceptual learning, understanding complex systems and CT all have a positive impact on learning transfer, when the learning is based on model construction. However, we have found two more important factors. One is that learning CT and learning how to think complex-ly have *independent* contributions to learning transfer. A second effect is that conceptual understanding in science impacts transfer only through a particular perspective – whether the students understand the micro-level behaviors of the particles, or individual entities in the system.

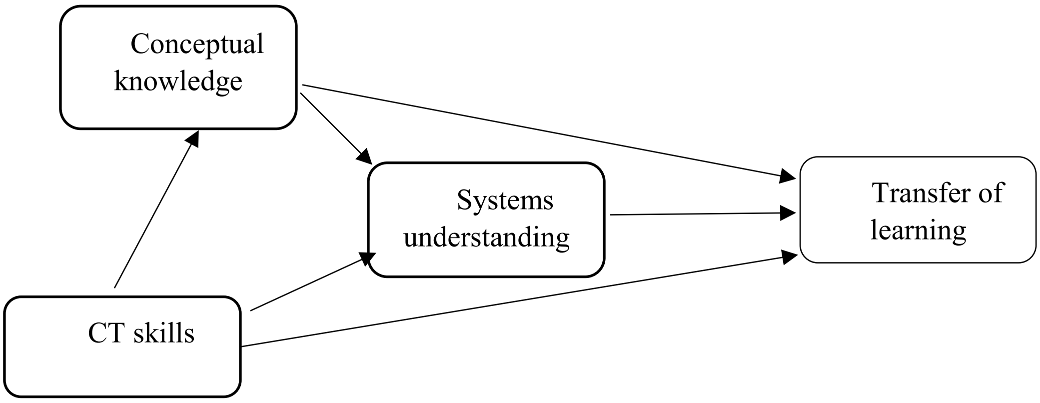
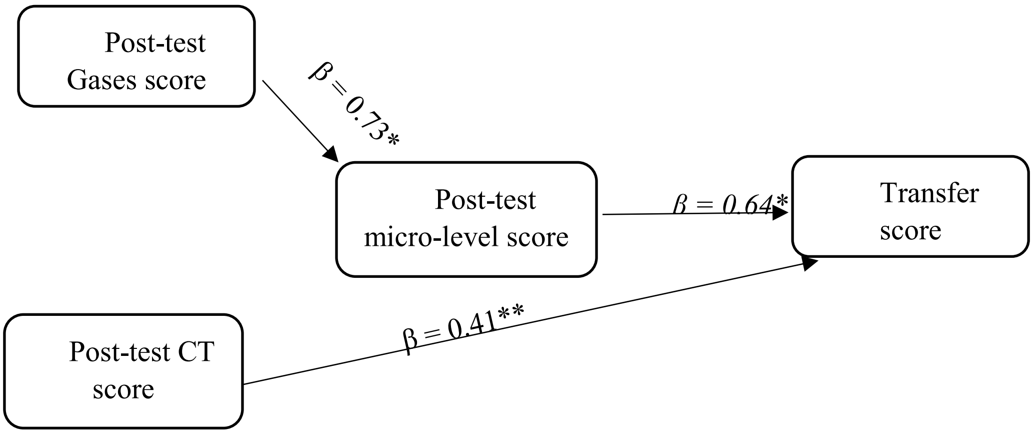


Figure 3. A hypothesis path model



* $p < 0.05$
** $p < 0.01$

Figure 4. Causal paths with statistically significant direct effects

Scholarly significance

The paper addresses a construct that has only rarely been researched in the past decade – transfer of learning – especially in schools and among students who learn science. The design of the focal learning environment aspired for learning transfer by guiding students' actions in programming towards a complexity-based structure, which can be generalized across many phenomena. The research examined students' conceptual learning, systems learning, learning of CT, and near and far transfer of learning. In all categories, the experimental group outperformed the comparison group. The main contribution of a complexity perspective is understanding entities and interactions at the micro-level of the system. In addition, independent contributions were revealed of developing a complex view of scientific phenomena and learning CT on the far transfer of learning. A central theoretical contribution of this work suggests a method for enhancing far transfer: using *visual epistemic scaffolds* of the general thinking processes we wish to support and *incorporating these visual structures into the core problem-solving activities*.

References

Barnett, S. M., & Ceci, S. J. (2002). When and where do we apply what we learn?: A taxonomy for far transfer. *Psychological bulletin*, *128*(4), 612.

Bar-Yam Y (2003). *Dynamics of complex systems*. Perseus Publishing, New York.

Bransford, J. D., Brown, A. L., & Cocking, R. R. (Eds.) (2000). *How People Learn: Brain, Mind, Experience, and School (Expanded)*. Washington, D.C: The National Academies Press.

Basu, S., Kinnebrew, J. S., & Biswas, G. (2014). Assessing student performance in a computational-thinking based science learning environment. In *International conference on intelligent tutoring systems* (pp. 476–481). Springer, Cham.

Chi, M. T., & VanLehn, K. A. (2012). Seeing deep structure from the interactions of surface features. *Educational Psychologist*, *47*(3), 177–188.

Day, S. B., & Goldstone, R. L. (2012). The Import of Knowledge Export: Connecting Findings and Theories of Transfer of Learning. *Educational Psychologist*, 47(3), 153–176.

Denning, P. J. (2017). Remaining Trouble Spots with Computational Thinking. Communications of the ACM, 60(6), 33-39. http://dx.doi.org/10.1145/2998438

Epstein J., & Axtell R. (1996). *Growing artificial societies: social science from the bottom up*. Brookings Institution Press, Washington.

Fuchs, L. S., Fuchs, D., Prentice, K., Burch, M., Hamlett, C. L., Owen, R., Hosp, M., & Jancek, D. (2003). Explicitly Teaching for Transfer: Effects on Third-Grade Students' Mathematical Problem Solving. *Journal of Educational Psychology*, *95*(2), 293–305.

Gick, M. L., & Holyoak, K. J. (1983). Schema induction and analogical transfer. *Cognitive Psychology*, *15*, 1–38.

Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. *Cognitive science*, *7*(2), 155-170.

Gobert, J. D., & Buckley, B. C. (2000). Introduction to model-based teaching and learning in science education. *International Journal of Science Education*, *22*(9), 891–894.

Goldstone, R. L., & Sakamoto, Y. (2003). The transfer of abstract principles governing complex adaptive systems. *Cognitive psychology*, *46*(4), 414–466.

Goldstone, R. L., & Son, J. Y. (2005). The transfer of scientific principles using concrete and idealized simulations. The Journal of the Learning Sciences, 14, 69–110.

Hummel, J. E., & Holyoak, K. J. (2003). A symbolic-connectionist theory of relational inference and generalization. *Psychological review*, *110*(2), 220.

Holland, J. (1998). *Emergence: From chaos to order*. New York: Addison-Wesley Longman.

Klahr, D., & Chen, Z. (2011). Finding one's place in transfer space. Child Development Perspectives, 0(0), 1–9.

Levy, S. T., & Wilensky, U. (2009). Crossing levels and representations: The Connected Chemistry (CC1) curriculum. *Journal of Science Education and Technology, 18*(3), 224–242.

Levy, S. T., Saba, J., Hel-Or, H. (2019). *Much.Matter.in.Motion (MMM) platform: Block-based platform for constructing computational models in science.* Systems Learning & Development Lab, University of Haifa, Israel.

Lobato, J. (2006). Alternative Perspectives on the Transfer of Learning: History, Issues, and Challenges for Future Research. *Journal of the Learning Sciences*, 15(4), 431–449.

Marton, F. (2006). Sameness and differences in transfer. *The Journal of the Learning Sciences*, *15*, 501–538.

Resnick, M., Maloney, J., Monroy-Hernández, A., Rusk, N., Eastmond, E., Brennan, K., Millner, A., Rosenbaum, E., Silver, J., Silverman, B., & Kafai, Y. (2009). Scratch: Programming for all. Communications of the ACM, 52(11), 60–67.

Rosholm, M., Mikkelsen, M., & Gumede, K. (2017). Your move: The effect of chess on mathematics test scores. PLoS ONE, 12(5): e0177257. https://doi.org/10.1371/journal.pone.0177257.

Saba, J., Hel-Or, H., & Levy, S. T. (2021). Much. Matter. in. Motion: learning by modeling systems in chemistry and physics with a universal programing platform. *Interactive Learning Environments*, 1–20.

Sala, G., & Gobet, F. (2017). Does Far Transfer Exist? Negative Evidence From Chess, Music, and Working Memory Training. Current Directions in Psychological Science, 26(6), 515–520. http://dx.doi.org/10.1177/0963721417712760.

Terwel, J., van Oers, B., van Dijk, I. & van den eeden, P. (2009). Are representations to be provided or generated in primary mathematics education? Effects on transfer, Educational Research and Evaluation, 15(1), 25–44.

Thorndike, E. L. (1906). *Principles of teaching*. New York: A. G. Seiler.

Wilensky, U., & Resnick, M. (1999). Thinking in levels: A dynamic systems perspective to making sense of the world. Journal of Science Education and Technology, 8(1), 3–19.

Wilkerson-Jerde, M., Wagh, A., & Wilensky, U. (2015). Balancing Curricular and Pedagogical Needs in Computational Construction Kits: Lessons From the DeltaTick Project. *Science Education*, 99(3), 465–499.

Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33.