Learning Electricity through Constructing Computational Models of Complex Systems

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Abstract

The paper explores students' learning of electric circuit in physics through constructing computational models of complex systems using Much.Matter.in.Motion platform. This study focuses on development of mental models that associate properties of a circuit at the macro level with elements at the micro level. We compared the learning of electricity, systems components by eighth-grade students using the MMM platform with students' learning following a normative curriculum using textbooks. Results show that the experimental group successfully cultivated their learning at the micro level more than the comparison group and their reasoning included connecting between the macro and micro levels. Using clustering methods, a novel progression of five mental models were found that can provide for better scaffolding of learning electricity.

Keywords: Complex Systems, Constructionism, Modelling, Mental Models.

Background

This study focuses on introducing the concept of electric current through the lens of complex systems via construction of computational models. In this study we focus on how students develop mental models that associate properties of a circuit at the macro level, such as the magnitude and direction of the electric current, with elements at the micro level such as the motion of electrons

(Eylon, & Ganiel, 1990). We examine the students' development of mental models as they construct computational models with the novel Much.Matter.in.Motion (MMM) platform. This platform allows students to create a micro-level model of an electric conductor, and then run the computational model and examine its dynamic behavior.

Electricity is the main form of energy transfer used in the 21st century, and its understanding is of central importance. Research shows that electricity is a challenging topic in physics among students of all ages (Reiner, Slotta, Chi & Resnick, 2000). One of the main challenges in learning this topic, is to conceptualize the electric circuit as a system in which electric current emerges from the interaction between the circuit elements. Even after extensive instruction, students fail to grasp some of the very basic characteristics of an electric circuit (Cohen et al. 1983; Eylon & Ganiel, 1990; Sengupta & Wilensky, 2009).

Complex systems

"Complex systems" is a general term for systems with many similar interacting entities that display emergent and often non-linear behaviors (Bar-Yam, 1997). Computational models such as agent-based simulations are common educational tools for promoting understanding of complex systems (Sengupta & Wilensky, 2009; Sherin, diSessa, & Hammer, 1993; Wilensky, 1999a). Agent-based simulations raise awareness to the entities that compose the system, and promote an understanding of the emergent behavior of systems in a bottom-up manner as a result of the interactions between these entities.

Mental models

Learners rely on cognitive constructions termed "mental models" when trying to understand the world around them (Norman, 1983). These mental models assist students in articulating ideas relating to new phenomena that are difficult to be experienced directly (Harrison & Treagust 1996; Taylor, Barker & Jones, 2003). Mental models are constructed by learners through interactions with the environment and physical systems, but are often partial, unstable and inaccurate.

Researches have revealed several mental models that students express when explaining the behavior of electric current in a circuit (Figure 1):

(1) The unipolar model (Duit & *Rhöneck*, 1997): There is no current in the returning path.
(2) The clashing currents model (Osborne, 1983; Shipstone, 1985): Current flows from both terminals of the battery and "clash" at the lightbulb.
(3) The attenuation model (Osborne, 1983; Shipstone, 1985): when the current passes through the lightbulb, some of it is consumed.
(4) The sharing model (Shipstone, 1985): two bulbs burn equally bright in a series electric circuit but the current's strength weakens on the retuning path to the battery.

All of these models refer to the macroscopic representation of current, they do not entail a particle-level view of the phenomenon. People do not develop mental models of electric current that include a particle-level view, without schooling (Tarciso Borges & Gilbert, 1999). Nevertheless, the particle-level view is essential for explaining some macro-level electric phenomena such as charging a capacitor (Eylon & Ganiel, 1990). The simplest particle-level model of electric conduction is Drude's model (Sengupta & Wilensky, 2009). According to this model, electrons move in a wire accelerated by an electric field, but their motion is stalled by the metal atoms that are viewed as stationary obstacles.

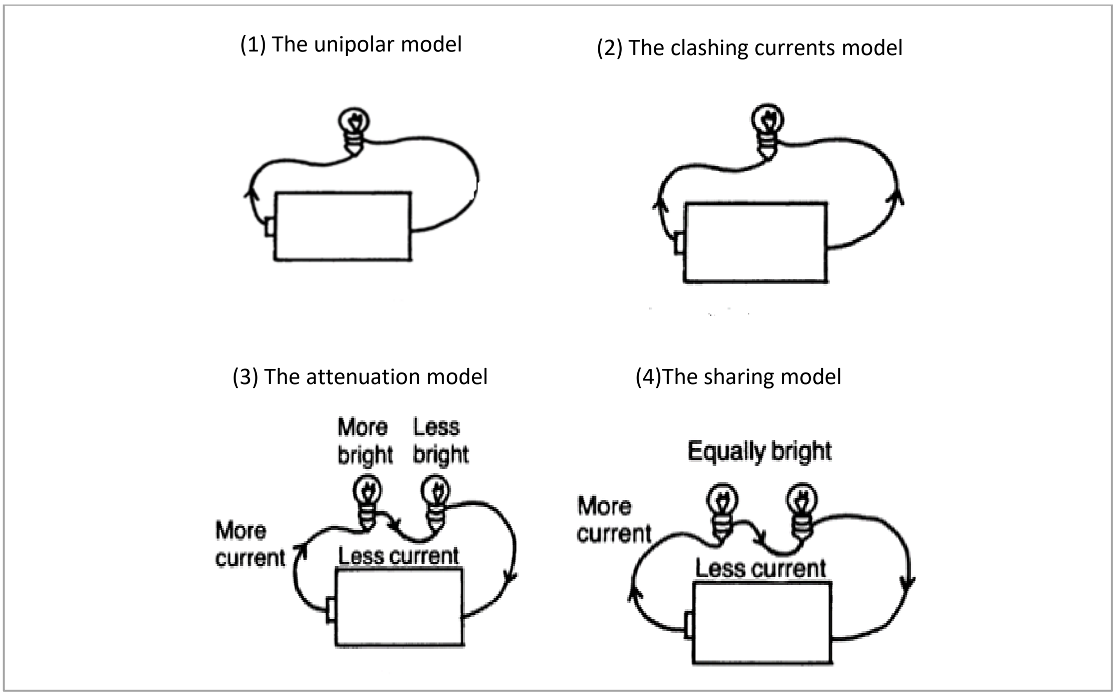


Figure 1. Alternative mental models of students on the behavior of electric current

Model construction vs. Model exploration

Most studies that examine student learning of electricity using computational platforms focused on macro-level representations of circuits (e.g., Zacharia, 2007; Roll et al., 2018). These simulations are designed as virtual experiments in which circuit components such as light-bulbs can be manipulated and current can be "measured". Few environments attempted to introduce the electric circuit from a complex systems perspective, namely, the repulsion between electrons as a driving force for current (Frederiksen, White & Gutwill, 1999) and the deflection of electrons by atoms in the conductor (Sengupta & Wilensky, 2009).

Exploring readymade computational simulations is a widespread practice. However, engaging students in actually constructing computational model can yield deeper learning about emergent phenomena (Wagh & Wilensky, 2018). Engaging in model construction involves using environments that allow students to construct the model or to change the features of a readymade model. After planning what to add or change in the model, students can run the computational model and to judge whether their decisions produced reasonable behavior. As far as we know, no study examined the affordances of constructing micro-level computational models for electric circuits.

The Design of Much.Matter.in.Motion

The MMM platform (Levy, Saba, Hel-Or, & Langbeheim, 2019) is an agent-based modeling technological tool for constructing computational models of a variety of complex system in physics and chemistry. It was developed using NetLogo (Wilensky, 1999b). A conceptual framework underlies the MMM platform, which was tested and improved over three studies in chemistry (Saba, Hel-Or, & Levy, under review). We found that this framework promotes understanding of systems in science based on a simple and coherent explanatory core and may develop a computational understanding of science. This framework suggests that complex systems can be described and modeled by defining its entities, their actions, interactions with each other, with macro-level boundaries and with fields (such as electric field or gravity) (Figure 2). Within the MMM platform, these entities are circular elements termed *balls* which can be interactively added to the model being created. These balls have initial properties of: size, speed, heading, and color. Macro-level entities such as walls are drawn in manually.

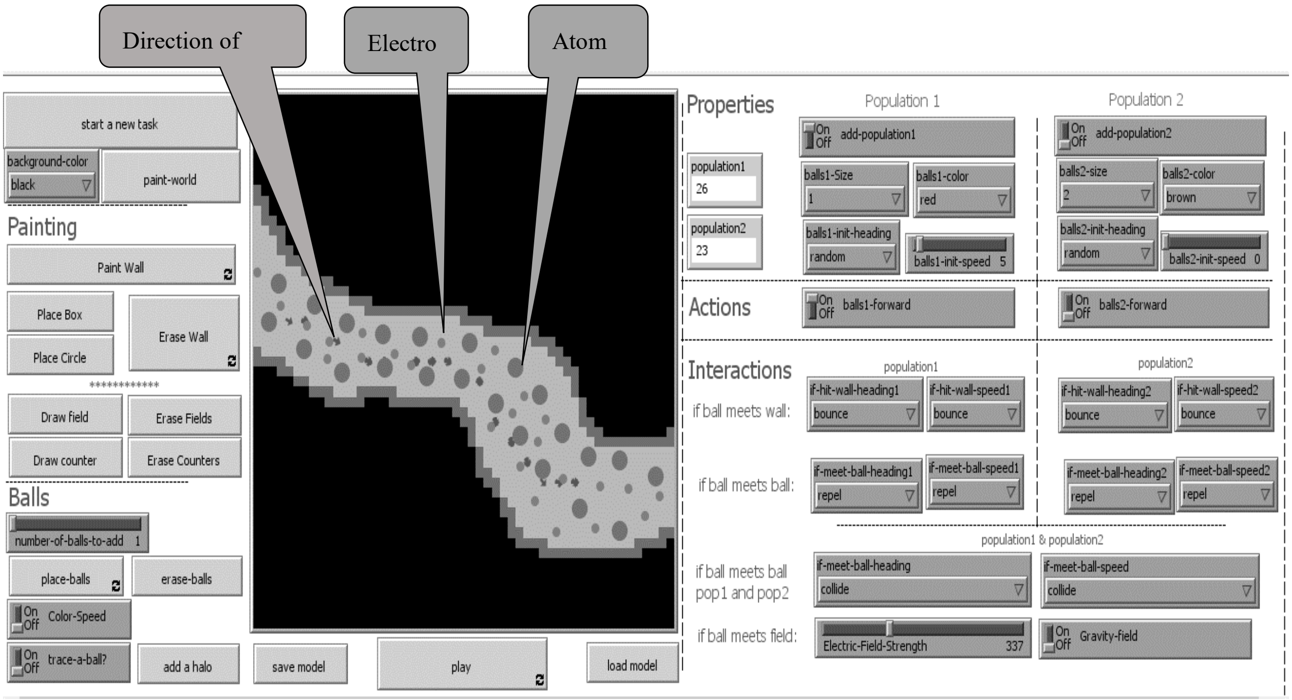


Figure 2. MMM platform for learning about electricity.

In our research we focus on 8th grade students studying computational models of electric current. We focus on the mental models that students develop while using computational modeling tools. These mental models are treated as "mental simulations" of the real phenomena (Greca & Moreira, 2000).

Research question

This study presents the research conducted on learning the topic of electric circuits in physics through modeling. The following research questions guide this exploration.

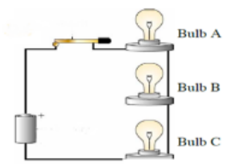
- Conceptual knowledge, Systems understanding. To what extent does the process of modeling of complex systems in electricity using MMM advance students' conceptual understanding of the science concepts and systems?
- Mental models. What knowledge elements do eighth grade students express when explaining electric circuits? How can the mental models based on these knowledge elements be characterized?

Methods

The study is a quasi-experimental, pretest-intervention-posttest-control comparison group design, 56 eight-grade students from a regular urban school in Israel participated in the study**.** We compared the learning of electricity, systems components, and modeling practices by the experimental group (n=33) who learned the topic of electric circuits using the MMM platform with the comparison group (n=23) who learned this topic using a normative approach based on lectures, experiments, discussions. The study extended over six 1.5-hour sessions for both groups.

Both groups answered identical pre- and post-test questionnaires. Questionnaire items included 13 items (7 multiple-choice, 6 open-ended).See Table 1 for example questions. The questions examined students' mental models of the behavior of simple circuits. Systems components are analyzed with the same items as conceptual understanding testing both macro-level and micro-level.

Table 1. Examples of questionnaire items.

7.	What happens to electrons when an electric light bulb is lit? Mark the correct answer. (correct answer is C) (A) The electrons are absorbed into the bulb components and disappear. (B) The electrons become light particles, are emitted and disappear. (C) The electrons remain in the conducing wire but transmit their energy to light energy. (D) There are no electrons in a light bulb, they stop inside the wire that is connected to the bulb.
10.	All the bulbs in the figure are identical to each other. Will they all glow equally brightly? If not, which one will glow most brightly? Please explain the reason for your answer. 

Findings

Conceptual Learning.

Table 2 summarizes the quantitative analysis of the questionnaire scores for the two groups. A larger learning gain is seen for the experimental group. Both groups showed learning, and a significant time effect ($F(1,54)=116$,$p<0.01$) was found from pre to post-test. However, the interaction between time and group ($F(1,54)=6.67$,$p<0.05$) shows the superior learning of the experimental group. The specific component that contributes to this significance is the micro-level reasoning on the systems.

Table 2. Conceptual understanding before and after experiencing either the MMM learning unit or the normative learning unit (comparison $N = 23$, experimental $N = 33$).

			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(1,54)	p	η_p^2	F(1,54)	p	η_p^2
Science concepts	Overall	13	46 (21)	45 (15)	63 (21)	72 (13)	**116**	**0.00**	0.68	**6.67**	**0.013**	**0.11**
Systems components	Micro	2	46 (33)	48 (34)	48 (35)	79 (28)	**10.71**	**0.02**	0.17	**8.03**	**0.006**	**0.13**
	Macro	7	52 (25)	44 (20)	71 (18)	67 (17)	**56.96**	**0.006**	0.52	0.33	0.563	**0.006**
	Micro/Macro	4	43 (24)	48 (32)	59 (32)	75 (21)	**26.49**	**0.00**	0.33	1.67	0.201	**0.30**

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

Mental model.

The students' answers to the open questions were first analyzed to identify knowledge elements, basic concepts and ideas upon which students build their answers (Sherin, 2013). A coding scheme was constructed based on the students' answers. Students' answers were then coded according to the schema by four researchers. Cohen's (1968) Kappa was high, 0.889 on average for six questions. Disagreements were resolved by discussion.

A two-step cluster analysis was conducted on the students' responses based on similarities in knowledge elements within a group, and distinction in knowledge elements between the groups (Stains & Sevian, 2015). The analysis reveals five clusters (Figure 3).

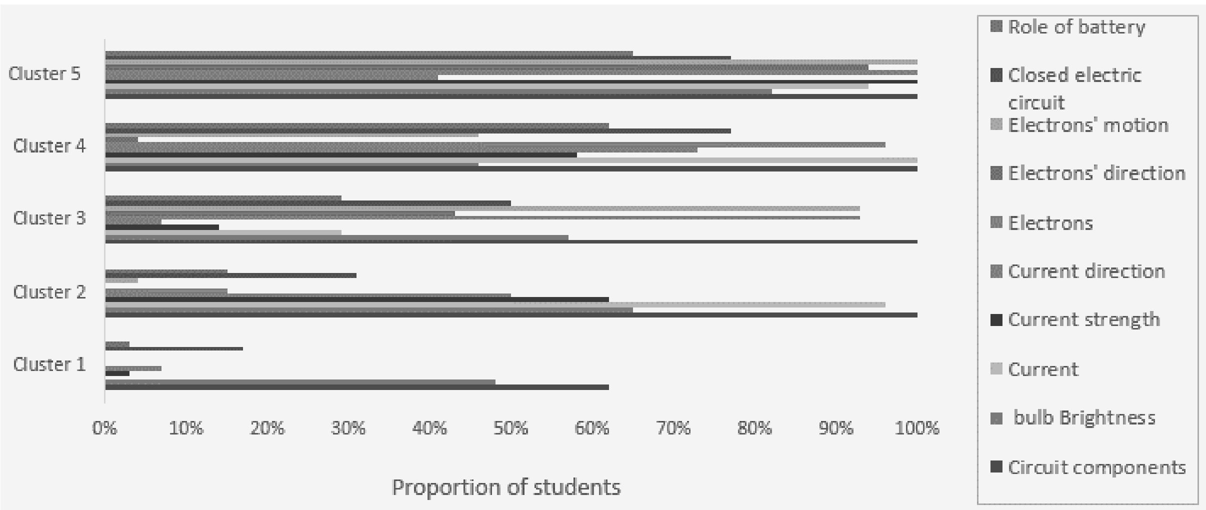


Figure 3. Clusters in reasoning about electric circuits, derived from two-step cluster analysis of students' knowledge elements in questionnaires (comparison $n = 23$, experimental $n = 33$).

These five clusters represent five mental models used by students when they reason about simple electric circuits. When classifying these clusters based on knowledge elements, seven main dimensions distinguish between the clusters (Table 3).

Table 3. Dimensions that distinguish between the five mental models. Changing in circles' size (black circles) represents a gradual increase of containing certain dimension though the mental models that are related to System-wide constraint and Input knowledge elements. For other knowledge elements the visualization of full big circle (grey circles) represents a categorical variable for containing the knowledge element within mental model.

Mental Model	Physical Components	Output[2]	Macro-level[3]	Dynamic[4]	Micro-level[5]	System-wide	Input[7]
1: Components	●	●				•	•
2: Components-Macro	●	●	●	●		●	●
3: Components-Micro	●	●	●	●	●	●	●
4: Components-Macro-Micro-Partial	●	●	●	●	●	⬤	⬤
5: Components- Macro-Micro-Full	●	●	●	●	●	⬤	⬤

[1]wires, bulb and battery
[2] brightness of bulb
[3] current, current direction and current strength
[4] current flow and motion of the electrons
[5] electrons, electron's motion, electrons direction
[6] whether or not the circuit is closed, a condition for electric flow
[7] role of battery with relation to electrons

Physical components, such as wires, bulb and battery, are the basis for enabling an explanation; *Output* of the system combines between two knowledge elements: brightness of bulb and physical components; *Macro-level* refers to reasoning at the macro level by using knowledge elements such as current, current direction and current strength; *Micro-level* illustrates reasoning at the micro level by relying on knowledge elements such as electrons, electron's motion, electrons direction; *Dynamic* refers to representing system in a dynamic manner such as the current flow and motion of the electrons; *System-wide constraint* refers to noting whether or not the circuit is closed, a condition for electric flow; *Input* focuses on the battery that requires a more advanced mechanistic understanding of the system, in particular, the role of battery with relation to electrons. Table 4 presents examples from the students' answers that express these five mental models.

Table 4. Examples for answers that are representative for each cluster.

Mental model	**Examples of students' statements in each mental model.**
Cluster 1: **Components**	- Bulb c will illuminate most strongly because the distance between the battery and the bulb is the shortest. - The Bulb will illuminate in system A because wires are connected from both sides of the battery.
Cluster 2: **Components-Macro**	- The bulb consumes electricity when it operates, therefore the current decreases. - The currents coming out of both sides of a battery will be the same. - Bulb C will illuminate at its maximum intensity because it is closest to the battery.
Cluster 3: **Components-Micro**	- Electrons move from the battery to the bulb and they turn on the bulb. - The electrons move from the switch to the battery. Therefore the largest number of electrons will reach bulb C and it will shine most strongly… then the electrons will reach bulb B, it will light up moderately… after that the electrons will reach bulb A, and it will light the weakest.
Cluster 4: **Components-Macro-Micro-Partial**	- The current strength doesn't change in both directions [of the battery]. - The electrons are in the conductors and the battery's role is to "push" the electrons. - The circuit is a closed circuit, the current remains constant, ... Bulb C will shine stronger because this bulb is closer to the battery, other bulbs are closer to the switch.
Cluster 5 **Components-Macro-Micro-full**	- The current is constant within the circuit and the electrons are moving with the same motion ... the electrons in the electric circuit are moving in the same direction. - The current strength does not change because the number of electrons is the same... The three bulbs shine with the same intensity because there is the same number of protons and electrons and so the current is conserved. - There are electrons in the conductor wire and the battery just conducts a current that causes the electrons to move in one direction and not randomly as it does without a battery .... The bulbs shine with the same intensity because there are the same number of electrons and protons in the electrical circuit causing the same electric current flows.

Changes in cluster distribution from pre- to post-test are presented in Figure 4. Pretest results show that most of the students have the two basic mental models: Components and the Components-Macro. Post-test results show that most of the students transition from the first two mental models to the more sophisticated models: Components-Macro-Micro-Partial and Components-Macro-Micro-full.

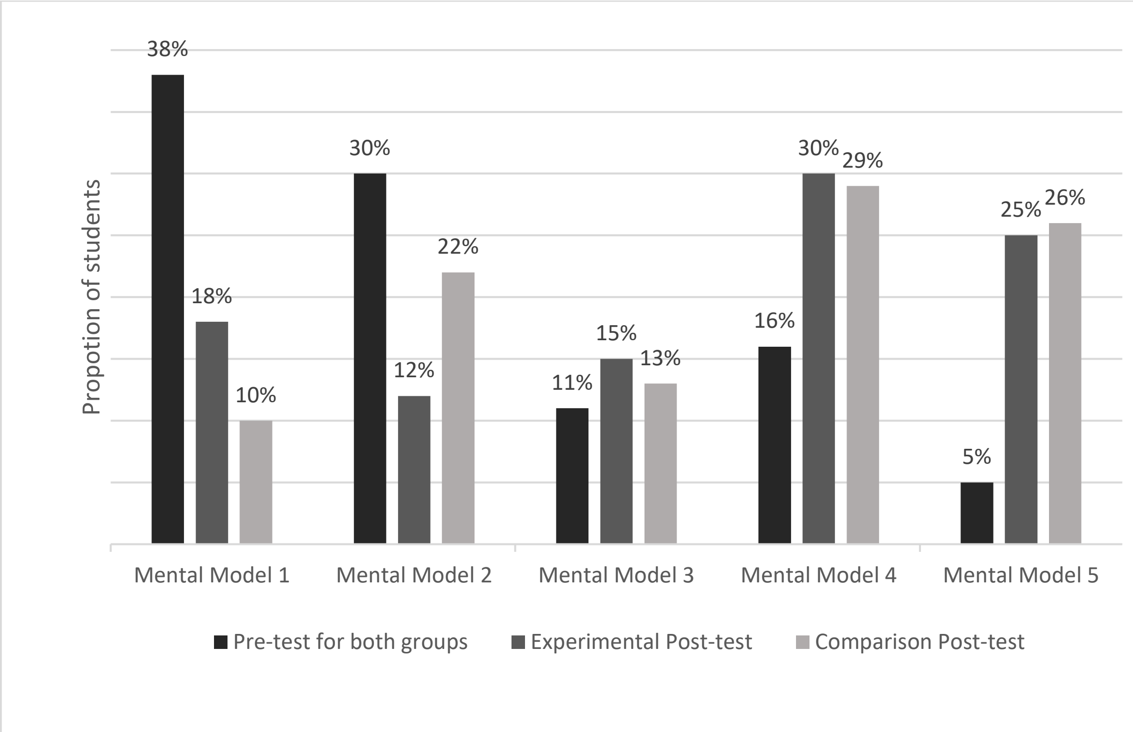


Figure 4. Changes in mental models based on pre- and post-test questionnaires (N=56). Mental Model 1: Components; Mental Model 2: Components- Macro; Mental Model 3: Components-Micro; Mental Model 4: Components –Micro-Macro- Partial; Mental Model 5: Components-Micro-Macro-Full.

Comparing the magnitude of mental model transitioning across the two groups, shows a significant transition magnitude for the experimental group between pre- and post-testing compared to the comparison group. Figure 8 shows that 67% of the experimental group expressed simpler mental models in the pre-test; In the post-test, they improved in their conceptual understanding and expressed more sophisticated mental models (shades of grey cells). However, the comparison group displays a different pattern than the experimental group in the pretest; Rather than expressing only simpler mental models, the students hold a variety of mental models covering the entire range of models; 48% of the students expressed more sophisticated models from pre to post-test (shades of grey cells). In addition, 30% of students in the experimental group retained the same mental model in the post-test (light grey cells) and 3% regressed (black cells).compared with the comparison group, 43% remained in the same cluster (dark grey cells), and 9% regress in their mental modeling (orange cells).

Another interesting result is that 48% of the students, from the experimental group, held the simpler mental models at pre testing (mental model 1 and Mental Model 2) and they advanced to more sophisticated mental models (Mental Model 3, Mental Model 4, and Mental Model 5) in post testing; within the comparison group, only 26% of the students held the simpler mental models at pre testing (Mental Model 1 and Mental Model 2) and they advanced to more sophisticated mental models (Mental Model 3, Mental Model 4,) in post testing

Post-test Mental models			Pre-test Mental models				
			Mental Model 1	Mental Model 2	Mental Model 3	Mental Model 4	Mental Model 5
	Experimental group	Mental Model 1	5	1			
		Mental Model 2	2	2			
		Mental Model 3	3	1	1		
		Mental Model 4	4	2	2	2	
		Mental Model 5	3	3	1	1	
	Comparison group	Mental Model 1	1	1			
		Mental Model 2	2	2		1	
		Mental Model 3		3			
		Mental Model 4	1	2		4	
		Mental Model 5			2	1	3

	Student who regressed one mental model.
	Students who rely on the same mental model.
	Students who advanced one mental model.
	Students who advanced two mental models.
	Students who advanced three mental models.
	Students who advanced four mental models.

Figure 5. Transitions in students' mental models for the experimental and comparison groups, the number in each cell represents the number of students who transitioned from Mental Model i (i=1,2,3,4,5) in the pre-test to Mental Model j (j=1,2,3,4,5) in the post – test. Mental Model 1: Components; Mental Model 2: Components – Macro; Mental Model 3: Components-Micro; Mental Model 4: Components – Micro-Macro – Partial; Mental Model 5: Components- Micro-Macro-Full.

Classifying the five mental models according to alternative mental models mentioned in the literature.

The data was re-analyzed with respect to macro-level alternative mental models from the literature. Manifestations of the unipolar model and sharing model were rare in our sample and were not included in this analysis. Figure 6 illustrates the decrease in expression of both the attenuation model and clashing currents model from pretest to posttest. Decrease is more marked for the experimental group; however, this may be due to a higher proportion of students in the group originally holding these alternative models in the pretest. Nevertheless, it is important to notice that students in the experimental group did not all relinquish these alternative currents model. It would have been interesting to analyze these results with respect to the approach presented in this paper of mental models of electrical systems by knowledge components. Unfortunately, the actual numbers of students holding these models is too small for a quantitative analysis.

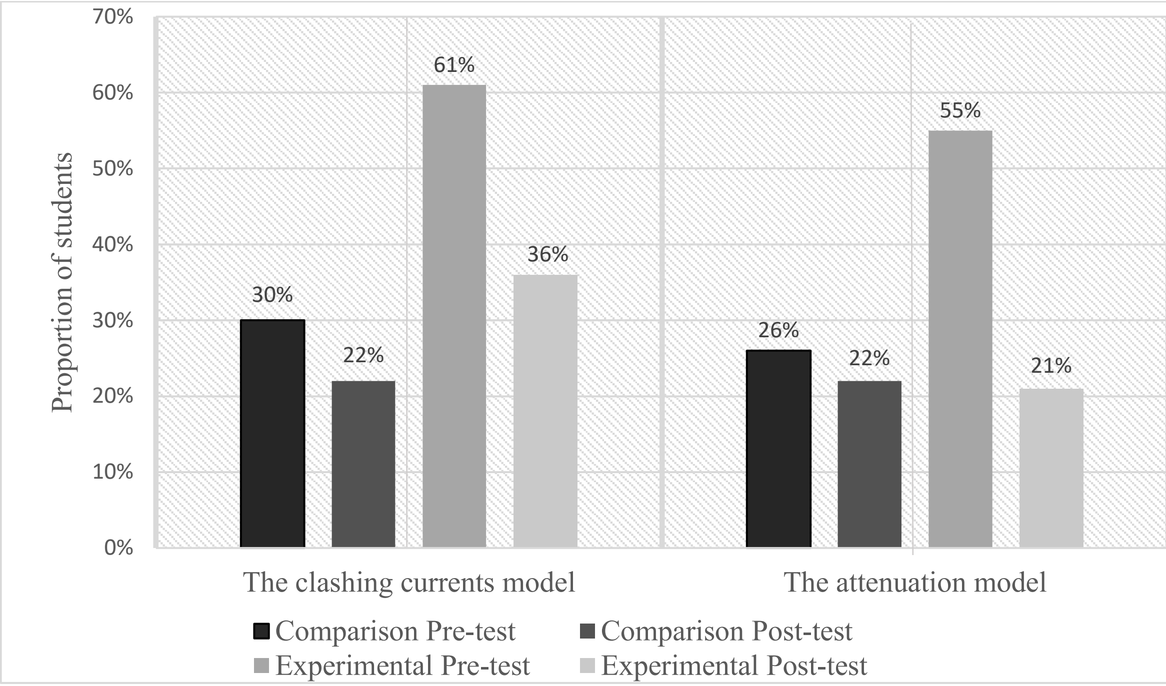


Figure 6. Proportion of student responses that reflect one of the two standard mental models – the clashing currents model (left) and the attenuation model (right), before and after the learning unit.

Scholarly significance

Our findings show that constructing and exploring particle-level computational models is beneficial for interpreting concepts at the macro-level and promotes more sophisticated explanations of the behavior of electric circuits. These findings were corroborated by the cluster analysis that revealed five, distinct clusters of answer that differ across several features: the balance between physical macro-level components and micro-level descriptions and the degree of integration between the micro and macro levels. We found that students in the experimental group, advanced from low-level Mental Models to high-level Mental Models, more than their counterparts in the comparison group. A surprising finding was the prevalence of the macro-level "clashing currents" mental model even among students who expressed sophisticated micro-macro connections. These students might have assimilated the observations of moving electrons in the computational model, to a macro-level model in which two currents flow to the light bulb from each direction of the battery. We believe this unexpected result reflects an over-emphasis on the particle-level in the construction of *the section* of a wire (see figure 1) without explicating its relation to the complete circuit.

To conclude, our study shows that constructing particle/micro-level models of electric conductors, advances micro/particle-level conceptualization of the electric circuit, and does not diminish its overall macro-level understanding. In addition, the cluster analysis is an important methodological advancement compared to prior studies (e.g., Wagh & Wilensky, 2018) that examined individual responses without an integrated approach that combines all of the knowledge elements expressed by each student. Finally, the prevalence of the flawed, "clashing currents" model after instruction, indicates that mental-models formed while interacting with computational models do not necessarily change misconceived mental models. Perhaps, particle-level models can be supplemented by interacting with platforms such as Phet (Roll et al., 2018) that show the flow direction of the current in a macro-level circuit to conceptually relate the particle-level model to the macro-level one.

References

Chi, M. T.H., Feltovic, P. J. and Glaser, R. (1981) Categorization and representation of physics problems by experts and novices. *Cognitive Science*, 5, 121–152.

Cohen, R., Eylon, B., & Ganiel, U. (1983). Potential difference and current in simple electric circuits: A study of students' concepts. *American Journal of Physics*, *51*(5), 407–412.

De Kleer, J., & Brown, J. S. (1983). Assumptions and ambiguities in mechanistic mental models. In D. Gentner & A. L. Stevens (Eds.), Mental Models (pp. 163–198). New York and London: Lawrence Erlbaum Associates & Psychology Press.

Duit, R., & von Rhöneck, C. (1997). Learning and understanding key concepts of Electricity. *Connecting research in physics education with teacher education*, 1-6.

Eylon, B. S., & Ganiel, U. (1990). Macro-micro relationships: the missing link between electrostatics and electrodynamics in students' reasoning. *International Journal of Science Education*, *12*(1), 79–94.

Frederiksen, J. R., White, B. Y., & Gutwill, J. (1999). Dynamic mental models in learning science: The importance of constructing derivational linkages among models. *Journal of Research in Science Teaching*, *36*(7), 806-836.

Greca, I. M., & Moreira, M. A. (2000). Mental models, conceptual models, and modelling. *International journal of science education*, *22*(1), 1–11.

Harrison, A. G., & Treagust, D. F. (1996). Secondary students' mental models of atoms and molecules: Implications for teaching chemistry. *Science education*, *80*(5), 509–534.

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

Reiner, M., Slotta, J. D., Chi, M. T., & Resnick, L. B. (2000). Naive physics reasoning: A commitment to substance-based conceptions. *Cognition and instruction*, *18*(1), 1–34.

Norman, D. A. (1983). Some observations on mental models. Mental Models, 7(112), 7–14.

Roll, I., Butler, D., Yee, N., Welsh, A., Perez, S., Briseno, A., & Bonn, D. (2018). Understanding the impact of guiding inquiry: The relationship between directive support, student attributes, and transfer of knowledge, attitudes, and behaviors in inquiry learning. *Instructional Science*, *46*(1), 77-104.

Saba, J., Hel-Or, H., & Levy, S. T. Under review.

Bar-Yam, Y. (1997). *Dynamics of complex systems.* Reading, MA: Addison-Wesley.

Sengupta, P., & Wilensky, U. (2009). Learning Electricity with NIELS: thinking with electrons and thinking in levels. *International Journal of Computers for Mathematical Learning*, 14(1), 21–50.

Sherin, B., diSessa, A., & Hammer, D. (1993). Dynaturtle revisited: Learning physics through collaborative design of a computer model. Interactive Learning Environments, 3(2), 91–118.

Sherin, B. (2013). A computational study of commonsense science: An exploration in the automated analysis of clinical interview data. Journal of the Learning Sciences, 22(4), 600–638.

Shipstone, D. (1985). Electricity in Simple circuit. In Driver, R. (Eds.), Children's ideas in science (pp. 33-51). McGraw-Hill Education (UK).

Stains, M., & Sevian, H. (2015). Uncovering implicit assumptions: A large-scale study on students' mental models of diffusion. Research in Science Education, 45(6), 807–840.

Tarciso Borges, A., & Gilbert, J. K. (1999). Mental models of electricity. *International Journal of Science Education*, *21*(1), 95–117.

Taylor, I., Barker, M., & Jones, A. (2003). Promoting mental model building in astronomy education. *International Journal of Science Education*, *25*(10), 1205–1225.

Wagh, A., & Wilensky, U. (2018). EvoBuild: A Quickstart Toolkit for Programming Agent-Based Models of Evolutionary Processes. *Journal of Science Education and Technology*, *27*(2), 131-146.

Wilensky, U. (1999a). GasLab: An extensible modeling toolkit for exploring micro- and macro-views of gases. In Feurzig, W., and Roberts, N. (Eds.), *Modeling and simulation in science and mathematics education*, Springer, New York, pp. 151–178.

Wilensky U. (1999b) NetLogo. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston. http://ccl.northwestern.edu/netlogo.

Zacharia, Z. C. (2007). Comparing and combining real and virtual experimentation: an effort to enhance students' conceptual understanding of electric circuits. *Journal of Computer Assisted Learning*, *23*(2), 120-132