TYPE Original Research
PUBLISHED 25 April 2023
DOI 10.3389/feduc.2023.1137828

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RECEIVED 04 January 2023
ACCEPTED 07 April 2023
PUBLISHED 25 April 2023

CITATION
Langbeheim E, Ben-Hamo S, Weintraub G and Shapira S (2023) Reasoning about crowd evacuations as emergent phenomena when using participatory computational models. *Front. Educ.* 8:1137828.
doi: 10.3389/feduc.2023.1137828

Reasoning about crowd evacuations as emergent phenomena when using participatory computational models

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How do students apply systems thinking to make sense of a computational model of crowd evacuation? We developed a participatory simulation in which users play the role of evacuees that move through a narrow passageway. This simulation demonstrates that when exceeding a certain speed, moving through narrow bottlenecks, is more likely to create clogs, leading to a slower passing rate. The participatory simulation was introduced in a lesson about school evacuation in a group of 9th graders. Their explanations of crowd evacuation, were compared to a similar group of 9th graders who learned the same ideas in a lecture without using the simulation. We found that using the simulation did not improve students' system thinking about crowd evacuation compared to lecture-based instruction. About 80% of the students in both groups suggested partial/incomplete explanations of the inverse relationship between the desire to move faster as individuals and the opposite consequence of slower evacuation. Interviews with students revealed that some of them perceived the simulation scenario to be different from the organized and coordinated evacuation drills that they partook. Others, were engrossed in their own experiences as evacuees, that obscured their ability to relate the motion of individual evacuees and the overall evacuation rate of the crowd. In a second study, we examined whether prior learning of a different emergent process (spread of a disease) with a computational model, can prepare students for learning the counterintuitive phenomenon of crowd evacuation. We found that introducing a participatory simulation of the spread of a disease in a different group of 9th graders, increased their appreciation of the evacuation simulation as a learning tool, and consequently– their explanations. We conclude that computational models have the potential to enhance systems thinking, but their affordances depend on prior preparation for learning with other complex systems models.

KEYWORDS

systems thinking, computational models, participatory simulations, agent-based models, crowd evacuation

10.3389/feduc.2023.1137828

1. Introduction

Clogging appears when a large group of people moves too fast through a narrow opening. When individuals race towards the opening to save themselves, they can stumble and collide with others, thereby slowing the average evacuation rate, and increase the risk of injury and even death (Shapira et al., 2018; Zhou et al., 2018). One known example of the deadly materialization of such a threat occurred during The Station Nightclub fire in Rhode Island, United States, in February 2003. The rush of the crowd towards the club's exits and the subsequent congestion resulted in the death of 100 people and the injury of nearly 200 other people (Aguirre et al., 2011). The "faster-is-slower" phenomenon refers to situations in which the desire to move faster, creates a congestion, as shown in laboratory experiments in which higher individual efforts to evacuate, decreased the average evacuation rate of the crowd (e.g., Hoogendoorn and Daamen, 2005; Garcimartín et al., 2016). Similarly, simulations of pedestrian evacuation calculate the trajectories and motion of computationally driven particles and reveal the onset of clogging (Helbing et al., 2000). These computational models of crowd evacuation allow users to determine variables such as the 'desired' speed of the computational agents, their density and their size in relation to the narrow opening, and to examine the influence of these variables on the actual passing rate. For example, the simulation in Figure 1 shows an evacuation scenario through a narrow opening at the bottom of the two yellow walls, and a graph showing the number of passages vs. time. A temporary clog is a period of time in which no agent moves through the passageway, and is represented by the flat section of the graph indicated by the arrow.

In order to observe the faster-is-slower effect, one needs to run the simulation several times, to produce a series of graphs that resembles the one shown in Figure 2. These graphs reveal that as the desired speed increases from 0.4 to 0.7–so does the number of people who pass through the bottleneck. However, when exceeding the speed of 0.7 (orange curve)–the overall number of people who pass through the bottleneck–decreases, as shown by the lower number of overall passes of the red curve. This means that the overall passing rate through the bottleneck has a critical value or a tipping-point (at a given crowd density and passage width) below the desired speed of 0.7. Raising the speed towards the opening is likely to increase to faster passing rate, but above that speed – the average passing rate decreases. The reason for this decrease, is the increase in the occurrence of temporary clogging events.

Clogging in bottlenecks is a universal phenomenon that appears in human crowds, herds of sheep, and even granular materials (Zuriguel et al., 2014), all of which, are complex systems. Complex systems are ubiquitous to science education, and the "emergence" of patterns such as the abovementioned faster-is-slower phenomenon, is a paradigmatic aspect of their behavior (National Research Council, 2012). Emergent processes in complex systems can be described from two complementary perspectives: using aggregate or *system dynamics* models, and using *agent-based models* (Stroup and Wilensky, 2014). *System dynamics* models relate changes in macro-level properties of the system such as stocks or flows, to changes in the behavior of other variables of the systems or the environment. For example, the SIR (Susceptible, Infected, Recovered) model of the spread of a disease, relates the rate of infection (new cases per day) to the ratio of sick to healthy individuals in the population (Meyer and Lima, 2022). An agent-based model of the same phenomenon, describes it as an accumulation of individual agent interactions. The model is composed of agents that move in a random-walk pattern, and if they encounter nearby "sick" agents, they may become infected (Stroup and Wilensky, 2014). The agent-based disease model, is usually realized as a computer simulation with a random-walk algorithm, and a procedure that calculates the infected agents at each time step. Such models show that emergent patterns, are rooted in random events and interactions and lack central control–i.e., the overall behavior of the system cannot be attributed to a single agent or entity (Chi et al., 2012). Agent-based models are therefore important bridges between modeling and systems thinking – the subject of this special issue and our paper highlights their implementation for learning about crowd evacuation through bottlenecks.

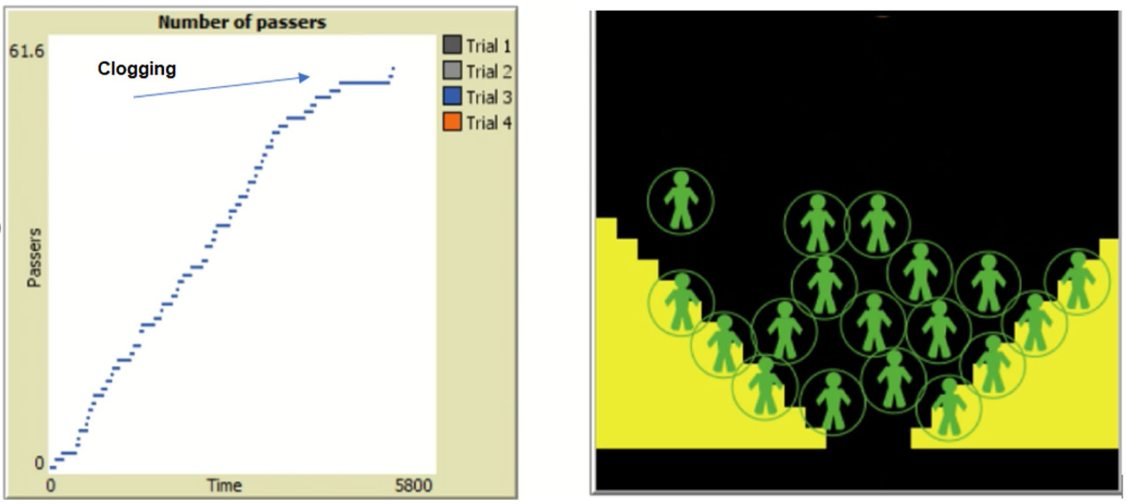

FIGURE 1
A bottleneck simulation in which a crowd moves towards a narrow passage at the bottom of the screen (right). The blue graph (left) shows the number of people that pass through the opening vs. time. The horizontal section marked by the arrow, represents temporary clogging.

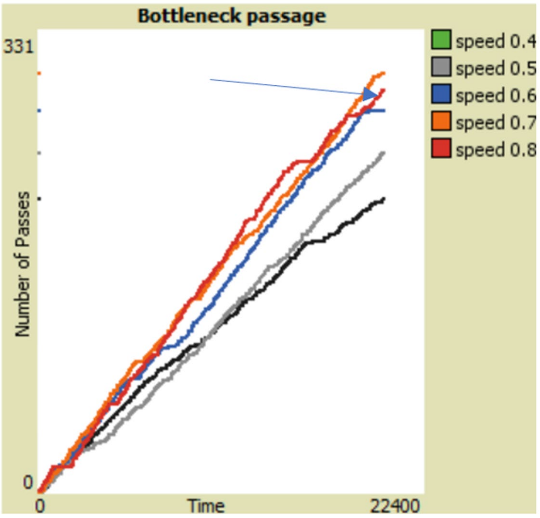

FIGURE 2
A graph showing the faster-is-slower effect to the number of passes increase with speed from 0.4 to 0.7, but then it decreases for 0.8. The arrow shows that the number of passes is lower for the red curve, than for the orange curve.

The two complementary models of emergent processes, reflect two possible learning goals for students, in terms of scientific systems thinking. One form of systems thinking is realized in macro-level *system dynamics* explanations that focus on the causal relationships between variables, rate of changes in the processes, and cyclic, feedback loops (Batzri et al., 2015). Such forms of systems thinking are common in earth science processes such as the water cycle (Lee et al., 2019) or the carbon cycle (Batzri et al., 2015), that are described as a sequence of steps or events. The other form of systems thinking reflects explanations that construe the macro-level properties of the system from the motion and interactions between its constituent-entities that are called agents. In systems composed of few types of agents, and emergent processes that cannot be broken down into a sequence of sub-processes, students are expected to link the agent-level to the macro-level, either by creating a "midlevel" – a small subset of agents (Levy and Wilensky, 2008) or by showing how summing/averaging the properties of the agents, produces the macroscopic state of the system (Chi et al., 2012).

The latter method of averaging or summing, brings to mind an important aspect of systems thinking: it often entails quantitative explanations and predictions. Let us consider the following explanation for the faster-is-slower effect: "clogs form in a bottleneck and their onset is attributed to collisions between people and walls. The probability of these collisions increases, when people move faster. Therefore, moving faster can result in more frequent clogging events, and an overall slower flow through the bottleneck." Verbal explanation include quantitative terms such as "probability," "increases" and "faster" but quantitative systems thinking often also requires students to interpret patterns in graphs, and critical values at which the system undergoes a drastic change. For students to develop quantitative systems thinking, learning requires an underlying mathematical or computational model (e.g., Helbing et al., 2000). In light of these considerations, this study focuses on the following question: what aspects of systems thinking do students develop when exploring computational models of crowd evacuation through bottlenecks?

2. Using computational models to explain emergent processes

Computational models are central pedagogical tools for fostering student systems thinking. Computational models such as SageModeler (Damelin et al., 2017) or InsightMaker (Fortmann-Roe, 2014) illustrate the system dynamics model perspective, while agent-based environments such as Net Logo (Wilensky, 1999) illustrate the agent-based model perspective. Students' engagement with computational models can be further divided into activities in which students construct and revise models on their own (Wilensky and Reisman, 2006; Tullis and Goldstone, 2017), and others in which they use readymade models (Chi et al., 2012; Xiang et al., 2022). Building computational models using SageModeler has been shown to boost systems thinking of the system dynamics type (Nguyen and Santagata, 2021), and NetLogo has been shown to enhance the second, agent-based type of systems thinking (Saba et al., 2022), when compared to traditional instruction.

Among computational models, participatory simulations are particularly effective for building conceptual connections between agent-level interactions and observed emergent processes such as the vaporization of liquids (Langbeheim and Levy, 2019). In participatory simulations, users play the role of an agent in the system, and observe the macro-level pattern, that emerges from their interactions with other agents. Role playing in participatory simulations raises attention to the agent-based interactions, and the playful game-like format, promotes enjoyment. Enhanced engagement, partially explains the affordances of participatory simulations when compared to regular non-participatory simulations (Langbeheim and Levy, 2019).

Computer simulations are helpful for cultivating systems thinking because they ground abstract system ideas in concrete visual representations (Goldstone and Wilensky, 2008). Participatory simulations can further concretize ideas, by providing embodied interaction (Langbeheim and Levy, 2019). However, some of the system-related concepts are not only abstract, they are also counterintuitive, and hinder the ability to explain complex systems mechanisms, even with the utility of computational models. Science education researchers suggested two main conjectures, or approaches to the difficulty of comprehending and explaining emergent processes in complex systems. The first, "soft" approach identifies the main difficulty in connecting the macro-level and the micro/agent-level (Wilensky and Resnick, 1999). This approach claims that the challenging reputation of complex systems originates from intricacies of the agent-based models that do not lend themselves to a clear explanation. This leads to messy descriptions of the micro and macro levels and to inter-level "slippage"–i.e., carrying attributes of the individual agents over to the emergent macro-level pattern. The second, "intractable" approach, relates the difficulties to a clash between the *decentralized* mechanism of the system and the centralized "mindset" of the students (Resnick, 1996). According to Resnick (1996), a mindset is a biased worldview, which, in our case, is an inclination to interpret processes as controlled by a supervising authority. Put slightly differently, there is a clash between the ontology of agent-based models of emergent processes, that is rooted in an indirect causality, and the way people usually view these processes: as sequential or direct (Chi et al., 2012; Henderson et al., 2017). This "clash" between the direct causal mindset or personal ontology, and the actual complex decentralized mechanism of agent-based models, prevents students from perceiving the complexity of emergent processes that are depicted in computer simulations.

The two approaches regarding the source of difficulty of comprehending complexity, give rise to two educational "remedies." The first "soft" approach, focuses on scaffolding the computational explorations with discussions or worksheets that are aimed at eliciting the connections between the micro/agent level behavior and macro level one (e.g., Chang and Linn, 2013; Li and Black, 2016; Samon and Levy, 2017). The second, "intractable" approach focuses on preparing students to "overcome" the decentralized/sequential mindsets, by providing ontological trainings that distinguish and contrast explanations of emergent/decentralized processes and explanations based on direct/centralized causation (Slotta and Chi, 2006; Chi et al., 2012). These trainings provide examples of emergent processes and discuss their invariant attributes, as a preparation for future learning (PFL) about similar systems and processes (Bransford and Schwartz, 1999; Goldstone and Wilensky, 2008). Ontological trainings were successful for fostering systems reasoning about complex systems of particles such as electrons in a conductor (Slotta and Chi, 2006) or dye molecules in a process of diffusion (Chi et al., 2012). However, the decentralized control of systems composed of particles, may be easier to comprehend than human-based systems such as an evacuating crowd. In these cases, it is more likely to perceive the system as controlled by individual, "leader" agents, and not by random events. We therefore set to examine how using computational participatory simulations of evacuation through a bottleneck, influenced students' systems thinking, and specifically, their understanding of the "faster-is-slower" phenomenon. The paper describes two studies: the first study examines students' development of complex systems thinking in light of their perceptions of the computational model vis-à-vis the actual dangerous phenomenon of clogging during evacuation. In the second study, we examine the differences in learning about the faster-is-slower effect, after an ontological training experience with a different participatory simulation of the spread of a disease.

3. Methods

In the first study, students used a "bottleneck" participatory simulation programmed with Netlogo (Wilensky, 1999) to learn about the hazards of evacuation, and specifically, the "faster-is-slower" effect. The goal of the participating agent in this simulation is to pass through a narrow opening as fast as possible, while avoiding "hitting" the other agents that try to evacuate as shown in Figure 3. After initial attempts with the simulation, students were instructed to increase the desired speed of the agents, and to realize that when the desired speed of the agents moving towards the bottleneck increases – the likelihood of temporary clogs also increases, and so the average passing rate – decreases.

We examined student learning using a quasi-experimental research design, assigning classrooms to two conditions: The experimental group entailed two 9th grade classrooms ($N=26$) from all-girls schools in the south of Israel. These classrooms were introduced to the phenomenon of emergency indoor evacuation with a powerpoint presentation, and then used the participatory simulation to investigate the conceptual connections between their motion and the overall passing rate. Another 9th grade all-girl classroom ($N=16$) served as a comparison condition. This classroom learned about clogging and the faster-is-slower phenomenon in a traditional lecture-based lesson using a powerpoint presentation that included snapshots and animation of the computer simulation, as shown in Figure 4.

The comparison group did not use the participatory simulation, but spent more time discussing the behaviors that can prevent clogging and congestion. At the end of the lesson, students in both groups responded to a conceptual knowledge questionnaire. The questionnaire was a modified and independently validated version of the instrument used by Schwartz et al. (2014) to assess knowledge, attitudes, and perceptions related to emergency scenarios. The questionnaire was piloted with twenty-one 8th-grade students and refined to the final version which included multiple choice and open-ended questions related to appropriate behavior during an indoor emergency evacuation, and understanding of the "faster-is-slower" phenomenon. The full questionnaire can be found in the appendix. In addition, the questionnaire included three rating items regarding their experience with the simulation.

Three students from the experimental group were chosen based on their performances on the questionnaire and were interviewed about their experience with the simulation. One of the interviewees was high-performing student, and two were intermediate. In these semi-structured interviews, we aimed at gaining some insight into students' reasoning about the mechanism of crowd evacuation. For example, we asked them, whether they as individuals can influence the evacuation of the entire class and how they perceive the relation between the simulation and an actual evacuation scenario.

Study 2, was conducted with a third group of 9th grade students ($N=17$) from a different school in the same urban area, that included boys and girls. The group learned about disease spread model before learning the model of crowd evacuation. The students explored the agent-based model of disease spread using the "Disease solo" participatory simulation (Wilensky, 2005), as ontological training for learning about crowd evacuation. In the disease simulation, shown in Figure 5, users can move one of the agents in a system with 100 agents that move randomly. At initialization, an agent chosen at random is infected, and the virus spreads (with a certain probability) every time infected agents come into contact with "healthy" ones. The overall phenomenon is represented by the logistic curve of the number of infected individuals, The study was conducted during a temporary school shutdown due to Covid-19.

Two 90-min lessons about disease spread were taught by the 3rd author. The students first reviewed real Covid-19 infection and mortality data, and were then introduced to the agent-based model and discussed the simplifications that were used to construct it. Next, they downloaded the model and used the "setup" and "Go" buttons to run it. They were instructed to try to move and to prevent their agent from getting infected as long as they could, and competed against each other. They explored the model further by changing the infection chance, and other features that are shown the panel in Figure 5, and ran the model again. Then, they were given a worksheet with conceptual questions about the model, and specifically, the effect of various parameters such as the density of the agents or the chance of transmitting the virus, on the infection curve.

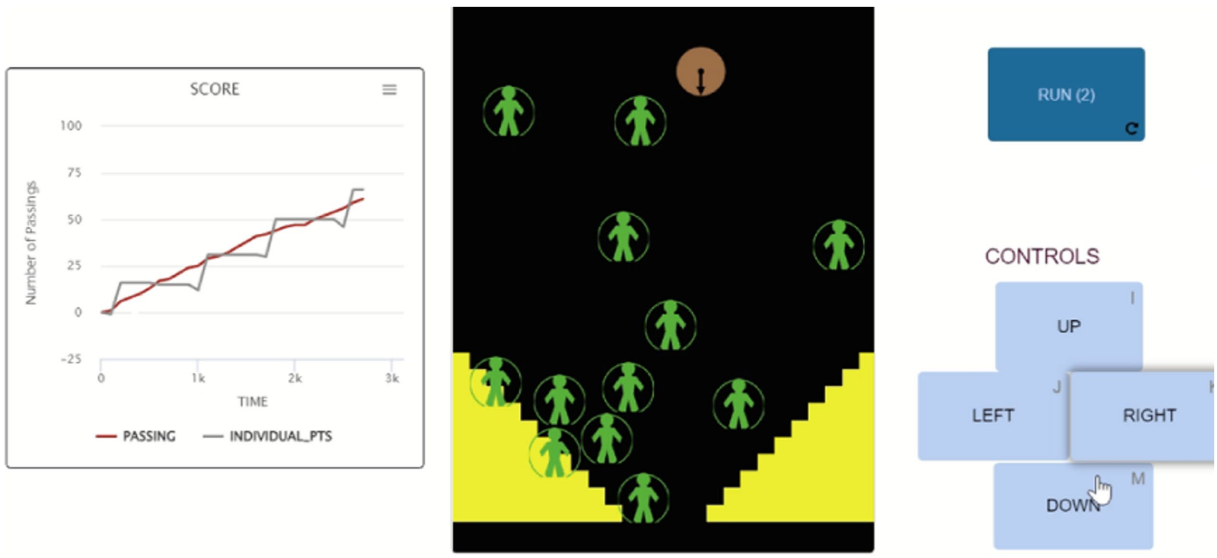

FIGURE 3
the participatory simulation of evacuation through a bottleneck: The brown circle is controlled by the user with the up-down-left–right control keys (right). The graph (left) shows the points gained by the user (20 point for each successful pass, minus one point taken away by each collision) in the gray curve, and the overall passing rate in the red curve.

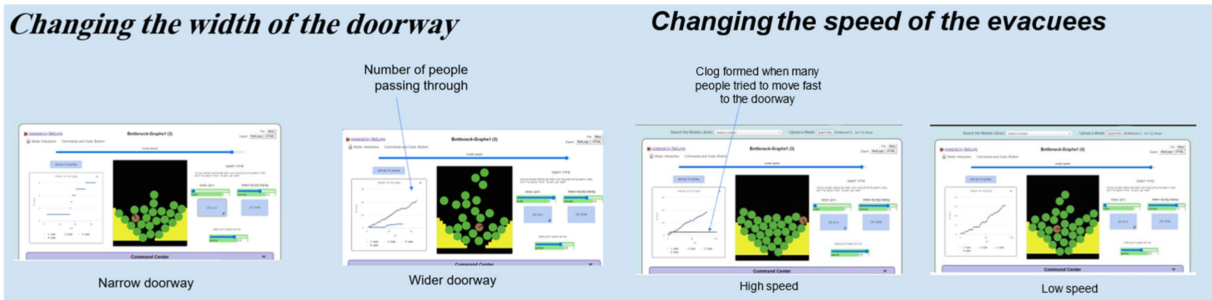

FIGURE 4
Two slides from the presentation shown to both groups, that shows the bottleneck simulation: the width of the doorway (left) and the influence of speed (right) on the passing rate.

In a third, subsequent lesson, this ontological training group learned about the bottleneck phenomenon with the same teacher (the 2nd author), and the same participatory simulation and powerpoint presentation that was used in study 1. Seven slides that compared and contrasted the disease and bottleneck models as two examples of complex systems that yield emergent phenomena were added to the presentation. Some of the slides are shown in Figure 6. The lesson ended with the same conceptual and attitudinal questionnaire that was used in study 1 (see Appendix). The averages of the ontological trainings group, were compared to the experimental classrooms from study 1 ($N = 26$), who learned about the faster-is-slower phenomenon using the participatory simulation (but without using the disease simulation and learning about behavior of complex systems beforehand). Two attitudinal questions were added to assess how students perceived the contribution of the disease simulation and the complex systems framing, to learning the bottleneck model and the faster-is-slower effect.

3.1. Data analysis

Written responses to the open-ended questions were scored based on the level of complex systems thinking that students expressed. As in Rates et al. (2022), we identified explanations that reflect "expert" level complex systems-thinking that view macro-level phenomena as emerging from agent-level interactions. "Intermediate" level explanations, misinterpreted agent-level interactions, and novice-level ones lacked a clear mechanism. For example, responses to question 8–"During a schoolwide assembly in the gym, an emergency warning was announced and students were asked to evacuate themselves from the building into an open outside area. How should they proceed with the evacuation?," that related the interactions at the agent level to the overall evacuation rate, or mentioned the formation of clogs, were identified as "full" or "expert" and received 2 points. Explanations that merely stated that moving too fast causes a slower passing rate or mentioned the faster-is-slower effect as related to the average speed of the evacuees, without a clear micro–macro connection, reflect an

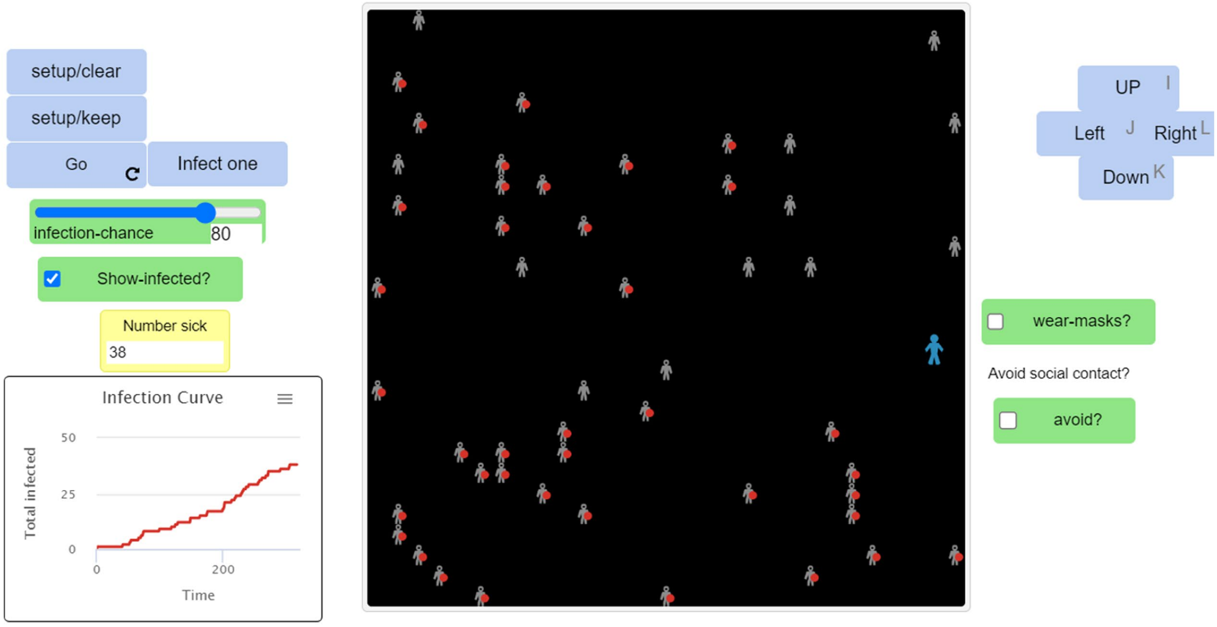

FIGURE 5
The adapted "Disease solo" participatory simulation. The user controls the blue agent. Agents with red dots are "infected" and those without are "healthy." The graph shows the number of infected agents vs. time.

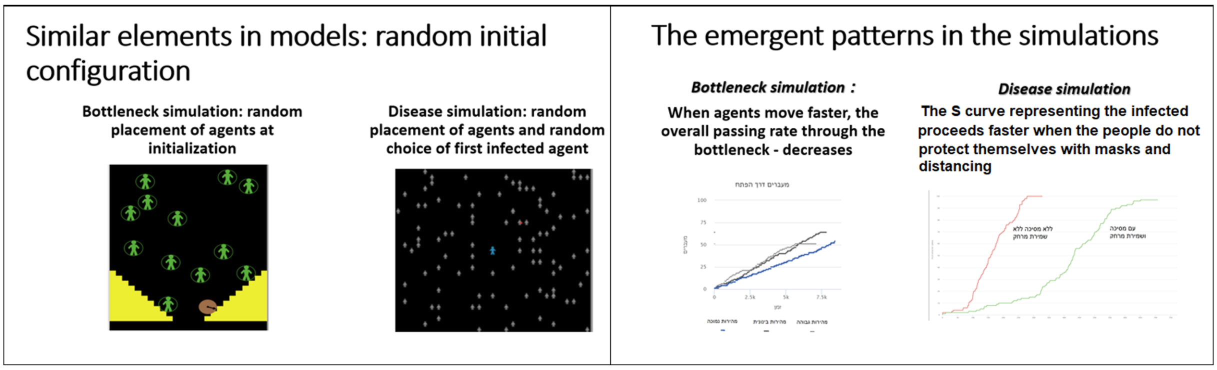

FIGURE 6
Slides presented after interacting with both the disease and the bottleneck simulations. The left slide mentions the random setup of both systems and right slide presents how parameters influence the emergent pattern in each simulation, as represented by the graphs of the overall passers through the bottleneck and the overall infected individuals.

"intermediate" level systems thinking. The intermediate level responses, were given 1 point, whereas responses that did not mention the danger of moving too fast were given a score of 0. Table 1 shows the scoring rubric for this question. Student explanations were coded separately by the 1st and 2nd authors. Each one coded ten explanations separately, then compared their coding and discussed coding discrepancies until consensus was reached and rubrics were clarified.

We performed reliability analyzes for both the knowledge scale and the appreciation of the simulation scale. The internal consistency of the latter scale ($\alpha = 0.71$) was based on the experimental group students from study 1 and the students from study 2 ($N = 43$), and the internal consistency of the of the conceptual questions ($\alpha = 0.65$) was based on all students in both studies ($N = 59$).

The interviews were transcribed and open-coded, to identify the main themes (Charmaz, 2006). The codes were used to characterize the students' mindsets and to gain an in-depth understanding of the mechanism through which the simulation contributed (or not) to students' comprehension of the "faster-is-slower" phenomenon. Finally, interview excerpts were triangulated with the students' responses in the conceptual questionnaire.

4. Findings

The first objective of study 1, was to evaluate the affordances of the participatory simulation for learning about evacuation and the faster-is-slower phenomenon. We found that the difference between the

TABLE 1 Categorization and scoring of student answers for question 8.

Category(score)	Description	Example
Novice (0)	Responses that do not mention the danger of moving too fast, or that lack a clear mechanism	*"They should evacuate quickly and responsibly so that no one would get hurt"*
Intermediate (1)	Addressing the faster-is-slower effect by suggesting to move at a uniform moderate pace, but without reference to collisions or the formation of clogs	*"They should leave the classroom at a uniform pace, move fast, but not too fast"*
Full/Expert (2)	Addressing the faster-is-slower effect by suggesting that the motion of individuals should be adjusted to the motion of those around them to prevent collisions and clogs	*"They should evacuate not by running, but by walking quickly and keeping safe distances, to prevent collisions and clogs"*

TABLE 2 Descriptive statistics of the groups in study 1 and study 2.

	Study 1			Study 2	
Group	Control (N=16)	Experiment (N=26)	Sig. difference	Ontological training (N=17)	Sig. difference exp. group study 1
Conceptual overall – pct correct	63%	61%	$t = (-0.37)$, $p = 0.717$	69%	$t = 1.45$, $p = 0.16$
Item 1 (faster-is-slower)	8/16	21/26	χ^2=4.39, $p = 0.036$**	13/17	χ^2=0.11, $p = 0.73$
Item 2 (release of clogs)	1.50	1.42	$U = 186$, $p = 0.575$	1.75	$U = 153$, $p = 0.16$
Item 3 (true/false)	5.25	5.04	$U = 161$, $p = 0.23$	5.06	$U = 196.5$, $p = 0.78$
Item 4 (moving out the fastest)	11/16	12/26	χ^2=2.04, $p = 0.15$	4/17	χ^2=2.25, $p = 0.13$
Item 5 (mark the most correct)	4/16	15/26	χ^2=1.88 $p = 0.17$	12/17	χ^2=2.49, $p = 0.11$
Item 6 (open-ended)	0.94	0.77	$U = 176$, $p = 0.41$	1.23	$U = 133$, $p = 0.03$ **
Item 7 (tipping point)	3/16	5/26	χ^2=0.002, $p = 0.97$	6/17	χ^2=1.39, $p = 0.24$
Item 7 (open-ended)	0.63	0.44	$U = 165$, $p = 0.36$	1.00	$U = 131$, $p = 0.06$ *
Item 8 (optimal evacuation)	1.06	0.96	$U = 191.5$, $p = 0.68$	1.31	$U = 153.5$, $p = 0.16$
Appreciation learning with simulation	NA	3.24	NA	4.22	$p = 0.009$**

conceptual questionnaire scores of the experimental (participatory simulation) condition ($N = 26$, Mean = 61%), and the comparison condition ($N = 16$, Mean = 63%), was not significant ($t = -0.29$, $p = 0.717$). Table 2 shows that only the responses to item number 1 revealed a significant difference between the experimental condition (21/26 correct) and the comparison condition (8/16 correct, chi-squared = 4.39, $p = 0.036$). The difference is due to more students in the comparison group who stated incorrectly that both widening the doorway *and* moving faster will ensure quicker evacuation through the passageway–a statement that contradicts the faster-is-slower phenomenon. Another notable finding, is that only 5/26 of the students in the experimental and 3/16 of the students in the comparison condition, responded correctly to question 7–that one cannot know based on the information given, which classroom will evacuate faster. Most students claimed that students in classroom B that move faster, will eventually evacuate slower than their counterparts in classroom C. This indicates that the concept of the "tipping-point" in the behavior of the system–i.e., that moving faster will result in slower motion, only beyond a certain speed–was grasped by relatively few students in both conditions.

The second objective was to relate the students' appreciation of using the computational model to their conceptual understanding. We found a significant correlation between students' appreciation of the computational model and their knowledge scores ($r = 0.58$, $p = 0.002$). Namely, students with higher appreciation of the participatory simulation in terms of its contribution to their learning, also performed better on the conceptual knowledge test, and vice versa.

The final objective of this study was to relate students' understanding of the faster-is-slower phenomenon, to their mindsets. Students' mindsets are their mental inclinations to interpret the processes as either emergent/decentralized or sequential/centralized. The identification of the mindsets is based on a qualitative analysis of the responses to the open-ended questions in the questionnaire and to the interview questions Most of the responses of the students in the experimental condition (15/26) were categorized as "intermediate" according to Table 1, while only (5/26) students' responses were categorized as "full." As shown in Table 1, intermediate level responses to question 8, often suggested that evacuees should move to the bottleneck, in a "uniform, moderate" speed, when in reality, the bottleneck slows the flow of the evacuees, so that their speed is not uniform. Full responses that represent adequate complex systems thinking, acknowledge the danger of collisions and clogs in crowd evacuation, and suggest that evacuees should adjust their speed to the

TABLE 3 Student utterances in the interviews, their interpretations, and their open-ended question responses.

Student	Interview statement	Responses to questionnaire	Interpretation
A	"*If I'm under pressure I can stop and freeze, and [other] girls might bump into me. However, I can also be the one who takes responsibility and calms others down…*" "*They should evacuate like soldiers in the army, robots, one after the other, someone should organize* [them]"	"*Classroom C, since this way students will not fall and get injured and slow the others down*" (Q7 - full) "*To move in a uniform pace, without pushing and being pushed*" (Q8 - intermediate)	Believes that an evacuation process should be organized by a controlling agent, and although she acknowledges the danger in collisions, she does not mention clogs.
B	"*We cannot control the situation, we are under pressure, and focused only on ourselves, without noticing whether others need help*" "*Order, it needs to be organized*"	"*Classroom C, since they move with more caution, there will be less injuries*" (Q7 - intermediate) "*To leave slowly with caution, and not to push the others*" (Q8 - intermediate)	Focuses on self-inflicted injuries and is not aware of the role of collisions and interactions between agents. She mentions order, but not control.
C	"*There is a class that runs during the alarm… they rush to the entrance, the girls push each other…if they walk slower, each when her turn comes, they will not push and no one will fall.*" "*I do not think that he [the agent controlled by the student] has an effect. he might not want to pass, but he does not manage the others*"	"[*classroom C] The slower the pace, the higher the chance to pass faster through the doorway, since it is possible to know what happens, and prevent clogs*" (Q7- Full) "*Not slowly, quickly, but with caution, to prevent clogs from forming at some point*" (Q8 - Full)	Opposes the idea of a controlling agent, and perceives the process as decentralized. She is aware of the role of collisions, or pushes in the formation of clogs, and the faster-is slower phenomenon.

motion of their neighbors to prevent collisions/clogs. The interviews with students revealed two main themes related to their mindsets that may explain the difference between students who expressed intermediate responses and full responses. The first theme is awareness to the motion and interactions of single agents, and the second concerns the perception of whether real evacuation should (or could) be organized by a "supervising" agent. The interviews included two students (A and B) who provided intermediate level responses, and one student (C) who provided full responses as indicated in Table 3.

In her responses to the questionnaire, student C, was aware of the role of clogs in slowing down the motion of the evacuees: "[classroom C will evacuate faster] since the slower the pace, the higher the chance to pass faster through the doorway, since it is possible to know what happens, and prevent the formation of clogs". In the interview, she relates the evacuation speed, to pushes and collisions between the evacuees: "There is a class that runs during the alarm… they rush to the entrance, the girls push each other... if they walk slower, each when her turn comes, they will not push and no one will fall." That is, for student C the collisions between the agents are a salient aspect of the evacuation process. Similarly, as shown in Table 3, student A, acknowledged collisions between the agents both in the interview ("girls might bump into me"), and in the questionnaire ("will not fall and get injured and slow the others down"). However, her answer to question 8 in the questionnaire "They should move at a uniform, medium pace, without pushing or being pushed" was scored as intermediate since it indicates an unclear connection between the micro ("without pushing") and the faster-is-slower phenomenon.

Unlike student A and C, student B focused on self-inflicted dangers to individual agents and did not mention collisions between evacuees at all: "they [the agents in the simulation] are disorganized, they stumble and fall." This shows that for student B, individual agents will slow down when moving too fast, because they may stumble and fall. This is indicated also by her response to question 7 of the questionnaire. When asked which classroom will evacuate faster, she wrote "classroom C, since they move with more caution, there will be less injuries." According to student B, the *injuries themselves* slow the individual agents down, and not collisions between agents that create clogs.

The second theme that characterizes the differences between the interviewees' mindsets, is the role of supervision and control in an actual evacuation process. For example, student C related the evacuation process depicted by the simulation to the real scenario, stating that "in reality, we have no control because everyone can go out how they want." In addition, when asked whether the brown agent (the student's avatar in the participatory simulation), can influence the average evacuation rate, she said: "I do not think that he [the agent/avatar] has an effect. He might not want to pass, but he does not manage the others." Her friend, student B also commented that: "[in real evacuation] we cannot control the situation, we are under pressure and are aware only to ourselves without seeing if anyone else needs help." Both responses echo the idea that real evacuation is a chaotic process with no central control.

The responses of student A were quite different from those of student B and C. When asked whether single people/agents can impact the evacuation process, student A said: "Obviously! … If I'm under pressure, I can stop and freeze, and [other] girls might bump into me. However, I can also be the one who takes responsibility and calms others down and tries to help them leave one after the other in an orderly manner." This response described two ways in which the student as agent would experience an emergency evacuation: either by freezing with panic, or by being aware of the danger and helping others evacuate. When asked about her perception of proper evacuation, student A said: "They should evacuate like soldiers in the army, robots, one after the other, someone should organize [them]." These two quotes describe a super-agent that has control over other agents, indicating a centralized mindset.

To conclude, both the perception of evacuation as a controlled process by student A and the focus on individual injuries, and not on collisions by student B, prevented them from developing proper systems thinking about the faster-is-slower phenomenon. Only student C, who seemed to have a less centralized mindset, and was aware of the collisions between agents, was able to provide a proper explanation to the faster-is-slower phenomenon.

4.1. Study 2–the influence of ontological training

In the second part of the study, we examined whether introducing the general principles of complex systems, and demonstrating them with a different system, influenced students' readiness of learning from the computational model, and consequently, the depth of their systems thinking about the bottleneck phenomenon.

4.1.1. Findings of study 2

The first objective of the study was to examine the influence of the ontological training on students' systems thinking about the bottleneck phenomenon. We found that the ontological training group (Mean = 69%) outperformed the regular group from study 1 (Mean = 61%) in the conceptual knowledge about the bottleneck phenomenon after the intervention, but the difference was not significant ($t = -1.45$, $p = 0.16$). The difference between the groups in the scores of the open-ended questions was significant: the ontological training group had a mean score of 3.52 (of 6), and the group from study 1 had a mean score of 2.14 ($t = -2.81$, $p = 0.009$). This reflects a much higher proportion of "full" responses (8/17), that represent a complex, decentralized mindset, compared to (5/26) in the regular group from study 1. In addition, more than a third of the ontological training group (6/17) responded correctly to question 7–that one cannot know based on the information given, which classroom will evacuate faster, which is slightly higher than the proportion of the students in study 1 (5/26), but the difference is not significant (see Table 2).

The second objective of this study was to identify the role of the computational model in the ontological training. The last row of Table 2, shows that the ontological training group had a significantly higher appreciation of the effectiveness of computational models for learning (mean of 4.22 on a scale of 1–5) than the experimental group from study 1 (Mean of 3.24, $t = -4.65$, $p < 0.001$). In addition, we found that 11 / 17 of the ontological training students stated that the disease-spread simulation was "helpful," or "very helpful" for understanding the bottleneck participatory simulation. Only 2/17 stated that the simulation was "unhelpful" or that it "helped a little." Likewise, 12/17 stated that the complex systems framing was "helpful" or "very helpful" for understanding evacuation through narrow passageways, and none of the students reported that the complex systems framing was "unhelpful" or that it "helped a little."

5. Discussion

The findings of study 1 indicate that the short learning experience with the participatory simulation, did not enhance students' systems thinking, compared to the traditional lecture-based format. These findings differ from a prior comparison study in which students who used the participatory simulation to learn particle-based explanations of evaporation, outperformed their peers who studied with a regular simulation (Langbeheim and Levy, 2019). The difference between these two results has two possible origins: The first is related to the ontological framing of the systems' agents. While particle-agents are not likely to be perceived as having control over the system - people-agents can be perceived as having control. That is, direct causality is more likely to obscure agent-level and macro-level connections in the crowd evacuation model, than in the particle-based liquid model. The second explanation is related to the duration of the interaction with computational model. In the current study, students interacted with the simulation for 15–20 min, while in Langbeheim and Levy (2019), they explored the model for about 35–40 min, in two different lessons. The longer exposure to the simulation in two subsequent lessons, provided better acquaintance with the simulation as a learning aid. The strong correlation between the appreciation of learning with the simulation, and the conceptual knowledge score – corroborates this result. As in similar studies on learning with computational models of complex systems (Brom et al., 2017), students who rated the simulation as more helpful, were also more likely to perform well on the conceptual questionnaire. Furthermore, the finding from study 2, that students in the ontological training group, who used a different participatory simulation beforehand, appreciated learning with simulation significantly more than their counterparts who were not exposed to a similar simulation–is also a strong indication that students needed more time and guidance to make better use of the simulation for learning. However, at least for two of the 17 students, the important part of the training, was the "ontological" framing of the two phenomena within the perspective of complex systems, and not the use of the computational model *per-se*.

Despite the lack of an overall learning effect in study 1, the responses to item 1 (see Table 1), indicate that engagement with the participatory simulation provided clearer understanding of the faster-is-slower effect. This shows that using computational models can contribute to systems thinking, in the context emergent processes. Finally, the interviews show that students' perceptions of the evacuation phenomenon are shaped by the fact that the agents in the system are human. Some of the students, such as student A identified agents as having control over the evacuation phenomenon, and produced partial explanations of the faster-is-slower phenomenon. This may indicate a "clash" between the ordered, centralized mindset that frames evacuation as an organized process, and the disorganized depiction of the process in the simulation (Resnick, 1996). In addition, the responses of student B showed that her focus on injuries, seemed to prevent her from acknowledging the role of collisions between people, that leads to the faster-is-slower phenomenon. In order to overcoming the tendency of automatically analyzing human activity through the "direct" causality perspective, students need to develop "flexible" systems thinking that allows them to view collective phenomena also from an emergent, complex systems perspective. Indeed, student explanations of the evacuation process were more aligned with proper, emergent perspective, in study 2. However, we did not interview these students and cannot say that their mindsets were different.

Furthermore, study 2 shows that ontological training about complex systems with the disease spread participatory simulation, brought to the fore the mechanism of clogging, as indicated by the higher proportion of "full" responses. Similar to prior studies on the phenomenon of diffusion (Chi et al., 2012) and electric conduction (Slotta and Chi, 2006), framing of the evacuation phenomenon within the complex systems perspective, fostered more sophisticated systems thinking and formulate more "full" explanations that link the macro level phenomenon to agent-level interactions. However, the ontological training that was based on the computational model did not contribute much to understanding the tipping-point aspect in the faster-is-slower effect. The responses to question 7, indicate that only few students acknowledged only beyond a certain speed. Behaviors that change abruptly at tipping points, or in which local events have a dramatic effect on the system, like the "butterfly effect," are aspects of complex systems that are especially difficult to explain and comprehend (Jacobson et al., 2017).

One caveat in our study is that although participants from both studies come from the same urban area, the students in study 2 were not from the same school, and had different science teachers than the students in study 1. We cannot therefore conclude that the difference in response patterns between the group of study 2 and the group of study 1, is only a result of the intervention. However, the unanimous high rating of the contribution of the complex systems training to understanding among the students in study 2, is strong evidence that at least part of the difference in systems thinking between the groups, is attributed to the ontological training with the disease simulation.

6. Conclusions and implications

Our two studies investigated the contribution of computational models to students' system thinking about emergent, counterintuitive phenomena that are common in science education. One unique aspect of our studies is the use of participatory simulations, which are interactive forms of computational models where users play the roles of agents. Another novelty is the composition of the systems under investigation: a crowd of humans, and not animals or particles that are usually studies in science curricula. In this special issue, our studies highlight how bridging systems thinking and modeling in the context of systems of human crowds, depend on students' mindsets (i.e., an inclination to perceive the system as abiding to central control), and their readiness to learn from computational models.

Study 1 showed that the short learning experience with the bottleneck participatory simulation, did not enhance students' systems thinking compared to their counterparts that did not use the computational model (although responses to one item indicated that learning with the participatory simulation raised students' attention on the faster-is-slower phenomenon). Since prior studies on complex systems, revealed significant affordances to learning with agent-based simulations (Samon and Levy, 2017; Langbeheim and Levy, 2019), current results required further explanation. We found that students ratings of contribution of the computational model (the participatory simulation) to their understanding, was correlated with their system thinking scores. From the interviews, we realized that some students' perceptions of the computational model were obscured by their experiences with evacuation drills that were organized by teachers and supervisors. This means, that for most students, systems thinking when using an agent-based computational model in which the agents represent humans, is rooted in a direct, centralized mindset.

In study 2, we found that prior engagement with a computational model of a different phenomenon – the spread of a disease, resulted in higher readiness to learn from the bottleneck participatory simulation. This is indicated in significantly higher appreciation of the simulation among students, when compared to the participants in study 1. In addition, we found that the responses to the open-ended questions in study 2 reflected more sophisticated micro–macro connections than their counterparts in study 1. These findings shed light on the unexpectedly small learning effect in study 1, where only few students provided 'full' responses that explain the faster-is-slower phenomenon with proper agent-level and macro/crowd-level connections. It is therefore likely that the short encounter with the participatory simulation, without explicitly framing it within the complex systems perspective, was not enough for many of the students in study 1, and most of them maintained their preconceived views of evacuation as an organized, controlled process. Further research is needed to explore whether the enhanced performance was due to exposure to another model interface, or to the framing provided by the teacher, that discussed the similar attributes of the two models.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by Chief Scientist, Israeli Ministry of Education. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

EL and SS are the principal investigators. EL wrote the paper which is based on the master's theses of SB-H and GW. All authors contributed to the manuscript read, and approved the submitted version.

Funding

This study was conducted with the support of Ben-Gurion University's R&D internal grant for interdisciplinary research.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2023.1137828/full#supplementary-material

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